Study on integrated energy microgrid energy purchase strategy with demand-side response in market environment

Zhenkun Li [a], Yicong Yao [a], Nan Zhao [b], Jie Shan [a], Yang Fu [a,*]

[a] *Engineering Research Center of Offshore Wind Technology Ministry of Education, Shanghai University of Electric Power, Shanghai 200090, China*
[b] *School of Engineering, Lancaster University, LA1 4YW, Lancaster, UK*

Corresponding author: Yang Fu

E-mail: yaoyicong98@163.com

Abstract

Integrated energy microgrids (IEM) have emerged as an effective way to improve energy efficiency and promote distributed energy utilization. IEM systems acquire electricity and gas from external markets and supply electricity/heat/cold to users. In this paper, we study the optimal energy purchase strategy for IEM, considering the impact of demand response incentives. Firstly, considering the uncertainties, we construct an IEM medium- and long-term market multi-energy purchase model based on conditional value-at-risk, optimizing the portfolio of electricity and gas purchases, as well as their proportion in total energy amount. Subsequently, based on medium- and long-term daily energy supply curves and day-ahead load forecast results, a spot market energy purchase model is established to optimize the spot purchase of electricity and gas, maintaining the supply-demand balance while minimizing operating costs. Furthermore, we design demand response incentives and develop a master-slave game model between IEM and users to guide the formulation of the energy purchase strategy by incorporating corrected load data as feedback. The energy purchase strategies are resolved by the GUROBI solver, while the optimization of demand response incentives is carried out through the PSO algorithm, all based on the MATLAB platform. The adaptability of the proposed model and strategy is verified.

Keywords: Integrated energy microgrid; Electricity and gas markets; Energy purchase strategy; Conditional value-at-risk theory; Demand response incentives

1. Introduction

With the strategic goal of "carbon peaking" and "carbon neutral" proposed by the Chinese government, integrated energy microgrid (IEM) has emerged as a prominent research topic in recent years due to its effectiveness in improving energy utilization efficiency and promoting the consumption of renewable energy [1-4]. In the whole process of energy flow, IEM plays a crucial intermediary role by procuring electricity and natural gas from the upper-level networks and supplying energy to the lower-level users. In the market environment, as an independent entity, IEM faces the challenge of optimizing its benefits while mitigating potential market risks. Consequently, conducting a study on the energy purchase strategy of IEM becomes imperative.

Nomenclature

Abbreviations

AC	absorption chiller
CHP	combined heat and power
CVaR	conditional value-at-risk
EB	electric boiler
EC	electric chiller
ESS	electricity storage system

HSS heat storage system
IEM integrated energy microgrid
PV photovoltaic units
WT wind turbines

Sets and indices

i energy
$L(x_Y, s)$ IEM energy purchase cost risk loss function associated with the strategy set x_Y and the scenario s
n user
s typical scenarios set
t time
w energy storage system
x_D energy purchase strategy in the spot stage for IEM
x_n strategies for user n
x_Y energy purchase strategy in the medium- and long-term stage for IEM

Parameters and constants

C_D^e / C_D^g spot electricity/gas costs
$C_{D,s}^e$ / $C_{D,s}^g$ spot electricity/gas costs under scenario s
C_{ESS} / C_{HSS} maintenance costs of *ESS/HSS*
C_Y^e / C_Y^g medium- and long-term electricity/gas costs
f risk aversion factor
H low calorific value of natural gas
p_M^e / p_M^h maintenance price of *ESS/HSS*
p_t^i TOU price of energy i
$p_t^{i,\max}$ / $p_t^{i,\min}$ maximum/minimum limits of TOU price of energy i
$price_{D,f,t}^e$ / $price_{D,f,t}^g$ forecasted spot electricity/natural gas price at time t
$price_{D,s,t}^e$ / $price_{D,s,t}^g$ spot electricity/natural gas price at time t under scenario s
$price_Y^e$ / $price_Y^g$ medium- and long-term electricity/natural gas price
$prob$ the probability of satisfying the mathematical expressions in parentheses
$P_{AC,t}$ power of *AC* at time t
$P_{AC}^{\max}$ / $P_{AC}^{\min}$ maximum/minimum power of *AC*
$P_{connect}^e$ / $P_{connect}^g$ supply power of the external grid/gas network
$P_{connect}^{e,\max}$ / $P_{connect}^{g,\max}$ maximum supply power of the external grid/gas network
$P_{CHP,t}^e$ / $P_{CHP,t}^h$ electric power/thermal power of *CHP* at time t
$P_{CHP}^{e,\max}$ / $P_{CHP}^{e,\min}$ maximum/minimum electric power of *CHP*
$P_{CHP}^{h,\max}$ / $P_{CHP}^{h,\min}$ maximum/minimum thermal power of *CHP*
$P_{extra,t}^e$ the power exceeding the upper limit of IEM consumption at time t
$P_{EB,t}$ power of *EB* at time t
$P_{EB}^{\max}$ / $P_{EB}^{\min}$ maximum/minimum power of *EB*
$P_{EC,t}$ power of *EC* at time t
$P_{EC}^{\max}$ / $P_{EC}^{\min}$ maximum/minimum power of *EC*
$P_{L,f,t}^e$ / $P_{L,f,t}^h$ / $P_{L,f,t}^c$ forecasted electric/thermal/cooling loads at time t on the spot stage
$P_{L,s,t}^e$ / $P_{L,s,t}^h$ / $P_{L,s,t}^c$ electric/thermal/cooling load at time t under scenario s
$P_{n,t}^e$ / $P_{n,t}^h$ / $P_{n,t}^c$ user n initial electric/thermal/cooling load at time t
$P_{PV,s,t}$ power of *PV* at time t under scenario s
$P_t^{e,\text{int}}$ / $P_t^{h,\text{int}}$ / $P_t^{c,\text{int}}$ IEM initial electric/thermal/cooling power at time t
$P_{wSS}^{c,\max}$ / $P_{wSS}^{d,\max}$ power limits for energy charge/discharge
$P_{WT,s,t}$ power of *WT* at time t under scenario s
$r_{n,t}^e$ / $r_{n,t}^h$ / $r_{n,t}^c$ the normalized user n load ratio at time t
$r_{n,t}^{'i}$ the load difference of the ratios between user n and the strategy at time t
R_{CVaR} risk loss value based on the *CVaR*
R_D^e revenue from the sale of electricity
R_n^{int} user n initial cost
R_n user n cost
R_{VaR} maximum possible risk of loss at confidence level β
$S_{wSS,t}$ energy storage state of *wSS* at time t

$S_{wSS}^{\max}$ / $S_{wSS}^{\min}$ energy storage state limits of *wSS*
U_n^C cost satisfaction of user n
U_n^U energy use satisfaction of user n
β confidence level
δ auxiliary variable in the calculation
η_{AC} cooling power efficiency of *AC*
η_{CHP}^e / η_{CHP}^h electric / thermal power efficiency of *CHP*
η_{EB} power generation efficiency of *EB*
η_{EC} cooling power efficiency of *EC*
$\eta_n^{eh,sub}$ / $\eta_n^{ec,sub}$ electric thermal/cooling load conversion efficiency of user n
η_w^c / η_w^d charge / discharge power efficiency of *wSS*
$\lambda_{n,t}$ discount received by user n at time t
ξ_s auxiliary variable in the calculation
$\sigma_{n,t}$ the similarity of user n at time t
τ satisfaction weight preference of user n
ϕ_s probability of occurrence of scenario s
ω_1 / ω_2 / ω_3 the influence coefficients of interruptible load, transferable load and substitutable load on user satisfaction

Variables
$P_{D,s,t}^e$ / $P_{D,s,t}^g$ the simulated winning spot electric/gas power at time t under scenario s
$P_{D,t}^e$ / $P_{D,t}^g$ spot electric/gas power at time t
$P_{n,t}^{'i}$ user n load power after IDR at time t
$P_{n,t}^{i,cut}$ / $P_{n,t}^{i,sh}$ / $P_{n,t}^{i,sub}$ user n interruptible/ transferable/ substitutable load at time t
$P_{wSS,t}$ power of *wSS* at time t
$P_{Y,t}^e$ / $P_{Y,t}^g$ supply power for the medium- and long-term contract of electricity/gas at time t
r_t^e / r_t^h / r_t^c the normalized ratio of IEM optimal energy supply powers at time t
λ_0 the optimal discount
$\mu_{wSS,c,t}$ / $\mu_{wSS,d,t}$ 0-1 variables for charge/discharge states at time t
σ_D / σ_S discontinuity points

IEM allows for the separate procurement of electricity and natural gas from various submarkets within the external market. However, there is a notable dearth of literature concerning IEM energy purchase strategy, as existing research predominantly focuses on the electricity market alone. In reference [5], electricity retailers allocated the proportion of electricity purchased from the contract, day-ahead, and real-time markets to reduce risk and increase profits. Reference [6] explored the electricity portfolio optimization problem for large consumers, taking into account self-generation power, day-ahead spot market, and forward contracts, and proposed a mixed-integer programming model to minimize expected costs and risks. References [7-8] considered the risk preferences of electricity buyers and constructed a model to identify the best procurement portfolio scheme, while quantitatively assessing risk. Several studies have analyzed the electricity purchasing strategies of retailers with the aim of considering profit risk while utilizing the conditional value-at-risk (CVaR) as a risk metric [9-11]. Reference [12] designed a genetic algorithm for determining the optimal short-term demand-side offer in both the day-ahead and intraday markets, optimizing the proportion of energy purchased by electricity sellers in each market. Reference [13] introduced a unified energy portfolio optimization framework for data centers to determine the optimal utilization portfolio. In [14], electricity sellers utilized self-generation, forward contracts, call options, and interruptible contracts to hedge risk by managing the portfolio between different contracts, in order to determine the best power procurement strategy. A power purchase model for electricity sales companies that combines renewable energy output and medium- and long-term power trading has been developed based on CVaR [15]. The above research provides valuable insights into the development of IEM's energy purchase strategy. However, existing works still lack considerations for the natural gas market. In contrast to conventional electricity procurers, IEM possesses internal energy coupling property that enables it to fulfill energy demands by buying either electricity or gas. Moreover, the quantities of electricity and gas IEM acquired exhibit a mutually influential relationship. Facing price fluctuations originating from both the electricity and gas markets, the energy procurement challenge in IEM lies in the portfolio of electricity and gas quantities, as well as the allocation of proportions for medium- and long-term market and spot market purchases, for both electricity and gas. For now, few studies have been conducted on both energy selection preference and time-scale allocation in the energy purchase strategy of IEM.

