Operation Cost Optimization Method of Regional Integrated Energy System in Electricity Market Environment Considering Uncertainty

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***Abstract*—In the electricity market environment, the regional integrated energy system (RIES) can reduce the total operation cost by participating in electricity market transactions. However, the RIES will face the risk of load and electricity price uncertainties, which may make its operation cost higher than expected. This paper proposes a method to optimize the operation cost of the RIES in the electricity market environment considering uncertainty. Firstly, based on the operation cost structure of the RIES in the electricity market environment, the energy flow relationship of the RIES is analyzed, and the operation cost model of the RIES is built. Then, the electricity purchase costs of the RIES in the medium- and long-term electricity markets, the spot electricity market, and the retail electricity market are analyzed. Finally, considering the risk of load and electricity price uncertainties, the operation cost optimization model of the RIES is established based on conditional value-at-risk. Then it is solved to obtain the operation cost optimization strategy of the RIES. Verification results show that the proposed operation cost optimization method can reduce the operation cost of high electricity price scenario by optimizing the energy purchase and distribution strategy, constrain the risk of load and electricity price uncertainties, and help balance the risks and benefits.**

***Index Terms*—Conditional value-at-risk, electricity market, uncertainty, operation cost, regional integrated energy system (RIES).**

I. Introduction

THE regional integrated energy system (RIES) integrates multi-energy resources in a region, which can coordinate the scheduling of the internal energy units, improve energy efficiency, promote the consumption of renewable energy and reduce pollution emissions [1], [2]. In recent years, it has developed rapidly all over the world. At the same time, with the electric power system reform in China, the construction of the spot electricity market has been in the pilot phase, and the market-oriented electricity trading mechanism has been initially formed [3]. In the electricity market environment, the RIES can make full use of its own advantages and further reduce the overall operation cost by optimizing the collaborative scheduling strategy among its internal energy units when participating in electricity market transactions. However, the RIES will face the risk of loads and electricity price uncertainties, which may make its operation cost higher than expected. Therefore, it is necessary to study the method to reduce the operation cost of RIES in the electricity market environment.

At present, some research has been carried out on the operation optimization of RIES. In [4], the modeling method of heat, electricity and gas supply networks in the RIES is studied, and the operation of the RIES is optimized by using the fruit fly algorithm. Reference [5] summarizes and analyzes several modeling and solution methods for optimal operation of integrated thermal and electrical systems. Based on graph theory, [6] establishes a unified matrix form of the integrated energy system model. Aiming at a practical community integrated energy system, [7] establishes the equipment model and the operation optimization strategy, which improve the reliability and economy of the system. In [8], the day-ahead optimal scheduling model of integrated energy system is established and solved by second-order cone programming. However, the above optimization methods do not consider the uncertain factors such as the output power of wind power and photovoltaic, electricity prices, and energy demand in the integrated energy system. Therefore, there may be a large gap between the theoretical values and the actual optimization results.

In view of the uncertainty in the integrated energy system, [9] and [10] establish a robust optimization model to give priority to satisfy the operation constraints and improve the operation stability of the power system. In [11], the stochastic optimization method is adopted and the Latin hypercube sampling is used to generate multiple scenarios for analysis,

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which effectively reduces the negative impact caused by uncertainty. Reference [12] applies interval optimization theory to deal with the uncertainty of wind power and proposes the coordinated operation strategy of a gas-electricity integrated energy system considering demand side response. References [13]-[15] study the method of guiding users to improve energy consumption behavior through the demand response of multiple energy sources, which improves the matching degree of supply and demand and the operation economy of the integrated energy system. In the electricity market environment, the price of electricity is uncertain. In [16], considering the uncertainty of energy demand, wind power output, and electricity prices, an optimal scheduling model based on fuzzy theory is proposed for multi-energy systems. Considering the uncertainty of thermal load, power load and real-time price, [17] proposes a stochastic optimal operation model of multiple-energy carrier systems based on conditional value-at-risk (CVaR). The above studies only consider the overall operation optimization method of integrated energy system under the uncertainty of renewable energy generation, user demand, and electricity prices, but lack of modeling and analysis of the electricity market in detail, which cannot reflect how exactly the RIES participates in electricity market transactions in reality.

In the studies of the electricity market, [18] summarizes the trading mode of the electricity market of China and proposes a portfolio optimization method of electricity retailers based on CVaR. In [19], the conditional drawdown-at-risk is used to model the risk of load and electricity price uncertainties in the market, so as to reduce the risk of trading in the electricity market. Reference [20] applies the information gap decision theory to limit the risk of market transactions and uses the demand response to further hedge the risk and lock in the profits in advance. Reference [21] proposes a bi-level stochastic optimization method in spot electricity market, which improves the revenue of strategic retailers by optimizing joint demand and virtual bidding strategy. Reference [22] compares and analyzes the three risk assessment methods, namely minimax regret, chance-constrained, and CVaR criteria, to help the electricity retailers choose the appropriate way to make trading decisions. Reference [23] adopts the mixed stochastic-interval model to deal with the uncertainty and proposes the operation optimization strategy of the hybrid energy generation company in the electricity market. Considering the investment of investors, the profit of bidding decision and the clearing of electricity market, [24] proposes the optimal planning method of electricity to gas energy storage facilities in electricity market. Based on the above studies and the basic rules of Guangdong electricity market [25] of China, the market entity in the electricity market is each user of the RIES, including the users who participate in wholesale electricity market transactions and those who participate in retail electricity market transactions. Therefore, the RIES cannot be simply regarded as a whole to participate in the electricity market transactions. In addition, there are many different settlement ways in the electricity market. The settlement prices may be fixed or uncertain, and the assessment fees should be considered. However, there is no existing research on the modeling and analysis of RIES participating in electricity market transactions in detail and the strategy of jointly scheduling the energy units of RIES to reduce operation costs while participating in electricity market transactions.

The contributions of this paper are listed as follows.

1) Based on the rules of Guangdong electricity market, the users of RIES are divided into wholesale and retail buyers, and the operation cost structure and model of RIES are proposed. The electricity purchase cost of the RIES in the wholesale and retail electricity markets are analyzed in detail.

2) Based on CVaR theory, the optimal operation strategy of RIES is proposed to reduce the operation cost considering the uncertainty of spot prices and multiple energy loads.

3) Case studies are carried out and the results in the generated and actual scenarios are analyzed. Furthermore, the electricity purchase strategy of the RIES and the output of the energy conversion equipment and energy storage equipment are analyzed.

II. Operation Cost Model of RIES in Electricity Market Environment

This section constructs the operation cost structure and builds the operation cost model of RIES in the electricity market environment, so as to provide the basis for the later optimization strategy.

A. Operation Cost Structure of RIES in Electricity Market Environment

According to the basic rules of Guangdong electricity market, electricity consumers can be divided into two categories, i.e., the large consumers who can participate in wholesale electricity market transactions or retail electricity market transactions, and the general consumers who can only participate in retail electricity market transactions. In this paper, the large consumers who participate in the wholesale electricity market transactions are called wholesale buyers; the large consumers or general consumers who participate in the retail electricity market transactions are called retail buyers. For the convenience of analysis, when analyzing the electric energy flow, all the wholesale buyers of RIES are regarded as a whole, while all the retail buyers of RIES are regarded as another group, so the electricity in the RIES is divided into two parts: electricity purchased in the wholesale electricity market and that purchased in the retail electricity market.

The operation cost structure of the RIES in the electricity market environment is shown in Fig. 1. The energy purchase cost of the RIES mainly includes electricity purchase cost, gas purchase cost, and heat purchase cost. For the electricity purchase cost, it can be divided into two parts, namely the cost of electricity purchased in the wholesale electricity market and the cost of electricity purchased in the retail electricity market. In addition, in the RIES, there are various energy conversion equipment and energy storage equipment, including electric boilers (EBs), electric refrigerators (ERs), gas boilers (GBs), absorption refrigerators (ABs), batteries (BATs), gas holders (GHs), thermal storage tanks (TSs), etc. Among them, the batteries are only for the internal users of the RIES, not directly connected to the power system. Moreover, the power generation equipment in the RIES, such as gas turbines, wind turbines, and solar generators, sells electricity through the electricity market without affecting the operation of other equipment. Therefore, they are not part of the operation cost of the RIES and will not be considered in this paper.

