Cooperative optimal configuration of integrated energy system considering uncertainty factors of source-load

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Abstract. Existing studies have focused on the source-load uncertainty in the integrated energy system (IES), but ignored the impact of the integrated demand response (IDR) uncertainty. Therefore, this paper comprehensively considers the uncertainties of renewable energy, load and IDR, and proposes a two-layer optimal and configuration model. In addition, non-parametric density estimation and Copula theory are combined to improve the traditional source-load uncertainty probability model. Meanwhile, based on the double uncertainty of baseline load and price elasticity coefficient, interval fuzzy calculation method is proposed to modify the elastic coefficient. On this basis, aiming at the minimum annual comprehensive operating cost of the system, the configuration of energy hub equipment was solved in layers. The calculation results show that including IDR in configuration calculation helps to suppress the net load curve of the system, reduce the influence of user energy and intermittent power output uncertainty on system configuration results, and make the system run economically and environmentally.

1. Introduction
Integrating renewable energy into IES is an effective solution to cope with the randomness of renewable energy output [1]. As an abstract mathematical model of IES, Energy Hub (EH) is defined as a framework for production, conversion, storage and consumption of different Energy flows [2]. The diversification of Energy generation modes and the flexibility of consumption forms in EH cause strong uncertainties on both the source and demand side of EH, which brings challenges to the flexible operation of the system [3].

Wind and Pv output is greatly affected by the environment, presenting obvious uncertainty, which profoundly affects the implementation of IES planning and configuration. Moreover, the opening of the market further promotes the source-load interaction ability, and users also actively participate in the optimization scheduling work. IDR extends the traditional single form of power demand response to the multi-energy system, and can use "multi-energy complementarity" to guide users to participate in the power grid "peak clipping and valley filling" more flexibly. Compared with the traditional demand response, the effect is more obvious and the user satisfaction is higher. However, the existing IDR models all adopt deterministic models. Due to the large fluctuation of load in IES and the strong
correlation between IDR and user’s electricity consumption behavior, IDR has multiple uncertainties. In this trend, the uncertainty of both sides of source load becomes an important factor affecting the planning and configuration of integrated energy system.

Bai Kaifeng, Wang Jinran et al. has established a multi-objective optimization scheduling model taking into account the load and photovoltaic uncertainties, aiming at the supply and demand imbalance and node voltage/pressure overlimit caused by load change and photovoltaic access of IES [4-5]. Liu Mengyi et al. transformed the uncertainty problem of high proportion renewable energy system into scene analysis problem through Latin hypercube sampling method [6]. C He, X Zhang et al. proposed a distributed robust scheduling model of electric-gas integrated energy system under uncertainty to analyze the influence of real-time IDR changes on energy market clearing and regional energy sales price [7]. H. R. Massrur et al. analyzed integrated energy systems considering IDR, renewable energy and various load types under uncertain conditions, and conducted sensitivity analysis on various uncertain factors [8]. In the Literature [9], the normal distribution function is used to describe the uncertainty of load, and the interaction between energy systems is analyzed. Chen Sheng et al. considered the correlation between uncertain factors and analyzed that the higher the correlation, the higher the expected operating cost [10].

To sum up, in the current research, considering the uncertainties of both the source-load side into the optimization of IES, there are few studies. Therefore, comprehensive consideration of source-load uncertainty is more meaningful for the construction of market mechanism and IES in the future.

2. IES structure

Figure 1 shows structure of IES considering multi-energy coupling. The EH input side consists of renewable energy power generation, electric energy and gas energy as the equivalent injection source, and the user’s electric/heat/cold load are on the output side.

![Figure 1. Structure of IES.](image)

3. Uncertainty factor modeling and scene generation

3.1. Generating scenes considering uncertainty and correlation of wind power and Pv power

Kendall rank correlation coefficient, nonparametric estimation and Copula theory are used to generate the joint probability density function of scene output required for scene analysis, and clustering method is used to reduce the generated scenes. In addition, while describing the characteristics of uncertain data of variables, the correlation between them is taken into account. The specific process is as follows:

(1) Determining the edge distribution of WT and Pv output by kernel density estimation method. The first is to classify the historical data by season, for each season, $X_i^t$ and $Y_i^t$ is the sample of WT and Pv output at time $t$ on day $i$. Suppose that the probability density function of output is $f_{WT}(x^t)$ and $f_{Pv}(y^t)$ at time $t$ respectively, then the kernel density estimates are respectively:

\[ f_{WT}(x^t) = \frac{1}{n} \sum_{i=1}^{n} K_{h^t}(x^t - X_i^t) \]

\[ f_{Pv}(y^t) = \frac{1}{n} \sum_{i=1}^{n} K_{h^t}(y^t - Y_i^t) \]
Where $N_0$ is the total number of samples; $h$ is the bandwidth of the kernel density function; $K(\cdot)$ is the kernel function, and the most widely used Gaussian kernel function is selected in this paper. After the probability density function is obtained, the marginal distribution function $F_{WT}(x^i)$ and $F_{Pv}(y^i)$ of the variable can be obtained by integrating it.

(2) Calculating the correlation coefficient.

Kendall rank correlation coefficient is used to describe the correlation of WT and Pv output in the same area. The formula of Kendall rank correlation coefficient is as follows:

$$\tau = P\{(x'_i - x'_j) (y'_i - y'_j) > 0\} - P\{(x'_i - x'_j) (y'_i - y'_j) < 0\}$$

(2)

Where $\tau$ is the correlation coefficient of sample data calculated by Kendall rank correlation coefficient method. $(x'_i, y'_i)$ and $(x'_j, y'_j)$ are different subsamples randomly selected from samples $(X,Y)$.

(3) Establishing the joint probability distribution function based on Copula theory.

Choosing the Frank Copula function that can take into account the non-negative and negative correlations can obtain the joint probability distribution function of WT and Pv output as follows:

$$F(x'_i, y'_i) = c(F_{WT}(x'_i), F_{Pv}(y'_i))$$

(3)

(4) Sampling data and Reducing scenes

The joint probability distribution function of each period is sampled and the established joint distribution function of WT and Pv output is repeatedly inverted through the Monte Carlo simulation method to generate a large number of WT and Pv output data considering the uncertainty and correlation. The clustering way is used to reduce scenes, and finally obtain a typical day scene of WT and Pv output.

3.2. Modeling of baseline load uncertainty

(1) By kernel density estimation method to determine the edge distribution of WT and Pv output.

By Latin Hypercube Sampling (LHS) technology to generate relevant scenes of the target user’s load demand. In the Literature [11], the Gaussian distribution function is selected to generate the load demand scenes of the target users, and the expression is as follows:

$$F(x'_i, \sigma^2_i) = \frac{1}{\sqrt{2\pi}\sigma^2_i} \int_{-\infty}^{x'_i} \exp \left[ -\frac{(x'_i - \mu'_i)^2}{2\sigma^2_i} \right] dx'_i$$

(4)

Where $\mu_i$ is the average value of random variables; $\sigma^2_i$ is the standard deviation of random variables; $x'_i$ is the value of the random variable at time $t$. The steps for sampling load demand variables that conform to the Gaussian distribution using LHS are as follows:

Step 1: Dividing the load demand distribution function into $N$ equal probability intervals;

Step 2: $P_{\text{demand}}$ is randomly selected from any equal probability interval $[(i-1)/N, i/N]$:

$$P_{\text{demand}} = \text{rand}[0,1] + (i-1)/N$$

(5)

Step 3: Inverting the probability distribution representing the cold/heat/electric load demand, and obtain the baseline load demand within the probability range $[(i-1)/N, i/N]$:

$$P_{\text{demand}} = F^{-1}(P_{\text{demand}})$$

(6)

Step 4: Judging whether the current sample number reaches the set initial scene number $K$. If the initial number of scenes is not reached, go back to step 2 and continue the simulation until the initial number of scenes is reached. On the contrary, the number of scenes is output.

3.3. IDR uncertainty model

The sensitivity of different energy users to energy prices is significantly different. The demand price elasticity coefficient $\varepsilon$ is used to describe the sensitivity of energy users to energy sales prices. The implementation of price demand response to controllable load changes is:
Where, \( \Gamma \) contains three loads; \( \Gamma_{Lt} \) is the load at time \( t \) after IDR; \( \Psi(EL, HL, CL) \) is price elasticity coefficients of electric, heat and cold loads respectively, which are expressed in the Formula (8).

