

Article

Optimized Operation of Integrated Cooling-Electricity-Heat Energy Systems with AA-CAES and Integrated Demand Response

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Abstract: Integrated energy systems (IESs) have been implemented with the objective of enhancing the efficiency of energy utilization and facilitating the sustainable transition of society and energy systems. To further explore the multi-energy coupling capacity and carbon reduction potential of the IESs, this study presents the design of an integrated cold-electricity-heat energy system (ICEHS) with advanced adiabatic compressed air energy storage (AA-CAES). AA-CAES has the capacity to not only store and release electric energy, but also to provide cold and heat energy, which makes it an ideal choice for this application. The main work of this study is fourfold: (1) the energy hub concept is employed to describe the energy transformations within AA-CAES, thereby reducing the modeling complexity; (2) integrated demand response (IDR) for cooling, heating, and electric loads, including shiftable loads, adjustable loads, interruptible loads, and replaceable loads, is considered; (3) Latin hypercubic sampling in conjunction with K-means clustering is employed to address the issue of source-load uncertainty; and (4) an ICEHS operation optimization model is developed with the objective of minimizing the daily operating cost, where the possible cost terms include energy purchase cost, operation and maintenance cost, demand response cost, and carbon emission cost. A typical community integrated energy system is employed as an illustrative example, and four different scenarios are established to validate the effectiveness of the proposed model. The results indicate that AA-CAES and IDR can effectively reduce the daily operating cost and carbon emissions of an ICEHS. In comparison to the Scenario that did not incorporate AA-CAES and IDR, the daily operating cost and carbon emissions are reduced by 4.8% and 10.3%, respectively.

Keywords: integrated energy system; AA-CAES; optimal operation; integrated demand response; source-load uncertainty



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1. Introduction

1.1. Motivation

The gradual depletion of fossil fuels and the intensification of environmental pollution present significant challenges to the global energy structure. In light of these challenges, there is a pressing need to further adjust the mode of energy production and consumption to meet the developmental requirements of the new era. The integrated energy system (IES) has garnered considerable attention in energy research circles due to its capacity to facilitate the efficient utilization of various energy forms—such as cold, heat, electricity, and gas—and to effectively promote the adoption of renewable energy sources [1]. The IES employs integrated planning and optimized operation to enhance energy efficiency and operating economics while reducing environmental impacts. Furthermore, by integrating renewable energy sources, the IES encourages the consumption of renewable energy and contributes to carbon reduction. Consequently, the IES not only fulfills energy demand

but also facilitates the development of robust and sustainable energy supply systems that effectively mitigate environmental pressures [2].

Energy storage represents a crucial component of IESs, serving to enhance energy utilization efficiency and promote renewable energy consumption. Compressed air energy storage (CAES) is an innovative energy storage technique that uses electric energy to compress air during periods of low power demand and releases compressed air to drive a turbine to generate electricity during periods of peak power demand [3]. CAES has several advantages, including sustainability, scheduling flexibility, and scalability. In contrast to traditional CAES, advanced adiabatic compressed air energy storage (AA-CAES) is capable of utilizing the heat generated by compressed air for heat supply and the low-temperature air released during the expansion process for cold energy supply. Furthermore, the efficiency of AA-CAES is significantly enhanced due to the minimal energy loss in an adiabatic environment. The multi-energy cogeneration feature enables AA-CAES to be employed as a micro-integrated energy system, achieving up to 90% primary energy utilization of the input energy through energy cascading and flexible energy utilization patterns. However, the internal structure of AA-CAES is intricate, posing a significant challenge in modeling it in a manner that balances complexity and effectiveness.

Integrated demand response (IDR) is a form of demand response applied in a multi-energy system. In IDR, energy consumers can respond not only by reducing energy consumption or choosing to consume energy during off-peak hours but also by changing the type of energy consumed. IDR can break the boundaries between different types of energy sectors to realize a deep response to demand-side resources [4], thereby improving the economic efficiency of the energy system and unlocking the potential of demand response resources [5].

Source-load uncertainty can have a significant impact on IES operational optimization. As renewable energy sources constitute an ever-increasing proportion of the electricity supply, their inherent unpredictability and indirectness are becoming increasingly evident. This has the potential to threaten the stability of power grids and the balance of supply and demand.

In order to enhance the operational efficiency of IESs, it is possible to integrate AA-CAES and IDR while considering source-load uncertainty. Such integration enables IESs to leverage the multi-energy cogeneration capabilities of AA-CAES and the depth of response to demand-side resources inherent in IDR while mitigating the impact of uncertainty on system operations.

1.2. Literature Review

In order to achieve the dual objectives of consuming renewable energy and moderating load fluctuations, the IESs proposed in existing studies are designed to integrate energy storage devices. Zhou et al. [6] established a regional IES with a seasonal thermal energy storage system coupled with heat pumps and solar collectors. This was done in order to address the issue of large differences in user loads and renewable energy sources between seasons. Similarly, Tan et al. [7] proposed a three-stage scheduling optimization model for an integrated electricity and heat system with seasonal and short-term thermal energy storage. Chen et al. [8] developed an integrated biomass energy system with electrochemical energy storage and proposed a model to optimize its operation. The objective functions were to achieve the lowest economic cost and the highest renewable energy utilization rate. Shen et al. [9] classified parameters and variables into fast and slow time scales according to scheduling requirements and proposed an optimized operation model for IESs featuring a hybrid energy storage system composed of batteries and hydrogen storage. Wang et al. [10] constructed an electric-thermal coupling model of the hydrogen energy storage unit and proposed a CSPO-GE optimization algorithm for the operation of an IES with hydrogen storage. Jia et al. [11] established a regional IES integrated renewable energy, energy storage, and power/thermal sharing between stations and proposed a multi-objective optimization model involving economic benefits, carbon reduction, and

reliability. Recently, Zou et al. [12] designed an aggregator-network coordinated P2P multi-energy trading framework. The uncertainties from renewable generation are handled by an adaptive PSO approach with a scenario-based ambiguity set. Li et al. [13] proposed an energy scheduling method for a multi-energy rural microgrid with renewable energy and biomass resources, aiming to satisfy the rural electrical, thermal, natural gas, and irrigation demands economically.

The technical characteristics, application scenarios, and system efficiency of different energy storage devices vary considerably. Electrochemical energy storage is a widely utilized technology in IESs due to its advantageous characteristics, including high technological maturity, high energy density, high conversion efficiency, and a wide range of potential application scenarios. However, electrochemical energy storage also presents certain challenges, including concerns about environmental impact, difficulties in disposal after scrapping, and shorter service life. In comparison, AA-CAES offers significant advantages, including high capacity, long service life, low cost, and low pollution, positioning it as a highly promising large-scale energy storage technology [14,15]. Cao et al. [16] and Wu et al. [17] designed hybrid energy storage systems integrating thermal energy storage and CAES. With regard to the optimization of IES operational optimization, Jadidbonab et al. [18] optimized the risk-constrained scheduling of a wind-integrated IES and evaluated its operation in combination with CAES, thermal, and electrical demand responses. Wang et al. [19] proposed a two-layer optimization model to enhance the reliability and cost-effectiveness of IESs with AA-CAES and IDR. The upper-layer capacity configuration model aims to minimize the operating costs of AA-CAES during the planning period, whereas the lower-level scheduling model is responsible for solving the optimal operation of the IES. Similarly, Adib et al. [20] developed a design approach based on bi-level programming for an IES comprising wind turbines, CAES, and diesel generators for remote areas with limited access to reliable and affordable energy sources. Zhang et al. [21] presented a stochastic optimal dispatch model of a combined heat and power system integrating AA-CAES considering uncertainty associated with wind power output, load, and outdoor temperature. Li et al. [22] presented a reserve capacity model of AA-CAES for power system optimal joint energy and reserve scheduling, considering the practical limitations and operation characteristics of AA-CAES.

IDR is better suited to the energy supply characteristics of IESs than traditional electrical demand response. Xiong et al. [23] devised an optimal scheduling framework for an IES that integrates multi-energy sharing and IDR to fully utilize the energy resources of different IESs, achieve local energy consumption efficiency, and enhance demand-side flexibility. Yang and Liu [24] proposed a collaborative optimization model for cooling, heating, and electricity in an IES considering a ladder carbon trading mechanism and multi-energy demand response. Duan et al. [25] developed an IES low-carbon economy optimization model that considers refined P2G and longitudinal electricity/gas demand response as well as horizontal electricity/gas demand response. Wang et al. [26] proposed an IES operation method to reduce total operating cost and carbon emissions, where electric and heating loads jointly participate in demand response, considering the peak-to-valley complementarity of electric and heating loads in time distribution. Ren et al. [27] developed a system dynamics-based IDR model for IESs with a multi-energy coupling that incorporates flexible loads, energy storage, and electric vehicles as the main participants.