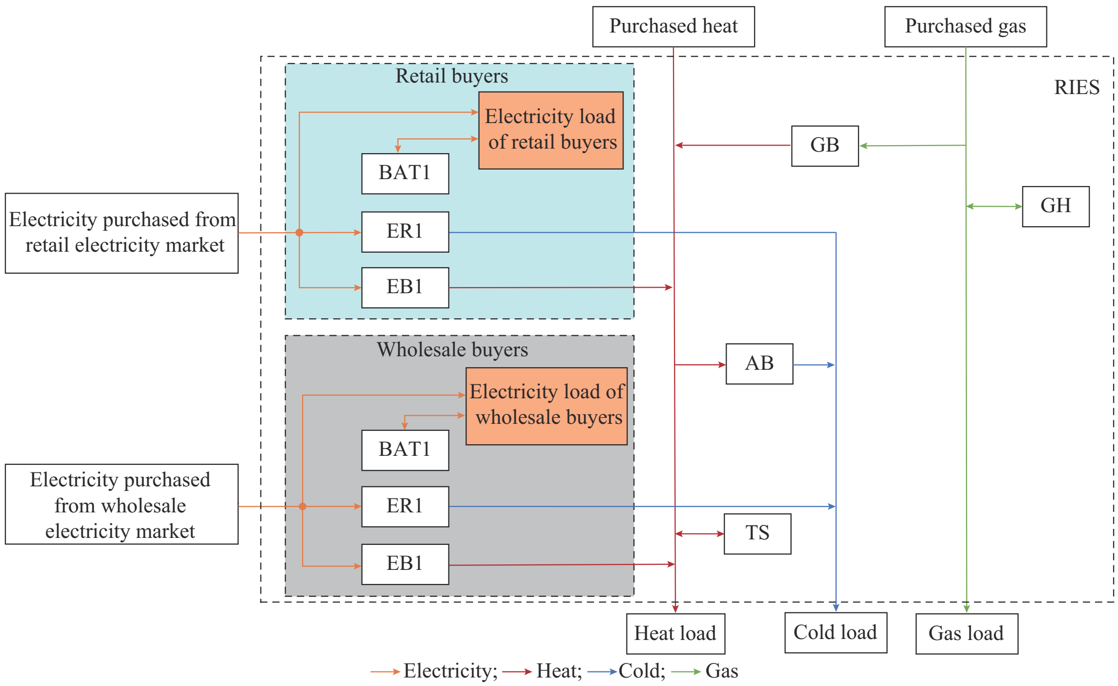

Fig. 1. Operation cost structure of RIES in electricity market environment.

B. Operation Cost Model of RIES in Electricity Market Environment

According to the above analysis, the total operation cost of the RIES in the electricity market environment f_{total} is given as:

$$f_{total}=\sum_{t=1}^{T}\left(f_{E,wholesale,t}+f_{E,retail,t}+f_{H,t}+f_{F,t}\right) \tag{1}$$

where $f_{E,wholesale,t}$ and $f_{E.retail,t}$ are the electricity purchase costs of wholesale and retail electricity markets at time t, respectively; $f_{H,t}$ and $f_{F,t}$ are the costs of purchasing heat and gas at time t, respectively; and T is the total time period.

C. Operation Constraints of RIES in Electricity Market Environment

In order to ensure the safe and stable operation of RIES, it is necessary to meet the constraints of energy supply and demand balance of cold, heat, electricity, and gas, and the constraints of safe operation of equipment. According to Fig. 1, there are four kinds of energy loads in RIES, namely cold, heat, electricity, and gas loads. Among them, the electricity load is mainly supplied by purchasing electricity from the electricity market and users' own batteries; the heat load can be supplied by EBs, GBs, TSs, and purchased heat; the cold load is mainly supplied by ERs and ABs; and the gas load is mainly met by GHs and purchased gas. Therefore, the balance equations of the supply and demand of cold, heat, electricity, and gas are shown as:

$$C_{ER1,t}+C_{ER2,t}+C_{AB,t}=C_{load,t} \tag{2}$$

$$H_t+H_{EB1,t}+H_{EB2,t}+H_{GB,t}+H_{TS,t}-C_{AB,t}/\eta_{AB}=H_{load,t} \tag{3}$$

$$Q_{retail,t}-C_{ER1,t}/\eta_{ER1}-H_{EB1,t}/\eta_{EB1}+Q_{BAT1,t}=Q_{load,retail,t} \tag{4}$$

$$Q_{wholesale,t}-C_{ER2,t}/\eta_{ER2}-H_{EB2,t}/\eta_{EB2}+Q_{BAT2,t}=Q_{load,wholesale,t} \tag{5}$$

$$F_t-H_{GB,t}/\eta_{GB}+F_{GH,t}=F_{load,t} \tag{6}$$

where $Q_{wholesale,t}$ and $Q_{retail,t}$ are the actual total electricity consumption of wholesale and retail buyers of the RIES at time t, respectively; $C_{ER1,t}$, $C_{ER2,t}$, $C_{AB,t}$, $H_{EB1,t}$, $H_{EB2,t}$, and $H_{GB,t}$ are the output power of ER1, ER2, AB, EB1, EB2, and GB at time t, respectively; $Q_{BAT1,t}$ and $Q_{BAT2,t}$ are the electricity charged/discharged by BAT1 and BAT2, respectively, and the value is positive for discharging and negative for charging; $H_{TS,t}$ is the heat stored/released by TS at time t, and the value is positive for heat storage and negative for heat release; $F_{GH,t}$ is the gas stored/released by GH at time t, and the value is positive for gas storage and negative for gas release; $Q_{load,wholesale,t}$, $Q_{load,retail,t}$, $H_{load,t}$, $F_{load,t}$, and $C_{load,t}$ are the electricity load of wholesale buyers, the electricity load of retail buyers, heat load, gas load, and cold load in the RIES, respectively; H_t and F_t are the quantities of heat and gas purchased at time t, respectively; and η_{ER1}, η_{ER2}, η_{AB}, η_{EB1}, η_{EB2}, and η_{GB} are the energy conversion efficiencies of ER1, ER2, AB, EB1, EB2, and GB, respectively.

The constraints for the safe operation of equipment mainly include the operation constraints of all kinds of energy conversion equipment and energy storage equipment.

For the energy conversion equipment, the operation constraints are mainly the upper and lower limits of the output power as:

$$0 \le P_{i,t} \le P_{i,\max} \tag{7}$$

where $P_{i,t}$ is the output power of the i^{th} energy conversion equipment at time t; and $P_{i,\max}$ is the upper output limit of the i^{th} energy conversion equipment.

For the energy storage equipment, the operation constraints are mainly the upper and lower limits of the output power and the upper and lower limits of capacity:

$$0 \le P_{k,in,t} \le P_{k,in,\max} \tag{8}$$

$$0 \le P_{k,out,t} \le P_{k,out,\max} \tag{9}$$

$$0 \le S_{k,t} \le S_{k,\max} \tag{10}$$

where $P_{k,in,t}$ and $P_{k,in,\max}$ are the charging or storage power of the k^{th} energy storage equipment at time t and its upper limit, respectively; $P_{k,out,t}$ and $P_{k,out,\min}$ are the discharging or release power of the k^{th} energy storage equipment at time t and its upper limit, respectively; and $S_{k,t}$ and $S_{k,\max}$ are the capacity of the k^{th} energy storage equipment at time t and its upper limit, respectively.

The capacity of energy storage equipment is calculated by:

$$S_{k,t+1} = S_{k,t}\left(1-\eta_{k,loss}\right) - \left(\frac{P_{k,out,t}}{\eta_{k,out}} - P_{k,in,t}\eta_{k,in}\right)\Delta t \tag{11}$$

where $\eta_{k,loss}$, $\eta_{k,out}$, and $\eta_{k,in}$ are the self-discharging rate, discharging efficiency, and charging efficiency of the k^{th} energy storage equipment, respectively; and Δt is the unit time interval.

