

Risk-averse Optimal Scheduling of Regional Electricity-heating Integrated Energy System Considering Interface with Microgrids

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Abstract—A regional electricity-heating integrated energy system (REH-IES) can make extensive use of renewable energy sources, realize complementary and coordinated operation of multiple energy sources, reduce carbon emissions and promote the development of zero/low carbon systems. This paper proposes a risk-averse stochastic optimal scheduling model for REH-IES. An energy flow framework for the REH-IES is proposed considering energy interaction between the electric-heating microgrids (EHMs) and electricity distribution network and the heating network. Then, considering the uncertainties of power output of renewable energy sources, dynamic characteristics of pipelines in the heating network, and thermal inertia of smart buildings, a stochastic optimal scheduling model for the REH-IES is established. Uncertainties of renewable energy sources bring financial risks to optimal scheduling of the REH-IES. Therefore, conditional value-at-risk (CVaR) theory is adopted to measure the risk and to limit the risk within an acceptable range, to achieve minimum expected scheduling cost of the REH-IES. The stochastic programming-based problem is transformed into a second-order cone programming (SOCP) model through second-order cone relaxation method. Case studies verify the stochastic optimal scheduling model can reduce expected scheduling cost of the REH-IES, promote consumption of renewable energy sources and reduce carbon emissions.

Index Terms—Conditional value-at-risk, electric-heating microgrid, regional electricity-heating integrated energy system, smart buildings, SOCP.

I. INTRODUCTION

IN recent years, the problems of exhaustion of traditional fossil energy and deterioration of the environment have become increasingly severe. Increasing the proportion of clean energy power generation, vigorously implementing carbon emission reduction and building zero/low-carbon energy systems are regarded as effective means to solve the above issues [1], [2]. Therefore, a regional electricity-heating inte-

grated energy system (REH-IES) has received extensive attention. Coordinated operation of electricity and heating multi-energy systems can improve energy utilization efficiency [3], reduce fossil energy consumption and carbon emissions [4]–[6]. Meanwhile, the grid-connected operation of the electric-heating microgrid (EHM) [7] with a large amount of distributed renewable energy generation can promote coupling of multiple energy sources and increase the proportion of renewable energy power generation. However, renewable energy sources have brought huge uncertainties to the system, which lead to financial risks when regional electricity-heating integrated energy system agents (REH-IESA) carry out optimal scheduling.

At present, research on the coordinated operation of regional integrated electricity and heating systems have been widespread. The structure of the integrated energy system and the three subsystem models of power supply, heating and cooling are introduced in [8], and based on the characteristics of energy consumption and system operation, a complete scheduling program is established. Technical and economic feasibility of thermal storage tanks and electric boilers (EBs) under the electricity network and actual operating regulations are discussed in [9], and a mixed-integer linear optimal model is shown for the REH-IES. A decentralized market framework of energy transactions under a power distribution network and heating network based on the distribution electricity market and locational marginal price is investigated in [10]. Based on a heat current model of heating network and admittance matrix network equations of distribution network, a unified power flow model of the integrated energy system with electric-heat conversion and heat transfer/storage units is established in [11]. An integrated power generation expansion planning framework that simulates the iterative process of independent system operators, generation companies, and heating system companies is proposed [12]. A bi-level optimization problem that incorporates the flexible energy demand of the aggregators into a scheduling model of heat and electricity integrated energy system is described in [13]. DR on the EH structure configuration is discussed in [14] to minimize operational fuel and capital investment costs. A two-stage MES optimal configuration model, considering the system reserve value is studied to minimize the operating, investment, and maintenance costs [15]. However, the above research do not fully consider interaction between EMHs and electricity distribution

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networks and heating networks.

Research on the coupling relationship between a microgrid and the integrated energy system has received much attention from scholars. Aiming at an electricity-heating integrated energy system with CHP units and demand response, a hybrid energy sharing framework based on multi-time scale characteristics and multi-microgrids is constructed in [16]. An analytical model that considers the thermal dynamic characteristics of the heating network and buildings and promotes analysis, planning and operation of integrated energy systems is provided in [17]. A two-layer optimal operation framework for a building in the heating network in the integrated electric-heating community energy system is proposed in [18]. The building can respond to the heating demand of the integrated community energy system. In order to ensure safe operation of the integrated energy system and the thermal comfort of users, a day-ahead adaptive robust scheduling model is formulated in [19]. The framework for aggregating residential demands based on an incentive-based demand response program is described in [20], which introduces comfort indicators and proposes an advanced reward system. A coordinated scheduling model of electricity-heating integrated energy systems considering the thermal inertia of the heating network and aggregate buildings is proposed in [21]. An optimal operation model of an integrated energy system is constructed in [22], which combines the thermal inertia of the heating network and building to improve consumption of wind energy. In order to take advantage of the flexibility of smart buildings and realize flexible operation of active distribution networks, a modeling and optimal scheduling method of active distribution networks combined with smart buildings is proposed in [23]. Considering the dynamic characteristics of heating networks and thermal inertia of smart buildings with different heating modes, a distributed optimization scheduling model of an integrated energy system is established in [24]. In view of the current, continuous increase in the penetration rate of renewable energy, financial risks would affect scheduling and operation of the integrated energy system, which are not described in detail in the above works.

In view of the uncertainties in the system scheduling process, many works have adopted a conditional value-at-risk (CVaR) theory to effectively avoid financial risks. Considering the uncertainties of electricity demand, electricity price, and natural gas price, a new scenario-based smart energy hub optimization model is proposed [25], in which the CVaR is used to manage uncertainties. Based on the simultaneous calculation of robust profit and optimization of conditional robust profit, a risk management method for power producers bidding in the hour-ahead or day-ahead electric market is investigated in [26]. Taking into account the uncertainties of the probability distribution of wind power forecast errors, energy prices and solar power generation, a robust collaborative scheduling model based on CVaR is constructed in [27], [28]. An energy hub programming model considering renewable energy and energy storage systems is built in [29], in which the CVaR is used to measure risk. Formulation and solution of the optimal energy storage management problem is described in [30], which considers the risk and cost of energy interaction with the

electricity distribution network. Based on the CVaR theory, the risk behavior avoidance of microgrid aggregators and demand-side aggregators is studied in [31], [32]. A two-stage stochastic game model considering Cournot Nash pricing mechanism and the CVaR theory is shown in [33], which describes the profit function of each microgrid. In summary, research on optimal scheduling of the REH-IES seldom takes into account the thermal inertia of demand-side smart buildings in the EHMs and the financial risk of the uncertainties of renewable energy at the same time.

In order to promote consumption of renewable energy, mitigate carbon emissions, and build of zero/low carbon energy system, this paper proposes a risk-averse stochastic optimal scheduling model for the REH-IES considering the interface with EHMs. The main contributions of the paper are as follows:

1) A stochastic optimal scheduling model for the REH-IES considering the interface with the EHMs is proposed. Interaction between EHMs and the electricity distribution network and heating network is considered, while the EHMs can provide demand-side response capacities for the two energy networks. Operating constraints of internal energy sources in the EHMs and the detailed building thermal model are also taken into account in the REH-IES.

2) CVaR is used to measure financial risk in the scheduling process of the REH-IES caused by uncertainties of the WPs and photovoltaics (PVs) power output. Then combined with operation constraints of the electricity distribution network, the heating network and the EHMs, a stochastic optimal scheduling model for the REH-IES considering risk aversion and the EHMs is constructed.