The manipulation of IEM in the energy market aims to mitigate the risk on the energy purchase side. However, similar uncertainty also prevails on the load side, where disparities in energy consumption between the actual load and the forecasted load can lead to losses for IEM. In this context, demand response (DR) serves as a regulatory tool for the power system, enabling increased flexibility and economic efficiency while minimizing the effects of load fluctuations. With conventional energy services progressively falling short in catering to the varied demands of users, integrated demand response (IDR) emerged. Reference [16] presented an optimal operational strategy for an integrated gas-electric energy system that takes into account IDR and uncertainty in wind power generation. In [17], a data-driven two-stage distributionally robust CIES scheduling model was constructed to coordinate IDR and uncertainty in renewable energy generation. Reference [18] proposed a coordination approach that addresses uncertainty and IDR across different scheduling stages in integrated energy system operation. IDR has been well-established to be effective in mitigating load uncertainty and optimizing energy procurement. However, guiding users to participate in the response remains a challenge that operators must address. Traditional approaches, such as time-of-use (TOU) price or incentive distribution for response [19-21], do not account for differences among users and may not motivate them effectively. A solution proposed in the reference [22] is to create retail packages that incorporate IDR and provide different discounts for consumers. Another overlooked point is that electric/thermal/cooling energy only responds individually without coordinating different loads simultaneously to match the optimal electric/thermal/cooling power within IEM, which instead hinders the efficient consumption of purchased energy and the overall optimal operation. In light of the participation in demand response leading to load volume changes, it becomes imperative to consider the impact of demand response incentives on user loads in advance when formulating the energy purchase strategy of IEM.

Considering the above issues, this paper proposes an IEM two-stage energy purchase strategy, which decides the proportional allocation of energy purchases at the medium- and long-term scale and the spot scale and the optimal portfolio of electricity and gas purchases. Firstly, an IEM medium- and long-term market multi-energy purchase model based on CVaR is constructed to minimize the annual cost. By evaluating various energy purchase schemes, this model enables IEM to achieve the optimal selection of electricity and gas and the optimal allocation of medium- and long-term markets and spot markets, determining the medium- and long-term energy purchase quantities. Then, combined with the daily medium- and long-term supply curves and the forecast results of the next day's load demand, renewable energy production, and spot price, a spot market energy purchase model is established, which optimizes spot electricity and gas purchase quantities and eliminates energy deviations during operation. Additionally, we develop differentiated demand response incentives, optimizing incentive parameters and user loads through a master-slave game between IEM and users. The corrected load informs the adjustment of the energy purchase strategy. Finally, the rationality of the method is verified through the simulation.

The major contributions of this paper are as follows:

- We develop an energy purchase strategy for IEM in the electricity and gas markets, considering the uncertainties in the energy purchase process, which achieves the optimal portfolio of purchased electricity and gas, as well as the optimal allocation of purchased energy in the medium- and long-term scale and the spot scale.
- IEM two-stage energy purchase optimization models are established, namely the medium- and long-term multi-energy purchase market and the spot market energy purchase model. The former uses CVaR to minimize the risk caused by uncertainties, while the latter aims to minimize the spot cost.
- A similarity index between the electric/thermal/cooling load of user consumption and the optimal energy supply powers of IEM is proposed, which provides differentiated demand response incentives to users according to the similarity.
- A master-slave game model between IEM and users is established to simulate the load variation under different incentives. The corrected loads are fed back to IEM, providing a reference for the formulation of an energy purchase strategy.

The remainder of this paper is organized as follows. Section 2 introduces the system structure and energy purchase architecture of IEM. IEM energy purchase optimization models in the market environment are proposed in Section 3. After that, Section 4 proposes model solving. Section 5 details the case simulation. Finally, conclusions are drawn in Section 6.

2. System structure and energy purchase architecture of IEM

2.1. System structure of IEM

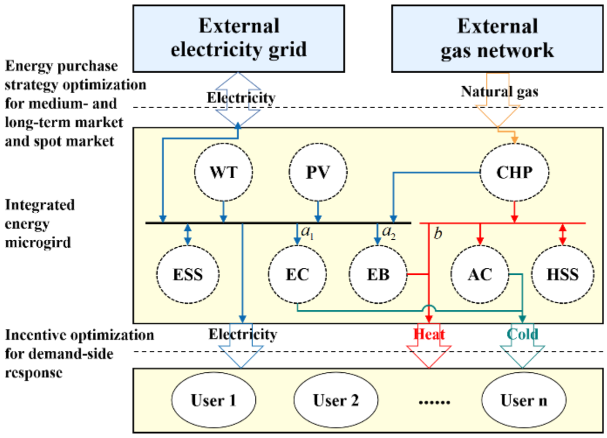

Fig. 1. The system structure of IEM.

The system structure of IEM is shown in Fig. 1. The IEM is characterized by the interdependence and interaction between various energy sources, and it allows for the acquisition of electricity and natural gas from external networks. Due to the internal coupling conversion, IEM is able to meet the demand for electricity, heat, and cold on the user side by the energy supply from the grid or the gas network.

During the electricity procurement process, the IEM establishes transactions with the external grid through the electricity market, encompassing the electricity medium- and long-term market and the electricity spot market. Likewise, to secure the supply of natural gas, IEM actively engages in the gas medium- and long-term market and the gas spot market. The medium- and long-term market is critical for energy consumers as it provides a means to hedge the spot price risk and achieve optimal allocation of resources. Due to the uncertainties of long-term forecasting and the substantial fluctuations in both load and renewable energy production, the energy purchased through medium- and long-term contracts may not align with the future actual energy demand. Consequently, the utilization of the spot market becomes necessary to ensure power balance.

The electricity market operates differently from the natural gas market in transactions. The electricity market is characterized by spot transactions as the dominant form of trading, complemented by medium- and long-term contracts. Conversely, natural gas transactions primarily occur in the medium- and long-term market. The advent of policies that promote medium- and long-term trading is likely to engender growth in the medium- and long-term procurement of electricity [23].

2.2. IEM two-stage energy purchase architecture with demand-side response

On the energy procurement side, the cost of operating the IEM is affected by electricity and natural gas prices. By replacing expensive energy with cheaper ones and leveraging the substitutability between internal energy, the IEM can effectively minimize expenses. This cost advantage can then be leveraged as a pricing advantage.

The energy purchase architecture can be divided into medium- and long-term stage and spot stage, as shown in Fig. 2. The IEM makes energy procurement decisions based on the electricity and gas markets, prioritizing the acquisition of energy sources that are priced lower or exhibit stable price trends according to its risk tolerance. This energy source serves as the primary supply, while another type of energy is used as a supplement. This approach ensures minimal price volatility risks. From time scales, market competitiveness results in spot prices often exhibiting characteristics of high peak prices. IEM protects its interests by signing medium- and long-term energy to counterbalance the high cost of spot energy. However, the transaction opening window for medium- and long-term market contracts is early, and the future spot price trend is unpredictable. Recklessly and blindly signing medium- and long-term purchase quantities will cause economic losses. To address this, we propose the IEM two-stage energy purchase architecture.

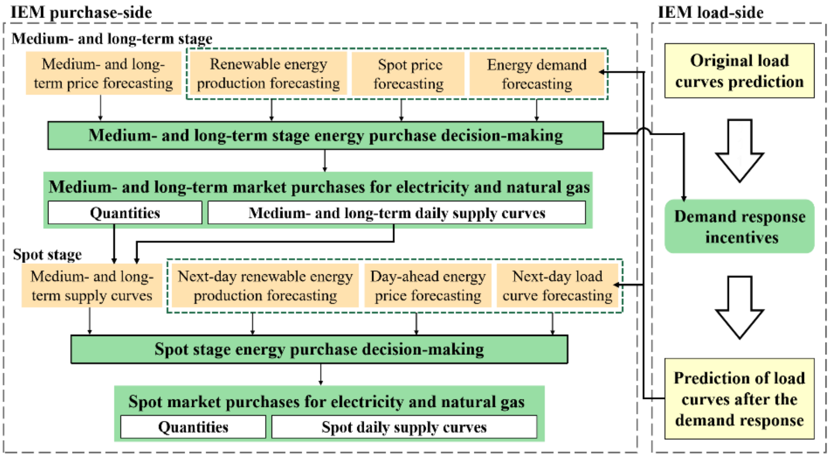

Fig. 2. Two-stage energy purchase architecture with demand-side response.

In the medium- and long-term stage, it is the basic task of IEM to forecast the energy demand, renewable energy production, and monthly prices for the coming year. Based on the forecast results, IEM makes decisions on different energy purchase schemes, which involve a specific allocation of energy purchase quantities for various energy sources and at different time scales, determining the medium- and long-term purchases. In the spot stage, external networks provide electricity and natural gas to IEM according to the agreed-upon medium- and long-term contracts. After updating the forecast of the next day's spot price, renewable energy production and user loads, the IEM purchases low-priced spot energy to maintain the balance of supply and demand.

On the load side, the IEM formulates demand response incentive measures aligned with the medium- and long-term stage energy procurement scheme. Under the influence of demand response incentives, the original load curves can change. Therefore, when predicting the load curve, it is imperative to proactively consider this factor.

3. IEM energy purchase optimization model in market environment

3.1. IEM medium- and long-term market multi-energy purchase model

Although energy demand, renewable energy production, and spot prices are all subject to uncertainties, daily load curves typically adhere to a consistent pattern within the same month, while daily renewable energy production curves also exhibit some degree of similarity. Furthermore, the daily spot price trend of the same month is relatively unchanging. As such, this paper employs historical data to simulate the three and creates a typical scenario set that includes daily typical load curves, daily typical renewable energy production curves, and daily spot prices for each month. For the medium- and long-term electricity and gas prices, an average of historical contract prices is taken.

Based on the forecast results, the IEM utilizes portfolio theory to diversify its energy purchases across multiple markets. By optimizing the purchase share of different types of energy and allocating the purchasing ratios of the same type of energy at two different time scales, while evaluating the risk of various energy procurement schemes with CVaR, the daily medium- and long-term purchasing quantities can be determined. This quantity is then multiplied by the number of days in the month to compute the energy procurement required for the entire month. By summing up the energy procurement for each month, the annual medium- and long-term purchasing quantities are yielded.