A variety of approaches have been put forth to address the issue of source load uncertainty. These methods can be grouped into four main categories: Scenario reduction, stochastic optimization, robust optimization, and fuzzy optimization. Zhou et al. [28] presented a two-stage stochastic robust optimization model for day-ahead and real-time markets, tackling uncertainties in wind and solar power generation, and electric and heating loads. Similarly, Li et al. [29] developed a stochastic robust optimal operation model of community IESs considering the IDR of electric, gas, cooling, and heating loads. Song et al. [30] proposed a coordinated optimization method considering long-term and short-term hydrogen energy storage and demand response and established a multi-time-

scale scheduling model for zero-carbon hydrogen-based IESs, in which the uncertainty of renewable energy output and load demand is considered to realize Scenario generation and reduction. Wang et al. [31] proposed a multi-timescale game optimization scheduling model for park-level IESs that considers multiple types of demand response models. This model characterizes the uncertainty of the predicted value of distributed renewable energy and multi-type energy load based on the fuzzy chance-constrained programming method. Yang et al. [32] established a non-complete interval multi-objective IES scheduling model to improve the operation efficiency of IESs and to reduce the external impacts of IESs, considering the uncertainties of renewable energy, load, and demand response.

In conclusion, the majority of the existing literature on IES with AA-CAES operates within a deterministic framework. Similarly, the majority of AA-CAES and IDR modeling only considers electric and heat energy, with cold energy being largely overlooked. Moreover, the majority of studies conducted on IDR have focused on shiftable and interruptible loads, employing the time-of-day price of energy to modify the demand curve for that energy source. However, IDR encompasses a range of energy types, and there is also an inter-substitution between different energy types in response to price fluctuations. For instance, there is inter-substitution between electric energy and heat energy, as well as inter-substitution between electric energy and cold energy. There is a clear need for further research on the optimal operation of multi-energy IESs with AA-CAES and IDR under source-load uncertainty. This is the primary focus of this paper.

1.3. Contributions and Organization

The contributions of this paper are highlighted as follows. (1) The energy hub concept is utilized to streamline the modeling of the multi-energy co-generation characteristics of the AA-CAES, thereby reducing the complexity of the inherent variations within the AA-CAES. (2) An integrated cold-electricity-heat energy system (ICEHS) with AA-CAES and IDR is developed. In order to more effectively utilize multiple energy sources, the system also integrates a variety of energy conversion and storage equipment, as well as a range of load types that can participate in IDR, including shiftable, adjustable, interruptible, and replaceable loads. (3) Based on the proposed model, the impacts of AA-CAES and IDR on system operation costs and carbon emissions are analyzed, and a sensitivity analysis for IDR is implemented.

The remainder of the paper is organized as follows. Section 2 presents the system architecture for the ICEHS. Section 3 addresses system modeling, encompassing the formulation of models for AA-CAES, IDR, and source-load uncertainty. Section 4 develops the operational optimization model for the ICEHS. Section 5 provides case studies and sensitivity analysis. Finally, Section 6 concludes the paper.

2. System Architecture

The ICEHS has the potential to facilitate multi-energy complementarity and enhance energy efficiency by integrating cooling, heating, and power supply functions. The structural configuration of the system is depicted in Figure 1 and comprises four principal components:

- (1) Energy supply: this includes wind turbines (WT), electricity grids (Grid), and natural gas companies (Gas).
- (2) Energy conversion equipment: this encompasses gas turbines (GT), gas boilers (GB), waste heat boilers (WHB), heat pumps (HP), electric refrigeration (ER), and absorption chillers (AC).
- (3) Energy storage equipment: this comprises AA-CAES, heat storage (HS), and cold storage (CS).
- (4) Energy demand: this includes electric loads, heating loads, and cooling loads.

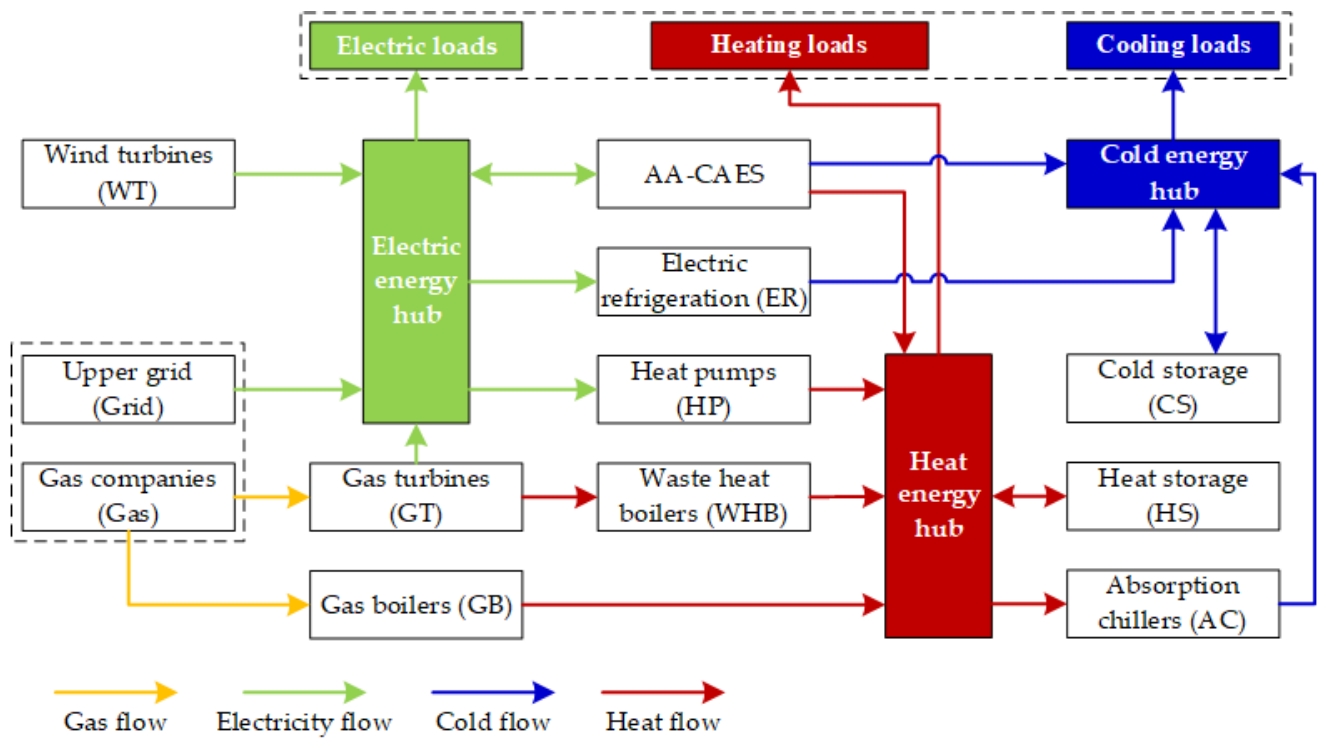


Figure 1. Structure of an ICEHS.

The WT is the main source of electrical power for an ICEHS. In the event that the WT is unable to meet the electrical requirements of the system, it is necessary to purchase electricity from the Grid or to purchase gas, which is then used to generate electricity by the GT. In addition to meeting electric loads, electrical energy can be used by the HP for heating and by the ER for cooling. Excess electrical energy is stored in the AA-CAES. The AA-CAES is capable of generating heat for heating during the air compression stage and absorbing heat for cooling during the air expansion stage, thus improving IES compatibility. The sources of heat energy include the AA-CAES, HP, WHB, and GB. In instances where the supply of heat energy exceeds the heating loads, the remaining heat energy is either stored in the HS or employed by the AC for cooling. The sources of cold energy include the AA-CAES, ER, and AC. In the event of a surplus of cold energy, the excess cold energy is stored in the CS.

3. System Modeling

3.1. IDR Modeling

The purpose of this subsection is to model the IDR process for cooling, heating, and electric loads. The loads that participate in the IDR process can be classified into four categories: shiftable loads, adjustable loads, interruptible loads, and replaceable loads.

3.1.1. Shiftable Loads

Shiftable loads may be shifted from one time period to another during the dispatch period in response to changes in energy prices. Typical devices with shiftable loads include washing machines, dishwashers, and electric vehicles. In this study, shiftable loads are limited to electric loads due to the delay in the transmission of heating and cooling loads. As is the case with numerous other studies, this paper employs price-based DR measures to delineate the response of shiftable loads, as elucidated in the following equations [33]:

$$\Delta L_{e,t}^{shift} = L_{e,t}^{prime} \sum_{h=1}^T e(t,h) \frac{p_h^{shift} - p_t^{prime}}{p_t^{prime}} \quad (1)$$

$$|\Delta L_{e,t}^{shift}| \leq \Delta L_{e,t,max}^{shift} \quad (2)$$

where $\Delta L_{e,t}^{shift}$ represents the amount of electric load that can be shifted at time t ; $\Delta L_{e,t,max}^{shift}$ denotes the upper limit of $\Delta L_{e,t}^{shift}$; $L_{e,t}^{prime}$ and p_t^{prime} represent the amount of electric load and the price of electricity at time t before the load shift, respectively; $e(t, h)$ represents the cross-elasticity of electricity demand from time t to time h , which reflects the sensitivity of electricity demand at time t to changes in the price of electricity at time h ; p_h^{shift} indicates the price of electricity at time h after the load shift; and T denotes the operating period, which is 24 h.