3) The relationship between expected scheduling cost and risk coefficient is discussed. In addition, impact of the demand-side response of the EHMs on renewable energy consumption and expected scheduling costs is analyzed.

The rest of the paper is organized as follows: The framework of the REH-IES is described in Section II. The risk-averse stochastic optimal scheduling model for the REH-IES is constructed in Section III. A case study is shown in Section IV. The conclusion is written in Section V.

II. PROBLEM DESCRIPTION

An electricity distribution network, heating network, EHMs, gas turbines (GTs) and CHP units are covered in the REH-IES. The distribution network and the heating network are coupled by the CHP units and EHMs. The specific framework of the REH-IES is shown in Fig. 1.

Electricity and heat loads in the electricity distribution network and heating network can be obtained through the upper-layer grids, CHP units and EHMs. WPs, PVs, electrical energy storage (EES), heating energy storage (HES), EBs [9], [34], smart buildings, partial electrical loads and heat loads are included in the EHMs. The framework of the EHMs is shown in Fig. 2. Power sources that provide electrical energy in the EHMs mainly include WPs and PVs, which first supply the electrical load of the microgrid itself, and remaining electricity will be transmitted to the electricity distribution network. In

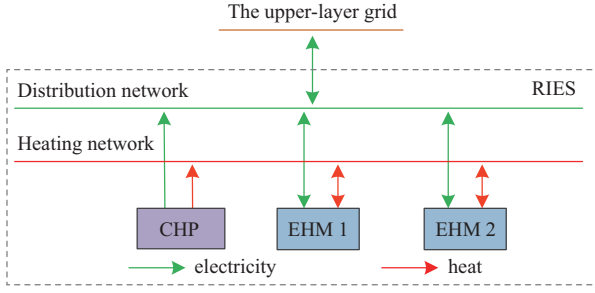


Fig. 1. Framework of the REH-IES.

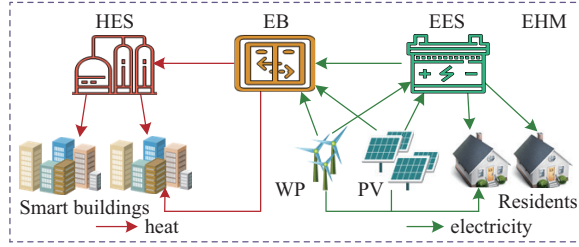


Fig. 2. Framework of the electric-heating microgrid.

addition, remaining power can also be stored in the EES, which can respond to fluctuation of the load and renewable power generation. Meanwhile, the main source of heat energy in the EHMs is the EBs, which converts electrical energy into heat energy. Generated heat energy meets the needs of users, and heat can be stored in the HES, which can alleviate the impact of heat load fluctuations in the heating network. Thermal inertia of smart buildings is considered in the EHM, and reasonable adjustment of the indoor temperatures of the smart buildings can improve flexibility in the REH-IES. Energy exchanged between EHMs and the distribution network is settled using distribution locational marginal pricing (DLMP).

The electricity distribution network and heating network studied in the paper are not two independent stakeholders but assumed to be managed by an economic entity to maximize social benefits. Therefore, this paper assumes the electricity distribution network and the heating network are scheduled and managed by the REH-IESA to achieve efficient use of energy. The specific framework of the REH-IESA centralized optimal scheduling is shown in Fig. 3.

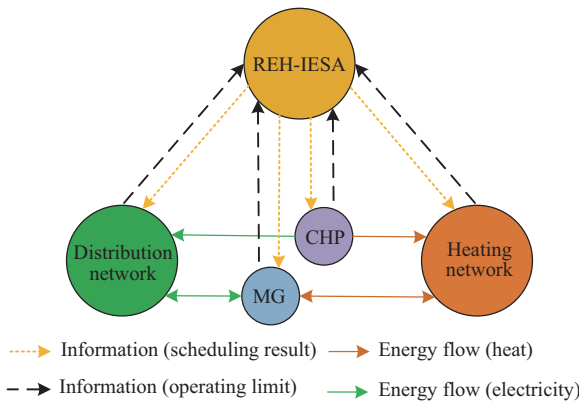


Fig. 3. Framework for optimal scheduling.

The REH-IESA collects loads and network operating limits in the electricity distribution network and heating network, as well as operating information of the EHMs and the CHP units. According to collected information, the REH-IESA takes minimum expected cost as the objective function for optimal scheduling, taking into account risk aversion and the EHMs.

III. PROBLEM FORMULATION

A stochastic optimal scheduling model of the REH-IES is formulated in this section. The electricity distribution network, heating network, and the EHMs models are considered. The CVaR is introduced to avoid financial risks brought by the uncertainties of WPs and PVs.

A. Stochastic Optimal Scheduling Model

1) Objective Function

This paper proposes a stochastic optimal scheduling model for the REH-IES, the objective function of which is to minimize expected operating cost of the REH-IES under scenarios. The objective function mainly includes five terms. The first to fourth terms are cost of purchasing electricity from the upper-layer grids, the GTs, the PVs and the WPs. The last term is the cost of purchasing natural gas.

$$F = \min \left\{ \sum_{w=1}^W \rho_w \left[\sum_{t=1}^{24} \left(C_{\text{buy},i,t} P_{i,t}^{\text{buy},w} + C_{\text{GT},i,t} P_{i,t}^{\text{GT},w} + C_{\text{PV},i,t} P_{i,t}^{\text{PV},w} + C_{\text{WP},i,t} P_{i,t}^{\text{WP},w} + C_{\text{CH}_4,i,t} N_{\text{CH}_4,i,t}^w \right) \right] \right\} \quad (1)$$

where W is the total number of scenario s . ρ_w is the probability of occurrence of each scenario w . $C_{\text{buy},i,t}$, $C_{\text{GT},i,t}$, $C_{\text{PV},i,t}$ and $C_{\text{WP},i,t}$, represent electricity prices provided by the upper-layer grids, the GTs, the PVs and the WPs, respectively. $C_{\text{CH}_4,i,t}$ is the price of natural gas. $P_{i,t}^{\text{buy},w}$, $P_{i,t}^{\text{GT},w}$, $P_{i,t}^{\text{PV},w}$ and $P_{i,t}^{\text{WP},w}$ represent electricity purchased by the REH-IESA from the upper-layer grids, the GTs, the PVs and the WPs, respectively. $N_{\text{CH}_4,i,t}^w$ represents the amount of natural gas purchased at node i at time t in scenario w .