The operation and management of energy storage equipment are periodic. So, in order to facilitate the operation and management, the capacity at the beginning of the scheduling period is the same as that at the end of the scheduling period, which can be expressed as:

$$S_{k,start} = S_{k,end} \tag{12}$$

where $S_{k,start}$ and $S_{k,end}$ are the capacities at the beginning and end of the scheduling period of the k^{th} energy storage equipment, respectively.

III. Operation Cost Analysis of RIES in Electricity Market Environment

On the basis of the operation cost model of RIES in the electricity market environment in Section II, this section will make a detailed analysis of various operation costs of RIES in the electricity market environment, especially the electricity purchase cost.

A. Electricity Purchase Cost Analysis of RIES in Wholesale Electricity Market

The wholesale electricity market includes electric energy market and ancillary service market. Among them, the electric energy market includes medium- and long-term market and spot market. The buyers in wholesale electricity market mainly purchase electricity through the electric energy market. Therefore, the electricity purchase cost of RIES in the wholesale electricity market is mainly the electricity purchase cost in the medium- and long-term markets and spot market expressed as:

$$f_{E,wholesale,t} = f_{E,long,t} + f_{E,spot,t} \tag{13}$$

where $f_{E,long,t}$ is the electricity purchase cost in the medium- and long-term markets; and $f_{E,spot,t}$ is the electricity purchase cost in the spot market.

1) Electricity Purchase Cost of RIES in Medium- and Long-term Markets

There are many kinds of transactions in the medium- and long-term markets, including bilateral negotiation, centralized bidding, listing trading, etc. The medium- and long-term contracts need to stipulate the electricity quantity, contract price, and decomposition curve. The electricity quantity of medium- and long-term contracts is the total amount of a period of time, which needs to be decomposed to each hour according to the decomposition curve. And the medium- and long-term contracts are settled on the basis of the difference between the contract price and day-ahead price.

Suppose that all the wholesale buyers of RIES have signed N contracts, and the decomposed electricity quantity and the price of the n^{th} contract at time t are $Q_{long,n,t}$ and $p_{long,n,t}$, respectively. The day-ahead price at time t is $p_{day,t}$, then the total electricity quantity of medium- and long-term contracts at time t is expressed as:

$$Q_{long,t} = \sum_{n=1}^{N} Q_{long,n,t} \tag{14}$$

The average price of medium- and long-term contracts at time t is expressed as:

$$p_{long,t} = \frac{\sum_{n=1}^{N} Q_{long,n,t}\, p_{long,n,t}}{\sum_{n=1}^{N} Q_{long,n,t}} \tag{15}$$

Then, the electricity purchase cost in medium- and long-term markets at time t is expressed as:

$$f_{E,long,t} = Q_{long,t}\left(p_{long,t} - p_{day,t}\right) \tag{16}$$

2) Electricity Purchase Cost of RIES in Spot Market

Spot electricity trading can be divided into two categories, namely day-ahead electricity trading and real-time electricity trading. At present, in the spot market, the generation side will submit the quantity-price curves, whereas the consumer side will only submit the electricity quantity curves. That is, the consumer side is the price receiver, and the submitted electricity quantity curves on the consumer side are only used as the basis for settlement instead of market clearing. The settlement of day-ahead market shall be carried out on the basis of the submitted electricity quantity curve and day-ahead price. In the real-time market, the settlement shall be carried out on the basis of the difference between the actual electricity consumption curve and the submitted electricity quantity curve and the real-time price. In addition, in order to prevent market participants from speculative arbitrage, when the deviation between the submitted electricity quantity curve and the actual electricity consumption curve is too large, the wholesale buyers will be charged assessment fees. To sum up, the electricity purchase cost in spot market is mainly composed of three parts: the electricity charge of day-ahead market $f_{E,day,t}$, the electricity charge of real-time market $f_{E,real,t}$, and the assessment fee $f_{E,err,t}$. The electricity purchase cost in spot market is expressed as:

$$f_{E,spot,t}=f_{E,day,t}+f_{E,real,t}+f_{E,err,t} \tag{17}$$

When participating in spot electricity trading, the wholesale buyers of the RIES will independently participate in the spot electricity trading, submit the electricity quantity curves and settle the expenses. However, it is too complicated to analyze the trading strategy of each wholesale buyer separately, and it is not conducive to the overall optimization to calculate the electricity purchase cost of wholesale buyers in the spot market separately. If these wholesale buyers can be considered as a whole, this problem can be greatly simplified. The electricity charges of day-ahead and real-time markets are given in (18) and (19), respectively.

$$f_{E,day,t}=p_{day,t}Q_{day,t} \tag{18}$$

$$f_{E,real,t}=p_{real,t}\left(Q_{wholesale,t}-Q_{day,t}\right) \tag{19}$$

where $p_{real,t}$ is the real-time price at time t; and $Q_{day,t}$ is the total submitted electricity quantity of wholesale buyers of the RIES at time t. For every wholesale buyer, the day-ahead price is the same, and the real-time price is also the same [26]. Therefore, when calculating the electric charges of day-ahead and real-time markets, all the wholesale buyers of RIES can be regarded as a whole.

According to (18) and (19), when the real-time price is higher than the day-ahead price, the more the submitted electricity quantity of wholesale buyer, the lower the electricity purchase cost in spot market. When the real-time price is lower than the day-ahead price, the submitted electricity quantity of wholesale buyer is less, and the electricity purchase cost in spot market is lower. This provides a large space for the wholesale buyers to carry out speculative arbitrage in the electricity market. However, after adding the assessment fee, the electricity purchase cost in spot market is shown in Fig. 2, and the upper limit of allowable deviation λ_0 is set to be 10%. And the deviation is $(Q_{wholesale,t}-Q_{day,t})/Q_{wholesale,t}$.

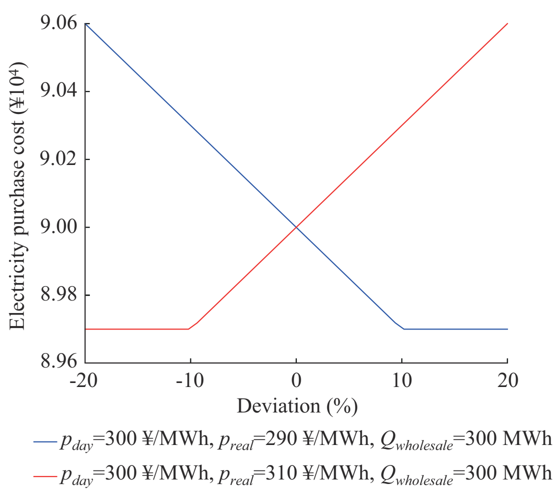

Fig. 2. Electricity purchase cost in spot market under different deviations.

As can be observed from Fig. 2, the speculative arbitrage gains that exceed the allowable deviation will be recovered, but the loss from speculative arbitrage will not be compensated, so the speculative arbitrage behavior of the wholesale buyer is restricted. As the assessment fee is related to the submitted electricity quantity curve and actual electricity consumption curve of each wholesale buyer, there will be errors if the wholesale buyers are considered as a whole. However, we can guide the wholesale buyers to adopt similar trading strategies, so as to facilitate the overall optimization of the operation cost of the system and reduce the calculation error of the assessment fee. Therefore, in the case of little difference of the day-ahead trading strategies of wholesale buyers, there is little difference between calculating the assessment fee as a whole and calculating it separately for each wholesale buyer. Therefore, when calculating the assessment fee, all the wholesale buyers can also be regarded as a whole. Then the assessment fee of the RIES is expressed as:

$$\begin{aligned} f_{E,err,t}=&\max\left\{0,Q_{day,t}-Q_{wholesale,t}\left(1+\lambda_0\right)\right\}\max\left\{0,p_{real,t}-p_{day,t}\right\}+\\ &\max\left\{0,Q_{wholesale,t}\left(1-\lambda_0\right)-Q_{day,t}\right\}\max\left\{0,p_{day,t}-p_{real,t}\right\} \end{aligned} \tag{20}$$

For (21) and (22), the continuous variables a_t, b_t, the Boolean variables $u_{1,t}, u_{2,t}, u_{3,t}, u_{4,t}$, and the large positive numbers M_1, M_2 are introduced to linearize the formula.