Note that the estimation of the value of $e(t, h)$ is contingent upon statistical analysis of a substantial corpus of historical data, which is beyond the scope of this study. Consequently, in accordance with the extant literature, this paper assumes that the value of $e(t, h)$ is given.

3.1.2. Adjustable Loads

The primary focus of adjustable loads is on heating and cooling loads. By exploiting the human body's inaccurate perception of temperature, users are encouraged to adjust the temperature settings of heating and cooling units through a subsidy, thereby achieving peak shaving and valley filling of loads. The specific expressions are as follows [34]:

$$\Delta L_{h,t}^{adjust} = -H^A V^A \Delta T_t^h \quad (3)$$

$$\Delta L_{c,t}^{adjust} = H^A V^A \Delta T_t^c \quad (4)$$

$$|\Delta T_t^h| \leq \Delta T_{max} \quad (5)$$

$$|\Delta T_t^c| \leq \Delta T_{max} \quad (6)$$

where $\Delta L_{h,t}^{adjust}$ and $\Delta L_{c,t}^{adjust}$ indicate the adjustable amount of heating and cooling loads at time t , respectively; H^A and V^A denote the volumetric heat index and external volume of the building, respectively; ΔT_t^h represents the temperature change at time t under heating conditions; ΔT_t^c represents the temperature change at time t under cooling conditions; and ΔT_{max} indicates the maximum range of temperature change.

3.1.3. Interruptible Loads

$$0 \leq \Delta L_{\tau,t}^{cut} \leq \Delta L_{\tau,t,max}^{cut} \quad (7)$$

where $\Delta L_{\tau,t}^{cut}$ represents the amount of load that is reduced by load type $\tau \in \{\text{cooling, heating, electricity}\}$ at time t ; and $\Delta L_{\tau,t,max}^{cut}$ represents the upper limit of $\Delta L_{\tau,t}^{cut}$.

3.1.4. Replaceable Loads

Replaceable loads refer to the substitution of low-priced energy for high-priced energy to meet load demand. To illustrate, if electricity prices are high while heating prices are low, it is reasonable to opt for a direct heat energy supply for heating loads that can be met indirectly by electric energy or directly by heat energy. In this study, we limit our consideration to the mutual substitution between electric energy and heat energy, and electric energy and cold energy, as described by the following equations:

$$\Delta L_{eh,t}^{replace} = \frac{\Delta L_{rh,t}^{replace}}{coe_{eh}} \quad (8)$$

$$\Delta L_{ec,t}^{replace} = \frac{\Delta L_{rc,t}^{replace}}{coe_{ec}} \quad (9)$$

$$\Delta L_{he,t}^{replace} = \Delta L_{re,t}^{replace} coe_{eh} \quad (10)$$

$$\Delta L_{ce,t}^{replace} = \Delta L_{re,t}^{replace} coe_{ec} \quad (11)$$

$$0 \leq \Delta L_{eh,t}^{replace} + \Delta L_{ec,t}^{replace} \leq \Delta L_{e,t,max}^{replace} \quad (12)$$

$$0 \leq \Delta L_{he,t}^{replace} \leq \Delta L_{h,t,max}^{replace} \quad (13)$$

$$0 \leq \Delta L_{ce,t}^{replace} \leq \Delta L_{c,t,max}^{replace} \quad (14)$$

where coe_{eh} and coe_{ec} represent the coefficient of substitution between electric loads and heating loads, and between electric loads and cooling loads, respectively; $\Delta L_{eh,t}^{replace}$, $\Delta L_{ec,t}^{replace}$, $\Delta L_{he,t}^{replace}$, and $\Delta L_{ce,t}^{replace}$ indicate the amount of electric load replaced by heating load, electric load replaced by cooling load, heating load replaced by electric load, and cooling load replaced by electric load, respectively; $\Delta L_{rh,t}^{replace}$, $\Delta L_{rc,t}^{replace}$, and $\Delta L_{re,t}^{replace}$ indicate the substitution amounts for heating, cooling, and electric loads, respectively; and $\Delta L_{e,t,max}^{replace}$, $\Delta L_{h,t,max}^{replace}$, and $\Delta L_{c,t,max}^{replace}$ represent the upper limit of the substitution amounts for electric, heating, and cooling loads, respectively.

3.2. Uncertainty Modeling

The load and renewable energy output are inherently uncertain. In this study, we propose a methodology that employs Latin hypercube sampling (LHS) in conjunction with K-means clustering to address these uncertainties. Our approach involves the generation of multiple scenarios using LHS, with the objective of modeling forecast errors for wind generation and various load types. Subsequently, the simulated scenarios are reduced using K-means clustering, and the probability of each reduced Scenario is determined to assess the expected output of wind generation and various load types.

The LHS is a stratified sampling technique that, in contrast to Monte Carlo random sampling, ensures comprehensive coverage of sample values across the entire sample space of random variables. LHS divides the probability distribution into N equal intervals, with the midpoint of each interval representing a state. Then, the inverse transformation of the cumulative distribution function is used to obtain the operating state values of each midpoint [35]. The existing literature indicates that prediction errors of loads typically follow a normal distribution, as shown in Equation (15), while prediction errors of wind power output are better represented by a beta distribution [36], as shown in Equation (16).

$$f_{normal}(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (15)$$

$$f_{beta}(x) = N_d x^{\alpha-1} (1-x)^{\beta-1} \quad (16)$$

where parameters μ and σ are the mean and variance of the normal distribution, respectively, while α and β represent the shape and scale parameters of the beta distribution. Additionally, N_d represents the normalization factor.

Indeed, K-means clustering is a widely used unsupervised learning algorithm for partitioning a dataset into K non-overlapping clusters with similar characteristics. In this algorithm, K represents the number of clusters, and the “mean” represents the centroid, or the center of each cluster. The K-means clustering process typically involves the following steps:

- (1) Randomly selecting K initial centroids or utilizing alternative initialization methods.
- (2) Each sample point is assigned to the cluster with the nearest centroid.
- (3) The mean of all sample points in each cluster is computed to obtain the new centroids.
- (4) Steps (2) and (3) are iterated until the centroids converge or the maximum number of iterations is reached.

This paper employs a combination of LHS and K-means clustering to derive the expected prediction error of energy supply and demand. The calculation is as follows:

$$E(e_{i,t}) = \sum_{j=1}^N e_{i,t}^j \times p_j \quad (17)$$

where the parameter N indicates the total number of scenarios after clustering; the symbol i represents the type of energy, including wind power output, cooling loads, heating loads, and electric loads; $e_{i,t}^j$ denotes the prediction error of energy type i in Scenario j at time t ; p_j denotes the probability of the Scenario j ; and $E(e_{i,t})$ denotes the expected prediction error of energy type i at time t .

Consequently, in consideration of the inherent uncertainty associated with the source-load output, the actual output of each energy type can be determined by adding the predicted value to the calculated prediction error. This calculation process can be described as follows:

$$P_{i,t}^r = P_{i,t}^p + E(e_{i,t}) \quad (18)$$

where $P_{i,t}^p$ and $P_{i,t}^r$ denote the predicted value and the actual output of energy type i at time t , respectively.

3.3. AA-CAES Modeling

The concept of the energy hub was introduced by a research team at the Power Systems and High Voltage Laboratory at ETH Zurich, as part of the “Vision of Future Energy Networks” project. It is defined as a central location where various energy carriers are produced, converted, stored, and consumed, making it a promising option for the integrated management of multi-energy systems [37]. The energy hub concept facilitates the simplification of the multi-energy cogeneration characteristics of the AA-CAES, thereby reducing the complexity of the variations within the AA-CAES. Furthermore, it enables the description of the energy transformations within the AA-CAES through the use of a distribution matrix and an efficiency matrix. As illustrated in Figure 2, the input to AA-CAES is excess wind power, which is converted by the energy hub to output electric, cooling, and heat energy.

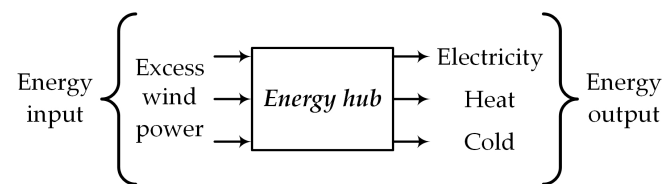


Figure 2. Schematic diagram of AA-CAES energy exchange.

The AA-CAES described in this paper employs a two-stage compression and two-stage expansion process. Firstly, a portion of the excess wind power input to AA-CAES is allocated to the primary compressor and another portion to the secondary compressor. If electric energy losses are not accounted for, the above process can be described as follows:

$$P_a^{WT} \begin{bmatrix} d_1 \\ d_2 \end{bmatrix} = \begin{bmatrix} I_1 \\ I_2 \end{bmatrix} \quad (19)$$

where P_a^{WT} represents the excess wind power input to AA-CAES; I_1 and I_2 denote the electric energy allocated to the primary and secondary compressors, respectively; and d_1 and d_2 indicate allocation ratios, with $d_1 + d_2 = 1$.