2) Electricity Distribution Network Constraints

Node power balance constraints are modeled in (2)–(3). The voltage drop equation at the beginning and ending nodes of the branch is expressed in (4). The node voltage upper and lower limit constraints are written in (5). The line power flow constraint after second-order cone relaxation is represented (6), and the GTs operation constraints are shown in (7)–(8).

$$\sum_{i \in J_1} P_{ij,t}^w - I_{ij,t}^w x_{ij} - P_{L,j,t}^w - \sum_{j \in J_1} P_{jk,t}^w + P_{j,t}^{\text{EHM},w} + P_{j,t}^{\text{CHP},w} + P_{j,t}^{\text{GT},w} + P_{j,t}^{\text{buy},w} = 0 \quad (2)$$

$$\sum_{i \in J_1} Q_{ij,t}^w - I_{ij,t}^w x_{ij} + Q_{j,t}^{\text{GT},w} + Q_{j,t}^{\text{buy},w} - Q_{L,j,t}^w - \sum_{j \in J_1} Q_{jk,t}^w = 0 \quad (3)$$

$$U_{i,t}^w - U_{j,t}^w - 2(r_{ij}P_{ij,t}^w + x_{ij}Q_{ij,t}^w) + (r_{ij}^2 + x_{ij}^2)I_{ij,t}^w = 0 \quad (4)$$

$$U_{i,\min} \leq U_{i,t}^w \leq U_{i,\max} \quad (5)$$

$$\left\| \begin{matrix} 2P_{ij,t}^w \\ 2Q_{ij,t}^w \\ I_{ij,t}^w - U_{i,t}^w \end{matrix} \right\| \leq I_{ij,t}^w + U_{i,t}^w \quad (6)$$

$$P_{j,\min}^{\text{GT}} \leq P_{j,t}^{\text{GT},w} \leq P_{j,\max}^{\text{GT}} \quad (7)$$

$$Q_{j,\min}^{\text{GT}} \leq Q_{j,t}^{\text{GT},w} \leq Q_{j,\max}^{\text{GT}} \quad (8)$$

where $P_{ij,t}^w$ and $Q_{ij,t}^w$ represent the active and reactive power flow of line ij at time t in scenario w , the direction of which flows from node i to node j . J_1 and J_2 indicate the set of the beginning and ending nodes of the line ij , respectively. $I_{ij,t}^w$ denotes the square of the current flow of the line ij . r_{ij} and x_{ij} express resistance and reactance of the line ij . $P_{L,j,t}^w$ and $Q_{L,j,t}^w$ represent the active and reactive loads of node j at time t . $P_{j,t}^{\text{EHM},w}$ indicates the active power injected by the EHM. $P_{j,t}^{\text{GT},w}$, $Q_{j,t}^{\text{GT},w}$, $P_{j,t}^{\text{buy},w}$ and $Q_{j,t}^{\text{buy},w}$ indicate the active and reactive power injected by the GTs and the upper-layer grids at node j . $P_{j,t}^{\text{CHP},w}$ denotes the active power injected by the CHP units. $U_{i,t}^w$ denotes the square of the voltage at node i . $U_{i,\max}$ and $U_{i,\min}$ express the maximum and minimum voltages of node i , respectively. $P_{j,\max}^{\text{GT}}$, $P_{j,\min}^{\text{GT}}$, $Q_{j,\max}^{\text{GT}}$ and $Q_{j,\min}^{\text{GT}}$ indicate maximum and minimum active and reactive power output of the GTs, respectively.

3) Heating Network Constraints

Temperature of the hot water in the supply pipe and the return pipe before and after the mixing node are the same as described in (9)–(12). Upper and lower temperature limits of mixing nodes, supply pipes and return pipes are expressed in (13)–(18). Heat loss constraints in the pipes are modeled in (19)–(20). A heat load model is shown in (21). The heat source constraint is modeled in (22).

$$T_{u,t}^{s+,w} = T_{o,t}^{s,w} \quad u \in \Omega_1 \quad o \in \theta \quad (9)$$

$$T_{u,t}^{r+,w} = T_{o,t}^{r,w} \quad u \in \Omega_1 \quad o \in \theta \quad (10)$$

$$\sum_{v \in \Omega_2} (T_{v,t}^{s-,w} m_v^{s,w}) = T_{o,t}^{s,w} \sum_{v \in \Omega_2} m_v^s \quad o \in \theta \quad (11)$$

$$\sum_{v \in \Omega_2} (T_{v,t}^{r-,w} m_v^{r,w}) = T_{o,t}^{r,w} \sum_{v \in \Omega_2} m_v^r \quad o \in \theta \quad (12)$$

$$T_{u,\min}^s \leq T_{u,t}^{s+,w} \leq T_{u,\max}^s \quad (13)$$

$$T_{v,\min}^s \leq T_{v,t}^{s-,w} \leq T_{v,\max}^s \quad (14)$$

$$T_{u,\min}^r \leq T_{u,t}^{r+,w} \leq T_{u,\max}^r \quad (15)$$

$$T_{u,\min}^r \leq T_{u,t}^{r+,w} \leq T_{u,\max}^r \quad (16)$$

$$T_{\text{pipe},\min}^s \leq T_{\text{pipe},t}^{s+,w} \leq T_{\text{pipe},\max}^s \quad \text{pipe} \in \vartheta \quad (17)$$

$$T_{\text{pipe},\min}^r \leq T_{\text{pipe},t}^{r-,w} \leq T_{\text{pipe},\max}^r \quad \text{pipe} \in \vartheta \quad (18)$$

$$T_{v,t}^{s-,w} = (T_{u,t}^{s+,w} - T_{\text{en},t}^w) e^{\frac{-\lambda L}{C_p m_v}} + T_{\text{en},t}^w \quad (19)$$

$$T_{v,t}^{r-,w} = (T_{u,t}^{r+,w} - T_{\text{en},t}^w) e^{\frac{-\lambda L}{C_p m_v}} + T_{\text{en},t}^w \quad (20)$$

$$H_{o,t}^{d,w} = C_p m_o (T_{o,t}^{s,w} - T_{o,t}^{r,w}) \quad o \in \vartheta \quad (21)$$

$$H_{o,t}^{\text{CHP},w} + H_{o,t}^{\text{EHM},w} = C_p m_o (T_{o,t}^{s,w} - T_{o,t}^{r,w}) \quad o \in \vartheta \quad (22)$$

where $T_{u,t}^{s+,w}$, $T_{u,t}^{s-,w}$, $T_{u,t}^{r+,w}$ and $T_{u,t}^{r-,w}$ represent the inflow or outflow temperature of the supply water pipe or return water

pipe, respectively. $T_{o,t}^{s,w}$ and $T_{o,t}^{r,w}$ indicate temperatures of the mixing node of the supply pipe and the return pipe, respectively. Ω_1 and Ω_2 denote the sets of the inflow and outflow nodes of the pipeline in the heating network, respectively. θ and ϑ express the mixing nodes of the pipe and the set of pipelines in the heating network. m_v and m_r represent the mass flow at node v in the supply and return pipe v , which are known as constants. $T_{u,\max}^s$, $T_{u,\min}^s$, $T_{u,\max}^r$ and $T_{u,\min}^r$ indicate the upper and lower temperatures in the supply pipe or return pipe, respectively. $T_{\text{en},t}^w$ denotes the ambient temperature at time t . λ represents the heat dissipation coefficient of the pipe. L is the length of the pipe. C_p indicates the specific heat capacity of water. m_o is the mass flow of the mixing node o . $H_{o,t}^d$ denotes the heat load of the mixing node o at time t . $H_{o,t}^{\text{CHP},w}$ represents the heat produced by the CHP unit at time t . $H_{o,t}^{\text{EHM},w}$ represents the sum of the heat sources in the EHMs.