$$f_{E,err,t}=a_t\max\left\{0,p_{real,t}-p_{day,t}\right\}+b_t\max\left\{0,p_{day,t}-p_{real,t}\right\} \tag{21}$$

$$\begin{cases} a_t\geq 0\\ a_t\geq Q_{day,t}-Q_{wholesale,t}\left(1+\lambda_0\right)\\ a_t\leq M_1\left(1-u_{1,t}\right)\\ a_t\leq Q_{day,t}-Q_{wholesale,t}\left(1+\lambda_0\right)+M_1\left(1-u_{2,t}\right)\\ u_{1,t}+u_{2,t}\geq 1\\ b_t\geq 0\\ b_t\geq Q_{wholesale,t}\left(1-\lambda_0\right)-Q_{day,t}\\ b_t\leq M_2\left(1-u_{3,t}\right)\\ b_t\leq Q_{wholesale,t}\left(1-\lambda_0\right)-Q_{day,t}+M_2\left(1-u_{4,t}\right)\\ u_{3,t}+u_{4,t}\geq 1\\ u_{1,t},u_{2,t},u_{3,t},u_{4,t}\in\left\{0,1\right\} \end{cases} \tag{22}$$

B. Electricity Purchase Cost Analysis of RIES in Retail Electricity Market

In RIES, there are also retail buyers who participate in retail electricity market transactions. Retail buyers will sign various retail contracts with electricity retailers according to their own demands, such as fixed price contract, time-of-use price contract, peak-valley price contract, step tariff contract, and real-time price contract. In this paper, we only consider the peak-valley price contracts signed by retail buyers and electricity retailers. For the total actual electricity consumption of all the retail buyers of the RIES $Q_{retail,t}$, the contract price at time t is $p_{retail,t}$, and the electricity purchase cost of RIES in retail electricity market $f_{E,retail,t}$ is expressed as:

$$f_{E,retail,t}=p_{retail,t}Q_{retail,t} \tag{23}$$

C. Other Operation Cost Analysis of RIES

In addition to participating in the electricity market to purchase electricity, the RIES also needs to purchase heat and gas, and the prices of heat and gas are relatively fixed. Suppose that the prices of heat and gas are p_H and p_F, respectively. The costs of purchasing heat and gas, i.e., $f_{H,t}$ and $f_{F,t}$, are given by:

$$f_{H,t} = p_H H_t \tag{24}$$

$$f_{F,t} = p_F F_t \tag{25}$$

where H_t and F_t are the quantities of heat and gas purchased, respectively.

IV. Operation Cost Optimization Strategy of RIES in Electricity Market Environment

RIES will face the risk of load and electricity price uncertainties when participating in electricity market transactions, which may lead to the actual operation cost much higher than expected. Therefore, the RIES needs to evaluate the risks faced, measure its own risk tolerance, and take corresponding measures to reduce the risks while meeting its own operational demands. In this section, the CVaR method is adopted to evaluate the risk of the RIES participating in electricity market transactions, and the operation cost optimization strategy of RIES in electricity market environment is proposed.

A. CVaR Model

CVaR model is proposed by Rockafellar and Uryasev on the basis of value-at-risk (VaR) model [27], [28], which means the expected loss of portfolio if the loss of portfolio is greater than a given VaR. The VaR model represents the maximum possible loss of a portfolio or asset during a specific period of time in the future at a certain confidence level. Due to some defects, for example, the coherent axiom is not satisfied, the tail loss measurement is not sufficient, or the probability model must satisfy the normal distribution, the application scope of VaR is limited. CVaR overcomes the defects of VaR, so it is widely used in risk assessment [29], [30]. In this paper, CVaR is used to evaluate the risk of spot electricity price and load uncertainty. The basic principle is shown as follows.

Suppose that $h(\boldsymbol{x},\boldsymbol{y})$ is the loss function of portfolio, $\boldsymbol{x}$ is the decision variable ($\boldsymbol{x} \in \boldsymbol{X}, \boldsymbol{X} \subset \mathbf{R}^k$, $\boldsymbol{X}$ is the feasible set of decision variables), and $\boldsymbol{y}$ is random variable ($\boldsymbol{y} \subset \mathbf{R}^m$), which indicates the uncertain factors in the market transactions. The probability density function of $\boldsymbol{y}$ is $p(\boldsymbol{y})$. When the confidence level is β, the formula of CVaR is expressed as:

$$\begin{aligned} CVaR_\beta = & \frac{1}{1-\beta}\int_{h(\boldsymbol{x},\boldsymbol{y}) \geq VaR_\beta} h(\boldsymbol{x},\boldsymbol{y})\, p(\boldsymbol{y})\,\mathrm{d}\boldsymbol{y} = \\ & VaR_\beta + \frac{1}{1-\beta}\int_{\boldsymbol{y} \subset \mathbf{R}^m} \max\left\{0, h(\boldsymbol{x},\boldsymbol{y}) - VaR_\beta\right\} p(\boldsymbol{y})\,\mathrm{d}\boldsymbol{y} \end{aligned} \tag{26}$$

As it is difficult to obtain the analytic expression of $p(\boldsymbol{y})$, we use the Latin hypercube sampling method [31] to generate the sample data and estimate the value of $CVaR_\beta$ approximately on the basis of the generated sample data. Suppose that there are W generated scenarios $\boldsymbol{y}^1, \boldsymbol{y}^2, \ldots, \boldsymbol{y}^W$, and the probability of each scenario is $1/W$. The approximate value of $CVaR_\beta$ is given by:

$$CVaR_\beta = VaR_\beta + \frac{1}{(1-\beta)W}\left(h(\boldsymbol{x},\boldsymbol{y}^w) - VaR_\beta\right)^+ \tag{27}$$

Then, we introduce the dummy variables $z_w\,(w = 1, 2, \ldots, W)$ and ξ. Using the following linear model, we can obtain $CVaR_\beta$.

$$\min\left[\xi + \frac{1}{(1-\beta)W}\sum_{w=1}^{W} z_w\right] \tag{28}$$

$$\begin{cases} z_w \geq 0 \\ z_w \geq h(\boldsymbol{x},\boldsymbol{y}^w) - \xi \end{cases} \tag{29}$$

In the optimal solution of the linear model, ξ corresponds to VaR_β. The minimum value of (28) is $CVaR_\beta$.

B. Operation Cost Optimization Strategy of RIES Based on CVaR

The flow chart of the proposed optimization method is shown in Fig. 3. Assuming that the operation day is day D, the wholesale buyers in the RIES will sign the medium- and long-term contracts before day $D-1$, so they can confirm their medium- and long-term electricity price and quantity on day D. The retail buyers will also sign retail contracts, so as to confirm their contract prices on day D. The medium- and long-term contracts and retail contracts signed on and after day $D-1$ are invalid for day D. Therefore, the medium- and long-term electricity prices of wholesale buyers and the contract prices of retail buyers are known before optimization. During the period from 00:00 to 13:00 on day $D-1$, the RIES should firstly forecast the cold, heat, electricity, and gas loads of its users, as well as the day-ahead and real-time prices, and generate W scenarios by Latin hypercube sampling. Then, based on the information of W scenarios and the parameters of each energy unit, the operation cost optimization objective function is constructed. After that, the operation strategy of the RIES is obtained by solving the model. Finally, the RIES guides the wholesale buyers to submit the electricity quantity curves in the day-ahead market, so that the total submitted electricity quantity in the day-ahead market is consistent with the strategy obtained by solving the model. On day D, the RIES operates according to the solution strategy. The electricity trading center will announce the clearing results of day-ahead and real-time market at 17:30 on day $D-1$ and day $D+1$, including the day-ahead price and real-time price. And on day $D+5$, the electricity trading center will announce the electricity fees of wholesale buyers on day D.

For the practical application of RIES, two schemes are designed to optimize the operation cost of the RIES in electricity market.

1) Scheme 1: only the price of the electricity market is assumed to be uncertain.

2) Scheme 2: the price of the electricity market and the heat, electricity, and gas loads are assumed to be uncertain.