Therefore, we develop a medium- and long-term market multi-energy purchase model to minimize annual costs considering risk factors. The mathematical expression of the model is as follows:

$$\min F_Y = (1-f)\cdot\sum_{s\in S}\phi_s\cdot\left(C_Y^e + C_Y^g + C_{D,s}^e + C_{D,s}^g\right) + f\cdot R_{CVaR} \tag{1}$$

a) Medium- and long-term electricity purchase costs

When conducting medium- and long-term market transactions, the IEM specifies the electric load curve and purchasing price in the contracts. Different months may choose different time-point curves, typically defaulting to the same time-point curve for all days in a single month. The electricity consumption entity is required to declare the transaction by point, and the purchase price remains constant, not subject to change over time. Therefore, the medium- and long-term electricity purchase costs can be expressed as the product of the contracted electricity quantity and the contract price:

$$C_Y^e = \sum_{t \in T} P_{Y,t}^e \cdot \Delta t \cdot price_Y^e \tag{2}$$

b) Medium- and long-term gas purchase costs

The details of natural gas procurement contracts are similar to that of electricity contracts. The medium- and long-term gas purchase costs are the product of the contracted gas purchase quantity and the purchased gas price:

$$C_Y^g = \sum_{t \in T} P_{Y,t}^g \cdot \Delta t \cdot price_Y^g \tag{3}$$

c) Spot electricity purchase costs

To mitigate the impact of uncertainties in the energy procurement process, we utilize the Monte Carlo method to simulate user loads, spot prices, and renewable energy production and replace all possible scenarios with a typical scenario set to assist the IEM in decision-making. The method selects historical data on daily load curves and daily spot prices for each month over the past year to generate the relevant probability distribution. The Beta distribution and Weibull probability distribution are utilized to model solar radiation and wind speed, respectively. Subsequently, by employing random sampling from the probability distribution models, we simulate scenarios for user loads, spot prices, solar radiation, and wind speed. Leveraging "solar radiation - PV output" and "wind speed - WT output" conversion formulas, scenarios for renewable energy production are derived.

Given the abundance of similar scenarios generated through random sampling, the K-means clustering algorithm is applied to simplify the calculation by reducing redundancy. After randomly selecting K data points as cluster centers, according to the Euclidean distance between each data point and each cluster center, the remaining data points are assigned to the nearest cluster center. Following data assignment, the cluster centers are updated based on the existing clustering results, and the above steps are repeated until the cluster centers stabilize, ultimately yielding a typical scenario set.

Based on the typical scenario set, the spot electricity purchase costs are the product of the winning quantity for each period and the spot price:

$$C_{D,s}^e = \sum_{t \in T} P_{D,s,t}^e \cdot \Delta t \cdot price_{D,s,t}^e \tag{4}$$

d) Spot gas purchase costs

Similarly, the spot gas purchase costs are the product of the winning gas quantity for each period and the spot gas price:

$$C_{D,s}^g = \sum_{t \in T} P_{D,s,t}^g \cdot \Delta t \cdot price_{D,s,t}^g \tag{5}$$

The medium- and long-term purchase quantities and the spot winning quantities together constitute the medium- and long-term stage energy procurement scheme for the IEM. However, in this stage, the spot market plays a role in providing a reference for decision-making regarding medium- and long-term purchase quantities, and the simulated winning quantity is unrelated to the spot purchase quantities in the next stage.

e) Conditional Value-at-Risk

By considering the tail risk of the distribution function, CVaR enables decision-makers to consider the downside risk associated with different options. This facilitates the development of effective energy purchase strategies that mitigate potential losses and maximize returns [24], which is in line with the attitude of the IEM toward the energy purchase risks. The mathematical expression is shown below:

$$\begin{cases} prob\left\{L\left(x_Y, s\right) \le R_{VaR}\right\} = \beta \\ \left[L\left(x_Y, s\right) - R_{VaR}\right]^+ = \max\left[0, L\left(x_Y, s\right) - R_{VaR}\right] \\ R_{CVaR} = R_{VaR} + \dfrac{1}{\left(1-\beta\right)} \sum_{s \in S} \phi_s \left[L\left(x_Y, s\right) - R_{VaR}\right]^+ \end{cases} \tag{6}$$

R_{CVaR} in Equation. (6) represents the risk loss associated with the IEM medium- and long-term energy purchase scheme, while f in Equation. (1) represents the subjective attitude of the IEM. A higher value of f indicates a greater influence of R_{CVaR} on the objective function. In such cases, IEM tends to adopt a more conservative approach by increasing the quantity of energy purchased in a market with lower volatility. This strategy aims to mitigate the occurrence of substantial losses in the future, albeit at the expense of higher costs. Conversely, when f is smaller, IEM leans towards minimizing the cost, albeit at the risk of facing significant losses in the future. In the calculation process, Equation. (6) can be simplified as:

$$R_{CVaR} = \delta + \frac{1}{1-\beta}\sum_{s\in S}\phi_s \cdot \xi_s \tag{7}$$

The constraints of IEM medium- and long-term market multi-energy purchase model are as follows:

a) Energy supply balance constraints

$$\begin{cases} P_{L,s,t}^{e} = \left[P_{Y,t}^{e} + P_{D,s,t}^{e} + P_{WT,s,t} + P_{PV,s,t} + P_{CHP,t}^{e}\right]\cdot\left(1-a_{1,t}-a_{2,t}\right) \\ P_{L,s,t}^{h} = P_{EB,t} + P_{CHP,t}^{h}\cdot b_t \\ P_{L,s,t}^{c} = P_{AC,t} + P_{EC,t} \end{cases} \tag{8}$$

where Equation. (8) represents the energy balance constraint of the IEM electric/thermal/cooling energy flow, a and b are the distribution factors of the electric and thermal energy flows respectively. They are influenced by the energy demand in each period and optimized simultaneously with the purchased energy in the decision-making process.

b) Risk constraints

$$\begin{cases} \xi_s \geq 0 \\ \xi_s \geq C_Y^e + C_Y^g + C_{D,s}^e + C_{D,s}^g - \delta \end{cases} \tag{9}$$

c) Equipment power constraints

$$\begin{cases} P_{CHP,t}^{e} = \left(P_{Y,t}^{g} + P_{D,s,t}^{g}\right)\cdot H\cdot\eta_{CHP}^{e} \\ P_{CHP,t}^{h} = \left(P_{Y,t}^{g} + P_{D,s,t}^{g}\right)\cdot H\cdot\eta_{CHP}^{h} \\ P_{EB,t} = \left[P_{Y,t}^{e} + P_{D,s,t}^{e} + P_{WT,s,t} + P_{PV,s,t} + P_{CHP,t}^{e}\right]\cdot a_{2,t}\cdot\eta_{EB} \\ P_{AC,t} = P_{CHP,t}^{h}\cdot\left(1-b_t\right)\cdot\eta_{AC} \\ P_{EC,t} = \left[P_{Y,t}^{e} + P_{D,s,t}^{e} + P_{WT,s,t} + P_{PV,s,t} + P_{CHP,t}^{e}\right]\cdot a_{1,t}\cdot\eta_{EC} \end{cases} \tag{10}$$

$$\begin{cases} P_{CHP}^{e,\min} \leq P_{CHP,t}^{e} \leq P_{CHP}^{\max} \\ P_{CHP}^{h,\min} \leq P_{CHP,t}^{h} \leq P_{CHP}^{h,\max} \\ P_{EB}^{\min} \leq P_{EB,t} \leq P_{EB}^{\max} \\ P_{AC}^{\min} \leq P_{AC,t} \leq P_{AC}^{\max} \\ P_{EC}^{\min} \leq P_{EC,t} \leq P_{EC}^{\max} \end{cases} \tag{11}$$

The operational scheduling of the energy storage systems is not considered at this stage.

d) Exchange power constraints between IEM and external electricity and gas networks

$$\begin{cases} -P_{connect}^{e,\max} \leq P_{connect}^{e} \leq P_{connect}^{e,\max} \\ 0 \leq P_{connect}^{g} \leq P_{connect}^{g,\max} \end{cases} \tag{12}$$

3.2. IEM spot market energy purchase model

In the spot stage, the actual daily load of users may differ from the predicted values in the prior stage. Since the medium- and long-term contract quantities have already been determined, the IEM optimizes the spot electricity and gas quantities to maintain the supply-demand balance based on the day-ahead forecast results. IEM builds the model to minimize the spot stage costs:

$$\min F_D = C_D^e + C_D^g + C_{ESS} + C_{HSS} - R_D^e \tag{13}$$

The spot electricity purchase costs and the spot gas purchase costs in this stage are as follows:

$$C_D^e = \sum_{t \in T} P_{D,t}^e \cdot \Delta t \cdot price_{D,f,t}^e \tag{14}$$

$$C_D^g = \sum_{t \in T} P_{D,t}^g \cdot \Delta t \cdot price_{D,f,t}^g \tag{15}$$

When the energy supply exceeds the load demand, the IEM can store the surplus electricity and heat in the storage system to avoid the waste of unconsumed energy and potential economic losses. While the IEM incurs daily maintenance costs, the integration of energy storage systems allows it to optimize spot energy procurement costs by purchasing energy in advance during valley periods and storing it in the energy storage system. Any excess electricity beyond the storage capacity is sold to the larger grid. It can be expressed as:

$$R_D^e = \sum_{t \in T} P_{extra,t}^e \cdot \Delta t \cdot price_{D,f,t}^e \tag{16}$$

$$C_{ESS} = \sum_{t \in T} \left| P_{ESS,t} \right| \cdot \Delta t \cdot p_M^e \tag{17}$$

$$C_{HSS} = \sum_{t \in T} \left| P_{HSS,t} \right| \cdot \Delta t \cdot p_M^h \tag{18}$$

where Equations. (17-18) represent the maintenance costs of the energy storage systems.

IEM in the spot stage disregards risk constraints and considers the energy storage systems constraints. The constraints are as follows:

a) Energy supply balance constraints

$$\begin{cases} P_{L,f,t}^e + P_{ESS,t} = \left[P_{Y,t}^e + P_{D,t}^e + P_{WT,f,t} + P_{PV,f,t} + P_{CHP,t}^e \right] \cdot \left(1 - a_{1,t} - a_{2,t} \right) \\ P_{L,f,t}^h + P_{HSS,t} = P_{EB,t} + P_{CHP,t}^h \cdot b_t \\ P_{L,f,t}^c = P_{AC,t} + P_{EC,t} \end{cases} \tag{19}$$

b) Energy storage systems constraints

$$\begin{cases} S_{wSS}^{\min} \le S_{wSS,t} \le S_{wSS}^{\max} \\ S_{wSS,t} = S_{wSS,t-1} + \eta_w^c \cdot P_{wSS,t}^c - P_{wSS,t}^d / \eta_w^d \\ S_{wSS,0} = S_{wSS,T}, \quad \mu_{wSS,c,t} + \mu_{wSS,d,t} \le 1 \\ -P_{wSS}^{c,\max} \cdot \mu_{wSS,c,t} \le P_{wSS,t} \le P_{wSS}^{d,\max} \cdot \mu_{wSS,d,t} \end{cases} \tag{20}$$

Equipment power constraints and exchange power constraints are consistent with the previous stage.