Subsequently, the electric energy of the primary and secondary compressors is converted into internal energy of the high-temperature and high-pressure air and heat energy stored in the HS. The process is described as follows:

$$I_1 \begin{bmatrix} d_3 \varphi_1 \\ d_4 \varphi_2 \end{bmatrix} = \begin{bmatrix} I_3 \\ I_4 \end{bmatrix} \quad (20)$$

$$I_2 \begin{bmatrix} d_5 \varphi_3 \\ d_6 \varphi_4 \end{bmatrix} = \begin{bmatrix} I_5 \\ I_6 \end{bmatrix} \quad (21)$$

where I_3 and I_4 represent the internal energy of the high-temperature and high-pressure air and the heat energy stored in the HS produced by the primary compressor, respectively; I_5 and I_6 denote the internal energy of the high-temperature and high-pressure air and the heat energy stored in the HS produced by the secondary compressor, respectively; d_3 , d_4 , d_5 , and d_6 are distribution ratios, with $d_3 + d_4 = 1$ and $d_5 + d_6 = 1$; and φ_1 , φ_2 , φ_3 , and φ_4 are compressor efficiency factors.

Therefore, the heat energy generated by the AA-CAES is shown in the following formula:

$$H_{AA-CAES} = I_4 + I_6 \quad (22)$$

Upon entering the expansion process, the stored high-temperature and high-pressure air must be heated, and the energy required is I_7 . A portion of the internal energy I_8 of the high-temperature and high-pressure air during the primary expansion process will be converted into electric energy, and the process is described as follows:

$$I_8 \begin{bmatrix} d_7 \varphi_5 \\ d_8 \varphi_6 \end{bmatrix} = \begin{bmatrix} I_9 \\ I_{10} \end{bmatrix} \quad (23)$$

where I_8 is calculated by $I_8 = I_3 + I_5 + I_7$; I_9 and I_{10} denote the electric energy produced during the first-stage expansion process and the residual internal energy of the air, respectively; d_7 and d_8 are distribution ratios, with $d_7 + d_8 = 1$; and φ_5 and φ_6 are primary expander efficiency factors.

Finally, the second-stage expansion process is the re-expansion of the air following the first-stage expansion. At this juncture, a portion of the residual internal energy of the air is converted into electric energy, while the remaining energy is converted into the cold energy of the low-temperature air. This process can be described as follows:

$$I_{10} \begin{bmatrix} d_9 \varphi_7 \\ d_{10} \varphi_8 \end{bmatrix} = \begin{bmatrix} I_{11} \\ I_{12} \end{bmatrix} \quad (24)$$

where I_{11} and I_{12} represent the electric energy and cold energy generated during the secondary expansion process, respectively; d_9 and d_{10} are distribution ratios, with $d_9 + d_{10} = 1$; and φ_7 and φ_8 are secondary expander efficiency factors.

Consequently, the electric energy and cold energy generated by the AA-CAES can be expressed as follows:

$$E_{AA-CAES} = I_9 + I_{11} \quad (25)$$

$$C_{AA-CAES} = I_{12} \quad (26)$$

4. Development of Operational Optimization Model

Building on the preceding section, the aim of this section is to develop an optimization model for ICEHS operation, considering IDR, the uncertainty of source-load output, and AA-CAES. The following subsections describe the objective function, constraints, and solution methods of the model.

4.1. Objective Function

The objective of the model is to reduce the total daily operating cost of an ICEHS. In order to align with the national goal of achieving carbon neutrality and carbon peaking, and to enhance the level of clean energy consumption, the cost of carbon emissions is further considered. Consequently, the total daily operating cost (C) of an ICEHS is comprised of

the following elements: energy purchase cost, operation and maintenance cost, demand response cost, and carbon emission cost. The specific formula for calculating the objective function is as follows:

$$\min C = C_{buy} + C_{o\&m} + C_{dr} + C_{ce} \quad (27)$$

where C_{buy} indicates the daily cost of procured energy; $C_{o\&m}$ denotes the daily cost of operation and maintenance; C_{dr} signifies the daily cost of demand response; and C_{ce} stands for the daily cost of carbon emissions.

The energy purchase cost (C_{buy}) encompasses the expenditure incurred for the acquisition of electricity and gas. In instances where the sale of excess electricity is permitted, the calculation of C_{buy} is based on the following formula:

$$C_{buy} = \sum_{t=1}^T p_t^{e,buy} P_t^{e,buy} + \sum_{t=1}^T p_t^{g,buy} P_t^{g,buy} - \sum_{t=1}^T p_t^{e,sell} P_t^{e,sell} \quad (28)$$

where $p_t^{e,buy}$ and $p_t^{e,sell}$ denote the purchase price and sale price of electricity at time t , respectively; $P_t^{e,buy}$ and $P_t^{e,sell}$ denote the amount of electricity purchased and sold at time t , respectively; and $p_t^{g,buy}$ and $P_t^{g,buy}$ denote the price and volume of gas purchased at time t , respectively.

The daily cost ($C_{o\&m}$) of operation and maintenance is calculated as follows:

$$C_{o\&m} = \sum_{t=1}^T \sum_{\mu \in U} P_t^{\mu} c_t^{\mu} \quad (29)$$

where set U contains the principal equipment of an ICEHS, including AA-CAES, GT, GB, WHB, ER, AC, HP, WT, HS, and CS; and P_t^{μ} and c_t^{μ} indicate the power of the equipment $\mu \in U$ and its O&M cost rate at time t , respectively.

The daily cost (C_{dr}) of demand response refers to payments made to customers who participate in DR. These payments cover both adjustable and interruptible loads, as calculated according to the following formula:

$$C_{dr} = \sum_{t=1}^T \left(p_h^{adjust} \Delta L_{h,t}^{adjust} + p_c^{adjust} \Delta L_{c,t}^{adjust} \right) + \sum_{t=1}^T \sum_{\tau} p_{t,cut}^{\tau} \Delta L_{\tau,t}^{cut} \quad (30)$$

where p_h^{adjust} and p_c^{adjust} denote subsidized prices for adjustable heating loads and adjustable cooling loads, respectively; and $p_{t,cut}^{\tau}$ represents the subsidized price when load type $\tau \in \{\text{cooling, heating, electricity}\}$ is engaged in the DR of interruptible load.

Given that the majority of electricity in the grid is not generated from renewable sources, the cost of carbon emissions must be calculated to include not only the carbon emissions resulting from the operation of the various types of equipment in an ICEHS, but also the carbon emissions associated with the purchase of electricity from the grid. Therefore, the daily cost (C_{ce}) of carbon emissions is calculated as follows:

$$C_{ce} = \kappa \sum_{t=1}^T \left(P_t^{GT} \varepsilon^{GT} + H_t^{GB} \varepsilon^{GB} + P_t^{e,buy} \varepsilon^e \right) \quad (31)$$

where P_t^{GT} represents the power generated by GT at time t ; H_t^{GB} indicates the heating power of GB at time t ; ε^{GT} and ε^{GB} denote the carbon emission coefficient of the corresponding equipment; ε^e indicates the carbon emission coefficient of purchased electricity; and κ denotes the carbon emission cost factor.

4.2. Constraints

The operation of an ICEHS must satisfy four types of constraints: power balance constraints, equipment operating state constraints, energy trading volume constraints, and initial state constraints.

4.2.1. Power Balance Constraints

Given the multi-energy flow characteristics of the ICEHS, it is necessary to consider the power balance constraints for cooling, heating and electric loads. The expressions are as follows:

$$C_t^{\text{Load}} - \Delta L_{c,t}^{\text{adjust}} - \Delta L_{c,t}^{\text{cut}} + \Delta L_{rc,t}^{\text{replace}} - \Delta L_{ce,t}^{\text{replace}} + C_t^{\text{CS},c} = C_t^{\text{ER}} + C_t^{\text{AC}} + C_t^{\text{CS},d} + C_t^{\text{CAES}} \quad (32)$$

$$H_t^{\text{Load}} - \Delta L_{h,t}^{\text{adjust}} - \Delta L_{h,t}^{\text{cut}} + \Delta L_{rh,t}^{\text{replace}} - \Delta L_{he,t}^{\text{replace}} + H_t^{\text{AC}} + H_t^{\text{HS},c} = H_t^{\text{WHB}} + H_t^{\text{GB}} + H_t^{\text{HP}} + H_t^{\text{HS},d} + H_t^{\text{CAES}} \quad (33)$$