In the actual process, similar to the uncertainty of traditional price DR, IDR uncertainty also comes from the following two aspects: uncertainty of load elasticity coefficient and baseline load, which is determined by the uncertain scene generation method in the previous section [12].

\[
\psi_{(\varepsilon_L, H_L, C_L)}(t, t^0) = \frac{\frac{p_{(E_L, H_L, C_L)}(t^0)}{I_{(E_L, H_L, C_L)}(t)}}{\frac{\partial f_{(E_L, H_L, C_L)}(t)}{\partial p_{(E_L, H_L, C_L)}(t)}}
\]

(8)

Where, \( L_{E,L,H,L,C,L} \) and \( \Psi_{(E_L, H_L, C_L)} \) are the baseline load and load elasticity coefficient after considering uncertainty respectively.

By using interval numbers to represent the user's demand elasticity coefficient, and simulate the actual response through the interval numbers. According to the historical load reduction range after the implementation of IDR, the upper and lower limits of the elasticity interval can be derived:

\[
\begin{align*}
\varepsilon_{\mu}^* - \varepsilon_{\sigma}^* & = \frac{\Delta P_{\mu_{\text{max}}} / P_0}{\Delta L_{\mu} / L_0} \\
\varepsilon_{\mu}^* + \varepsilon_{\sigma}^* & = \frac{\Delta P_{\mu_{\text{min}}} / P_0}{\Delta L_{\mu} / L_0}
\end{align*}
\]

(10)

Therefore, the determination interval of the elasticity coefficient is described as:

\[
[\varepsilon_{\mu}^* \cdot \min, \varepsilon_{\mu}^* \cdot \max] = \{\varepsilon_{\mu}^* \mid \varepsilon_{\mu}^* \cdot \min \leq \varepsilon_{\mu}^* \leq \varepsilon_{\mu}^* \cdot \max\}
\]

(11)

Fuzzy function can be used to express the uncertainty in the interval, and the upper and lower limits of the elasticity coefficient interval are used as the determined membership function parameters. Therefore, this article uses triangular membership functions to deal with the uncertainty.

The triangular membership function of the uncertainty of elasticity coefficient is as follows:

\[
f(\tilde{\varepsilon}_{\mu}^*) = \begin{cases} 
0 & \text{otherwise} \\
\frac{2(\tilde{\varepsilon}_{\mu}^* - \varepsilon_{\mu}^* \cdot \min)}{\varepsilon_{\mu}^* \cdot \max - \varepsilon_{\mu}^* \cdot \min} & \varepsilon_{\mu}^* \cdot \min \leq \tilde{\varepsilon}_{\mu}^* \leq \varepsilon_{\mu}^* \cdot \min + \varepsilon_{\mu}^* \cdot \max \\
\frac{2(\tilde{\varepsilon}_{\mu}^* - \varepsilon_{\mu}^* \cdot max)}{\varepsilon_{\mu}^* \cdot min - \varepsilon_{\mu}^* \cdot max} & \varepsilon_{\mu}^* \cdot min + \varepsilon_{\mu}^* \cdot max < \tilde{\varepsilon}_{\mu}^* \leq \varepsilon_{\mu}^* \cdot \max
\end{cases}
\]

(12)

Where \( \tilde{\varepsilon}_{L,H,C} \sim N(\varepsilon_{L,H,C}), \varepsilon_{\mu}^* \) and \( \varepsilon_{\sigma}^* \) respectively represent the expected value and standard deviation of the normal distribution \( N \). The tangent point of the arc curve represents the price elasticity coefficient before optimization, and the triangle represents the fuzzy number of the price elasticity coefficient triangle. Therefore, the price elasticity coefficient proposed is not a point, but a variable on a tangent line, which makes the price elasticity coefficient have a range of variation in the model.