3.3. Demand response incentives

3.3.1. Design of demand response incentives

The increased diversity of energy choices and energy substitutability on the user side exacerbate the randomness and unpredictability of loads. The resulting load fluctuations disrupt the supply-demand balance and affect the original operating scheme, which includes the internal energy flow being redistributed, and the balance will need to be restored through the purchase of spot energy or the curtailment of renewable energy power, leading to a multiplication of supply pressures for the IEM. In this study, we introduce the demand response incentive based on the electricity/heat/cold ratio as a means of minimizing the gap between the optimal energy supply in the expected operation scheme and user loads.

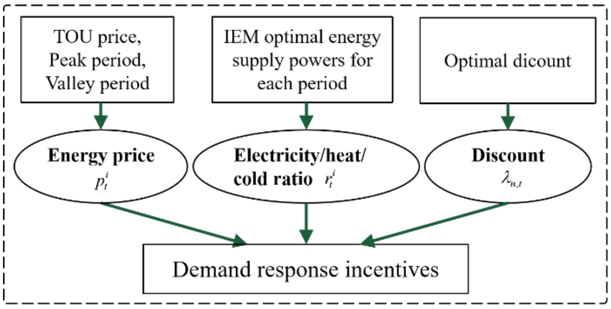

Fig. 3. Composition of the demand response incentives.

The demand response incentive is composed of elements such as energy price, electricity/heat/cold ratio, and discount, as shown in Fig. 3. In terms of energy prices, the IEM adopts the TOU pricing mechanism, dividing the entire day into peak and valley periods. In formulating the electricity/heat/cold ratio, the IEM employs a strategy whereby the ratio is determined based on the expected optimal electric/thermal/cooling supply power for each period. These powers are computed considering factors such as the predicted renewable energy outputs, the medium- and long-term stage planned energy purchase powers, and energy distribution factors. As for the discount, the IEM provides differentiated discounts to individual users based on the optimal discount.

In each month, IEM employs consistent prices, peak and valley periods, ratios, and the optimal discount. The strategy differs from one month to another.

Users receive corresponding discounts based on the similarity. The similarity is calculated as follows:

$$\begin{cases} \dfrac{r_{n,t}^i - r_t^i}{r_t^i} = r_{n,t}^{'i} \\ \bar{r}_{n,t}^{'} = \dfrac{\sum_{i\in I} r_{n,t}^{'i}}{3} \\ \sigma_{n,t} = \sqrt{\dfrac{\sum_{i\in I}\left(r_{n,t}^{'i} - \bar{r}_{n,t}^{'}\right)^2}{3}} \end{cases} \tag{21}$$

$$i \in I, I = \{e,h,c\}$$

$$r_t^e : r_t^h : r_t^c = \frac{P_t^{e,\mathrm{int}}}{P_t^{e,\mathrm{int}} + P_t^{h,\mathrm{int}} + P_t^{c,\mathrm{int}}} : \frac{P_t^{h,\mathrm{int}}}{P_t^{e,\mathrm{int}} + P_t^{h,\mathrm{int}} + P_t^{c,\mathrm{int}}} : \frac{P_t^{c,\mathrm{int}}}{P_t^{e,\mathrm{int}} + P_t^{h,\mathrm{int}} + P_t^{c,\mathrm{int}}} \tag{22}$$

$$r_{n,t}^e : r_{n,t}^h : r_{n,t}^c = \frac{P_{n,t}^e}{P_{n,t}^e + P_{n,t}^h + P_{n,t}^c} : \frac{P_{n,t}^h}{P_{n,t}^e + P_{n,t}^h + P_{n,t}^c} : \frac{P_{n,t}^c}{P_{n,t}^e + P_{n,t}^h + P_{n,t}^c} \tag{23}$$

where in Equation. (21), subtracting the ratio of IEM optimal energy supply powers from the user electric/thermal/cooling loads ratio, then comparing it with the ratio of optimal energy supply powers supplied to obtain the difference between the two. On this basis, the standard deviation of the load difference is computed and utilized as the similarity value of the user. The smaller the standard deviation, the closer the user loads ratio is to the IEM ratio. Equations. (22) and (23) represent the normalization of the ratio of IEM optimal energy supply powers and the normalization of the user loads ratio, respectively.

Considering some users may be unable to adjust their load ratios to be similar to the ratio supplied by the IEM due to their specific energy usage characteristics, they are billed the original price. On the other hand, if the user's similarity falls below σ_D, he will receive the optimal discount. The IEM offers differentiated discounts to users based on their electricity/heat/cold ratios, which protects the motivation and fairness of user participation in IDR [25]. Thus, the discount factor can be expressed as:

$$\lambda_{n,t} = \begin{cases} \lambda_0, & \sigma_{n,t} \le \sigma_D \\ \dfrac{\lambda_0}{\sigma_D - \sigma_S} \cdot \left(\sigma_{n,t} - \sigma_D\right) + \lambda_0, & \sigma_D \le \sigma_{n,t} \le \sigma_S \\ 0, & \sigma_S \le \sigma_{n,t} \end{cases} \tag{24}$$

Users pay the fee once a month. The cost of the user can be expressed as:

$$R_n = \sum_{t\in T}\sum_{i\in I} P_{n,t}^i \cdot p_t^i \cdot \left(1-\lambda_{n,t}\right) \tag{25}$$

3.3.2. IEM and user master-slave game model

The IEM introduces demand response incentives. Through TOU price and differentiated discounts, users are guided to participate in IDR in an orderly manner, enabling them to align all types of loads as closely as possible to the optimal energy powers while aids the IEM in reducing both costs and risks. To simulate users' load adjustment behavior and achieve optimal demand response incentives parameters, the IEM has established a game model that encompasses interactions between itself and the users, with the former acting as the leader and the latter as the follower. The model is shown in Fig. 4.

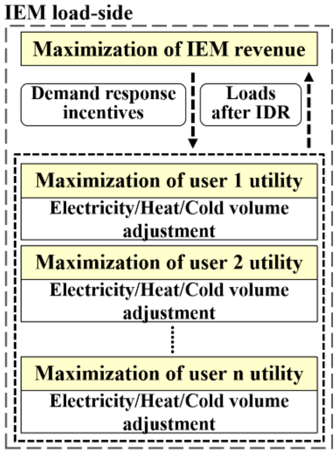

Fig. 4. Master-slave game between IEM and users.

Once the medium- and long-term energy purchase scheme is determined, IEM proceeds to optimize the elements of the demand response incentives, which aims to maximize the revenue generated by itself. The model is presented below:

$$\max U_{IEM} = \sum_{n\in N} R_n \tag{26}$$

The constraints of IEM include the TOU price constraint and the optimal discount constraint:

$$p_t^{i,\min} \le p_t^i \le p_t^{i,\max} \tag{27}$$

$$0 \le \lambda_0 \le 0.25 \tag{28}$$

After obtaining information on demand response incentives, each user aims to maximize their overall energy use utility by adjusting the loads in each period. Utility functions are widely employed to quantify the level of satisfaction experienced by users when consuming energy. By comparing the merits and drawbacks of different strategies, an optimal consumption plan can be determined. The mathematical expression of the model is as follows:

$$\max U_n = \tau \cdot U_n^C + \left(1-\tau\right)\cdot U_n^U \tag{29}$$

$$U_n^C = 1 + \frac{R_n^{\text{int}} - R_n}{R_n^{\text{int}}} \tag{30}$$

$$U_n^U = 1 - \left[\omega_1 \cdot \frac{\sum_{t\in T}\sum_{i\in I}\left|P_{n,t}^{i,cut}\right|}{\sum_{t\in T}\sum_{i\in I} P_{n,t}^i} + \omega_2 \cdot \frac{\sum_{t\in T}\sum_{i\in I}\left|P_{n,t}^{i,sh}\right|}{\sum_{t\in T}\sum_{i\in I} P_{n,t}^i} + \omega_3 \cdot \frac{\sum_{t\in T}\sum_{i\in I}\left|P_{n,t}^{i,sub}\right|}{\sum_{t\in T}\sum_{i\in I} P_{n,t}^i} \right] \tag{31}$$

The evaluation of user comprehensive energy utility includes two parts: energy cost satisfaction and energy use satisfaction. The former compares the energy cost after IDR with the original cost of energy purchased by the user, and the difference between the costs represents the improvement of the user's cost satisfaction. The latter takes into account the impact of user comfort caused by load volume changes due to participation in IDR. Different load types have varying effects on users, and the extent of their impact on user satisfaction is represented by assigning different coefficient values to each load category.

According to the loads characteristics, the loads involved in IDR are classified as interruptible loads, transferable loads, and substitutable loads [26-28].

a) Interruptible loads

Interruptible loads include some non-essential loads, which can be curtailed to some extent during peak periods. The power constraint of interruptible load can be expressed as:

$$0 \le P_{n,t}^{i,cut} \le P_{n,t}^{i} \cdot \theta_{n,t}^{i,cut} \tag{32}$$

where $\theta_{n,t}^{i,cut}$ is determined by the willingness of the user to participate and the actual power of the equipment. The higher the power, the stronger the willingness, and the larger the interruptible load.

b) Transferable loads

Transferable loads have a fixed working power, but their working time can be shifted to valley periods to avoid the peak of energy consumption. The power constraints of transferable loads can be expressed as:

$$\left| P_{n,t}^{i,sh} \right| \le P_{n,t}^{t} \cdot \theta_{n,t}^{i,sh} \tag{33}$$

$$\sum_{t \in T} P_{n,t}^{i,sh} = 0 \tag{34}$$

where Equation. (34) represents that the total amount of transferable loads remains constant throughout the dispatch cycle.

c) Substitutable loads

Energy conversion processes are not only present within IEM but also on the user side. The widespread use of electric thermal/cooling devices intensifies the pressure on the electricity supply. While these electric loads might have been replaced by a direct supply of thermal/cooling energy, the increasing production of renewable energy implies that these loads can increasingly be powered by electricity. The power constraint for substitutable loads can be expressed as:

$$0 \le P_{n,t}^{i,sub} \le P_{n,t}^{i,sub,\max} \tag{35}$$

$$P_{n,t}^{e,sub} = -\left(\eta_{n}^{eh,sub} \cdot P_{n,t}^{h,sub} + \eta_{n}^{ec,sub} \cdot P_{n,t}^{c,sub} \right) \tag{36}$$

where Equation. (36) indicates the changes in the thermal and cooling loads on the user side exhibit opposite trends to the changes in the electric loads.