4) The EHM Constraints

In the EHM, EESs, HESs, EBs, WPs, PVs and smart buildings are considered. The operating models of distributed power generation are shown in (23)–(35). Charging and discharging power constraints of the EES are described in (23)–(26). State of charge constraint of the EES in adjacent time periods is modeled in (27). The electricity balance inside the EHMs is defined in (28). Charging and discharging power constraints of the HES are described in (29)–(32). State of charge constraint of the HES in adjacent time periods is modeled in (33). Operating constraints of the EBs are shown in (34). Heating balance inside the EHMs is defined in (35).

$$0 \leq P_{i,t}^{\text{EES},\text{in},w} \leq P_{i,\max}^{\text{EES},\text{in}} \quad (23)$$

$$0 \leq P_{i,t}^{\text{EES},\text{out},w} \leq P_{i,\max}^{\text{EES},\text{out}} \quad (24)$$

$$E_{\text{EES},i,\min}^{\text{SOC}} \leq E_{\text{EES},i,t}^{\text{SOC},w} \leq E_{\text{EES},i,\max}^{\text{SOC}} \quad (25)$$

$$\frac{P_{i,t}^{\text{EES},\text{out},w}}{\eta_{\text{out}}^{\text{EES}}} \leq E_{\text{EES},i,t}^{\text{SOC},w} \quad (26)$$

$$E_{\text{EES},i,t}^{\text{SOC},w} = (1 - \sigma_{\text{EES}}) E_{\text{EES},i,t-1}^{\text{SOC},w} + P_{i,t}^{\text{EES},\text{in},w} \eta_{\text{in}}^{\text{EES}} - \frac{P_{i,t}^{\text{EES},\text{out},w}}{\eta_{\text{out}}^{\text{EES}}} \quad (27)$$

$$P_{i,t}^{\text{EHM},w} = P_{i,t}^{\text{EES},\text{out},w} - P_{i,t}^{\text{EES},\text{in},w} + P_{i,t}^{\text{WP},w} + P_{i,t}^{\text{PV},w} - P_{i,t}^{\text{EB},w} - P_{i,t}^{d,w} \quad (28)$$

$$0 \leq H_{o,t}^{\text{HES},\text{in},w} \leq H_{o,\max}^{\text{HES},\text{in}} \quad (29)$$

$$0 \leq H_{o,t}^{\text{HES},\text{out},w} \leq H_{o,\max}^{\text{HES},\text{out}} \quad (30)$$

$$S_{\text{HES},o,\min}^{\text{SOC}} \leq S_{\text{HES},o,t}^{\text{SOC},w} \leq S_{\text{HES},o,\max}^{\text{SOC}} \quad (31)$$

$$\frac{H_{o,t}^{\text{HES},\text{out},w}}{\eta_{\text{out}}^{\text{HES}}} \leq S_{\text{HES},o,t}^{\text{SOC},w} \quad (32)$$

$$S_{\text{HES},o,t}^{\text{SOC},w} = (1 - \sigma_{\text{HES}}) S_{\text{HES},o,t-1}^{\text{SOC},w} + H_{o,t}^{\text{HES},\text{in},w} \eta_{\text{in}}^{\text{HES}} - \frac{H_{o,t}^{\text{HES},\text{out},w}}{\eta_{\text{out}}^{\text{HES}}} \quad (33)$$

$$H_{o,t}^{\text{EB},w} = \eta_o^{\text{EB}} P_{i,t}^{\text{EB},w} \quad (34)$$

$$H_{o,t}^{\text{EHM},w} = H_{o,t}^{\text{EB},w} + H_{o,t}^{\text{HES},\text{out},w} - H_{o,t}^{\text{HES},\text{in},w} - H_{o,t}^{d,w} \quad (35)$$

where $P_{i,t}^{\text{EES,in},w}$, $P_{i,t}^{\text{EES,out},w}$, $H_{o,t}^{\text{HES,in},w}$ and $H_{o,t}^{\text{HES,out},w}$ represent the charging and discharging power of the EES and the HES at time t , respectively. $P_{i,\max}^{\text{EES,in}}$, $P_{i,\min}^{\text{EES,out}}$, $P_{o,\max}^{\text{HES,in}}$ and $P_{o,\min}^{\text{HES,out}}$ indicate maximum and minimum charge and discharge power of the EES and the HES at time t , respectively. $E_{\text{EES},i,\max}^{\text{SOC}}$, $E_{\text{EES},i,\min}^{\text{SOC}}$, $S_{\text{HES},o,\max}^{\text{SOC}}$ and $S_{\text{HES},o,\min}^{\text{SOC}}$ represent maximum and minimum allowable states of charge of the EES and the HES. $E_{\text{EES},i,t}^{\text{SOC},w}$ and $S_{\text{HES},o,t}^{\text{SOC},w}$ express the states of charge of the EES and the HES at time t . σ_{EES} and σ_{HES} indicate the self-loss coefficients of the EES and the HES. $\eta_{\text{out}}^{\text{EES}}$, $\eta_{\text{in}}^{\text{EES}}$, $\eta_{\text{out}}^{\text{HES}}$ and $\eta_{\text{in}}^{\text{HES}}$ denote charging and discharging efficiencies of the EES and the HES, respectively. $P_{i,t}^{\text{EHM},w}$ and $H_{i,t}^{\text{EHM},w}$ represent the sum of the power sources and heat source in the EHMs. $P_{i,t}^{d,w}$ and $H_{o,t}^{d,w}$ represent the electricity load and heat load in the EHMs. $P_{i,t}^{\text{EB},w}$ and $H_{o,t}^{\text{EB},w}$ express the electric power consumed and heating power generated by the EBs at time t . η_h^{EB} represents the conversion efficiency of the EBs.

5) CHP Unit Constraints

Electrical energy and heat energy are coupled with each other by the CHP unit and the EB. A detailed model of the operation of the CHP unit is shown in (36). The relationship between power generation and natural gas consumption is described in (37).

$$\begin{cases} P_{o,t}^{\text{CHP},w} = \sum_{b=1}^B \beta_{o,t}^{\text{CHP},b} P_o^{\text{CHP},b,w} \\ H_{o,t}^{\text{CHP},w} = \sum_{b=1}^B \beta_{o,t}^{\text{CHP},b} H_o^{\text{CHP},b,w} \\ \sum_{b=1}^B \beta_{o,t}^{\text{CHP},b,w} = 1 \\ 0 \leq \beta_{o,t}^{\text{CHP},b,w} \leq 1 \end{cases} \quad (36)$$

$$N_{\text{CH}_4,t}^w = \frac{P_{o,t}^{\text{CHP},w} \Delta t}{\eta_o^{\text{CHP}} \text{LHV}_{\text{CH}_4}} \quad (37)$$

where B denotes the number of extreme points in the feasible region. $\beta_{o,t}^{\text{CHP},b}$ indicates the electricity-heating coefficient of the CHP unit at time t . η_o^{CHP} represents efficiency of the CHP unit. LHV_{CH_4} expresses the low heating value of CH_4 , which mainly depends on fuel composition.

6) WPs and PVs Power Output Constraints

Considering the uncertainties of the WPs and the PVs power output, a scenario-based stochastic programming method [35] is utilized in this paper. Forecast errors are expressed by a standard deviation of the hourly forecast values [36] as a normal distribution function, and its mean value is 0. Then, a large number of uncertain scenarios are generated through the Monte Carlo simulation method to improve accuracy of the results, but a large number of scenarios will make it difficult to solve the model within an acceptable time in practical applications. Therefore, a widely accepted scenario reduction method is used to simplify a large number of scenarios into several scenarios to reduce computational burden. Power output limits of WPs and PVs are shown in (38) and (39).

$$0 \leq P_{i,t}^{\text{WP},w} \leq P_{i,\max}^{\text{WP}} (1 - \zeta^{\text{WP},w}) \quad (38)$$

$$0 \leq P_{i,t}^{\text{PV},w} \leq P_{i,\max}^{\text{PV}} (1 - \zeta^{\text{PV},w}) \quad (39)$$

where $P_{i,t}^{\text{WP},w}$ and $P_{i,t}^{\text{PV},w}$ indicate the power output of the WPs and PVs at time t in scenario w , respectively. $P_{i,\max}^{\text{WP}}$ and $P_{i,\max}^{\text{PV}}$ represent the maximum output of the WPs and PVs at time t . $\zeta^{\text{WP},w}$ and $\zeta^{\text{PV},w}$ denote forecast errors of the WPs and the PVs.

