

Article

Stochastic Optimal Scheduling of an Integrated Energy System with Thermoelectric Decoupling and Ammonia Co-Firing Considering Energy Storage Capacity Leasing

Bo Fu  and Zhongxi Wu *

Hubei Key Laboratory for High-Efficiency Utilization of Solar Energy and Operation Control of Energy Storage System, Hubei University of Technology, Wuhan 430068, China; fubofanxx@mail.hbut.edu.cn

* Correspondence: 102310322@hbut.edu.cn

Abstract

To address the problem of renewable energy curtailment and the need for operational economic optimization in integrated energy systems with high penetration of wind and solar power, a coordinated optimization method integrating thermoelectric decoupling, ammonia-blended combustion technology, and energy storage capacity leasing is proposed. First, a chaotic-improved Latin Hypercube Sampling (C-LHS) method, combined with an improved K-means clustering algorithm, is employed to generate representative wind–solar–load scenarios. This approach improves the efficiency of uncertainty scenario generation while reducing computational burden and maintaining solution accuracy. Secondly, by coordinating the operation of thermal energy storage and electric boilers, the “heat-led power generation” constraint is relaxed, and, in combination with ammonia-blended combustion in combined heat and power (CHP) units, the system’s flexibility and renewable energy accommodation capability are enhanced. Finally, with the objective of minimizing total operating cost, a day-ahead scheduling model incorporating electrical energy storage (EES) leasing optimization is established. For EES, under a shared energy storage market mechanism, the golden section search (GSS) algorithm is employed to optimize the day-ahead leasing capacity. The simulation results demonstrate that the proposed method improves renewable energy accommodation while maintaining economic performance, and effectively reduces the overall operating cost of the system. These findings confirm the effectiveness of the proposed strategy in enhancing both system flexibility and economic performance.

Keywords: integrated energy system; ammonia co-firing; thermoelectric decoupling; uncertainty analysis; shared energy storage



Academic Editor: Andrea De Pascale

Received: 9 March 2026

Revised: 24 March 2026

Accepted: 31 March 2026

Published: 3 April 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

An integrated energy system with high wind–solar penetration is a key pathway toward achieving global low-carbon transition and deep decarbonization objectives. However, the inherent uncertainty of renewable energy sources leads to significant wind and solar curtailment issues [1]. Conventional CHP units are constrained by the heat-led power generation mechanism, resulting in limited operational flexibility and further hindering renewable energy accommodation [2]. Existing studies have improved renewable energy accommodation and system flexibility through thermoelectric decoupling or hydrogen energy storage technologies [3,4]. Nevertheless, relying on a single approach makes it

challenging to simultaneously ensure economic performance and system reliability. With the increasing degree of energy coupling and the growing complexity of interconnected energy infrastructures, how to achieve coordinated multi-energy operation, refined dispatch, and optimal capacity allocation to ensure economic performance, operational security, and long-term system stability has become a critical issue that requires urgent attention [5].

As renewable penetration increases, the variability and uncertainty of renewable generation impose substantial challenges on system planning and operation, making uncertainty management a central research issue. In [6], uncertainties in renewable generation, load, and energy prices are represented as interval parameters and addressed via a two-stage decomposition framework. While this approach avoids the need for exact probability distributions, it typically results in conservative decisions biased toward worst-case realizations. In [7], representative wind–solar generation and load scenarios are constructed and incorporated into a multi-objective optimization framework with probabilistic weights to capture uncertainty characteristics. However, this approach is data-intensive and computationally demanding. In [8], a distributionally robust optimization framework based on the Wasserstein ambiguity set is developed to address uncertainty in renewable generation and system operation. While this method mitigates distributional ambiguity without relying on exact probability distributions, the use of a fixed-radius ambiguity set may limit adaptability to time-varying forecast error characteristics and increase computational complexity. In [9], demand response uncertainty is represented by triangular fuzzy numbers and converted into a deterministic optimization model using fuzzy chance-constrained programming. Nevertheless, the expert-dependent specification of membership functions introduces subjectivity and may underestimate extreme-event risks. In general, existing uncertainty optimization frameworks remain computationally demanding and require further enhancement to support power systems with high renewable penetration.

With increasing renewable penetration, inadequate system flexibility has emerged as a critical challenge. Developing integrated multi-energy systems that leverage diverse flexibility resources is therefore essential to enhance renewable energy accommodation and support the global low-carbon energy transition. Current research mainly concentrates on thermoelectric decoupling, ammonia co-firing, and energy storage planning to improve operational flexibility and economic performance.

In terms of thermoelectric decoupling, research primarily focuses on relaxing the rigid heat-led power generation constraint of CHP units. In [10], wind power accommodation is enhanced through thermal energy storage and demand-side response. However, reliance on demand-side regulation alone is insufficient to address severe source-side fluctuations. In [11], a coordinated decoupling strategy involving multiple CHP units and electric boilers is proposed, reducing operating costs and demonstrating the significant potential of thermoelectric decoupling in improving economic performance. In addition to these approaches, some studies employ detailed nonlinear thermodynamic models to more accurately describe the coupling relationship between heat and power outputs of CHP units (e.g., [12]). These models can capture complex operational characteristics, such as nonlinear feasible operating regions and part-load efficiency variations. However, their application in large-scale integrated energy system optimization is often limited by high computational complexity. In contrast, linearized CHP models, which approximate the feasible operating region using linear constraints, have been widely adopted due to their computational efficiency and tractability. Therefore, this study employs a linearized CHP model to characterize thermoelectric coupling, enabling efficient integration into large-scale stochastic optimization while maintaining a reasonable balance between modeling accuracy and computational performance. Nevertheless, existing studies on thermoelectric decoupling mainly emphasize short-term operational flexibility and lack integration with

low-carbon fuel technologies, thereby limiting the potential for deep decarbonization of system operation.