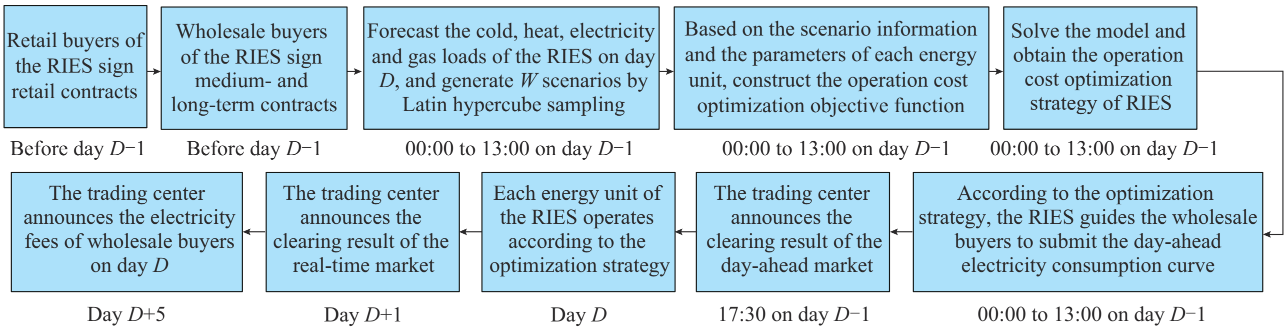

Fig. 3. Flow chart of proposed optimization method.

Scheme 1 is suitable for the situation where the RIES can effectively control the load, while Scheme 2 is suitable for more general situations. When adopting the CVaR model to solve the problem, it is necessary to determine the random variable $\boldsymbol{y}$, decision variable $\boldsymbol{x}$, and loss function $h(\boldsymbol{x},\boldsymbol{y})$. For Scheme 1, when the RIES participates in the electricity market transactions, the day-ahead price and real-time price are uncertain, so they are random variables $\boldsymbol{y}$. In Scheme 2, in addition to the day-ahead price and the real-time price, the cold, heat, electricity, and gas loads of the RIES are also uncertain. Therefore, these variables belong to random variable $\boldsymbol{y}$. Since the cold demand is mainly derived from the transformation of electricity and heat, its uncertainty can be regarded as the uncertainty of electricity demand and heat demand, so the cold load is assumed to be known here. We use the Latin hypercube sampling method to generate W scenarios. Take Scheme 1 as an example. For scenario $w \in W$, the generated data, which include the day-ahead price and real-time price in the whole scheduling period, are $\boldsymbol{y}^w = [p^w_{real,1}, p^w_{day,1}, p^w_{real,2}, p^w_{day,2}, \ldots, p^w_{real,t}, p^w_{day,t}, \ldots, p^w_{real,T}, p^w_{day,T}]$. In this scenario, the operation cost of the RIES is f^w_{total}, then the expected operation cost of the RIES for the W scenarios $f_{total,avg}$ is given by:

$$f_{total,avg} = \frac{1}{W}\sum_{w=1}^{W} f^w_{total} \tag{30}$$

The RIES needs to adopt reasonable energy purchase strategy and energy scheduling strategy, and these variables belong to decision variable $\boldsymbol{x}$. For Scheme 1, the decision variables of the RIES mainly include $Q_{day,t}$, $Q_{wholesale,t}$, $Q_{retail,t}$, F_t, H_t, and the operation schemes of energy conversion equipment and energy storage equipment in the RIES. For Scheme 2, due to the uncertainties of heat, electricity, and gas loads, $Q_{wholesale,t}$, $Q_{retail,t}$, F_t, H_t will be used to balance the fluctuation of the loads, i.e., to make up for the energy shortage supplied by energy conversion equipment and energy storage equipment in the RIES. Therefore, the energy purchased cannot be determined in advance. They are no longer decision variables, but random variables determined by supply and demand. In Scheme 2, the decision variables are $Q_{day,t}$ and the operation scheme of energy conversion equipment and energy storage equipment in the RIES. In addition to the random variables and decision variables, other variables belong to known variables.

We take the total operation cost of RIES as the loss function $h(\boldsymbol{x},\boldsymbol{y})$, introduce the risk aversion coefficient γ, combine the expected operation cost of the RIES for the W scenarios with CVaR, and finally obtain the operation cost optimization objective function f of the RIES considering CVaR, which is given by:

$$\min f = f_{total,avg} + \gamma\left[\xi + \frac{1}{(1-\beta)W}\sum_{w=1}^{W} z_w\right] \tag{31}$$

According to the constraints shown in (2)-(12), (22), and (29), this optimization problem is a mixed-integer linear programming problem, which can be solved by CPLEX solver [32]. And the optimal operation strategy of RIES can be obtained.

V. Case Studies and Discussions

A. Basic Data

Taking an RIES in a certain area in China as an example, the scheduling period is 24 hours, and the unit time interval Δt is 1 hour. The average price of medium- and long-term contracts signed by the wholesale buyers in the RIES $p_{long,t}$ is the same during the whole scheduling period. And the electricity of medium- and long-term contracts is divided into each hour on average. The parameters of the RIES are listed in Table I and other parameters in Table II. Among them, the maximum output of EB, ER, GB, AB, BAT, GH, and TS is the sum of the same type of equipment in the RIES, and the conversion efficiency is the average value of the same type of equipment. In addition, AB and ER also use external energy during operation, so the conversion efficiency is greater than 1. The 24-hour retail contract price, the forecasted 24-hour day-ahead price, and the real-time price are shown in Fig. 4. And the forecasted 24-hour cold, heat, electricity, and gas loads of the RIES are shown in Fig. 5.

In Scheme 1, only the uncertainty of electricity price is considered. Assuming that the day-ahead price and real-time price follow the normal distribution. The forecasted values of the day-ahead price and real-time price are taken as the mean values, and the standard deviations of the day-ahead price and real-time price are 30 and 60, respectively. In Scheme 2, the price of the electricity market and the heat, electricity, and gas loads of the RIES are assumed to be uncertain. The forecasted values of these variables are taken as the mean values. The standard deviations of the day-ahead price and real-time price are the same as those in Scheme 1. And the standard deviations of the heat, electricity, and gas loads are 10, 10, and 100, respectively. Latin hypercube sampling method is adopted to generate 1000 scenarios randomly. Then, we set the different risk aversion coefficient γ and calculate the average operation cost of 1000 scenarios on the basis of the above-mentioned operation cost optimization strategy of the RIES in the electricity market environment.

TABLE I
PARAMETERS OF EQUIPMENT IN RIES

Equipment	Parameter	Value
EB1	Maximum output (MW)	100
	Conversion efficiency (%)	95
EB2	Maximum output (MW)	100
	Conversion efficiency (%)	95
ER1	Maximum output (MW)	65
	Conversion efficiency (%)	280
ER2	Maximum output (MW)	65
	Conversion efficiency (%)	280
GB	Maximum output (MW)	100
	Conversion efficiency (MWh/m^3)	0.00972
AB	Maximum output (MW)	130
	Conversion efficiency (%)	250
BAT1	Capacity (MW)	30
	Maximum charging power (MW)	15
	Maximum discharging power (MW)	15
	Self-discharging rate (%)	0.001
	Charging efficiency (%)	90
	Discharging efficiency (%)	90
BAT2	Capacity (MW)	30
	Maximum charging power (MW)	15
	Maximum discharging power (MW)	15
	Self-discharging rate (%)	0.001
	Charging efficiency (%)	90
	Discharging efficiency (%)	90
TS	Capacity (MWh)	60
	Maximum storage power (MW)	30
	Maximum release power (MW)	30
	Self-release rate (%)	1
	Store efficiency (%)	85
	Release efficiency (%)	80
GH	Capacity (MWh)	6000
	Maximum storage power (MW)	3000
	Maximum release power (MW)	300
	Self-release rate (%)	0
	Store efficiency (%)	100
	Release efficiency (%)	100

B. Analysis of Results

By using different risk aversion coefficients, the corresponding average operation cost and CVaR of Scheme 1 and Scheme 2 are obtained, as shown in Figs. 6 and 7. It can be observed that high risk aversion coefficient can reduce CVaR, but will increase the average operation cost; low risk aversion coefficient can reduce the average operation cost, but will increase CVaR. As the uncertainty of load is considered in Scheme 2, the risk is higher. Compared with Scheme 1, the average operation cost is higher in Scheme 2.