7) Smart Building Constraints

Considering thermal inertia [24], smart buildings are heat loads with adjustable temperatures. A detailed model [37] is shown in (40)–(42).

$$C_{x,y}^{\text{wall}} \frac{dT_{x,y,t}^{\text{wall},w}}{dt} = \sum_{y \in N_{x,y}^{\text{wall}}} \frac{T_{y,t}^{\text{room},w} - T_{x,y,t}^{\text{wall},w}}{R_{x,y}^{\text{wall}}} + \gamma_{x,y} \alpha_{x,y} A_{x,y}^{\text{wall}} Q_{x,y,t}^{\text{rad}} \quad (40)$$

$$C_x^{\text{room}} \frac{dT_{x,t}^{\text{room},w}}{dt} = \sum_{j \in N_x^{\text{room}}} \frac{T_{x,y,t}^{\text{wall},w} - T_{x,t}^{\text{room},w}}{R_{x,y}^{\text{wall}}} + Q_{x,t}^{\text{int},w} + \pi_{x,y} \sum_{y \in N_x^{\text{room}}} \frac{T_{y,t}^{\text{room},w} - T_{x,t}^{\text{room},w}}{R_{i,j}^{\text{win}}} + \pi_{x,y} \tau_{x,y} A_{x,y}^{\text{win}} Q_{x,t}^{\text{rad}} + m_x^{\text{room}} C_{p,\text{air}} (T_{x,t}^{s,w} - T_{x,t}^{\text{room},w}) \quad (41)$$

$$T_{x,\min} \leq T_{x,t}^{\text{room},w} \leq T_{x,\max} \quad (42)$$

where $C_{x,y}^{\text{wall}}$ indicates the heat capacity of the wall between rooms x and y . $T_{y,t}^{\text{room},w}$ represents the temperature of the wall between rooms x and y at time t . $T_{x,y,t}^{\text{wall},w}$ denotes the temperature at room y . $N_{x,y}^{\text{wall}}$ expresses all the nodes adjacent to the wall between rooms x and y . $R_{x,y}^{\text{wall}}$ expresses the heat resistance between the centerline of wall and the side of the wall. $\gamma_{x,y}$ indicates the boolean variables of the sunlight state, 0 when the wall is not exposed to sunlight, or 1 otherwise. $\alpha_{x,y}$ denotes the heat absorption rate. $A_{x,y}^{\text{wall}}$ represents the surface area of the wall. $Q_{x,y,t}^{\text{rad}}$ denotes sunlight intensity corresponding to the direction of the wall at time t . C_x^{room} indicates the heat capacity of room x . N_x^{room} is the set of nodes adjacent to the room x . m_x expresses the air mass flow rate of the room. $\pi_{x,y}$ will be 0 if there is no window in the room, otherwise it will be 1. $\tau_{x,y}$ expresses the window transmittance. $A_{x,y}^{\text{win}}$ indicates the surface area of the window. $Q_{x,t}^{\text{int},w}$ denotes the heat source in room x during period t . $Q_{x,t}^{\text{rad}}$ represents sunlight intensity corresponding to the direction of room x at time t . $C_{p,\text{air}}$ denotes average specific heat capacity of indoor air. T_x^s represents indoor supply air temperature. $T_{x,\max}$ and $T_{x,\min}$ indicate upper and lower limits of indoor temperature at room x .

8) Daily Equivalent Carbon Emissions

A daily equivalent carbon emissions (DCE) formula is formulated in (43), which is used to evaluate the environmental performance of the REH-IES.

$$\text{DCE} = \sum_{w=1}^W \sum_{t=1}^{24} (P_{j,t}^{\text{buy},w} + P_{j,t}^{\text{GT},w} + P_{j,t}^{\text{CHP},w}) \cdot \text{CE} \quad (43)$$

where CE is the equivalent CO_2 emissions of the REH-IES, $0.572 \text{ kg CO}_2/\text{kWh}$ [1].

B. Risk-averse Stochastic Optimal Scheduling Model

1) Introducing the CVaR Theory

Uncertainties of the WPs and PVs power output bring financial risks to the REH-IES. This paper introduces a CVaR theory [29] into the above model, and establishes a risk-averse stochastic optimal scheduling model for the REH-IES considering the interface with the EHMs. The objective function is shown in (44).

$$\min\{F + \beta \cdot \text{CVaR}\} \quad (44)$$

$$\text{CVaR} = \min_{\xi, \eta_w} \left(\xi - \frac{1}{1 - \varepsilon} \sum_{w=1}^W p_w \eta_w \right) \quad (45)$$

$$F - \xi + \eta_w \geq 0 \quad \forall w \quad (46)$$

$$\eta_w \geq 0 \quad \forall w \quad (47)$$

where $\beta \in [0, 1]$ represents the risk coefficient. ξ indicates an auxiliary decision variable introduced to calculate the CVaR, and its optimal value ξ^* denotes the value-at-risk. η_w expresses the excess value of scheduling cost under scenario w , and its value is positive. F represents the objective function of the above-mentioned stochastic optimal scheduling model.

2) SOCP Model

A risk-averse stochastic optimal scheduling model for the REH-IES considering the interface with the EHMs is shown below. The objective function to minimize the total expected scheduling cost is described in (48).

$$\begin{aligned} \min \left\{ \sum_{w=1}^W \rho_w \left[\sum_{t=1}^{24} \left(C_{\text{buy},i,t} P_{i,t}^{\text{buy},w} + C_{\text{GT},i,t} P_{i,t}^{\text{GT},w} \right. \right. \right. \\ \left. \left. + C_{\text{PV},i,t} P_{i,t}^{\text{PV},w} + C_{\text{WP},i,t} P_{i,t}^{\text{WP},w} + C_{\text{CH}_4,i,t} N_{\text{CH}_4,i,t}^w \right) \right] \\ \left. + \beta \left(\xi - \frac{1}{1 - \varepsilon} \sum_{w=1}^W \rho_w \eta_w \right) \right\} \quad (48) \end{aligned}$$

Operating constraints of the electricity distribution network are shown in (2)–(8). Operating constraints of the heating network considering thermal inertia are modeled in (9)–(22). Operating constraints of the EHMs taking into account the operating mechanism of each device are described in (23)–(35). Operating constraints of CHP units are proposed in (36)–(37). Power output constraints of the WPs and PVs considering uncertainties are constructed in (38)–(39). Smart building constraints based on the node method and considering the heat storage characteristics of buildings are proposed in (40)–(42). Additional constraints after considering conditional value-at-risk are shown in (46)–(47).

The flowchart of the stochastic optimal scheduling model is shown in Fig. 4.

All programs of risk-averse stochastic optimal scheduling model proposed above are implemented in the CVX [38] toolbox in MATLAB R2014b on a PC with Intel Core i5 - 6200U CPU and 4 GB of RAM and the SOCP optimization problem is solved by the GUROBI solver [39].