The loads volume for users at each period after participating in IDR can be expressed as:

$$P_{n,t}^{'i} = P_{n,t}^{i} - P_{n,t}^{i,cut} + P_{n,t}^{i,sub} + P_{n,t}^{i,sh} \tag{37}$$

The user-side constraints are equivalent to Equation. (32)-Equation. (36).

4. Model solving

Based on forecast data of user loads, renewable energy production, and energy prices, this paper utilizes the GUROBI solver through the YALMIP toolbox to address the mixed-integer planning problem regarding medium- and long-term energy procurement in IEM. Based on the initial energy purchase scheme, a subprogram is invoked to tackle the master-slave game between IEM and users. A hybrid approach combined with the Particle Swarm Optimization (PSO) algorithm and the GUROBI solver is employed to compute IEM energy sales revenue and user energy satisfaction. The PSO algorithm optimizes demand response incentive parameters iteratively to maximize both parties' objectives, while the solver is used to compute IEM revenue and user energy consumption strategy. After the game concludes, the updated user loads are integrated into the medium- and long-term energy purchase model to re-optimize the energy purchase scheme, and the above process will be repeated until the iteration of this stage is completed. As for the spot stage energy purchase strategy of IEM, the GUROBI solver is similarly utilized to solve the spot energy purchase quantity.

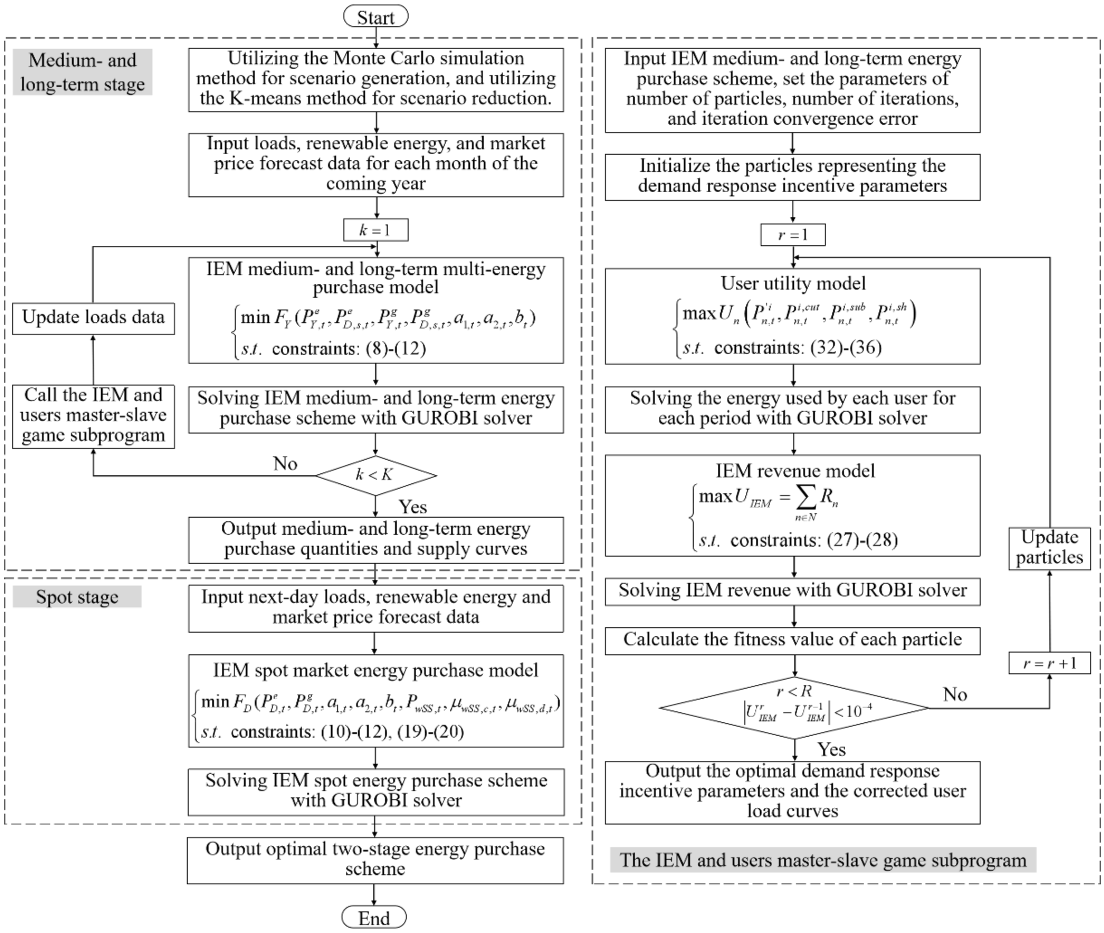

Fig. 5. Flow chart of model solving.

The flow chart is shown in Fig. 5, and the specific solution steps are as follows:

1) Initialization of forecast data and the number of iterations, followed by input into the medium- and long-term multi-energy purchase model.

2) Utilization of the GUROBI solver to optimize the medium- and long-term energy purchase scheme.

3) Invocation of the master-slave game subprogram to input the initial energy purchase scheme. Set the number of particles, iterations, and convergence error tolerance, and randomly initialize the demand response incentive parameters.

4) Calculation of IEM energy sales revenue and user energy satisfaction.

5) Computation of the particle's fitness values and update the demand response incentive parameters, the fitness function, the local best solution for each particle, as well as the global best solution for the particle swarm.

6) Evaluation of the iteration count and comparison of optimization results between the current and previous rounds.

7) Steps 3 to 6 are repeated, with outputting of the load after demand response to the medium- and long-term multi-energy purchase model.

8) Re-optimization of the medium- and long-term energy purchase scheme.

9) Steps 2 to 8 are repeated until the end of the iteration. The spot energy purchase scheme is solved based on the medium- and long-term purchase quantity and spot forecast data.

5. Case study

5.1. Basic Data

In this paper, an IEM is selected for the case study, given in the preceding Fig. 1, which includes WT, PV, CHP, EB, EC, AC, ESS, and HSS. The maximum power of WT and PV is 1200 kW and 400 kW, respectively. The upper limit of supply power between the external electricity grid and the IEM is 8000 kW, and the upper limit of supply power of the external gas network is 2500 m^3. The operating parameters of the equipment are detailed in Table A1, Appendix A. Furthermore, the maximum electric load power, maximum thermal load power, and maximum cooling load power for the IEM are 6000 kW, 5000 kW, and 2000 kW, respectively. In this case, there are 10 users on the load side. The weight preference of each user's satisfaction is uniformly set to τ as 0.5, while the influence coefficients ω_1, ω_2, and ω_3 of interruptible load, transferable load, and substitutable load on user satisfaction depend on the users. The risk aversion factor f is 0.9 and the confidence level β is 0.95 when developing the energy purchase strategy.

5.2. Optimization results of IEM energy purchases

5.2.1. IEM energy purchasing portfolio under different scenarios

Geographical disparities not only influence energy market structures but also lead to variations in energy prices. This section discusses the IEM energy purchasing portfolio under two distinct geographic location scenarios.

- Scenario I: The IEM is located in the northwest region of China, adjacent to renewable energy production bases. In this area, electricity prices are generally low but exhibit considerable volatility, in contrast to the relatively stable prices of natural gas.
- Scenario II: The IEM is located in the eastern coastal region of China, which acts as a central hub for electricity consumption. In this locality, electricity prices exhibit minimal fluctuations but are comparatively more expensive. Given its proximity to natural gas ports, the eastern region experiences a lower price for natural gas. However, natural gas spot prices display higher volatility.

The annual energy purchase of the IEM under the proposed strategy in different scenarios is presented in Table 1. In addition, it also gives the cost and the benefit of the IEM. The price fluctuations in each spot market are shown in Fig. B1- Fig. B4, Appendix B.

Table 1
The IEM annual energy purchases under the proposed strategy in different scenarios.

Scenario	Market	Quantity (MWh, 10^3 m^3)	Cost (10^4 CNY)	Benefit (10^4 CNY)
Scenario I	Electricity medium- and long-term market	23941.60	2549.3	2863.1
	Electricity spot market	9082.45		
	Natural gas medium- and long-term market	1938.53		
	Natural gas spot market	535.18		
Scenario II	Electricity medium- and long-term market	17965.21	2625.0	2813.9
	Electricity spot market	7192.46		
	Natural gas medium- and long-term market	2164.37		
	Natural gas spot market	1138.65		

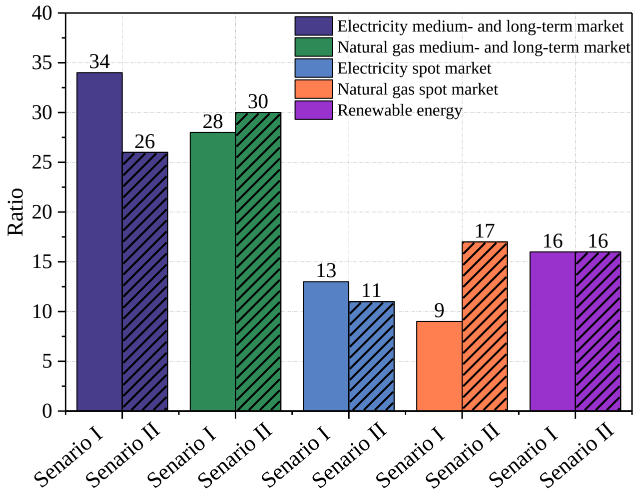

Fig. 6. Energy consumption structure diagram of the IEM in Scenario I and Scenario II.

Fig. 6 shows the energy consumption structure of the IEM in Scenario I and Scenario II, which consists of electricity, natural gas, and renewable energy. From the perspective of different energy, electricity represents a larger share of the IEM supply than natural gas does in Scenario I. The underlying factor behind this circumstance can be attributed to the region's close to renewable energy production bases, leading to lower electricity prices, which makes it more cost-attractive for IEM. However, the dramatic fluctuation in electricity prices also increases the risk of energy purchase for the IEM. Given that electricity is not the sole energy source, and to cut down on risks, the IEM retains a substantial portion of its purchases in the natural gas market. In Scenario II, the ratio of each market differs from that in Scenario I. The natural gas market has the largest share at 47%, and the electricity market has 37%.

In terms of the time scale, both scenarios exhibit a certain resemblance in the energy purchasing portfolio. Specifically, the medium- and long-term markets contribute approximately 60% of the energy supply, while the share of the spot markets is comparatively lower. This phenomenon arises from the simulated typical spot price scenario set, where average spot prices, depending on the scenario, can fluctuate, either falling below or exceeding the fixed prices in the medium- and long-term markets for both electricity and natural gas. Therefore, by engaging in large-scale energy procurements from medium- and long-term markets, the IEM effectively stabilizes the risk float. The operating results of the IEM for a given day are shown in Fig. B5, Appendix B.