Then, after the based on price IDR considering uncertainty, the load after IDR at time \( t \) is:

\[
\tilde{\Gamma}_{(E_L, H_L, C_L),t} = \frac{\tilde{\Gamma}_{0,t} \left(1 + \sum_{t'=1}^{T} \psi(t, t^0) \times \frac{p_{(E_L, H_L, C_L)}(t') - p_{0,t',t'}}{p_{0,t',t'}} \right)}{p_{0,t',t'}}
\]

(13)

4. A two-layer optimal configuration model considering uncertainty factors

In order to consider the influence of uncertain factors on the EH optimization configuration and operation, this section builds a two-layer multi-scenes planning model that combines EH planning and multi-scenes operation based on two-layer stochastic planning.
4.1. The upper layer model
The objective function is:

\[ \text{Min } C_{\text{total}} = C_{\text{inv}} + C_{\text{OM}} + C_{\text{IDR}} + C_{\text{eco}} + C_{\text{WT}} + C_{\text{PV}} \]  \hspace{1cm} (14)

(1) Investment cost:

\[ C_{\text{inv}} = \sum_{i=1}^{N} \sum_{m=1}^{\Omega_i} \left\{ \left( C_{\text{cap},i,m} P_{\text{rated},i,m} + C_{\text{fix},i,m} \right) \cdot \mu_{\text{CRF}}(r,n) \right\} \]  \hspace{1cm} (15)

Where \( i \) is the device type; \( \Omega_i \) is the set of device type \( i \); \( C_{\text{cap},i,m} \) is the Variable capacity unit investment cost of the \( m \)-th of the \( i \)-th device type; \( C_{\text{fix},i,m} \) is the Fixed capacity unit investment cost of the \( m \)-th of the \( i \)-th device type; \( \sigma_{i,m} \) is the binary variable of whether to configure the device.

(2) Operation and maintenance cost:

\[ C_{\text{OM}} = \left( C_{\text{mnt}}^{\text{op}} + C_{\text{mnt}}^{\text{op}} \right) \mu_{\text{CRF}}(r,n) \]  \hspace{1cm} (16)

Where \( C_{\text{mnt}}^{\text{op}} \) and \( C_{\text{mnt}}^{\text{op}} \) respectively are the maintenance cost and operation cost in \( n \)-th year.

(3) IDR cost:

Demand side response compensation cost can be expressed as follows:

\[ C_{\text{IDR}} = 365 \sum_{t=1}^{24} \left( \sum_{j=1}^{N_i} C_{\text{cut},t,j} P_{\text{cut},t,j} + \sum_{j=1}^{N_i} C_{\text{mov},t,j} |P_{\text{mov},t,j}| \right) \cdot \mu_{\text{CRF}}(r,n) \]  \hspace{1cm} (17)

Where \( C_{\text{cut},t,j} \) and \( P_{\text{cut},t,j} \) are respectively the unit compensation cost and load reduction of \( j \)-th load at time \( t \); \( C_{\text{mov},t,j} \) and \( P_{\text{mov},t,j} \) are respectively the unit compensation cost and transfer load of \( j \)-th load at time \( t \).

(4) Pollutant discharge penalty cost:

\[ C_{\text{eco}} = 365 \sum_{n=1}^{N_i} \sum_{q=1}^{Q} \left( \sum_{i=1}^{Q} \left( e_q \cdot \phi_{q,i} \cdot P_{\text{rated},i} + e_q \cdot \phi_{q,i} \cdot F_{\text{rated},i} \cdot \lambda_{i} \right) \right) \]  \hspace{1cm} (18)

Where \( q \) is the type of pollution gases; \( e_q \) is the treatment cost of type \( q \) pollution gas; \( \phi_{q,i} \) is the emission of type \( q \) pollutant gas. \( \Phi_{q,i} \) is the emission of type \( q \) pollutant gas when purchasing gas.

(5) Wind abandonment penalty cost:

\[ C_{\text{WT}} = 365 \sum_{t=1}^{24} \left( P_{\text{WT,max}}^{t} - P_{\text{WT,oc}}^{t} \right) \delta \]  \hspace{1cm} (19)

Where \( \delta \) is the penalty coefficient for abandoning wind power; \( P_{\text{WT,max}}^{t} \) is the maximum wind power at time \( t \); \( P_{\text{WT,oc}}^{t} \) is the wind power actually consumed by the IES at time \( t \).