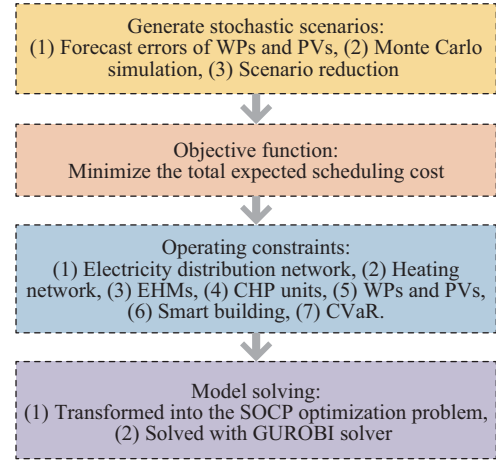


Fig. 4. Flowchart of the proposed stochastic optimal scheduling model.

IV. CASE STUDY

In order to verify the accuracy and effectiveness of the risk-averse stochastic optimal scheduling model for the REH-IES considering the interface with the EHMs, this paper uses two REH-IES for case studies, where a small system is coupled by a modified 33-node electricity distribution network and a 6-node heating network and the large system is coupled by modified 123-node electricity distribution network and the 32-node heating network. Meanwhile, the relationship between the scheduling cost of the system and the risk coefficient under different risk preferences is discussed, and the influence of building thermal inertia on REH-IES's scheduling decision is explored.

A. Modified E33-H6 Network

Topology of the test system is shown in Fig. 5. EHMs and the CHP units are located at nodes 7, 11, and 18 of the electricity distribution network, and located at nodes 4, 6, and 1 of the heating network, respectively. GTs are connected to nodes 22 and 30 of the electricity distribution network.

The load profiles of electricity and heating systems, as well as solar radiation and outside temperature are shown in Fig. 6. Simultaneously, it assumes the reactive power load in the electricity distribution network is 30% of the active load [40]. The occurrence probability of each scenario is shown in Table I. Relevant parameters such as capacity and quotation of renewable energy in REH-IES are depicted in Table II. Related parameters of heating network such as building parameters and pipeline temperatures are referred to [24]. In addition, natural gas price in the natural gas market is \$3/m³.

1) Impact of Different Risk Factors on Scheduling Strategies

In order to analyze the impact of risk coefficient on the expected cost of the REH-IES, this section calculates the expected cost of the system and the CVaR under different risk factors based on the SOCP model constructed above. Among them, the confidence level $\alpha = 0.95$.

The expected scheduling costs and the CVaRs under different risk coefficients are shown in Fig. 7. It can be seen that as the risk coefficient increases, the expected cost of scheduling of the REH-IES gradually increases, while the CVaR gradually

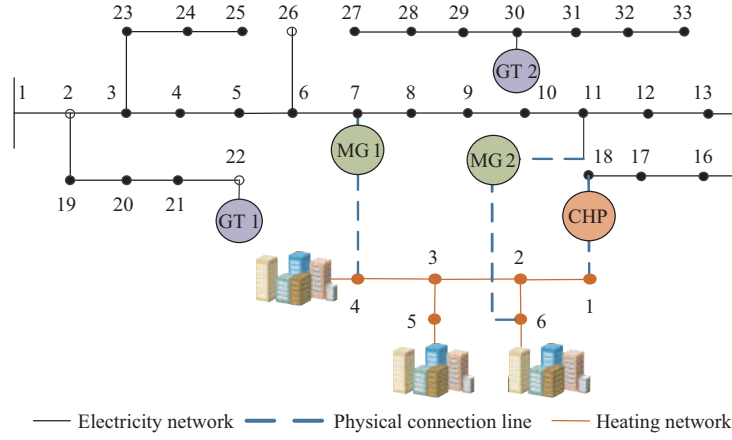


Fig. 5. Topology of the modified E33-H6 network.

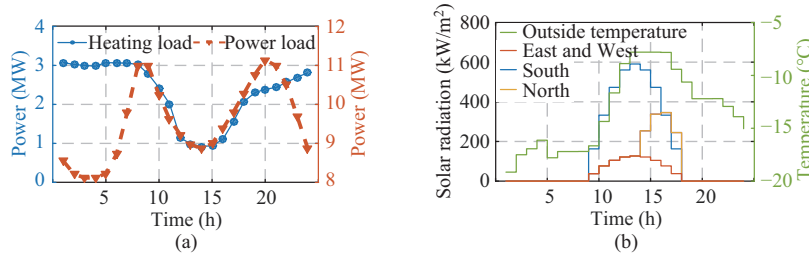


Fig. 6. Related data. (a) Load profiles of electricity and heating systems. (b) Solar radiation and outside temperature.

TABLE I
OCCURRENCE PROBABILITY OF EACH SCENARIO

Scenario	Probability	Scenario	Probability
1	0.074	6	0.204
2	0.103	7	0.068
3	0.053	8	0.084
4	0.086	9	0.066
5	0.097	10	0.165

decreases. When risk factor β is small, the REH-IESA begins to try to ignore risks, pursuing smaller power generation costs but facing greater risk of cost fluctuations. When risk factor β is large, the REH-IESA strives to avoid risks, pursuing lower cost fluctuation risks but facing higher total power generation costs.

Comparison of power generation scheduling results under three different risk factors is conducted below: i) slight risk aversion: $\beta = 0.5$. ii) moderate risk aversion: $\beta = 1$. iii) severe risk aversion: $\beta = 2$. Electricity purchased from the upper-layer grid and natural gas results in the three cases are shown in Fig. 8(a) and (b). Indoor temperatures of the smart building are compared in Fig. 9. It is obvious the REH-IESA purchases more electricity from the upper-layer grids and natural gas in order to avoid risks when β increases. At the same time, smart buildings provide more flexibility of resources by lowering the indoor temperatures when electricity price is high. Therefore, it is necessary to bear more power generation costs to avoid the risk cost caused by uncertainties.

2) Impact of Thermal Inertia of Smart Buildings on the Scheduling Strategies

This section mainly analyzes the impact of thermal inertia

TABLE II
RELEVANT DATA IN REH-IES

Parameter	Value	Parameter	Value
$C_{GT1,i,t}$	35 \$/MW	$C_{GT2,i,t}$	40 \$/MW
$P_{GT1,m,max}$	1.5 MW	$P_{GT2,m,max}$	1.5 MW
$P_{GT1,m,min}$	0 MW	$P_{GT2,m,min}$	0 MW
$Q_{GT1,m,max}$	1.2 MW	$Q_{GT2,m,max}$	1.2 MW
$Q_{GT1,m,min}$	-1.2 MW	$Q_{GT2,m,min}$	-1.2 MW
$P_{EES1,in,m,max}$	1.5 MW	$P_{EES2,in,m,max}$	1 MW
$P_{EES1,out,m,max}$	1.5 MW	$P_{EES2,out,m,max}$	1 MW
$E_{EES1,m,max}^{SOC}$	3 MW	$E_{EES2,m,max}^{SOC}$	2 MW
$E_{EES1,m,min}^{SOC}$	0 MW	$E_{EES2,m,min}^{SOC}$	0 MW
$P_{HES1,in,m,max}$	0.2 MW	$P_{HES2,in,m,max}$	0.1 MW
$P_{HES1,out,m,max}$	0.2 MW	$P_{HES2,out,m,max}$	0.1 MW
$S_{HES1,m,max}^{SOC}$	0.4 MW	$S_{HES2,m,max}^{SOC}$	0.2 MW
$S_{HES1,m,min}^{SOC}$	0 MW	$S_{HES2,m,min}^{SOC}$	0 MW
$\eta_{out}^{EES}/\eta_{in}^{EES}$	0.95	$\eta_{out}^{HES}/\eta_{in}^{HES}$	0.85
$\sigma_{EES}/\sigma_{HES}$	0.001/0.005	η_h^{EB}	0.90
$P_{EB1,c,max}$	0.5 MW	$P_{EB2,c,max}$	0.3 MW
$H_{EB1,c,max}$	0.3 MW	$H_{EB2,c,max}$	0.2 MW
$C_{PV1,i,t}$	30 \$/MW	$C_{PV2,i,t}$	33 \$/MW
$P_{PV1,i,max}$	1 MW	$P_{PV2,i,max}$	2 MW
$P_{PV1,i,min}$	0 MW	$P_{PV2,i,min}$	0 MW
$C_{WP1,i,t}$	36 \$/MW	$C_{WP1,i,t}$	38 \$/MW
$P_{WP1,i,max}$	2 MW	$P_{WP1,i,max}$	3 MW
$P_{WP1,i,min}$	0 MW	$P_{WP1,i,min}$	0 MW

of smart buildings on the expected cost of scheduling of the REH-IES. According to the aforementioned SOCP model, the