In the context of ammonia co-firing, hydrogen/ammonia production and ammonia co-firing technologies are employed to enable multi-energy complementarity and enhance system operational flexibility. In [13], a hydrogen fuel cell CHP model is developed to mitigate photovoltaic fluctuations by adjusting the electric-to-thermal output ratio. However, it is not integrated with thermoelectric decoupling technologies, thereby limiting the full exploitation of its flexibility potential. In [14], an electricity–heat–hydrogen integrated energy system is developed based on hydrogen-fueled gas turbines, enhancing renewable energy accommodation and peak-shaving capability through hydrogen energy storage. However, the high cost and technological immaturity remain key challenges. In [15], a coordinated framework integrating hydrogen energy storage, ammonia synthesis, and carbon capture is proposed to validate ammonia as a hydrogen carrier. Nevertheless, the fixed energy storage capacity constrains long-term economic performance.

In terms of optimal energy storage planning, existing studies primarily focus on long-term capacity expansion, resulting in a temporal mismatch with short-term operational scheduling. In [16,17], a system-level capacity optimization model incorporating wind power, electrolyzers, hydrogen storage tanks, and hydrogen-fueled gas turbines is developed to minimize total investment cost and determine optimal equipment capacities. However, the annual planning horizon limits its applicability to day-ahead dispatch decisions. In [18], an optimal configuration method based on hybrid energy storage is proposed, where an improved ant colony-based dynamic programming algorithm is employed for system parameter optimization. However, the planning horizon remains annual. In [19], a capacity optimization model for a hydrogen-integrated hybrid microgrid is developed and efficiently solved using an improved cat swarm algorithm. nevertheless, it also focuses on long-term planning. In recent years, the emergence of shared energy storage and energy storage leasing markets has provided a promising pathway to alleviate the temporal mismatch between planning and operation. In [20], it is proposed that, under the spot market mechanism, energy storage can participate in both day-ahead and intraday markets by submitting bids and being cleared in a manner similar to conventional generation units. In [21], capacity leasing is identified as one of the primary revenue streams for independent energy storage at the current stage. The leasing fee is correlated with the contracted capacity and lease duration, functioning as a periodic payment mechanism. Through capacity leasing, an integrated energy system can obtain flexible regulation capability without additional investment in energy storage, thereby better accommodating short-term operational optimization requirements. It should be noted that, at present, mature market-oriented leasing mechanisms mainly exist for EES. In contrast, thermal energy storage is typically operated in conjunction with district heating systems, and its capacity is closely coupled with heat demand and heating equipment, which limits the formation of an independent capacity leasing market. Hydrogen and ammonia energy storage systems, on the other hand, are primarily used for energy conversion and long-duration storage. These facilities are generally configured as internal system assets, and mature capacity sharing or leasing mechanisms have not yet been established. Therefore, introducing a capacity leasing mechanism for EES is currently more practical and feasible.

In summary, although significant progress has been achieved in uncertainty modeling, thermoelectric decoupling, ammonia co-firing, and energy storage planning, several critical gaps remain. (1) Existing scenario generation approaches exhibit limitations in computational efficiency and adaptability, making it challenging to simultaneously ensure solution accuracy and tractability. (2) Thermoelectric decoupling has not been deeply integrated with low-carbon fuel technologies such as ammonia co-firing, thereby failing to fully ex-

exploit the synergy between short-term operational flexibility and long-term decarbonization. (3) Most studies on storage optimization focus on long-term capacity expansion, leading to a temporal mismatch with short-term dispatch. To address the aforementioned issues, this paper proposes a day-ahead leasing optimization method for EES that integrates thermoelectric decoupling and ammonia co-firing technologies. First, a C-LHS method combined with an improved K-means clustering algorithm is employed to generate representative wind–solar–load scenarios, thereby improving scenario generation efficiency while reducing computational complexity without compromising accuracy. Second, by coordinating thermal storage and electric boiler operations, the heat-led power generation constraint of CHP units is relaxed. Integrated with ammonia co-firing technology, the proposed approach enhances system regulation capability and renewable energy accommodation. Finally, with the objective of minimizing total operating cost, a day-ahead leasing optimization dispatch model for EES is developed. Under a shared energy storage market mechanism, the GSS algorithm is employed to optimize day-ahead leasing capacity and system operating strategies. The results demonstrate the effectiveness of the proposed strategy in improving system flexibility and economic performance.

2. Integrated Energy System Modeling Framework

The overall configuration of the integrated energy system is illustrated in Figure 1. Electricity is supplied by wind power, photovoltaic (PV) power, CHP units, and hydrogen fuel cells, while heat is provided by CHP units and hydrogen fuel cells. The hydrogen subsystem consists of water electrolyzers, hydrogen storage tanks, and hydrogen fuel cells. The ammonia synthesis subsystem comprises an ammonia synthesis reactor, a pressure swing adsorption (PSA) unit for nitrogen production, water electrolyzers, and an ammonia storage tank.