4.2. The lower layer model
The lower layer takes the lowest operating cost of IES as its objective function, which mainly includes energy purchase cost and equipment maintenance cost. Its objective function is as follows:

\[ \text{Min } C_{\text{OM}} = ( C_{\text{mnt}}^{\text{op}} + C_{\text{mov}}^{\text{op}} ) \mu_{\text{CRF}}(r,n) \]  \hspace{1cm} (20)

(1) Annual maintenance cost:

\[ C_{\text{mnt}}^{\text{op}} = \sum_{i=1}^{N} \sum_{m=1}^{\Omega_i} \left( C_{\text{cap},i,m} P_{\text{rated},i,m} + C_{\text{fix},i,m} P_{\text{mov},i,m} \right) \cdot \lambda_{i,m} \]  \hspace{1cm} (21)

(2) Energy purchase cost:

\[ C_{\text{op,gen}} = 365 \cdot \sum_{i=1}^{N} \sum_{m=1}^{\Omega_i} \sum_{n=1}^{N_q} \sum_{t=1}^{24} \left( P_{\text{CHP},i,m,n,t}^{\text{gen}} \cdot L_{\text{gen}} + P_{\text{NSU},i,m,n,t}^{\text{gen}} \cdot \lambda_{q,t} \right) \]  \hspace{1cm} (22)

\[ C_{\text{op,grid}} = 365 \cdot \sum_{i=1}^{N} \sum_{m=1}^{\Omega_i} \sum_{n=1}^{N_q} \sum_{t=1}^{24} \left( P_{\text{buy},i,m,n,t}^{\text{puf}} \lambda_{b_{i,m,n,t}}^{\text{buy}} + P_{\text{sell},i,m,n,t}^{\text{puf}} \lambda_{s_{i,m,n,t}}^{\text{sell}} \right) \]  \hspace{1cm} (23)
Where $p_{buy, i,m,ss,t}$ is the electricity purchased from the grid in scene SS at time t; $\lambda_{buy, i,m,ss,t}$ is the price of power purchased from the grid in scene SS at time t.

4.3. Constraints

(1) Energy balance constraint:

$$\sum_{m \in CH} p_{CHP, m,ss,t} + \sum_{m \in WT} p_{WT, m,ss,t} + \sum_{m \in ES} p_{ES, char, m,ss,t} - \sum_{m \in ES} p_{ES, dis, m,ss,t} + \sum_{m \in CHP} p_{m,ss,t}^{CHP} + \sum_{m \in GT} p_{GT, m,ss,t}^{GT} = E_{ES, char} + E_{ES, dis} - E_{CHP, m,ss,t} - E_{GT, m,ss,t} - E_{LS, t}$$  (24)

(2) Energy purchase constraints:

$$p_{buy, i,m,ss,t} \leq p_{buy, max}$$
$$p_{sell, i,m,ss,t} \leq p_{sell, max}$$
$$0 \leq \zeta_{i,m,ss,t}^{buy} + \zeta_{i,m,ss,t}^{sell} \leq 1$$  (27)

Where $\zeta_{i,m,ss,t}^{buy}$ and $\zeta_{i,m,ss,t}^{sell}$ are 0-1 variables which do not occur at the same time.

(3) Operation constraints:

$$p_{GT, m,ss,t}^{GT} \leq P_{GT, m,ss,t}^{GT} \leq P_{GT, m,ss,t}^{GT, max}$$
$$p_{HR, m,ss,t}^{HR} \leq P_{HR, m,ss,t}^{HR} \leq P_{HR, m,ss,t}^{HR, max}$$
$$p_{CHP, m,ss,t} \leq P_{CHP, m,ss,t} \leq P_{CHP, m,ss,t}^{CHP, max}$$
$$p_{AC, m,ss,t} \leq P_{AC, m,ss,t} \leq P_{AC, m,ss,t}^{AC, max}$$
$$p_{EC, m,ss,t} \leq P_{EC, m,ss,t} \leq P_{EC, m,ss,t}^{EC, max}$$  (28)

(4) IDR constraints:

$$\Delta L_{ss,t,min} \leq \Delta L_{ss,t} \leq \Delta L_{ss,t,max}$$  (29)

Where $\Delta L_{ss,t,min}$ and $\Delta L_{ss,t,max}$ are the upper and lower limits of IDR respectively.