The IEM typically relies on external electricity and natural gas sources under normal state. In the event of a sudden interruption of the external electricity grid or external gas network, the remaining energy network is used to compensate for the shortfall in the IEM energy supply, which ultimately leads to a surge in spot purchases of either gas or electricity and subsequent spot price hikes during the interruption period. To mitigate these risks, a multi-market purchase strategy can be employed, helping to stabilize the energy supply during such disruptions.

5.2.2. Comparison of different energy purchase strategies

Based on Scenario II, we compare the energy procurement of IEM under the existing strategy and the strategy proposed in this paper, as exhibited in Table 2. Strategy 1 denotes the existing approach relying solely on a spot settlement mechanism [17,26], while Strategy 2 represents the method proposed in this paper.

Table 2

The IEM annual energy purchases under different energy purchase strategies.

Strategy	Electricity medium- and long-term market (MWh)	Electricity spot market (MWh)	Natural gas medium- and long-term market (10^3 m^3)	Natural gas spot market (10^3 m^3)	Cost (10^4 CNY)	Benefit (10^4 CNY)
1	0	23309.53	0	3512.13	3014.2	2387.2
2	17965.21	7192.46	2164.37	1138.65	2625.0	2813.9

Compared to Strategy 1, the IEM under the strategy proposed in this paper achieves a reduction of 12.91% in costs and an increase of 17.87% in benefits. Without participation in the medium- and long-term markets, the optimal allocation of the energy purchase portfolio is impossible. The energy procurement decision in Strategy 1 is simplified to an optimization problem that only requires cost considerations and is solely dominated by the spot market, where the risk is no longer under its control. Additionally, the implementation of IDR has effectively assisted IEM in reducing medium- and long-term energy purchases during high-priced periods, lowering the overall cost of energy purchases while increasing benefits.

The strategy proposed in this paper balances the stability of the medium- and long-term market and the flexibility of the spot market. Considering the uncertainty of energy prices in different markets and the IEM's risk attitude, the strategy facilitates optimal decisions for both medium- and long-term and spot markets, which also enables the IEM to adjust the quantity and types of energy purchases and determine the shares of electricity and natural gas markets. Ultimately, energy purchase costs and risks decline. Moreover, the strategy enhances energy utilization efficiency and further reduces costs by coordinating demand response to optimize the internal ratio of electric, thermal, and cooling loads.

5.2.3. The impact of renewable energy penetration within the IEM on energy purchases

The renewable energy penetration within IEM significantly impacts its market energy allocation. This study explores a situation wherein a higher share of renewable energy sources is integrated into the IEM while external energy prices remain consistent with those in Scenario II.

When the total installed capacity of renewable energy grows from 1600 kW to 5000 kW and the fluctuation in renewable energy power further intensifies, the operational risk of the IEM also increases. As depicted in the energy procurement scheme in Table 3, the rise in renewable energy penetration encroaches on the proportion of externally procured energy within the IEM energy consumption structure. The medium- and long-term and spot procurement quantities have decreased, yet the proportion of purchases in the medium- and long-term markets has heightened. The IEM has shifted its procurement strategy towards the medium- and long-term market to mitigate the risks associated with renewable energy uncertainty.

Table 3

The IEM energy purchases under higher shares of internal renewable energy sources.

Electricity medium- and long-term market (MWh)	Electricity spot market (MWh)	Natural gas medium- and long-term market (10^3 m^3)	Natural gas spot market (10^3 m^3)	Cost (10^4 CNY)	Benefit (10^4 CNY)
15487.29	3272.40	2037.18	894.27	2258.7	3137.4

5.3. Sensitivity study of key factors of IEM strategy

The IEM energy purchase strategy is affected by many factors, including the attitude toward market risk and the demand response incentive. This paper conducts a sensitivity analysis to explore these influences.

5.3.1. Influence of risk averse factor

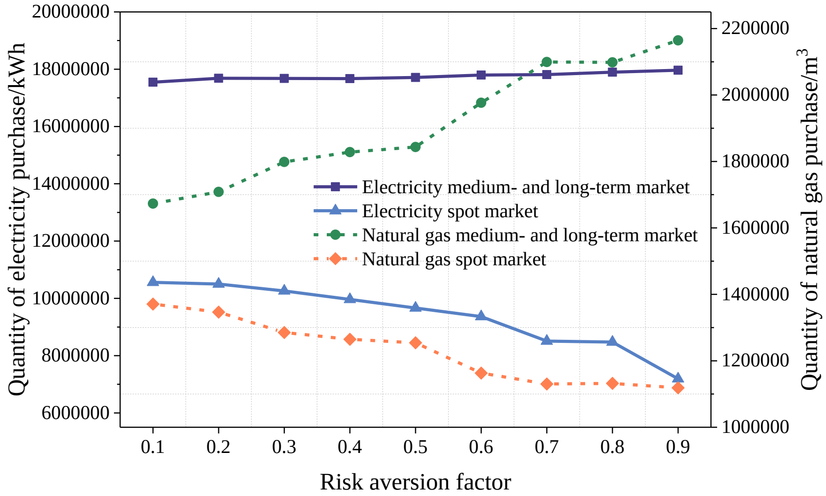

Fig. 7. Changes in the purchase quantity of various markets under different risk aversion factors.

Based on Scenario II, Fig. 7 illustrates the variations in the medium- and long-term stage energy purchase scheme of the IEM under different risk aversion factors. As the risk aversion factor experiences an increase, there is an upward trend in purchases within the medium- and long-term market. Conversely, both spot procurements display a declining pattern. Although the medium- and long-term price is higher than the spot price in some typical scenarios, the volatility-free nature of the medium- and long-term price caters more to the conservative attitude of the IEM in energy purchase decisions. Buying medium- and long-term energy in bulk mitigates the risk associated with the uncertainty of spot price fluctuations and limits the loss of energy purchase to an acceptable level. As a result, sharp fluctuations in spot prices can drive increased energy purchases in the medium- and long-term market. In this scenario, the intense volatility of natural gas spot prices prompts risk-averse IEM to augment procurement from the medium- and long-term natural gas market, aiming to hedge their risk. The lower price of natural gas compared to electricity makes it a more cost-effective option for the IEM, despite both the medium- and long-term electricity and natural gas markets serving equally in risk mitigation. Consequently, these result in a significant increase in the quantity of natural gas purchased in the medium- and long-term market.

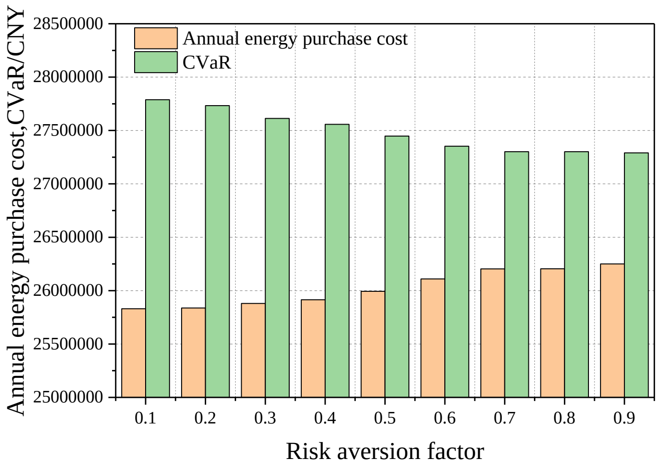

Fig. 8. Energy purchase cost and CVaR of the IEM under different risk aversion factors.

Fig. 8 presents the impact of various risk aversion factors on the energy cost and the CVaR. From a macro perspective, there is a rise in the cost as the risk aversion factor increases, accompanied by a decrease in the CVaR. With a lower value for this factor, the IEM takes an optimistic attitude toward risk and tries to purchase spot energy, seeking periods when the spot price is lower than the medium- and long-term price, which brings a large CVaR. On the contrary, a risk-averse attitude leads the IEM to prefer purchasing medium- and long-term energy to reduce its CVaR, but it also causes an increase in cost. In summary, the proposed method helps the IEM optimally coordinate cost and risk by sacrificing some benefits for security.

5.3.2. Influence of demand response incentives

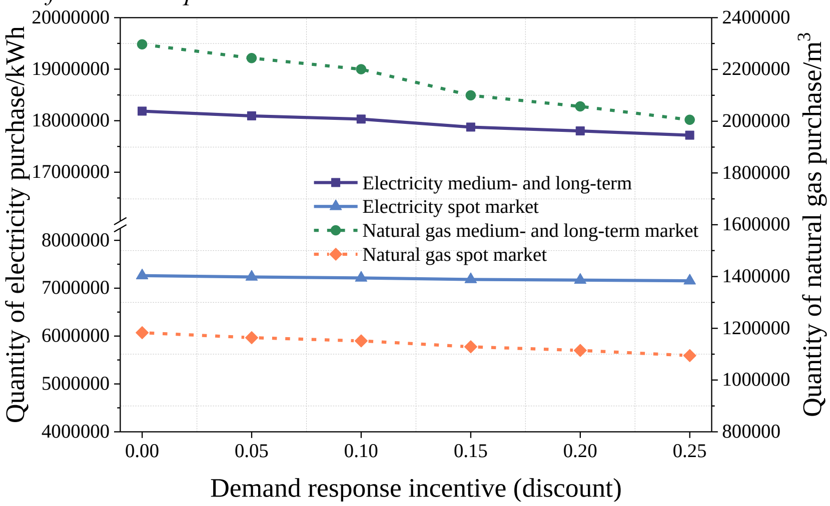

Fig. 9. Changes in the purchase quantity of various markets under different demand response incentives.

Fig. 9 illustrates that as demand response incentives increase (manifested by higher discounts), there is a decrease in the IEM energy procurements, particularly in the medium- and long-term markets. The rise in incentives motivates users to engage in more proactive load management, yielding a more balanced ratio of electric, thermal, and cooling load and improving energy efficiency, thus reducing energy purchases. The substantial reduction in load occurs during peak energy consumption hours, which coincides with the primary deployment period of medium- and long-term energy, leading to a quantity decline in this market. Enhancements in energy efficiency and incentives to direct loads towards lower-priced hours effectively reduce the acquisition of high-priced energy during peak hours, ultimately resulting in lower overall energy purchase costs. Notably, higher incentives do not necessarily guarantee better benefits. The optimization result of the discount based on Scenario II is 0.124.