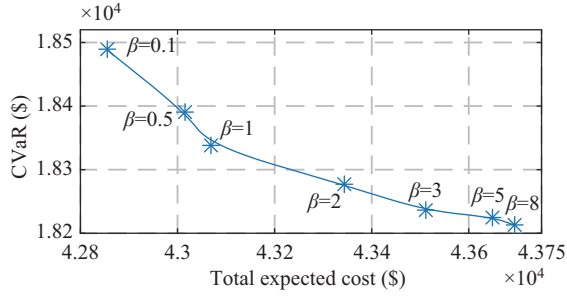


Fig. 7. Expected scheduling costs and the CVaRs under different risk factors.

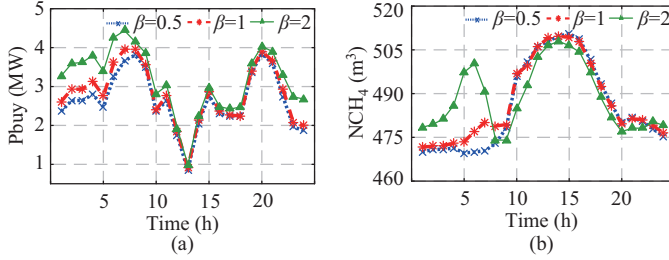


Fig. 8. Purchased electricity (a) and natural gas (b) in three cases.

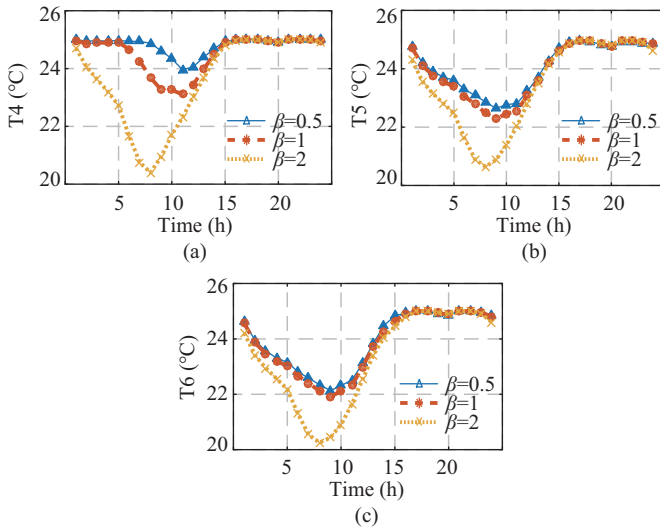


Fig. 9. The indoor temperature of smart buildings in three cases. (a) Smart building on node 4. (b) Smart building on node 5. (c) Smart building on node 6.

impact of maintaining different indoor temperature ranges in smart buildings on the expected cost of the system and the consumption of the WPs and PVs is analyzed.

Compare the following two cases:

Case 1: temperature adjustable range of the smart building is 22–24°C.

Case 2: temperature adjustable range of the smart building is 20–25°C.

Scheduling results in the scenario with the highest probability of occurrence are shown below.

Indoor temperatures of the smart building in the above two cases are displayed in Fig. 10(a) and (b). The difference of power output of PV and WP between Case 2 and 1 are shown in Fig. 11(a) and (b). It can be seen that when the

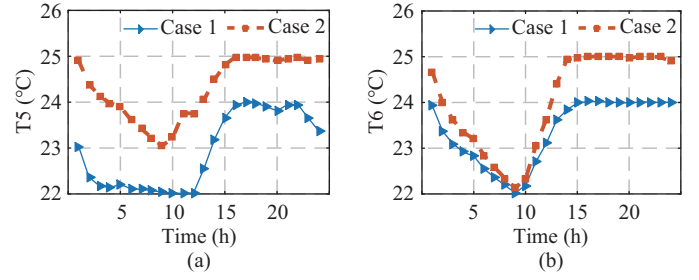


Fig. 10. The indoor temperatures of smart buildings in two cases. (a) Smart building on node 5. (b) Smart building on node 6.

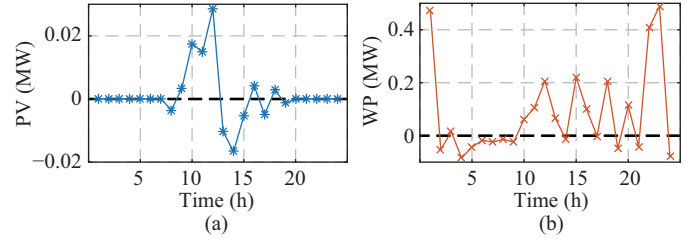


Fig. 11. The increases in power output of PV (a) and WP (b) in Case 2 over Case 1.

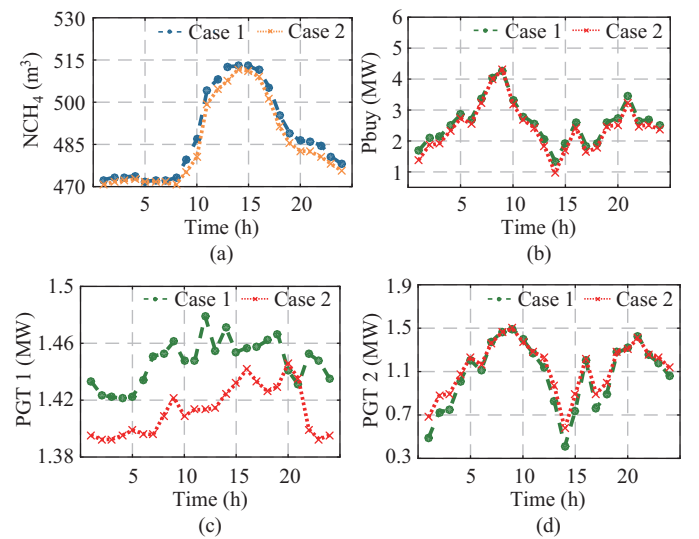


Fig. 12. The amount of natural gas purchased (a) and electricity purchased from the upper grid (b), GT1 (c) and GT2 (d) in two cases.

adjustable temperature range of smart buildings increases, the EHMs provide more electrical and heat energy to the REH-IES. The increase of flexible resources in REH-IES promotes the consumption of WPs and PV power generation.

The amount of natural gas purchased is shown in Fig. 12(a), The results of electricity purchased from the upper-layer grid, GT1 and GT2 are shown in Fig. 12(b), (c) and (d). It can be seen that when the adjustable temperature range of smart buildings increases, the amounts of purchased natural gas and electricity are reduced.