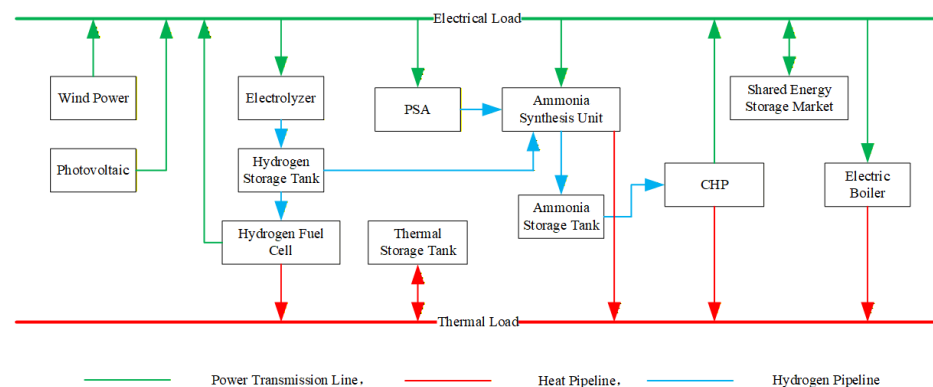


Figure 1. Integrated energy system structure diagram.

2.1. Ammonia Synthesis Subsystem

2.1.1. Water Electrolyzer

As a key technology for green hydrogen production, water electrolysis decomposes water molecules via electrochemical reactions, producing high-purity hydrogen and oxygen simultaneously. Proton exchange membrane (PEM) electrolysis has emerged as a leading technology due to its compact structure, fast dynamic response, and high energy conversion efficiency. The system operates the PEM electrolyzer during periods of surplus electricity to produce hydrogen. The relationship between the hydrogen production rate and power consumption is expressed as follows:

$$m_t^{H_2} = \eta^{H_2} P_t^{EL} / h_{H_2} \quad (1)$$

where $m_t^{H_2}$ denotes the hydrogen production in period t , P_t^{EL} represents the power consumption of water electrolysis in period t , η^{H_2} is the electrolyzer efficiency, and h_{H_2} denotes the unit energy consumption for hydrogen production.

2.1.2. PSA Unit

The PSA unit separates nitrogen from air. The relationship between nitrogen output and power input is given by:

$$m_t^{N_2} = P_t^{PSA} / h_{N_2} \quad (2)$$

where $m_t^{N_2}$ denotes the nitrogen production in period t , P_t^{PSA} represents the power consumption of the PSA unit in period t , and h_{N_2} denotes the specific energy consumption for nitrogen production.

2.1.3. Ammonia Synthesis Reactor

Hydrogen produced by water electrolysis and nitrogen generated by the PSA unit are fed into the ammonia synthesis reactor for the Haber–Bosch reaction, producing ammonia and releasing heat. The chemical reaction is expressed as follows:



where the stoichiometric molar ratio of N_2 , H_2 , and NH_3 is 1:3:2, and the corresponding molar mass ratio is 28:6:34.

The heat released during ammonia synthesis is incorporated into the district heating network. The relationship between ammonia production and power consumption is expressed as follows:

$$m_t^{NH_3} = P_t^{NH_3} / h_{NH_3} \quad (4)$$

$$P_t^{NH_3,h} = \eta^{NH_3} \sigma m_t^{NH_3} \quad (5)$$

where $m_t^{NH_3}$ denotes the ammonia production in period t , $P_t^{NH_3}$ represents the power consumption of the ammonia synthesis unit in period t , h_{NH_3} denotes the specific energy consumption for ammonia production, $P_t^{NH_3,h}$ is the heating power supplied by the power-to-ammonia system in period t , η^{NH_3} represents the heat recovery allocation coefficient, and σ denotes the heat released per unit of ammonia produced.

2.2. Thermoelectric Decoupling Modeling of CHP Units with Thermal Storage and Electric Boiler

CHP units are generally classified into two types: back-pressure units and extraction-condensing units. In this study, the extraction-condensing CHP unit is selected as the research object. The feasible operating region of the extraction-condensing unit is illustrated by the area ABCD in Figure 2a. For computational efficiency, the feasible operating region is approximated using linear constraints.

During periods of low electricity demand in the heating season, the unit is compelled to maintain a relatively high power output to satisfy heat demand, resulting in limited peak-shaving capability, reduced wind and PV power accommodation, and consequently increased renewable curtailment. The thermoelectric output relationship is expressed as follows:

$$\begin{cases} L_{AB} = -c_v P_t^h + P_t^{e,max} \\ L_{BC} = c_m P_t^h + P_t^{e,0} \\ L_{CD} = -c_v P_t^h + P_t^{e,min} \\ P_t^e \geq \max\{L_{BC}, L_{CD}\} \\ P_t^e \leq L_{AB} \\ 0 \leq P_t^h \leq P_t^{h,max} \end{cases} \quad (6)$$

where P_t^e and P_t^h denote the electrical and thermal outputs of the unit at time period t , respectively, $P_t^{e,max}$, $P_t^{e,min}$, and $P_t^{h,max}$ denote the maximum electrical output, minimum electrical output, and maximum thermal output of the unit, respectively, point P^{e0} represents the intersection of the extension of line BC with the vertical axis, points L_{AB} , L_{BC} , and L_{CD} denote the boundary operating points of the unit, and c_v and c_m denote the slopes of lines AB and BC, respectively.