5.4. Optimization results of loads

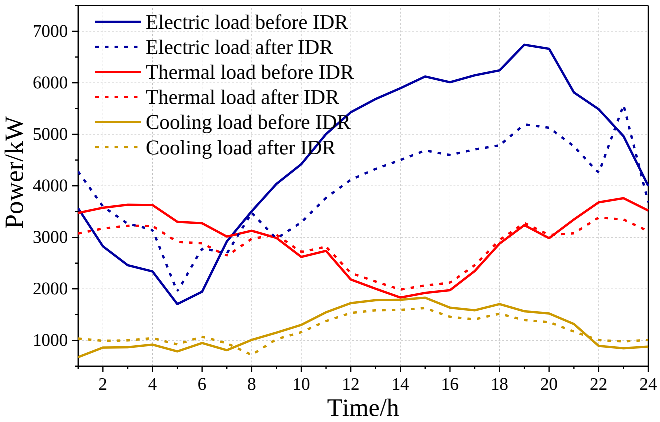

Fig. 10. Loads before and after IDR on a given day.

As shown in Fig. 10, there is a notable change in the loads before and after IDR. The peak periods for electricity and cooling loads predominantly occur during the daytime, with the loads decrease of 23.3% and 11.8% compared to the pre-IDR, respectively. During the valley periods, the electric load increases by 13.9%, and the cooling load increases by 17.8%. In terms of thermal load, the peak periods during the night exhibit a decrease of 10.4%, while the valley periods experience a 4.1% increase. The IEM ensured that the total load remained within the coverage provided by medium- and long-term contracts_as much as possible during post-IDR electricity peak hours, requiring only minimal energy supplementation during specific periods. Such load increase during the electricity valley period improves the IEM's consumption of renewable energy and low-price energy.

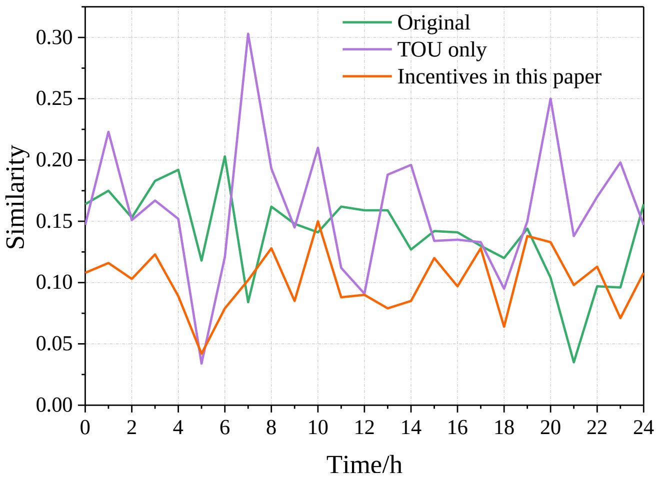

Fig. 11. Load similarity for each period under IEM implemented different energy sales strategies.

Fig. 11 presents the similarity of the whole loads for each period under IEM implemented different demand response incentives. Compared with the original similarity, the similarities in some periods decrease rather than increase after the implementation of TOU prices alone. Then the similarities of most periods acquired improvement through the conscious ratio guidance of user loads by the incentives designed by this paper. Therefore, the combination of discounts and TOU prices mechanism reduces the deviation between load and IEM energy supply and mitigates the pressure on energy purchase and supply. The ratio of IEM optimal energy supply powers for each period can be found in Table A2, Appendix A.

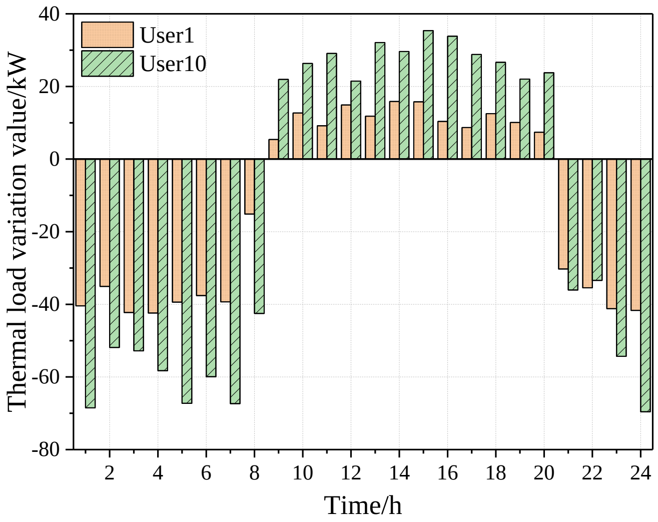

Fig. 12. Response volume of thermal load for different users.

Taking Users 1 and 10 as illustrative examples, the electric/thermal/cooling load ratio of User 1 is close to the ratio of IEM optimal energy supply powers, and the thermal demand of User 10 is significantly higher than that for electricity and cooling. Fig. 12 depicts the response magnitudes of their respective thermal loads. It can be observed that both User 1 and User 10 responded throughout the entire scheduling process. Although the IDR behavior of both is similar, there is a big difference in the response power. The thermal load reduction during peak periods and the response power during valley periods of User 1 are lower than User 10. Due to the load response of User 1 being influenced by the TOU prices and the discount, User 1's thermal load no longer operates independently but instead cooperates with the electricity/cooling load. This combined response allows for the adjustment of the load ratio to an optimal level that enables the user to obtain the maximum discount available. Users are provided with a higher level of cost satisfaction and energy use satisfaction compared to solely relying on blind adjustments in response power according to the TOU prices, which also achieves a win-win situation for both the IEM and the users. Combined with Table 4, User 10's satisfaction remains unchanged under the demand response incentives. The big difference between User 10's load ratio and the ratio of IEM optimal energy supply powers renders him unable to obtain the discount, only to respond following the TOU prices and improve overall satisfaction by increasing the amount of thermal load reduction.

Table 4
Different users' utility.

Users	Demand response incentives in this paper	TOU price
User 1	1.071	1.024
User 10	1.035	1.035

6. Conclusion

This paper presents a design of an energy purchase architecture for IEM across electricity and gas markets, focusing on medium- and long-term and spot markets for electricity and gas. Additionally, we put forward a two-stage energy purchase strategy and introduce demand response incentives based on energy ratios. Comparative analysis is carried out by case studies, to demonstrate the effectiveness and advantages of the proposed strategy. Based on the simulation results, the following conclusions are drawn:

1) The proposed method proficiently facilitates optimal decision-making for the IEM amidst fluctuating energy prices, ensuring optimal portfolio allocation for electricity and natural gas purchases across the medium-, long-term, and spot markets. Compared to energy purchases in the spot market only, the IEM succeeds in improving returns while reducing risks.

2) The risk-averse IEM exhibits a preference for augmenting their procurement of medium- and long-term energy sources with lower price volatility. However, this risk mitigation comes at the cost of increased costs. Furthermore, the IEM improves the overall robustness and security of energy purchasing by diversifying energy sources and procurement channels.

3) The guidance of user loads through the demand response incentives based on the

electricity/heat/cold ratio significantly reduces the deviation between load and energy supply and alleviates the cost of IEM energy supply and the risk of energy purchase, fostering a mutually beneficial paradigm.

This study independently forecasts electricity and gas spot prices. However, as the Integrated Energy System evolves, the coupling between these prices will strengthen, necessitating joint forecasting of electricity and gas prices. Furthermore, leveraging historical data and employing artificial intelligence and big data technologies are crucial for developing a precise forecast model. In addition, the focus of this paper on demand-side management is on examining the optimal proportional allocation of various types of user loads, including electricity, heating, and cooling. With the widespread popularization of electric vehicles (EVs) and the advancement of V2G technology, EVs assume a critical role as an electricity load and demand-side resource for the IEM. Thus, analyzing the impact of EV fleet charging and discharging strategies on IEM energy purchase schemes becomes imperative. These considerations will be integrated into our future research.

Acknowledgements

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Appendix A.

Table A1
IEM equipment parameters.

Device	Minimum power (kW)	Maximum power (kW，m^3)	Capacity (kWh)
CHP	100	6000	/
EB	100	5000	/
AC	0	2000	/
EC	0	2000	/
ESS	0	1000	5000
HSS	0	1000	5000

Table A2
The ratio of IEM optimal energy supply powers.

Time/h	Electricity	Heat	Cold	Time/h	Electricity	Heat	Cold
1	0.50	0.37	0.13	13	0.56	0.25	0.20
2	0.46	0.41	0.13	14	0.56	0.25	0.19
3	0.43	0.44	0.13	15	0.56	0.26	0.18
4	0.42	0.43	0.14	16	0.55	0.29	0.16
5	0.34	0.50	0.16	17	0.52	0.32	0.16
6	0.41	0.43	0.16	18	0.53	0.33	0.14
7	0.43	0.42	0.15	19	0.54	0.32	0.14
8	0.48	0.41	0.10	20	0.53	0.34	0.13
9	0.42	0.43	0.15	21	0.49	0.39	0.12
10	0.46	0.38	0.16	22	0.56	0.34	0.10
11	0.47	0.35	0.17	23	0.47	0.40	0.13
12	0.52	0.29	0.19	24	0.56	0.25	0.20

Appendix B.

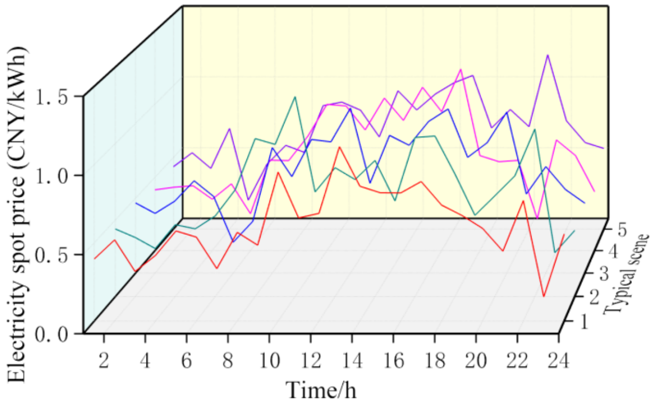


Fig. B1. Typical scenarios of spot electricity price on a certain day in Scenario I.

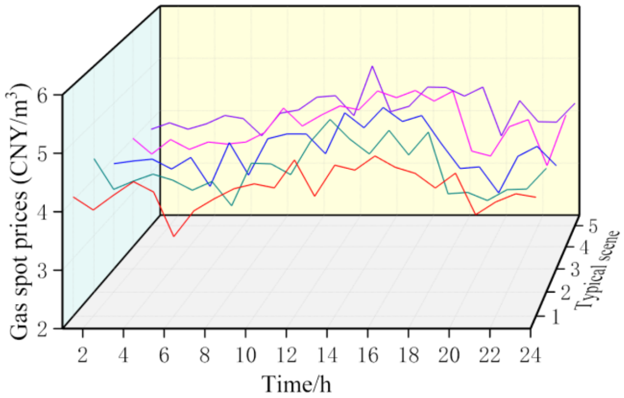


Fig. B2. Typical scenarios of spot gas price on a certain day in Scenario I.