$$P_t^{\text{Load}} + \Delta L_{e,t}^{\text{shift}} - \Delta L_{e,t}^{\text{cut}} + \Delta L_{re,t}^{\text{replace}} - \Delta L_{eh,t}^{\text{replace}} - \Delta L_{ec,t}^{\text{replace}} + P_{t,c}^{\text{CAES}} + P_t^{\text{HP}} + P_t^{\text{ER}} + P_t^{\text{e,sell}} = P_t^{\text{WT}} + P_t^{\text{GT}} + P_{t,g}^{\text{CAES}} + P_t^{\text{e,buy}} \quad (34)$$

where C_t^{Load} , H_t^{Load} , and P_t^{Load} represent the cooling, heating, and electric loads at time t , respectively; $\Delta L_{c,t}^{\text{cut}}$, $\Delta L_{h,t}^{\text{cut}}$, and $\Delta L_{e,t}^{\text{cut}}$ represent the amount by which the cooling, heating, and electric loads can be reduced at time t ; $C_t^{\text{CS},c}$ and $C_t^{\text{CS},d}$ refer to the energy charging and discharging power of CS at time t ; $H_t^{\text{HS},c}$ and $H_t^{\text{HS},d}$ indicate the energy charging and discharging power of HS at time t ; $P_{t,c}^{\text{CAES}}$ and $P_{t,g}^{\text{CAES}}$ are the powers of the compressor and expander in AA-CAES at time t , respectively; C_t^{CAES} and H_t^{CAES} denote the cooling power and heating power provided by AA-CAES at time t ; C_t^{ER} and C_t^{AC} represent the cooling power of ER and AC at time t , respectively; H_t^{AC} is the heat power consumption of AC at time t ; H_t^{WHB} and H_t^{HP} indicate the heating power of WHB and HP at time t , respectively; P_t^{HP} and P_t^{ER} are the electrical power consumption of HP and ER at time t , respectively; and P_t^{WT} is the electrical power output of WT.

4.2.2. Equipment Operating State Constraints

This type of constraint involves both energy storage and energy supply equipment. The constraints on energy storage equipment are described as follows:

$$\left\{ \begin{array}{l} I_c^t P_{c,\min}^{\text{CAES}} \leq P_{t,c}^{\text{CAES}} \leq I_c^t P_{c,\max}^{\text{CAES}} \\ I_g^t P_{g,\min}^{\text{CAES}} \leq P_{t,g}^{\text{CAES}} \leq I_g^t P_{g,\max}^{\text{CAES}} \\ I_{CS,c}^t C_{\min}^{\text{CS},c} \leq C_t^{\text{CS},c} \leq C_{\max}^{\text{CS},c} I_{CS,c}^t \\ I_{CS,d}^t C_{\min}^{\text{CS},d} \leq C_t^{\text{CS},d} \leq C_{\max}^{\text{CS},d} I_{CS,d}^t \\ I_{HS,c}^t H_{\min}^{\text{HS},c} \leq H_t^{\text{HS},c} \leq H_{\max}^{\text{HS},c} I_{HS,c}^t \\ I_{HS,d}^t H_{\min}^{\text{HS},d} \leq H_t^{\text{HS},d} \leq H_{\max}^{\text{HS},d} I_{HS,d}^t \\ Q_{\min}^{\text{HS}} \leq Q_t^{\text{HS}} \leq Q_{\max}^{\text{HS}} \\ Q_{\min}^{\text{CS}} \leq Q_t^{\text{CS}} \leq Q_{\max}^{\text{CS}} \\ Q_{\min}^{\text{CAES}} \leq Q_t^{\text{CAES}} \leq Q_{\max}^{\text{CAES}} \\ I_c^t + I_g^t \leq 1 \\ I_{CS,d}^t + I_{CS,c}^t \leq 1 \\ I_{HS,d}^t + I_{HS,c}^t \leq 1 \end{array} \right. \quad (35)$$

where $P_{c,\min}^{\text{CAES}}$, $P_{g,\min}^{\text{CAES}}$, $C_{\min}^{\text{CS},c}$, $C_{\min}^{\text{CS},d}$, $H_{\min}^{\text{HS},c}$, and $H_{\min}^{\text{HS},d}$ denote the lower power limits of corresponding energy storage equipment; $P_{c,\max}^{\text{CAES}}$, $P_{g,\max}^{\text{CAES}}$, $C_{\max}^{\text{CS},c}$, $C_{\max}^{\text{CS},d}$, $H_{\max}^{\text{HS},c}$, and $H_{\max}^{\text{HS},d}$ represent the upper power limits of corresponding energy storage equipment; $Q_{\min}^{\text{HS}}$, $Q_{\min}^{\text{CS}}$, and $Q_{\min}^{\text{CAES}}$ indicate the lower limits of the capacity of each energy storage equipment; $Q_{\max}^{\text{HS}}$, $Q_{\max}^{\text{CS}}$, and $Q_{\max}^{\text{CAES}}$ represent the upper limits of the capacity of each energy storage equipment; and I_c^t , I_g^t , $I_{CS,d}^t$, $I_{CS,c}^t$, $I_{HS,d}^t$, and $I_{HS,c}^t$ are 0–1 variables for the state of energy storage equipment, where a value of 1 indicates a charging state while a value of 0 indicates a discharging state.

The constraints on energy supply equipment are as follows:

$$\begin{cases} P_{min}^{WT} \leq P_t^{WT} \leq P_{max}^{WT} \\ P_{min}^{GT} \leq P_t^{GT} \leq P_{max}^{GT} \\ H_{min}^{WHB} \leq H_t^{WHB} \leq H_{max}^{HRB} \\ H_{min}^{GB} \leq H_t^{GB} \leq H_{max}^{GB} \\ H_{min}^{HP} \leq H_t^{HP} \leq H_{max}^{HP} \\ C_{min}^{ER} \leq C_t^{ER} \leq C_{max}^{ER} \\ C_{min}^{AC} \leq C_t^{AC} \leq C_{max}^{AC} \end{cases} \quad (36)$$

where P_{min}^{WT} , P_{min}^{GT} , H_{min}^{WHB} , H_{min}^{GB} , H_{min}^{HP} , C_{min}^{ER} , and C_{min}^{AC} denote the lower power limits of corresponding energy supply equipment; and P_{max}^{WT} , P_{max}^{GT} , H_{max}^{HRB} , H_{max}^{GB} , H_{max}^{HP} , C_{max}^{ER} , and C_{max}^{AC} represent the upper power limits of corresponding energy supply equipment.

4.2.3. Energy Trading Volume Constraints

In order to prevent an ICEHS from engaging in significant electricity and gas purchasing and selling activities during the optimization process, which could result in system instability, it is necessary to consider establishing upper and lower limits for the amount of electricity purchased, the amount of electricity sold, and the amount of gas purchased. The specific formulas are as follows:

$$\begin{cases} 0 \leq P_t^{e,buy} \leq P_{max}^{e,buy} I_{e,buy}^t \\ 0 \leq P_t^{e,sell} \leq P_{max}^{e,sell} I_{e,sell}^t \\ 0 \leq P_t^{g,buy} \leq P_{max}^{g,buy} \\ I_{e,buy}^t + I_{e,sell}^t \leq 1 \end{cases} \quad (37)$$

where $P_{max}^{e,buy}$, $P_{max}^{e,sell}$, and $P_{max}^{g,buy}$ denote the upper limit for the amount of purchased electricity, sold electricity, and purchased gas, respectively; and $I_{e,buy}^t$ and $I_{e,sell}^t$ are the 0–1 variables that indicate the state of purchasing and selling electricity at time t . A value of 1 indicates the state of purchasing electricity, while a value of 0 indicates the state of selling electricity.

4.2.4. Initial State Constraints

In order to guarantee the optimal functioning of an ICEHS, it is imperative that AA-CAES, HS, and CS possess a specific initial capacity. The specific constraints are outlined below.

$$\begin{cases} Q_0^{CAES} = Q_{24}^{CAES} \\ Q_0^{HS} = Q_{24}^{HS} \\ Q_0^{CS} = Q_{24}^{CS} \end{cases} \quad (38)$$

where Q_0^{CAES} , Q_0^{HS} , and Q_0^{CS} represent the initial capacity of AA-CAES, HS, and CS, respectively; and Q_{24}^{CAES} , Q_{24}^{HS} , and Q_{24}^{CS} denote the capacity of AA-CAES, HS, and CS, respectively, at the end of the day's operation of an ICEHS.

4.3. Solution Method

Figure 3 depicts the flow of optimizing ICEHS operation. Initially, the electric load, heating load, and cooling load are processed by LHS joint K-means clustering in order to obtain the respective desired outputs under the source-load uncertainty. Subsequently, DR is implemented and load curves are computed for each energy type following the response. Ultimately, the corresponding operational optimization model is constructed and solved. Given that the proposed model is a mixed-integer linear programming model, the CPLEX Solver can be directly invoked to solve it.