![Figure 2](image_url)

**Figure 2.** Solution method of the two-layer model considering uncertainty of the source-load.
5. Model solving
In this paper, the upper layer solves 0-1 state variables to determine equipment configuration in IES. In order to avoid processing discrete variables easily falling into local optimal solution, quantum genetic algorithm combined with quantum computing and genetic algorithm is used to increase the possibility of chromosome changes. The lower layer solves the continuous variable according to the upper discrete variable to determine the hourly output of the equipment, and then returns the solution result to the upper layer. After the genetic variation of the quantum revolving door, a new generation of upper variable group is generated. The upper and lower layer results are iterated continuously until the global optimal solution is obtained. The Figure 2 shows the specific solution process of IES planning model.

6. Case study

6.1. Analysis of uncertain scenes
Using K-means clustering method to reduce scenes from 10,000 uncertain and relevant WT and Pv output data, we can finally get 6 typical daily output scenes. In Figure 3, the results of scenes reflect the uncertainty and correlation of WT and Pv output, which is conducive to the optimization of the IES configuration. Using the LHS method to sample and generate 10000 load demand scenes and dividing the year seasonally. In order to reduce the amount of calculation, the backward reduction method is used to reduce the load demand scenes. And finally can get the typical scenes of load demand of 6 target users, as shown in Figure 4.
6.2. Analysis of optimized configuration results

In order to verify the effectiveness of the proposed optimal configuration method, three cases are designed for comparative analysis.

1) Case 1: Optimized EH configuration considering renewable energy uncertainty;
2) Case 2: Optimized EH configuration considering load uncertainty;
3) Case 3: Optimized EH configuration by considering source-load and IDR uncertainties;

By solving the above optimization configuration problems, the cost and optimization configuration results of EH in different cases are obtained, as shown in Table 1 and Table 2 respectively.

| Case  | Cinv/(M) | COM/(M) | Ceco/(M) | CIDR/(M) | CWT/(M) | Ctotal/(M) |
|-------|----------|---------|----------|----------|---------|------------|
| 1     | 1.95     | 3.4     | 1.59     | -        | 0.526   | 7.466      |
| 2     | 1.35     | 3.25    | 1.22     | -        | 0.425   | 6.245      |
| 3     | 1.58     | 3.06    | 1.38     | 0.1685   | 0.145   | 6.3335     |

Table 2. Optimized configuration result.

| CHP | GT | EC | AC | ES | HR | WT | Pv |
|-----|----|----|----|----|----|----|----|
| I   | II | I  | II | I  | II | I  | I  |
| Case1| 0  | 1  | 1  | 0  | 2  | 2  | 1  |
| Case2| 1  | 0  | 1  | 0  | 1  | 1  | 1  |
| Case3| 1  | 0  | 0  | 1  | 1  | 0  | 2  |

Considering that Case 1 requires the largest number of equipments to suppress the influence of strong uncertainties of WT and Pv, large capacity CHP units are required to ensure supply quality. The unit capacity investment of CHP units is high, so Case 1 has the highest investment cost. However, the energy consumption habit of users is less uncertain compared with the change of renewable energy, so the capacity of equipment needed to be invested in Case 2 is smaller and the number of equipment is reduced, in addition the investment cost is reduced by 30.77% compared with Case 1. The strong uncertainty of renewable energy makes the purchase of electricity required for case 1 to suppress the net load curve, so the penalty cost of wind curtailment in Case 2 is reduced by 19.2% compared with Case 1, and the emission cost is lower. The addition of IDR behavior in Case 3 to some extent suppressed the uncertainty on both sides of source-load, reduced the dependence on CHP unit capacity, and reduced the investment cost slightly compared with Case 1.Compared with Case 2, Case 3 comprehensively considers the uncertainties of source-load side and IDR, which is closer to the actual working condition.

7. Conclusions

In this paper, non-parametric density estimation and Copula theory are combined to improve the traditional source-side uncertainty probability model, and the interval fuzzy calculation method is proposed to obtain the source-side uncertainty model for the dual uncertainties of baseline load and load elasticity coefficient. On this basis, a two-layer IES planning and configuration model is proposed to minimize the annual comprehensive cost. The results show that when only considering the uncertainty of the renewable energy generation side and the user load side, the annual comprehensive cost of the system has increased significantly, but the comprehensive consideration of the IDR value can restrain WT, Pv output and load fluctuations to a certain extent, and smooth the net load curve. Therefore, taking into account the IDR is conducive to improving the economy and environmental protection of the system.
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