TABLE II
OTHER PARAMETERS IN CASE STUDIES

Parameter	Value	Parameter	Value
p_F (¥/m^3)	2.87	$Q_{long,t}$ (MWh)	268.687
p_H (¥/MWh)	460	β	0.95
$p_{long,t}$ (¥/MWh)	579	λ_0 (%)	10

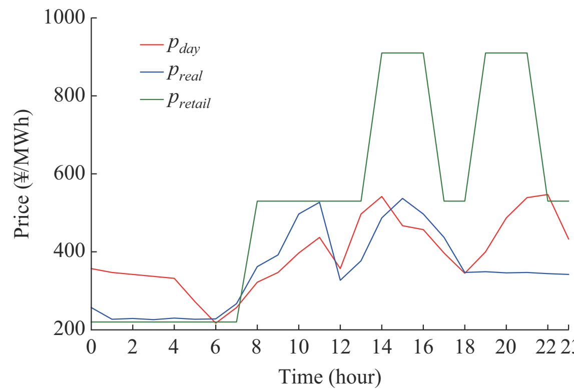

Fig. 4. 24-hour retail contract price, forecasted 24-hour day-ahead price, and real-time price.

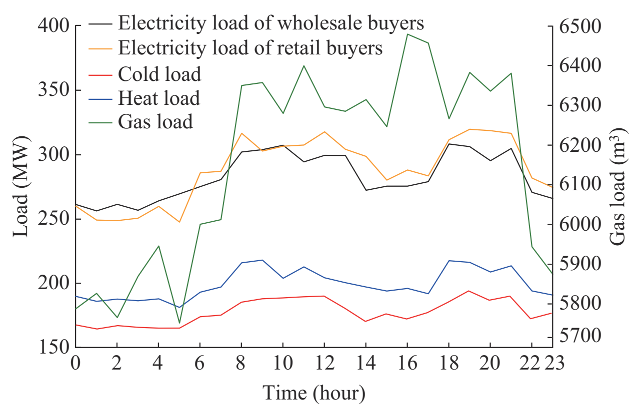

Fig. 5. Forecasted 24-hour cold, heat, electricity, and gas loads of RIES.

1) Comparison of Different Optimization Methods

To verify the effectiveness of the proposed method, the proposed method is compared with the traditional optimization method [7]. The traditional optimization method optimizes the operation cost based on the forecasted values of the loads and electricity prices. In this paper, the optimal operation decision obtained by the traditional optimization method is substituted into 1000 different electricity price scenarios to calculate the average operation cost, and the calculation results are compared with the proposed method.

The results of Scheme 1 and Scheme 2 (risk aversion coefficient $\gamma=1$) are compared with the traditional optimization method, as shown in Table III. It can be observed that the average operation costs of Scheme 1 and Scheme 2 in 1000 scenarios are lower than that of the traditional method, and the electricity purchase costs of Scheme 1 and Scheme 2 in the wholesale electricity market are far lower than that of the traditional method, while the heat and gas purchase costs are relatively higher. It shows that Scheme 1 and Scheme 2 reduce the electricity purchase cost in the electricity market and increase the cost of heat and gas with a relatively fixed price to reduce the risk as well as the average operation cost.

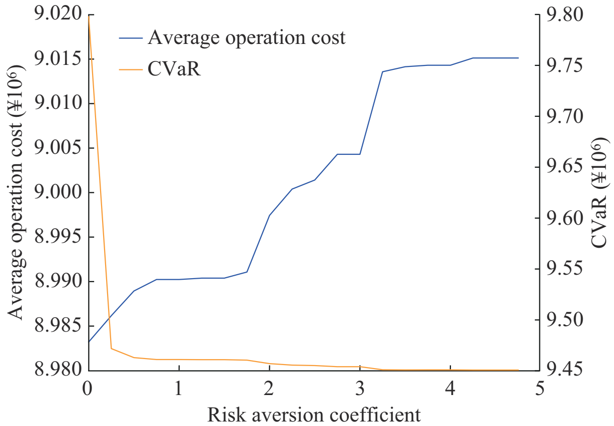

Fig. 6. Average operation cost and CVaR in Scheme 1.

In order to further verify the effectiveness of the proposed method, this paper uses the actual price data of Guangdong electricity market on August 1, 2020, August 11, 2020, August 14, 2020, and May 4, 2021. The forecasted loads are regarded as the actual loads. The optimal operation decision obtained by the methods above is substituted into these four actual scenarios to calculate the operation cost.

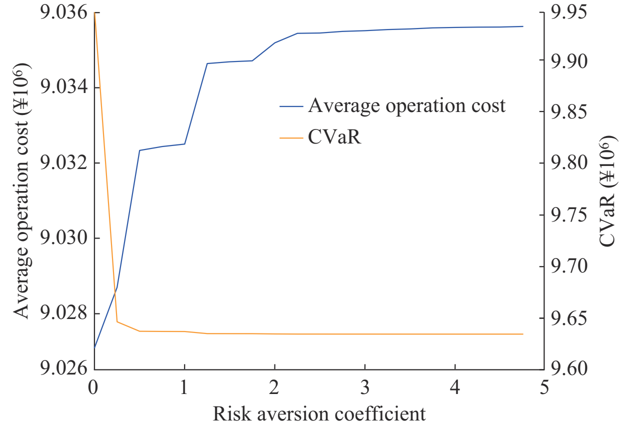

Fig. 7. Average operation cost and CVaR in Scheme 2.

The average electricity price and operation cost of the RIES are shown in Table IV. It can be observed that the operation cost of the traditional method is lower when the electricity price is lower than the forecasted value. However, when the electricity price is higher than the forecasted value, the operation cost of the proposed method is lower. It can be observed that the proposed method sacrifices the operation cost of low-electricity-price scenario, but limits the operation cost of high-electricity-price scenario, so that the average operation cost of RIES in multiple scenarios is lower. This method can find a trade-off between low operation cost and low risk, so that the RIES can operate at a relatively low operation cost, and reduce the operation cost in the extreme scenario. For the risk-averse RIES, the proposed method is of great significance.

TABLE III
RESULTS OF TRADITIONAL METHOD, SCHEME 1, AND SCHEME 2

Method	Average cost (¥)	Electricity purchase cost in wholesale electricity market (¥)	Electricity purchase cost in retail electricity market (¥)	Heat purchase cost (¥)	Gas purchase cost (¥)
Traditional method	9051738.86	3849696.56	3915136.90	360458.60	926446.79
Scheme 1 ($\gamma=1$)	8990233.14	3166424.64	3923192.22	785981.53	1114634.75
Scheme 2 ($\gamma=1$)	9032500.28	3140476.73	3923189.84	903713.41	1065120.31

TABLE IV
AVERAGE ELECTRICITY PRICE AND OPERATION COST OF RIES

Date	Average day-ahead price (¥)	Average real-time price (¥)	Operation cost with traditional method (¥)	Operation cost with Scheme 1 ($\gamma=1$) (¥)	Operation cost with Scheme 2 ($\gamma=1$) (¥)
August 1, 2020	180.97	86.81	8416885.60	8506778.72	8566407.89
August 11, 2020	253.74	268.33	9090036.49	9047284.50	9086787.70
August 14, 2020	205.45	206.37	8644983.85	8709581.93	8759716.48
May 4, 2021	355.17	391.17	10110595.56	9941570.83	9990637.31

2) Analysis of Optimal Operation Strategy

To study the operation strategy of the RIES in the electricity market, the electricity purchase strategy of the RIES in the wholesale electricity market and the characteristics of each energy conversion equipment and energy storage equipment are analyzed.

1) Result analysis of Scheme 1

Figure 8 shows the total submitted electricity quantity of wholesale buyers of the RIES $Q_{day,t}$ and the actual total electricity consumption of wholesale buyers of the RIES $Q_{wholesale,t}$ when the risk aversion coefficient γ is 0.1 and 1 in Scheme 1, respectively. Due to the uncertainty of spot electricity price in the wholesale electricity market, when the risk aversion coefficient is high, to reduce the risk, it is more inclined to consume less electricity during these periods; while when the risk aversion coefficient is low, it is more inclined to consume more electricity in the wholesale electricity market.