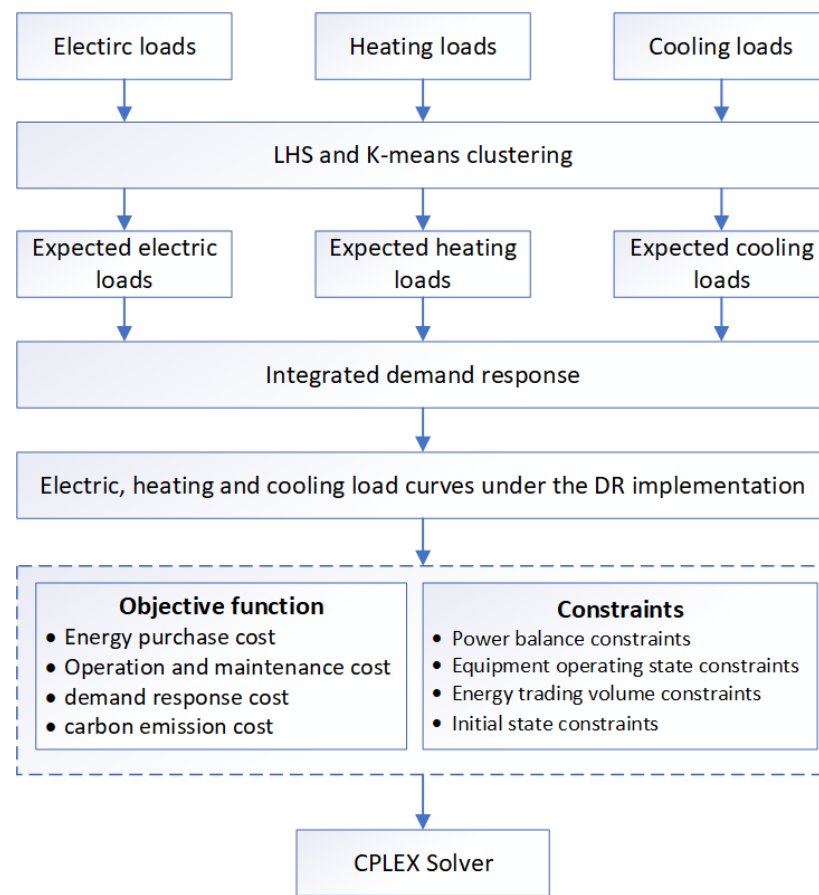


Figure 3. Solution process.

5. Case Study

This section aims to verify the effectiveness and feasibility of the proposed ICEHS operation optimization model through a regional IES. Initially, the relevant basic data of the regional IES are introduced. Subsequently, the results of the proposed model are introduced and compared by scenarios. Finally, a sensitivity analysis for DR is conducted.

5.1. Data Description

The sale price of electricity is 0.5 RMB/kWh, while the purchase price of gas is 0.35 RMB/kWh. Table 1 presents the cross-elasticity of electricity demand, while Tables 2–4 illustrate the implementation of a time-of-day tariff for electric heating, and cooling loads, respectively. The upper limits for purchased and sold electricity are 500 kW, with a lower power limit of 0. The upper power limit for purchased gas is 1000 kW, with a lower power limit of 0. The subsidized prices for cooling, heating, and electric loads to engage in the DR of interruptible load are equal to the respective real-time sale prices plus an additional 0.1 RMB. The subsidized prices for cooling and heating loads to engage in the DR of adjustable load are equal to the respective real-time sale prices. The carbon emission price is 0.031 RMB/kg.

Table 1. The cross-elasticity matrix of electricity demand.

	Peak Time	Shoulder Time	Valley Time
Peak time	−0.1	0.016	0.012
Shoulder time	0.016	−0.1	0.01
Valley time	0.012	0.01	−0.1

Table 2. The time-of-day tariff for electric loads.

Type	Time Period	Price (RMB/kWh)
Peak time	09:00–12:00	1.09
	19:00–22:00	
Shoulder time	08:00–09:00	0.68
	12:00–19:00	
	22:00–24:00	
Valley time	00:00–08:00	0.35

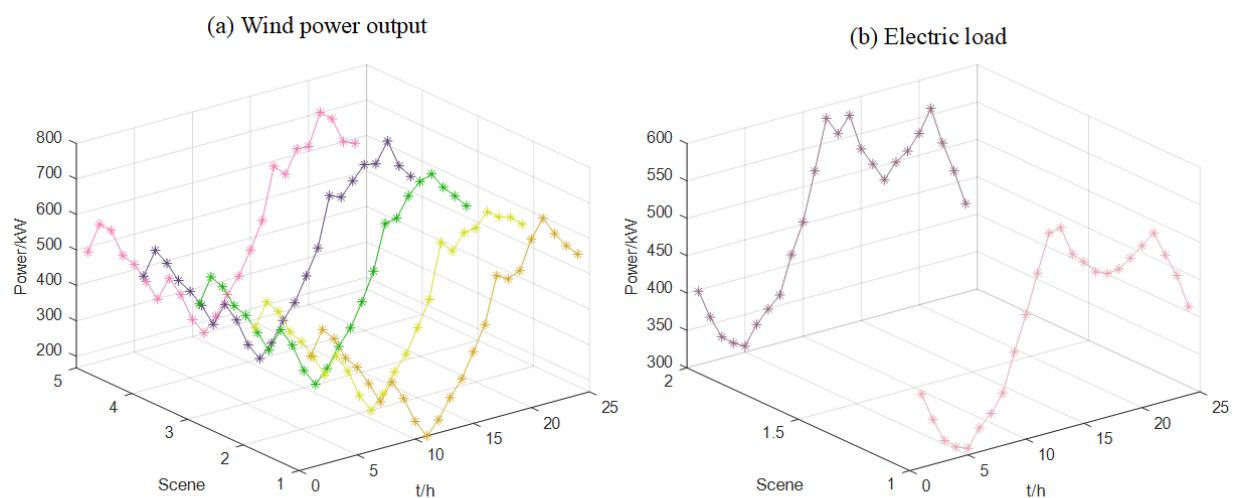
Table 3. The time-of-day tariff for heating loads.

Type	Time Period	Price (RMB/kWh)
Peak time	21:00–04:00	0.58
Shoulder time	04:00–07:00	0.36
	15:00–21:00	
Valley time	07:00–15:00	0.25

Table 4. The time-of-day tariff for cooling loads.

Type	Time Period	Price (RMB/kWh)
Peak time	10:00–14:00	0.58
	19:00–22:00	
Shoulder time	07:00–10:00	0.36
	14:00–17:00	
	22:00–24:00	
Valley time	00:00–07:00	0.25
	17:00–19:00	

The uncertainty is addressed through the use of LHS with K-means clustering, with a sampling number of 1000. Following this, the prediction error is reduced to five scenarios for wind power output and two for each of cooling, heating, and electric loads, as illustrated in Figure 4. The aforementioned Scenario division yields a total of 40 different combinations of load and wind power output. Then, these combinations are weighted according to probability to obtain the expected load curves and the expected wind power output, as shown in Figure 5.

**Figure 4.** Cont.

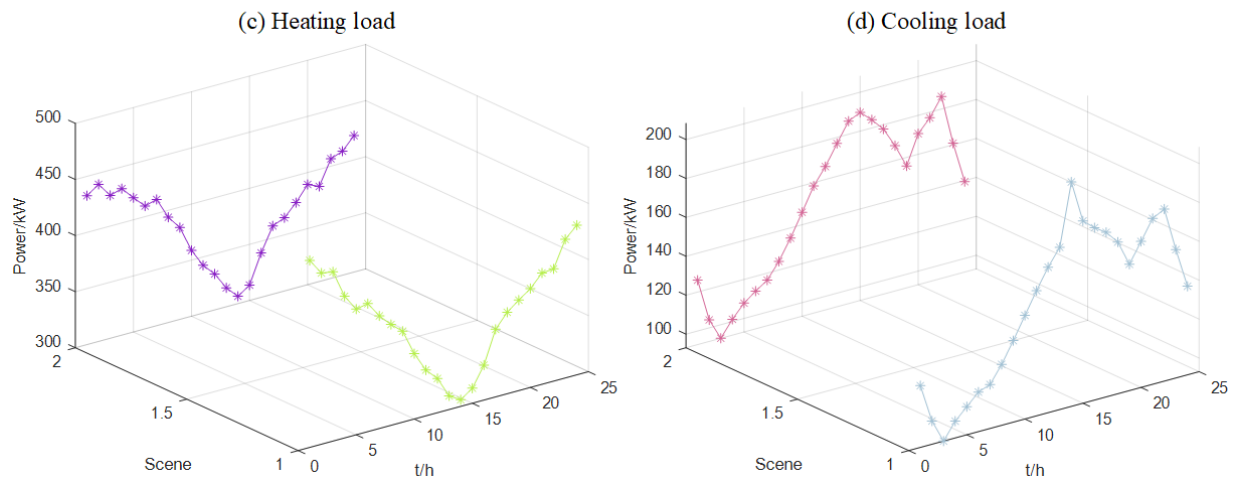


Figure 4. Scenario reduction results for loads and wind power output. Different colored curves show wind power output and electric, heating, and cooling loads in different scenarios.