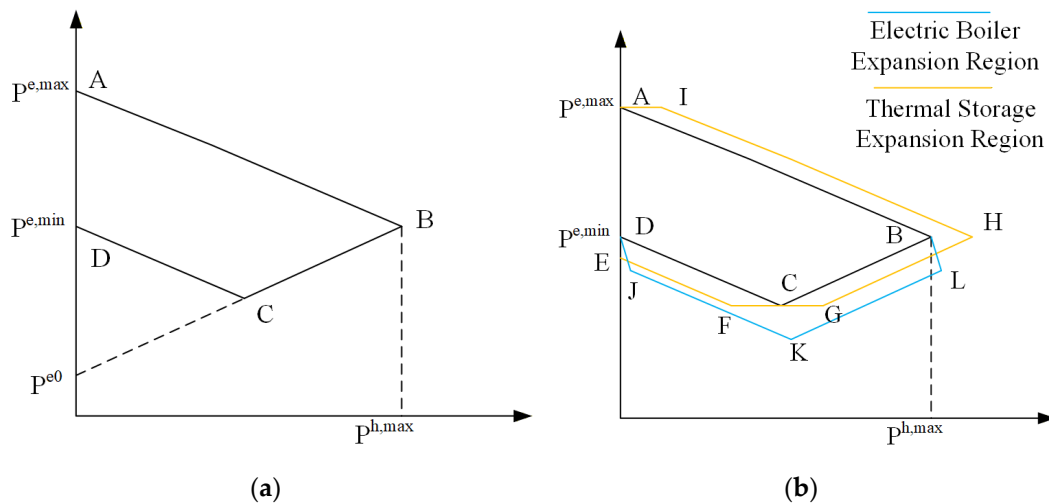


Figure 2. Feasible operating region before and after flexibility enhancement. (a) Feasible Operating Region Before Improvement; (b) Feasible Operating Region After Improvement. ABCD denotes the feasible operating region of the extraction–condensing CHP unit. AIHGFE denotes the feasible operating region after installing the thermal storage tank, and ABLKJD denotes the feasible operating region after installing the electric boiler.

After integrating a thermal storage tank and an electric boiler, the thermoelectric operating characteristics of the unit are altered, as illustrated in Figure 2b. In Figure 2b, region AIHGFE represents the feasible operating region after the installation of the thermal storage tank, while region ABLKJD represents the feasible operating region after the installation of the electric boiler. During periods of low electricity demand in the heating season, renewable energy accommodation can be enhanced through two approaches.

(1) Surplus electricity is converted into thermal energy via the electric boiler, thereby reducing the minimum technical output of the CHP unit.

(2) Heat is stored in the thermal storage tank during periods without renewable curtailment and released during low-demand periods, which further reduces the minimum technical output of the unit.

The thermoelectric output relationship can be expressed as follows:

$$\begin{cases} P_t^{DP,e} = P_t^e - P_t^{EB,e} \\ P_t^{DP,h} = P_t^h + P_t^{EB,h} + S_t^h - S_{t-1}^h \\ P_t^{EB,h} = \eta^{EB} P_t^{EB,e} \end{cases} \quad (7)$$

where $P_t^{DP,e}$ and $P_t^{DP,h}$ denote the electrical and thermal outputs of the decoupled unit at time period t , respectively, $P_t^{EB,e}$ and $P_t^{EB,h}$ denote the electrical energy consumption and thermal energy output of the electric boiler at time t , respectively, η^{EB} denotes the electrothermal conversion efficiency of the electric boiler, and S_t^h and S_{t-1}^h denote the thermal energy stored at time periods t and $t-1$, respectively.

2.3. Hydrogen Fuel Cells

Hydrogen fuel cells convert hydrogen directly into electricity and heat through electrochemical reactions. The reaction can be expressed as follows:

$$P_t^{FC,e} = \eta_e^{FC} m_t^{H_2,FC} h_{H_2} \quad (8)$$

$$P_t^{FC,h} = \eta_h^{FC} m_t^{H_2,FC} h_{H_2} \quad (9)$$

where $P_t^{FC,e}$ and $P_t^{FC,h}$ denote the electrical and thermal power outputs of the hydrogen fuel cell at time period t , respectively, η_e^{FC} and η_h^{FC} denote the electrical and thermal efficiencies of the fuel cell, respectively, and $m_t^{H_2,FC}$ denotes the mass of hydrogen consumed at time t .

2.4. Energy Storage System

To enhance the multi-energy complementary regulation capability of the integrated energy system, four types of energy storage are considered in this study: EES, thermal energy storage, hydrogen storage, and ammonia storage. Among them, the capacity of EES is obtained through a shared energy storage leasing mechanism and is treated as a decision variable in the optimization model. In contrast, the capacities of thermal storage, hydrogen storage, and ammonia storage correspond to existing on-site facilities and are therefore treated as known parameters in the model.

The detailed operational constraints of each energy storage system are provided in Section 3 (Constraints).

2.5. Coordinated Scheduling Mechanism

Under high penetration of wind and PV power, insufficient system flexibility and carbon emission constraints coexist in integrated energy systems. To enhance renewable energy accommodation and improve operational economic performance, this study establishes a coordinated scheduling mechanism that integrates thermoelectric decoupling, ammonia co-firing, and EES capacity leasing within a unified optimization framework.

At the structural level, the CHP unit is retrofitted with an electric boiler and a thermal energy storage device to reconstruct the thermoelectric output relationship. During periods of surplus electricity, the electric boiler performs power-to-heat conversion, while the thermal storage device enables inter-temporal heat shifting. Through coordinated operation, the minimum forced electrical output of the CHP unit is effectively reduced, thereby releasing additional regulation capacity on the power side and improving wind and solar energy utilization.

At the fuel substitution level, ammonia co-firing is introduced to partially replace coal consumption in the CHP unit. During periods of high renewable generation, surplus electricity is utilized for water electrolysis and ammonia synthesis, enabling electricity–hydrogen–ammonia energy conversion. During peak load periods or renewable power shortages, ammonia co-firing reduces coal consumption and carbon emissions. Meanwhile, the residual heat released during the ammonia synthesis process is recovered and supplied to the heating network, providing thermal-side compensation and further strengthening thermoelectric coordination capability.