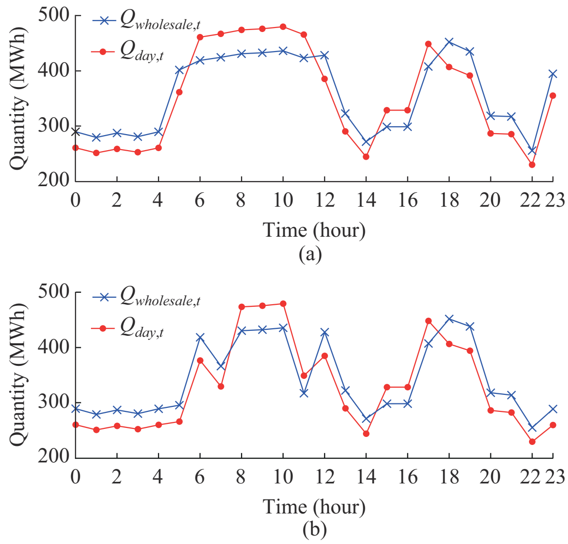

Fig. 8. Submitted electricity quantity and actual electricity consumption in Scheme 1. (a) $\gamma=0.1$. (b) $\gamma=1$.

In addition, combined with the analysis of forecasted day-ahead electricity price and real-time electricity price curves, it can be concluded that when the forecasted day-ahead electricity price is lower than the forecasted real-time price, the day-ahead submitted electricity quantity is higher than the actual consumption. And the higher or lower submitted electricity quantity is always close to the upper or lower limits of the allowable deviation. This result shows that in the proposed method, when participating in the electricity market transactions, the RIES makes full use of the space of speculative arbitrage. By comparing the forecasted day-ahead and real-time electricity prices, less or more electricity quantity can be submitted to reduce the expected operation cost. Since the electricity loads are known, the deviation between the day-ahead submitted electricity quantity and the actual electricity consumption can be accurately controlled by the RIES to ensure that it does not exceed the upper or lower limits of the allowable deviation.

Figure 9 shows the output of each refrigeration equipment in Scheme 1. It can be observed that, since retail buyers implement peak-valley price, the electricity price is relatively low in the valley period. During the flat and peak periods, the electricity price is higher than the forecasted day-ahead price, the forecasted real-time price, and the heat purchase price. Therefore, even if the spot electricity price in the wholesale electricity market has the risk of uncertainty, ER2 and AB are still preferred to ER1 during the flat and peak periods. Figure 10 shows the output of each heating equipment in Scheme 1. By comparing the outputs with the two risk aversion coefficients, the output of EB2 during certain periods when γ is 1 is significantly lower than that when γ is 0.1, which shows that when γ is high, the output of EB2 is reduced, and the electricity consumption in the wholesale electricity market is reduced as well as the risk.

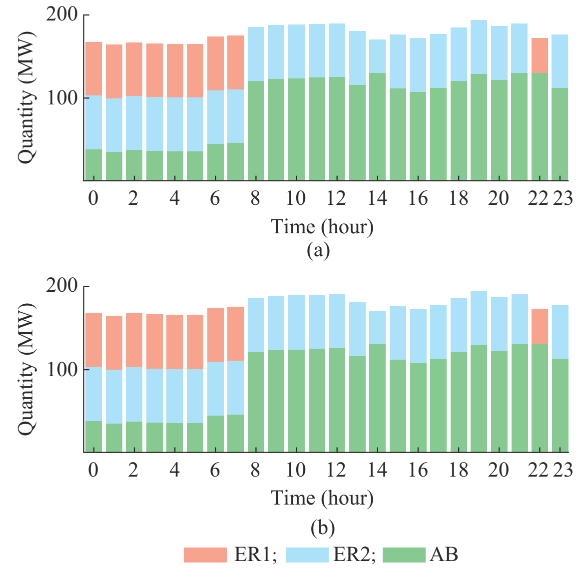

Fig. 9. Output of each refrigeration equipment in Scheme 1. (a) $\gamma=0.1$. (b) $\gamma=1$.

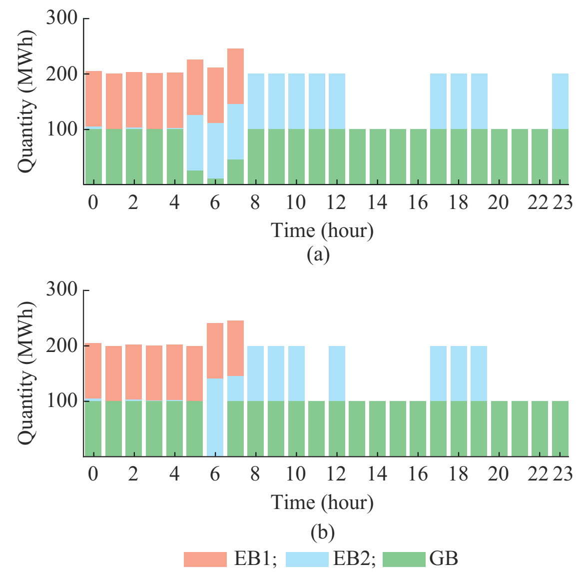

Fig. 10. Output of each heating equipment in Scheme 1. (a) $\gamma=0.1$. (b) $\gamma=1$.

Figure 11 shows the capacity of each energy storage equipment in Scheme 1. For the BATs, it can store electricity when the electricity price is low, and release electricity when the electricity price is high. Although the price of purchasing heat remains unchanged in the whole scheduling period, when the electricity price is low, a part of cheap heat energy can be generated by electric boiler and then stored in the TS. As the gas price remains unchanged during the whole scheduling period, there is no way to convert other energy into gas, so the GH cannot help reduce the operation cost.

From the above analysis, it can be concluded that when γ is low, the RIES will purchase more electricity from the wholesale electricity market, and correspondingly increase the output of EB2. Without changing the energy supply, the potential profit margin is improved, but the risk is also increased at the same time. When γ is high, the RIES will purchase less electricity from the wholesale electricity market, and correspondingly reduce the output of EB2. Without changing the energy supply, the profit margin is reduced, but the risk is also reduced at the same time.

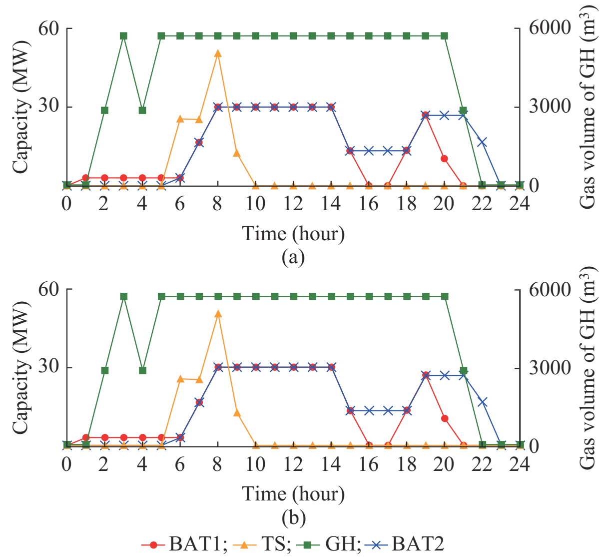

Fig. 11. Capacity of each energy storage equipment in Scheme 1. (a) $\gamma=0.1$. (b) $\gamma=1$.

2) Result analysis of Scheme 2

Figure 12 shows the total submitted electricity quantity and actual electricity consumption in Scheme 2 when the risk aversion coefficient γ is 0.1 and 1 considering the load uncertainty of the RIES. As can be observed from Fig. 12, as the actual electricity consumption cannot be determined in advance, it is impossible to determine the deviation between the day-ahead submitted electricity quantity and the actual electricity consumption. In this case, the day-ahead declaration strategy cannot set the deviation between the day-ahead submitted electricity quantity and the actual electricity consumption just at the upper and lower limits of the allowable deviation to obtain the maximum speculative arbitrage space. At this time, the day-ahead declaration strategy should be divided into two situations. One is that when the gap between the forecasted value of day-ahead electricity price and day-ahead electricity price is too large, it is almost possible to determine the level of day-ahead electricity price relative to real-time electricity price. Therefore, when the day-ahead electricity price is higher, the corresponding submitted electricity quantity can be as small as possible; and when the day-ahead electricity price is lower, the corresponding submitted electricity quantity can be as large as possible. In this way, even if part of the revenue is recovered, it will not reduce its own profit space. The other is that when the gap between the forecasted value of day-ahead electricity price and real-time electricity price is small, it is impossible to determine the level of day-ahead electricity price relative to real-time electricity price. Due to the existence of assessment fee, excessive deviation will not increase the revenue, but may cause greater losses. Therefore, the deviation between the submitted electricity quantity and the expected actual electricity consumption should be small. When the RIES carries out speculative arbitrage, the RIES needs to limit the possible losses. In addition, as in Scheme 1, when the risk aversion coefficient is high, the RIES reduces the actual electricity consumption, so as to reduce the risk of the spot electricity price uncertainty in the wholesale electricity market.