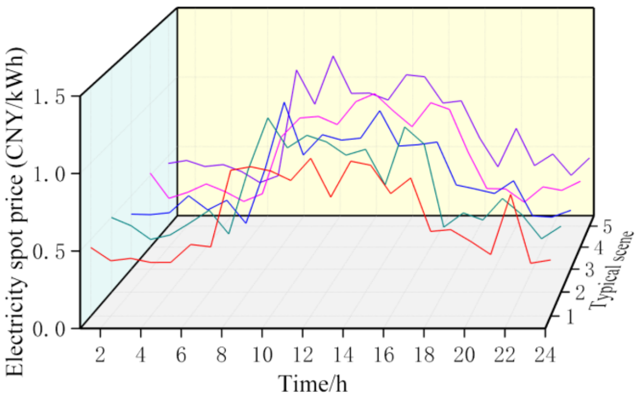


Fig. B3. Typical scenarios of spot electricity price on a certain day in Scenario II.

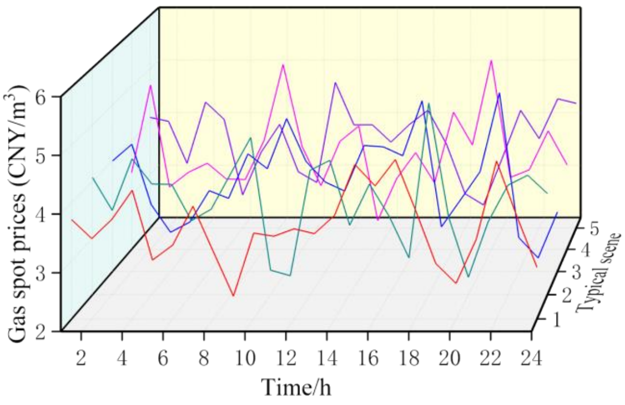
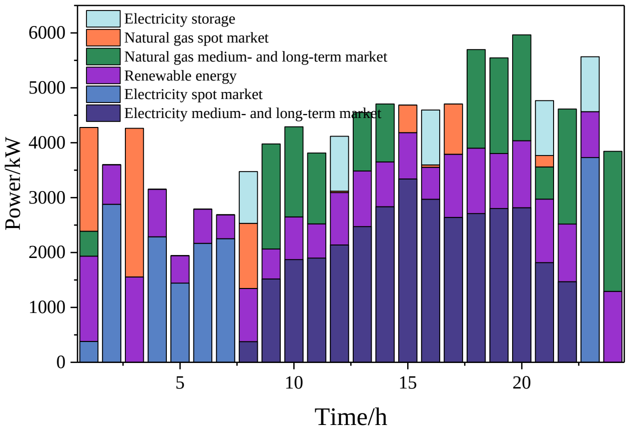
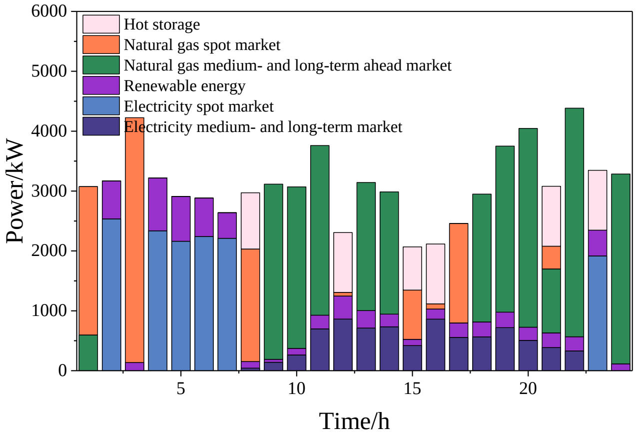


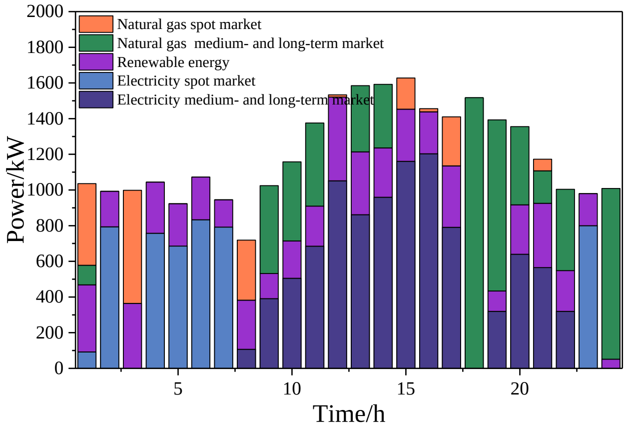
Fig. B4. Typical scenarios of spot gas price on a certain day in Scenario II.



(a) Energy consumption composition of the electric load.



(b) Energy consumption composition of the thermal load.



(c) Energy consumption composition of the cooling load.

Fig. B5. The energy consumption composition of loads on a certain day.

References

[1] Dong H, Fu Y, Jia Q, et al. Optimal dispatch of integrated energy microgrid considering hybrid structured electric-thermal energy storage. *Renewable Energy*, 2022, 199: 628-639.

[2] Tang L, Gou X, Liang J, et al. A two-stage planning optimization study of an integrated energy system considering uncertainty. *Sustainability*, 2022, 14(6): 3645.

[3] Jiang XS, Jing ZX, Li YZ, et al. Modelling and operation optimization of an integrated energy based direct district water-heating system. *Energy*, 2014, 64: 375-388.
[4] Su W, Wang J, Roh J. Stochastic energy scheduling in microgrids with intermittent renewable energy resources. *IEEE Transactions on Smart Grid*, 2014, 5(4): 1876-1883
[5] Fen L, Chuanbin C, Xiulan C, et al. Portfolio purchasing optimization model based on skewness-CVaR for electricity retailers under peak-valley prices. *2018 China International Conference on Electricity Distribution (CICED).* IEEE, 2018: 2794-2799.
[6] Canelas E, Pinto-Varela T, Sawik B. Electricity portfolio optimization for large consumers: Iberian electricity market case study. *Energies*, 2020, 13(9): 2249.
[7] Pan H, Gao H, Yang Y, et al. Multi-type retail packages design and multi-level market power purchase strategy for electricity retailers based on master-slave game. *Proceedings of the CSEE*, 2022, 42(13):4785-4800.
[8] Zhou M, Nie Y, Li G, et al. Long-term electricity purchasing and risk assessment in power markets. *Proceedings of the CSEE*, 2006(06):116-122.
[9] Yang J, Zhao J, Wen F, et al. A framework of customizing electricity retail prices. *IEEE Transactions on Power Systems*, 2017, 33(3):2415-2428.
[10] Yang J, Zhao J, Luo F, et al. Decision-making for electricity retailers: a brief survey. *IEEE Transactions on Smart Grid*, 2017, 9(5):4140-4153.
[11] Wang R, Shang J, Zhou X, et al. Conditional value at risk based optimization of power purchasing portfolio in multiple electricity markets and risk management. *POWER SYSTEM TECHNOLOGY-BEIJING-*, 2006, 30(20): 72.
[12] Herranz R, San Roque A M, Villar J, et al. Optimal demand-side bidding strategies in electricity spot markets. *IEEE Transactions on Power Systems*, 2012, 27 (3):1204-1213.
[13] Ghamkhari M, Wierman A, Mohsenian-Rad H. Energy portfolio optimization of data centers. *IEEE Transactions on Smart Grid*, 2017, 8(4):1898-1910.
[14] Hatami A, Seifi H, Sheikh-El-Eslami MK. A stochastic-based decision-making framework for an electricity retailer: Time-of-use pricing and electricity portfolio optimization. *IEEE Transactions on Power Systems*, 2011, 26(4):1808-1816.
[15] Yan H, Zhao W, Liu W. A risk management model of power retailers considering the participation of new energy. *Proceedings of the CSEE*, 2018, 38(23):6947-6954.
[16] Bai L, Li F, Cui H, et al. Interval optimization based operating strategy for gas-electricity integrated energy systems considering demand response and wind uncertainty, *Applied Energy*, 2016, 167: 270-279.
[17] Li Y, Han M, Shahidehpour M, et al. Data-driven distributionally robust scheduling of community integrated energy systems with uncertain renewable generations considering integrated demand response, *Applied Energy*, 2023, 335: 120749.
[18] Li, P, Wang, Z, Wang, J, et al. Two-stage optimal operation of integrated energy system considering multiple uncertainties and integrated demand response, *Energy*, 2021, 225: 120256.
[19] Gong, C, Tang, K, Zhu, K, et al. An optimal time-of-use pricing for urban gas: A study with a multi-agent evolutionary game-theoretic perspective, *Applied Energy*, 2016, 163: 283-294.
[20] Yang, P, Tang, G, Nehorai, A. A game-theoretic approach for optimal time-of-use electricity pricing, *IEEE Transactions on Power Systems*, 2012, 28(2): 884-892.
[21] Zheng S, Sun Y, Li B, et al. Incentive-based integrated demand response for multiple energy carriers under complex uncertainties and double coupling effects, *Applied Energy*, 2021, 283: 116254.
[22] Gao, H, Zhao, Y, He, S, et al. Demand response management of community integrated energy system: A multi-energy retail package perspective, *Applied Energy*, 2023, 330: 120278.
[23] Zhejiang Provincial Committee of CPC, Zhejiang Provincial People's Government. On the complete, accurate and comprehensive implementation of the new development concept to achieve carbon peak carbon neutral work implementation opinions, 2021. Available from: https://news.bjx.com.cn/html/20220217/1204854.shtml.
[24] Rockafellar R T, Uryasev S. Conditional value-at-risk for general loss distributions. Journal of banking & finance, 2002, 26(7): 1443-1471.
[25] Baharlouei Z, Hashemi M, Narimani H, et al. Achieving optimality and fairness in autonomous demand response: benchmarks and billing mechanisms, IEEE Transactions on Smart Grid, 2013, 4(2): 968-975.
[26] Cui Q, Ma P, Huang L, et al. Effect of device models on the multi-objective optimal operation of CCHP microgrids considering shiftable loads, Applied Energy, 2020, 275: 115369.
[27] Wang Y, Ma Y, Song F, et al. Economic and efficient multi-objective operation optimization of integrated energy system considering electro-thermal demand response, Energy, 2020, 205: 118022.
[28] Sezgen O, Goldman C A, Krishnarao P. Option value of electricity demand response, Energy, 2007, 32(2), 108-119.