The expected scheduling costs of the REH-IES in the two cases are shown in Table III. It can be seen the expected scheduling cost, financial risk cost and daily equivalent carbon emissions are decreased by 0.47%, 0.55% and 0.28% with

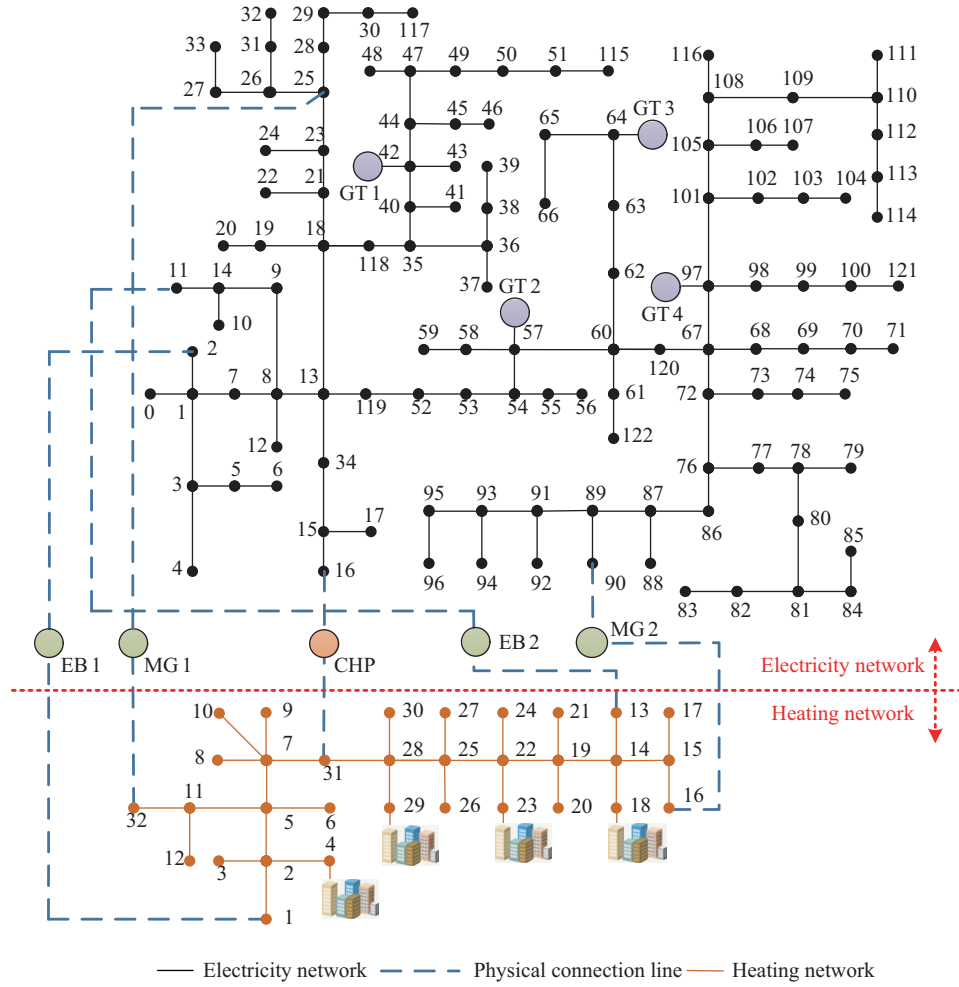


Fig. 13. Topology of the modified E123-H32 network.

TABLE III
EXPECTED COSTS AND CARBON EMISSIONS IN TWO CASES

Cases	Expected cost (\$)	CVaR (\$)	DCE (kg CO ₂)
Case 1	4.23×10^4	1.79×10^4	70.46
Case 2	4.21×10^4	1.78×10^4	68.47

increase of the adjustable temperature range of the smart buildings. In summary, when the adjustable temperature range of smart buildings increases, smart buildings in the EHMs would provide more flexibility, consumption of WPs and PVs will increase, carbon emissions will decrease and expected cost and risk cost of overall system will decrease. Taking into account that thermal inertia of the smart building can improve utilization of renewable energy sources and reduce scheduling costs of the REH-IES.

B. Modified E123-H32 Network

In order to further illustrate effectiveness of the proposed model, a modified E123-H32 network is used for verification. Detailed topology is shown in Fig. 13. The EHMs, CHP units and EBs are, respectively, connected to nodes 25, 90, 16, 2 and 11 of the electricity distribution network, and to nodes 32, 16, 31, 1 and 13 of the heating network, respectively. GTs are located at nodes 42, 57, 64 and 97 of the electricity distribution

network. The smart buildings are integrated at nodes 4, 18, 23, and 29 in the heating network. Related parameters can be queried in [24].

Based on the above case formulation, overall scheduling result of the REH-IES is analyzed by changing the temperature control range of the smart building. Comparing and analyzing Case 3 and Case 4, in which the temperature control ranges are 20–24°C and 19–25°C, respectively. The results in the highest probability scenario are shown below.

The difference of power output of PV and WP between Case 4 and 3 is shown in Fig. 14. Expected scheduling cost results of REH-IES in the two cases are described in Table IV. It is obvious that considering the thermal inertia of smart buildings

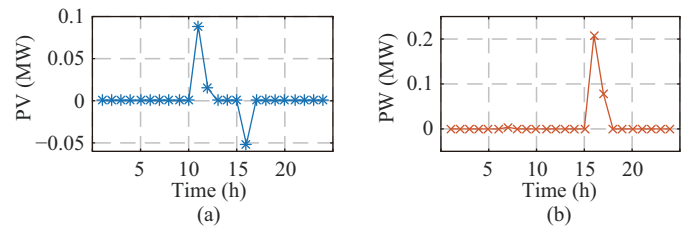


Fig. 14. The increase in power output of (a) PV and (b) WP in Case 4 over Case 3.

TABLE IV
EXPECTED COSTS IN TWO CASES

Cases	Expected cost (\$)	CVaR (\$)
Case 3	1.056×10^4	1.056×10^4
Case 4	1.035×10^4	1.041×10^4

can improve utilization rate of renewable energy sources and reduce expected scheduling cost and financial risk cost of the REH-IES. Results verify the validity and applicability of the proposed model in large-scale REH-IES.

In Case 4 of the modified E123-H32 network, the SOCP model constructed above has 266,020 equations and 389,631 variables. Its calculation time is 21.78 seconds, which is acceptable for day-head application. Relaxation accuracy of the branch power flow equation of each branch can be measured by the sum of the errors of each branch in the electricity distribution network. Second-order cone relaxation error of Case 4 in the modified E123-H32 network is 3.629×10^{-6} , which is within the allowable range.

V. CONCLUSION

This paper establishes a risk-averse stochastic optimal scheduling model for a REH-IES considering interface with the EHMs. The framework and model of the REH-IES optimal scheduling, considering the energy interaction among the EHMs and electricity distribution network and heating network, are introduced. Financial risks brought by the uncertainties of renewable energy power output are also considered and the CVaR is used to avoid risks. The stochastic programming-based problem is transformed into a SOCP model through second-order cone relaxation method. The objective function is to minimize total expected scheduling cost. By analyzing the impact of risk coefficient on expected scheduling cost, it demonstrates the proposed model is effectively risk-averse. Taking into account the thermal inertia of the smart building can improve utilization of renewable energy sources, mitigate carbon emissions and reduce scheduling costs of the REH-IES, thereby promoting development of a zero/low carbon energy system.

For future work, we will consider the structure of the natural gas network and an integrated energy system integrating electricity, heating and natural gas networks.

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