At the regulation level, an EES capacity leasing mechanism is incorporated, and the leased capacity is optimized in the day-ahead stage. The EES undertakes short-term power balancing and forms a dual-buffer structure together with the thermal storage device, providing coordinated electrical and thermal flexibility. Through optimal capacity decision-making, the system achieves a balance between flexibility enhancement and leasing cost control.

In summary, thermoelectric decoupling provides structural flexibility by reconstructing the heat–power coupling relationship of CHP units; ammonia co-firing enables low-carbon fuel substitution while contributing additional thermal compensation; and energy storage capacity leasing enhances short-term dynamic balancing capability. Under a unified optimization framework, the coordinated operation of these three mechanisms improves renewable energy accommodation and strengthens overall system stability.

3. Optimal Scheduling Model of Integrated Energy Systems

For the integrated energy systems with high shares of wind and solar power, a 24 h day-ahead stochastic optimal scheduling model is formulated, considering the stochastic nature of renewable generation and the variability of electrical and thermal loads. The objective of the model is to minimize the total daily operating cost of the system. Through the coordinated optimization of the operational strategies of multi-energy coupling units, the charging and discharging schedules of multi-energy storage systems, and the system supply–demand balance mechanism, the economic operation of the integrated energy system is ensured.

3.1. Uncertainty Model Based on Stochastic Scenarios

3.1.1. Stochastic Scenario Generation Based on C-LHS

Wind power, solar power, and load exhibit significant stochastic fluctuations that must be accurately represented in scenario-based optimization. It has been shown in [22] that the uncertainty characteristics of multi-energy system operation are highly complex. In practical systems, wind power, PV power, and load profiles usually exhibit both temporal and cross-correlations. To simplify the computational burden in practical engineering applications, the prediction errors of wind power, PV power, electrical load, and thermal load are assumed to be independent and follow normal distributions. Based on this assumption, a scenario generation approach is developed using LHS. It should be noted that the temporal patterns of the original forecast data are preserved, and the generated scenarios are constructed based on these baseline profiles. Therefore, part of the inherent temporal correlation is implicitly retained.

Explicit modeling of spatiotemporal correlations (e.g., using Copula-based methods or multivariate stochastic processes) would significantly increase model complexity and computational burden, and is therefore left for future work.

Although conventional LHS ensures stratified sampling across each marginal distribution, it may suffer from clustering effects and insufficient global uniformity, particularly in high-dimensional problems. To overcome these limitations, a chaotic sequence is embedded into the LHS framework. Owing to its ergodicity and deterministic randomness, the chaotic mapping enhances sample dispersion and improves coverage of the uncertainty space. The logistic chaotic map is adopted as follows:

$$x_{k+1} = \mu x_k(1 - x_k) \quad (10)$$

where μ is the chaotic parameter.

The generated chaotic sequence replaces the conventional pseudo-random number generator within the LHS stratification process, thereby constructing a C-LHS sampling scheme. The C-LHS method is then employed to simulate the prediction errors of wind power, PV power, electrical load, and thermal load. The actual values of wind power, PV power, electrical load, and thermal load can therefore be expressed as:

$$P_t^{WT} = P_t^{WT,pre} + \varepsilon_t^{WT} \quad (11)$$

$$P_t^{PV} = P_t^{PV,pre} + \varepsilon_t^{PV} \quad (12)$$

$$P_t^{L,e} = P_t^{L,e,pre} + \varepsilon_t^{L,e} \quad (13)$$

$$P_t^{L,h} = P_t^{L,h,pre} + \varepsilon_t^{L,h} \quad (14)$$

where $P_t^{WT,pre}$, $P_t^{PV,pre}$, $P_t^{L,e,pre}$, and $P_t^{L,h,pre}$ denote the predicted values of wind power, solar power, electrical load, and thermal load, respectively, ε_t^{WT} , ε_t^{PV} , $\varepsilon_t^{L,e}$, and $\varepsilon_t^{L,h}$ denote the corresponding prediction errors.

The implementation steps of the C-LHS method are described as follows:

(1) Chaotic Sequence Generation

Suppose that N independent random variables X_n following a given probability distribution have cumulative distribution functions (CDFs) denoted as

$$Y_n = F_n(X_n), n = 1, 2, \dots, N \quad (15)$$

Assume that the sampling size is M . The chaotic sequence is generated as

$$x_{k+1}^{(n)} = \mu x_k^{(n)} (1 - x_{k+1}^{(n)}), \begin{cases} n = 1, 2, \dots, N \\ k = 1, 2, \dots, M \end{cases} \quad (16)$$

where $x_{k+1}^{(n)}$ denotes the chaotic value of the n -th dimension at the k -th iteration, and μ is the chaotic parameter.

(2) Stratified Sampling and Normalization

For each dimensional chaotic sequence, sorting is performed to generate the ranking index:

$$x^{(n)} = [x_1^{(n)}, \dots, x_M^{(n)}] \quad (17)$$

$$I^{(n)} = \text{argsort}(x^{(n)}), x_{I_1}^{(n)} \leq x_{I_2}^{(n)} \leq \dots \leq x_{I_M}^{(n)} \quad (18)$$

where $x^{(n)}$ represents the sequence of the n -th dimension, and $I^{(n)}$ denotes the corresponding sorting index.

The sorted indices are then uniformly allocated into M subintervals:

$$U_m^{(n)} = \frac{I_m^{(n)} - \eta}{M}, m = 1, \dots, M \quad (19)$$

where $U_m^{(n)}$ is the sampling value of the n -th dimension in the m -th interval, and η is a small perturbation term.