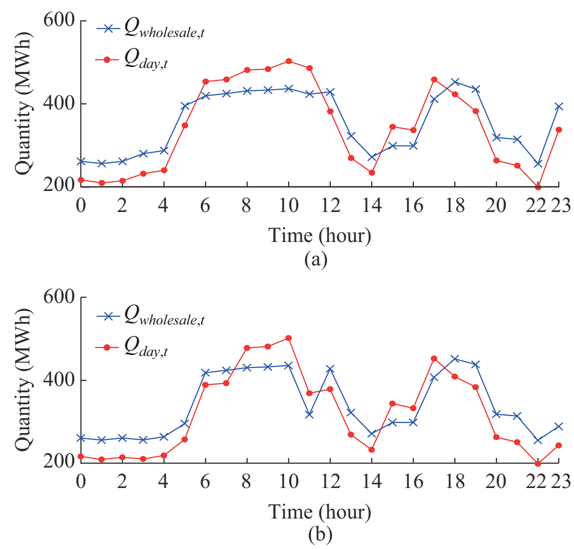

Fig. 12. Total submitted electricity quantity and actual electricity consumption in Scheme 2. (a) $\gamma=0.1$. (b) $\gamma=1$.

Figures 13 and 14 show the outputs of each refrigeration equipment and heating equipment in Scheme 2, respectively.

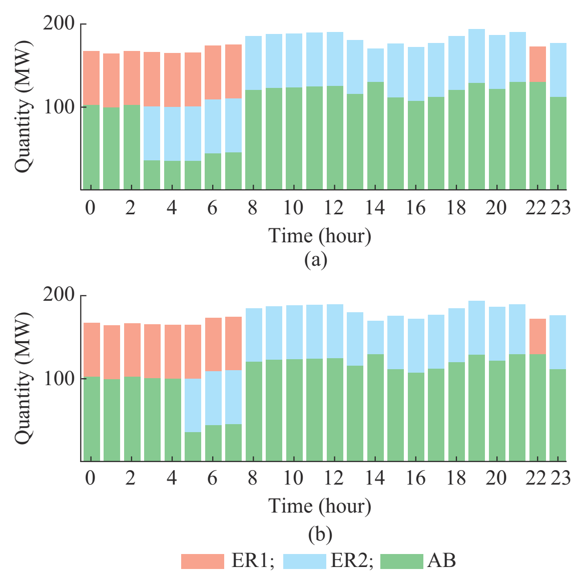

Fig. 13. Output of each refrigeration equipment in Scheme 2. (a) $\gamma=0.1$. (b) $\gamma=1$.

When the risk aversion coefficient γ is 1, the outputs of ER2 and EB2 of the RIES are reduced during certain periods compared with that when γ is 0.1, which reduces the actual electricity consumption in the wholesale electricity market, so as to reduce the risk. Figure 15 shows the capacity of each energy storage equipment in Scheme 2. It can be observed that the operation strategy of the energy storage equipment is similar to that in Scheme 1.

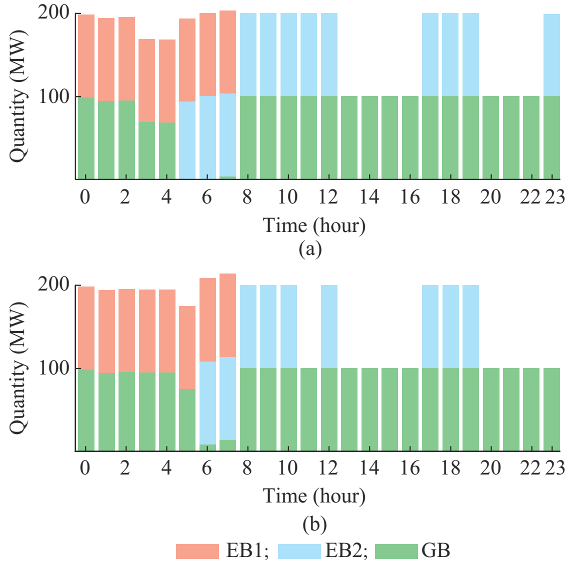

Fig. 14. Output of each heating equipment in Scheme 2. (a) $\gamma=0.1$. (b) $\gamma=1$.

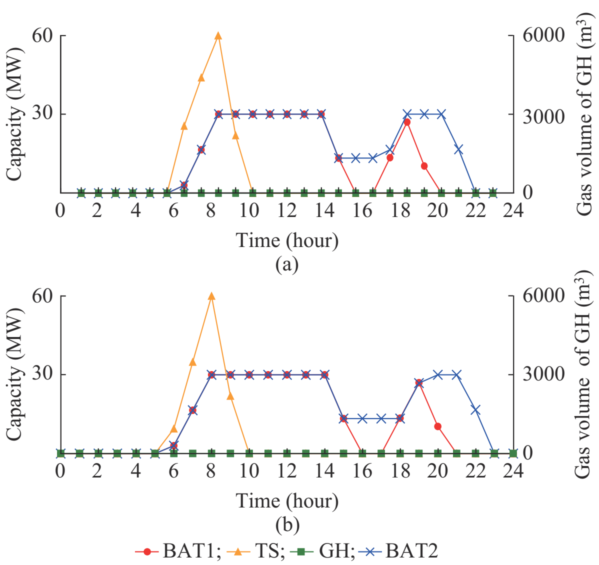

Fig. 15. Capacity of each energy storage equipment in Scheme 2. (a) $\gamma=0.1$. (b) $\gamma=1$.

From the above analysis, it can be observed that different from Scheme 1, the electricity purchase strategy in the wholesale electricity market is more complex and the RIES faces more uncertainties in Scheme 2.

VI. Conclusion

In this paper, the operation cost model of RIEM in the electricity market environment is established. And the risk of load and electricity price uncertainties are considered. The operation cost optimization model of RIES based on CVaR is proposed, and the optimization problem is transformed into a mixed-integer linear programming problem. The effectiveness of the model is verified by a real-world example. The following conclusions can be drawn.

1) Compared with the traditional method, the proposed method cannot reduce the operation cost in all cases. In the low-electricity-price scenario, the operation cost may be higher than the traditional method. However, the proposed method can effectively reduce the operation cost of high-electricity-price scenario and effectively restrict the risk of electricity market transactions, which is of great significance for the risk-averse RIES.

2) When the risk aversion degree of RIES is high, the conservative strategy can be selected to reduce the risk, but the expected operation cost will be higher. When the risk aversion degree of RIES is low, the aggressive strategy can be selected to reduce the expected operation cost, but the risk will be higher.

3) By reducing the actual electricity consumption in the wholesale electricity market and using the energy at a fixed price, the risk of spot electricity price uncertainty in the wholesale electricity market can be effectively reduced.

4) Under the condition that the loads can be effectively controlled, only the electricity prices are uncertain. The RIES can make full use of the speculative arbitrage space in the wholesale electricity market transactions, so as to reduce the electricity purchase cost in the wholesale electricity market as much as possible.

5) In the case of uncertain loads and electricity prices, the RIES cannot make full use of the speculative arbitrage space, but can choose the appropriate trading strategy according to the gap between the forecasted day-ahead electricity price and the forecasted real-time electricity price, so as to reduce the electricity purchase cost of the wholesale electricity market as much as possible.

In this paper, the operation cost optimization method only considers the optimization strategy before the day-ahead price is announced. In future, we will further study the operation optimization strategy of the RIES when the day-ahead electricity price is known.

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