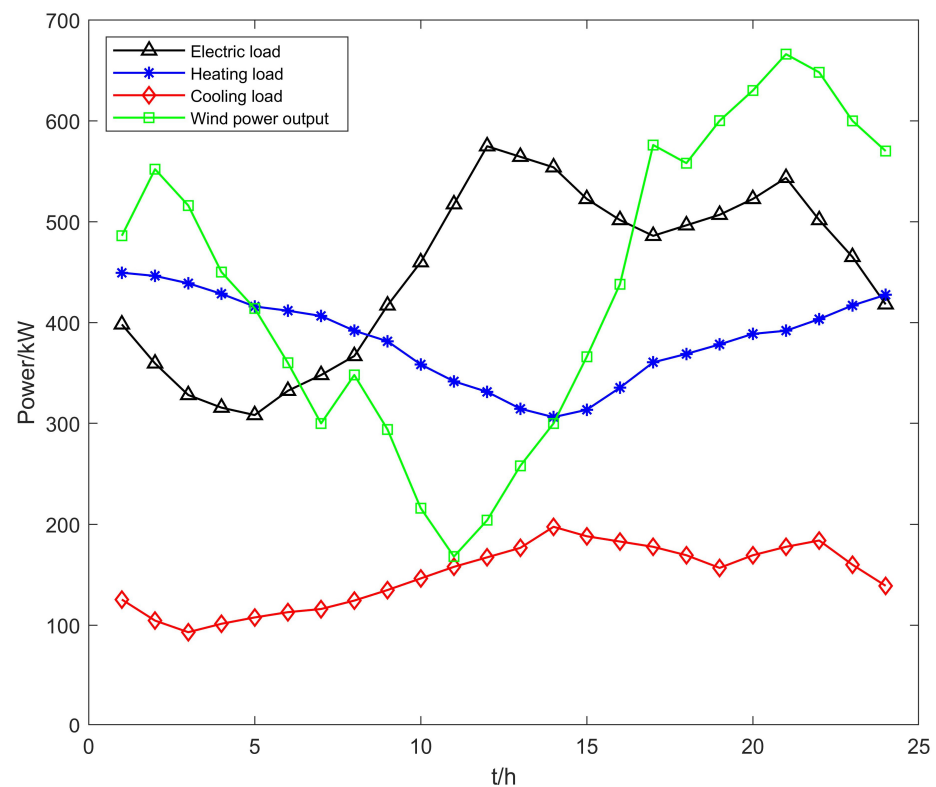


Figure 5. Expected load curves and wind power output.

The initial capacity of the AA-CAES is 80 kWh, with a maximum capacity of 500 kWh. Both the compressor and the expander have an efficiency of 85%, and the operation and maintenance costs are 0.02 RMB/kWh. The HS has an initial capacity of 80 kWh, a capacity limit of 500 kWh, an energy charging and discharging efficiency of 85%, and an operation and maintenance cost of 0.0016 RMB/kWh. CS has an initial capacity of 50 kWh, a capacity limit of 300 kWh, an energy charging and discharging efficiency of 85%, and an operation and maintenance cost of 0.0014 RMB/kWh. The remaining equipment parameters are presented in Table 5.

Table 5. Main parameters of other equipment.

Equipment	Upper Limit (kW)	Operation and Maintenance Cost (RMB/kW)	Carbon Emission (kg/kWh)	Efficiency
WT	1000	0.0296	0	—
GT	1000	0.0352	0.72	0.3
WHB	1000	0.025	0.4	0.8
GB	1000	0.02	0.46	0.85
HP	100	0.025	—	2.5
ER	100	0.02	—	2
AC	100	0.01	—	1
Grid	—	—	0.95	—

5.2. Analysis of ICEHS Operation Results

In this subsection, we present a comprehensive analysis of the ICEHS operation outcomes. A comparison of the cooling, heating, and electric load curves before and after the implementation of DR is illustrated in Figure 6. The following observations can be made from the figure:

- The electric load after DR is higher than before DR from 22:00 to 09:00 the following day. This phenomenon can be attributed to two main reasons. Firstly, the cost of electricity is typically lower at night, allowing for the use of additional electric loads to supplant cooling and heating loads. Secondly, some of the electric load that would normally occur during periods of higher electricity prices is shifted to this period. As a result, the load levels for heating and cooling have decreased due to the substitution with electric loads.
- The electric load after DR is lower than before DR, while the heating and cooling loads after DR are higher than before DR from 09:00 to 12:00. The rationale behind this is that the price of electricity is the highest during this period, leading to a portion of the electric load being replaced by cooling load or heating load. Additionally, a portion of the electric load is shifted to the period of lower electricity prices. A similar phenomenon also occurs during the period from 19:00 to 22:00.
- The electric loads before and after DR show minimal change, whereas the heating load after DR shows an increase and the cooling load after DR shows a decrease from 12:00 to 17:00. The reason for this is that both the demand for heating load and the price of heating are low during this period. Moreover, this is an off-peak period for electricity prices, which results in some electric loads being substituted for heating loads and some cooling loads being substituted for electric loads.
- The electric and cooling loads after DR are higher than before DR, whereas the heating load after DR shows a decrease from 17:00 to 19:00. The rationale is that this current period is an off-peak period for electricity prices. Consequently, some of the increased demand for heating loads is replaced by electric loads. Moreover, the demand for cooling loads decreases during this period, resulting in part of the electric load demand being replaced by the cooling load.

Figure 7 illustrates the operational results of each piece of equipment. During the valley electricity price period (00:00 to 08:00), the system purchases a substantial amount of electricity from the grid due to the lower prices. This electricity is used to charge the AA-CAES, HP, and ER, thereby meeting the electric load demand and, consequently, the demands for heating and cooling. The cold energy generated by the AA-CAES during the charging process is stored in the CS, as the demand for cooling is low at night. During the peak electricity price period (09:00 to 12:00 and 19:00 to 22:00), the higher cost of purchased electricity means that electric loads are primarily supplied by the WT, GT, and AA-CAES. The heating load demand is primarily satisfied by the WHB, with the remainder fulfilled by the HP. In contrast, the cooling load demand is predominantly met by the AC, CS, and the cold energy produced during the discharge of the AA-CAES. During the shoulder

electricity price period (08:00 to 09:00, 12:00 to 19:00, and 22:00 to 24:00), the system utilizes a combination of WT power and purchased electricity to meet the electric load. The heating load is primarily met by the HP and GB, while the cooling load is met by the ER and CS.

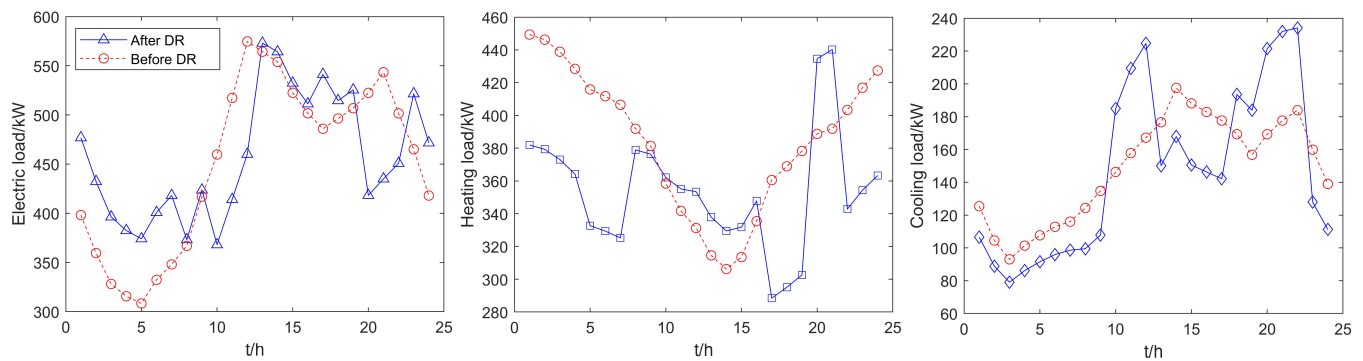


Figure 6. Load curves before and after DR.

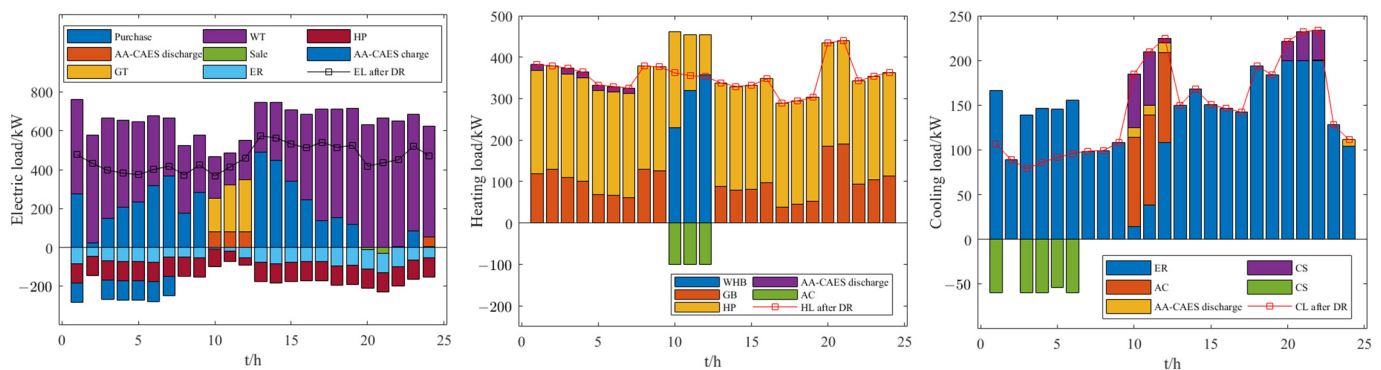


Figure 7. Operation results of the equipment.