(3) Inverse Transform Sampling

The uniformly distributed variable $U_m^{(n)}$ is mapped to the target distribution F_n :

$$X_m^{(n)} = F_n^{-1}(U_m^{(n)}) \quad (20)$$

Finally, an $N \times M$ sample matrix X is obtained.

3.1.2. Scenario Reduction Based on an Improved K-Means Clustering Algorithm

To enhance computational efficiency, the initially generated large-scale scenario set must be appropriately reduced. Directly incorporating a large number of scenarios would significantly increase the computational burden of the optimization model. Therefore, a scenario reduction technique is employed to select a small number of representative scenarios from the original scenario set and assign them corresponding discrete probability

weights. In this way, computational complexity is substantially reduced while maintaining solution accuracy.

The traditional K-means algorithm requires the number of clusters k to be specified in advance, and its performance is sensitive to the initialization of cluster centers. Inappropriate selection of k or poor initialization may lead to suboptimal clustering results that deviate from the underlying data distribution.

To address these limitations, an improved K-means algorithm is proposed in this study with two main enhancements:

(1) An adaptive determination of the optimal number of clusters using the Davies–Bouldin Index (DBI).

(2) An improved initialization strategy based on the maximum–minimum distance principle to enhance clustering stability.

Specifically, the DBI is introduced to evaluate clustering quality under different values of k within a predefined range, and the value of k that minimizes the DBI is selected as the optimal number of clusters.

The DBI is defined as

$$DBI = \frac{1}{k} \sum_{i=1}^k \max_{j \neq i} \left(\frac{S_i + S_j}{M_{ij}} \right) \quad (21)$$

where S^i and S^j denote the intra-cluster dispersion of the i -th and j -th clusters, respectively, and M_{ij} represents the distance between the centers of clusters i and j . A smaller DBI value indicates better clustering performance.

The procedure of the improved K-means algorithm is summarized as follows:

(1) Determine the candidate range of cluster numbers as $[2, N]$.

(2) For each k within the specified range:

Initialize the cluster centers according to the maximum–minimum distance criterion.

Apply the K-means algorithm to iteratively update the cluster centers until the objective function converges.

Compute the DBI value corresponding to the current clustering result.

(3) Compare the DBI values for different k and select the value of k that minimizes the DBI as the optimal number of clusters.

(4) Output the optimal cluster number and its corresponding clustering result.

Using the above method, the reduced wind power, solar power, electrical load, and thermal load scenarios can be obtained. These scenarios are then randomly combined to generate merged scenarios. Subsequently, a synchronous backward scenario reduction technique is applied to eliminate scenarios with relatively low probabilities, resulting in the final scenario set.

3.2. Objective Function

The objective function of the model proposed in this study is to minimize the total system operating cost, C , and is defined as follows:

$$C = \sum_s \left(C_s^{wt} + C_s^{pv} + C_s^{ab} + C_s^{CHP} + C_s^{CO2} + C_s^{wh} + C_s^{ep} + C_s^{es} \right) \cdot p_s \quad (22)$$

where s denotes the number of scenarios, p^s is the probability of scenario s , C_s^{wt} is the operating cost of wind power, C_s^{pv} is the operating cost of PV power, C_s^{ab} is the penalty cost for wind and solar curtailment, C_s^{CHP} is the operating cost of cogeneration units, C_s^{CO2} is the penalty cost for carbon emissions, C_s^{wh} is the operation and maintenance cost of equipment, C_s^{ep} is the environmental cost, and C_s^{es} is the energy storage cost. The detailed expressions for each component are provided below.

3.2.1. Penalty Costs for Wind, Solar, and Curtailment

$$\begin{cases} C_s^{wt} = c^{wt} \sum_{t=1}^T P_{t,s}^{wt} \\ C_s^{pv} = c^{pv} \sum_{t=1}^T P_{t,s}^{pv} \\ C_s^{ab} = c^{ab} \sum_{t=1}^T P_{t,s}^{ab} \end{cases} \quad (23)$$

where c^{wt} , c^{pv} , and c^{ab} denote the unit cost coefficients of wind power, PV power, and wind–solar curtailment, respectively, $P_{t,s}^{wt}$, $P_{t,s}^{pv}$, and $P_{t,s}^{ab}$ represent the outputs of wind power, PV power, and the curtailed wind–solar power at time t in scenario s , respectively.

3.2.2. Operational Costs of CHP Units

The coal consumption of a conventional thermal power unit can be expressed by the following equation:

$$m_{t,s}^{coal} = a(P_{t,s}^G)^2 + bP_{t,s}^G + c \quad (24)$$

where a , b , and c are the coal consumption coefficients of the unit, and P_t^G denotes the unit's power output.

For an extraction-type CHP unit, under purely condensing operation, the generated power output $P_{t,s}^G$ is given by

$$P_{t,s}^G = P_{t,s}^e + c_v P_{t,s}^h \quad (25)$$

where $P_{t,s}^e$ and $P_{t,s}^h$ denote the unit's power generation and heat output, respectively, and c_v represents the unit parameters.

From the above two equations, the coal consumption of the CHP unit is calculated as:

$$m_{t,s}^{coal} = a(P_{t,s}^e)^2 + 2ac_v P_{t,s}^e P_{t,s}^h + ac_v^2 (P_{t,s}^h)^2 + bP_{t,s}^e + bc_v P_{t,s}^h + c \quad (26)$$

In a CHP system with ammonia co-firing, replacing part of the coal in the boiler with ammonia according to a predetermined calorific ratio effectively reduces the unit's actual coal consumption. The coal consumption is then calculated as:

$$m_{t,s}^{coal,NH_3} = a(P_{t,s}^e)^2 + 2ac_v P_{t,s}^e P_{t,s}^h + ac_v^2 (P_{t,s}^h)^2 + bP_{t,s}^e + bc_v P_{t,s}^h + c - m_{t,s}^{NH_3} Q_{NH_3} / Q_{coal} \quad (27)$$

where the lower calorific values of ammonia and coal are denoted by Q_{NH_3} and Q_{coal} , and the coal and ammonia inputs during period t under scenario s are denoted by $m_{t,s}^{coal,NH_3}$ and $m_{t,s}^{NH_3}$, respectively.

Additionally, the ammonia co-firing ratio $\gamma_{t,s}$ of the CHP unit during period t under scenario s is defined as:

$$\gamma_{t,s} = m_{t,s}^{NH_3} Q_{NH_3} / (m_{t,s}^{coal,NH_3} Q_{coal}) \quad (28)$$

The operational cost of the CHP unit is calculated as:

$$C_s^{CHP} = c^{coal} \sum_{t=1}^T m_{t,s}^{coal,NH_3} \quad (29)$$

where c^{coal} represents the unit price of coal.

3.2.3. Carbon Emission Costs

By implementing ammonia co-firing technology, the CO₂ emissions of the CHP system can be reduced. The extent of emission reduction depends on the calorific substitution rate of ammonia for coal. The carbon emission cost is then calculated as:

$$\begin{aligned} E_s &= e^G \sum_{t=1}^T P_{t,s}^e + e^H \sum_{t=1}^T P_{t,s}^h \\ m_{t,s}^{CO_2} &= q^{CO_2} m_{t,s}^{coal, NH_3} \\ C_s^{CO_2} &= c^e (E_s - \sum_{t=1}^T m_{t,s}^{CO_2}) \end{aligned} \quad (30)$$

where the carbon emission quotas for the power supply unit and the heat supply unit are denoted by e^G and e^H , respectively, E_s represents the total carbon emission quota, $m_{t,s}^{CO_2}$ denotes the actual carbon emissions during period t under scenario s , q^{CO_2} denotes the CO₂ emissions per unit of coal burned, and c^e denotes the penalty coefficient for exceeding the quota.

3.2.4. Equipment Operation and Maintenance Costs

$$C_s^{wh} = \sum_{t=1}^T \sum_{r=1}^R \alpha^r P_{t,s}^r \quad (31)$$

where α^r is the unit power operation and maintenance cost coefficient for equipment r (including electrolysis cells, hydrogen fuel cells, ammonia production equipment, and electric boilers), and $P_{t,s}^r$ is the power generation or energy consumption power of equipment r in period t and scenario s .

3.2.5. Environmental Costs

During operation, the unit emits atmospheric pollutants such as SO₂ and NO_x. Previous studies have indicated that ammonia co-firing may alter the NO_x formation pathways and introduce certain emission uncertainties. However, NO_x formation can be effectively mitigated to some extent through combustion optimization strategies, such as staged combustion and improved combustion organization [23]. In addition, selective catalytic reduction (SCR), as one of the most widely applied and technologically mature denitrification methods, has been extensively implemented in coal-fired power plants and can further reduce NO_x emissions [24]. Therefore, in practical engineering applications, NO_x emissions are generally considered to be controllable, although additional operational costs may be incurred. Meanwhile, ammonia co-firing reduces CO₂ emissions but may also lead to variations in NO_x emissions, resulting in a potential environmental trade-off. Considering model tractability, the comparability of environmental costs across different operating scenarios, and the primary focus of this study on carbon emission reduction, the variation of NO_x emissions is not explicitly modeled. Instead, the same NO_x and SO₂ emission factors and calculation methods as those under conventional coal-fired conditions are uniformly adopted for all scenarios. The formula is given by

$$C_s^{ep} = \sum_{t=1}^T \sum_{j=1}^J \mu^j m_{t,s}^j m_{t,s}^{coal, NH_3} \quad (32)$$

where J is the number of pollutant types, μ^j is the unit emission cost of pollutant j , and m^j is the emission quantity per unit of pollutant j .

3.2.6. Energy Storage Costs

Since the EES participates in the integrated energy system through a capacity leasing mechanism, its cost is not modeled as a one-time investment expense. Instead, it is incorporated into the system operating cost in the form of leasing fees. The leasing fee is generally associated with the rented capacity scale and the leasing period, reflecting the economic cost required for the system to obtain storage flexibility services. In this study, the leasing period is set to one day. For simplicity, the leasing price is assumed to be constant over the scheduling horizon, which ensures model tractability and comparability across different operating scenarios. The incorporation of time-varying or demand-dependent pricing mechanisms is left for future research. Therefore, the daily leasing cost of EES can be expressed as:

$$C_e^{rent} = c_e^{rent} S_{e,s}^{rent} \quad (33)$$

where c_e^{rent} is the unit daily leasing cost per unit capacity, and $S_{e,s}^{rent}$ denotes the day-ahead leased EES capacity under scenario s .

The total storage-related cost under scenario s is then given by

$$C_s^{es} = C_s^{oper} + c_e^{rent} S_{e,s}^{rent} \quad (34)$$

where C_s^{oper} represents the operation and maintenance costs of the existing storage systems, including thermal storage, hydrogen storage, and ammonia storage.