5.3. ICEHS Benefit Analysis in Different Scenarios

In order to ascertain the rationality of AA-CAES and DR, this subsection establishes four comparison scenarios for analysis. The scenarios are as follows:

- Scenario 1 (considered in this paper): AA-CAES and DR considered together;
- Scenario 2: AA-CAES only without DR;
- Scenario 3: DR only and no AA-CAES are considered;
- Scenario 4: No AA-CAES and DR is not considered.

Table 6 shows the costs and carbon emissions of the four scenarios. A comparison between Scenario 1 and Scenario 2 reveals that in the absence of DR, the peaks of loads become larger, leading to an increased demand for energy purchases and higher loads on equipment. This, in turn, increases operation and maintenance costs and energy purchase costs, which in turn leads to an increase in carbon emissions. The comparison between Scenario 1 and Scenario 3 demonstrates that the absence of AA-CAES diminishes the capacity of an ICEHS for peak shaving and valley filling, resulting in an increased expenditure on purchased energy and carbon emissions. Conversely, the operation and maintenance cost of the system is reduced due to the absence of AA-CAES. However, the total daily operating cost remains higher than that of Scenario 2. A comparative analysis of Scenario 1 and Scenario 4 reveals that the simultaneous dismissal of AA-CAES and DR will result in the complete loss of the system's capacity for load leveling. The larger peak-to-valley difference in load not only increases the necessity for purchased energy but also requires the equipment to operate at high loads, resulting in a simultaneous increase in energy purchase costs, operation and maintenance costs, and carbon emissions. In conclusion, Scenario 2 has the lowest total daily operating cost and the least carbon emissions, indicating that

the introduction of AA-CAES and DR can effectively enhance the operating efficiency of an ICEHS.

Table 6. Comparative results for four scenarios.

Scenario	Operation and Maintenance Cost (RMB)	Energy Purchase Cost (RMB)	Carbon Emission Cost (RMB)	Demand Response Cost (RMB)	Total Daily Operating Cost (RMB)	Carbon Emissions (kg)
1	630.69	3860.72	214.51	240.28	4946.21	6919.81
2	656.82	4192.22	235.67	0	5084.71	7602.13
3	620.02	3922.82	216.81	240.28	4999.92	6993.78
4	643.23	4305.57	239.84	0	5188.64	7736.87

5.4. Sensitivity Analysis for IDR

This subsection presents a detailed examination of the influence of changes in the proportion of different types of demand response loads on the operational outcomes of an ICEHS, based on Scenario 1, and the results are illustrated in Figure 8.

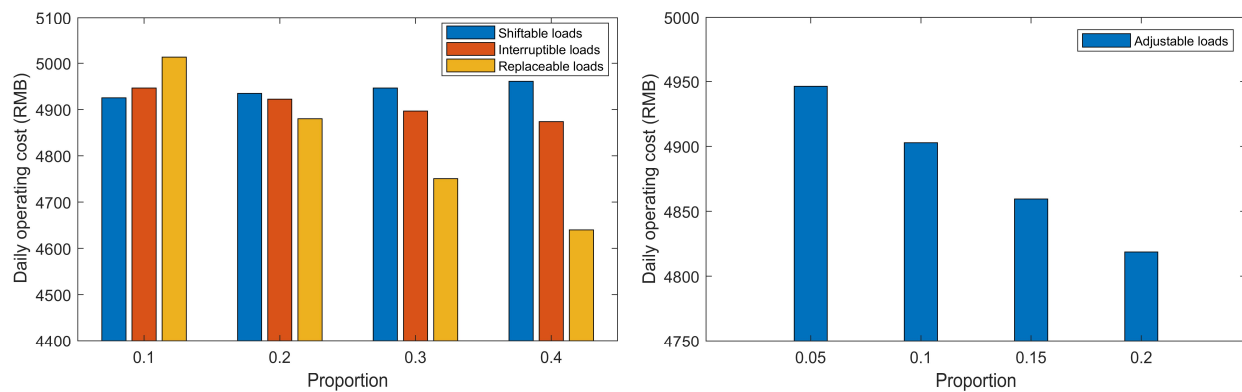


Figure 8. Relations between the proportion of demand response loads and the total daily operating cost.

Maintaining the proportion of other types of demand response loads constant, an increase in the proportion of shiftable loads from 10% to 40% results in an increase in daily operating costs. This indicates a positive correlation between daily operating costs and the proportion of shiftable loads. The rationale for this is that an increasing proportion of shiftable loads gives rise to new load peaks, which in turn leads to an increase in the cost of purchased energy and thus higher daily operating costs.

As the proportion of interruptible loads increases from 10% to 40%, while the proportion of other types of demand response load remains constant, the daily operating costs will continue to decrease. In other words, there is a negative correlation between daily operating costs and the proportion of interruptible loads. This is because an increase in the proportion of interruptible loads will result in a reduction in energy demand from users, which in turn will lead to a reduction in the cost of energy purchased by the system. However, the subsidy paid by the system to users is less than the savings in purchased energy costs, which ultimately leads to a decrease in the daily operating cost.

The proportion of other types of demand response loads remains constant, while the share of replaceable loads rises from 10% to 40%. This results in a reduction in daily operating costs. In other words, there is a negative correlation between daily operating costs and the proportion of replaceable loads. This is because an increase in the proportion of replaceable loads results in more electric loads being substituted for cooling or heating loads during periods of high electricity prices and more electric loads being used to substitute cooling or heating loads during periods of low electricity prices. The above demand response results reduce the system's cost of purchased energy and carbon emissions, which in turn leads to a decrease in daily operating costs.

It is inadvisable to allow adjustable loads to account for an excessive percentage of the total, given that they are calibrated based on the somewhat subjective human perception of comfort temperature. An incremental increase in the proportion of adjustable loads from 5% to 20%, while maintaining the proportion of other types of demand response loads at a constant level, will result in a reduction in the daily operating cost. In other words, there is a negative correlation between the daily operating cost and the proportion of adjustable loads. This is due to the fact that an increase in the proportion of adjustable loads results in a reduction in the peak load, which in turn leads to a decrease in the cost of energy purchases, carbon emissions, and demand response costs. Consequently, the daily operating costs are also reduced.

In conjunction with the aforementioned analysis, it becomes evident that the rational determination of the proportion of each type of demand response load is conducive to the improvement of the economic efficiency of system operation.

6. Conclusions

AA-CAES offers the advantage of storing and releasing electrical energy, as well as providing cold and heat energy. This makes it an ideal complement to the ICEHS. In this paper, we present the design of an ICEHS with AA-CAES and IDR, developed under the source-load uncertainty. Furthermore, we propose an operation optimization model with the objective of minimizing the daily operating cost of an ICEHS. In consideration of the ICEHS's multi-energy flow characteristics, the IDR for cooling, heating, and electric loads has the capacity to regulate the load curves of disparate energy sources across a more expansive range, a flexibility that extends beyond the scope of traditional DR, which is limited to considerations of electric loads. The results of the case study demonstrate that the integration of AA-CAES and IDR can effectively reduce the daily operating costs and carbon emissions associated with an ICEHS. In particular, the daily operating cost and carbon emissions are reduced by 4.8% and 10.3%, respectively, in comparison to the system that does not include AA-CAES and IDR. In comparison to the system comprising solely AA-CAES, the daily operating costs and carbon emissions exhibited a reduction of 2.7% and 8.98%, respectively. When contrasted with the IDR-only system, the daily operating cost and carbon emissions demonstrated a decrease of 1.07% and 1.06%, respectively.

In light of the findings presented in this paper, two avenues for future research can be identified. One avenue would be to consider the uncertainty of energy prices in the optimization of ICEHS operations. In this paper, it is assumed that the prices of all energy sources are known. Nevertheless, as the construction of the electricity market progresses, energy prices will be set in accordance with market forces. The second avenue for future research is the refinement of the modeling of AA-CAES. In this paper, the concept of an energy hub is employed to simplify the modeling of AA-CAES, enabling the description of the transformation of diverse energy types within AA-CAES in a straightforward manner. However, AA-CAES encompasses the coordination of numerous devices, necessitating a detailed examination of its modeling approach to fully realize the potential of AA-CAES to reduce costs and increase efficiency.

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remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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