3.3. Constraints

3.3.1. Electrical and Thermal Power Balance Constraint

$$P_{t,s}^{wt} + P_{t,s}^{pv} + P_{t,s}^e + P_{t,s}^{FC,e} + P_{t,s}^{D,e} = P_{t,s}^{L,e} + P_{t,s}^{EL} + P_{t,s}^{NH_3} + P_{t,s}^{PSA} + P_{t,s}^{EB,e} + P_{t,s}^{C,e} \quad (35)$$

$$P_{t,s}^h + P_{t,s}^{EB,h} + P_{t,s}^{FC,h} + P_{t,s}^{NH_3,h} + P_{t,s}^{D,h} = P_{t,s}^{L,h} + P_{t,s}^{C,h} \quad (36)$$

where $P_{t,s}^{C,e}$ and $P_{t,s}^{D,e}$ represent the charging and discharging power of the EES, and $P_{t,s}^{C,h}$ and $P_{t,s}^{D,h}$ represent the charging and discharging power of the heat storage tank.

3.3.2. Equipment Operation Constraints

(1) Cogeneration Unit Operation Constraints

$$-\Delta P_e^{max} \leq P_{t,s}^e - P_{t-1,s}^e \leq \Delta P_e^{max} \quad (37)$$

$$-\Delta P_h^{max} \leq P_{t,s}^h - P_{t-1,s}^h \leq \Delta P_h^{max} \quad (38)$$

where ΔP_e^{max} and ΔP_h^{max} represent the maximum electric and thermal ramp rates of the cogeneration unit.

(2) Hydrogen Fuel Cell Operation Constraints

$$P_{FC,e}^{min} \leq P_{t,s}^{FC,e} \leq P_{FC,e}^{max} \quad (39)$$

$$-\Delta P_{FC,e}^{max} \leq P_{t,s}^{FC,e} - P_{t-1,s}^{FC,e} \leq \Delta P_{FC,e}^{max} \quad (40)$$

$$-\Delta P_{FC,h}^{max} \leq P_{t,s}^{FC,h} - P_{t-1,s}^{FC,h} \leq \Delta P_{FC,h}^{max} \quad (41)$$

where $P_{FC,e}^{min}$ and $P_{FC,e}^{max}$ represent the minimum and maximum electric output of the hydrogen fuel cell, $P_{FC,h}^{min}$ and $P_{FC,h}^{max}$ represent the minimum and maximum thermal output, and $\Delta P_{FC,e}^{max}$ and $\Delta P_{FC,h}^{max}$ represent the maximum electric and thermal ramp rates of the hydrogen fuel cell.

(3) Electrolyzer Operation Constraints

$$P_{EL}^{min} \leq P_{t,s}^{EL} \leq P_{EL}^{max} \quad (42)$$

$$-\Delta P_{EL}^{max} \leq P_{t,s}^{EL} - P_{t-1,s}^{EL} \leq \Delta P_{EL}^{max} \quad (43)$$

where P_{EL}^{min} and P_{EL}^{max} represent the minimum and maximum output of the electrolyzer, and ΔP_{EL}^{max} represents the maximum ramp rate.

(4) Ammonia Production Equipment Operation Constraints

In practical applications, ammonia synthesis units typically operate in a relatively stable and continuous manner. Therefore, the unit is assumed to operate under quasi-steady-state conditions within the day-ahead scheduling horizon.

The startup and shutdown processes are not explicitly modeled. Instead, the operational flexibility is approximated by minimum/maximum output constraints and ramping constraints, as given in Equations (44) and (45).

$$P_{NH_3}^{min} \leq P_{t,s}^{NH_3} \leq P_{NH_3}^{max} \quad (44)$$

$$-\Delta P_{NH_3}^{max} \leq P_{t,s}^{NH_3} - P_{t-1,s}^{NH_3} \leq \Delta P_{NH_3}^{max} \quad (45)$$

where $P_{NH_3}^{min}$ and $P_{NH_3}^{max}$ represent the minimum and maximum output of the ammonia production equipment, and $\Delta P_{NH_3}^{max}$ represents the maximum ramp rate.

(5) Electric Boiler Operation Constraints

$$P_{EB,h}^{min} \leq P_{t,s}^{EB,h} \leq P_{EB,h}^{max} \quad (46)$$

$$-\Delta P_{EB,h}^{max} \leq P_{t,s}^{EB,h} - P_{t-1,s}^{EB,h} \leq \Delta P_{EB,h}^{max} \quad (47)$$

where $P_{EB,h}^{min}$ and $P_{EB,h}^{max}$ represent the minimum and maximum output of the electric boiler, and $\Delta P_{EB,h}^{max}$ represents the maximum ramp rate.

3.3.3. Ammonia Blending Constraint

$$-0 \leq \gamma_{t,s} \leq \gamma^{max} \quad (48)$$

where γ^{max} represents the maximum ammonia blending ratio of the cogeneration unit. In Japan, a trial of co-firing 20% ammonia in a 1000 MW coal-fired unit at the Hekinan Thermal Power Plant is planned, aiming to achieve this target in the mid-2030s [23]. In this study, the same technical route is adopted, and the maximum ammonia blending ratio is set to 20%.

3.3.4. EES Capacity Leasing Constraints

The EES participates in system operation through a capacity leasing mechanism. Its state-of-charge SOC dynamics are expressed as

$$S_{t,s}^e = S_{t-1,s}^e + \eta^{C,e} P_{t,s}^{C,e} - \frac{1}{\eta^{D,e}} P_{t,s}^{D,e} \quad (49)$$

where $S_{t,s}^e$ denotes the stored electrical energy at time t under scenario s , $P_{t,s}^{C,e}$ and $P_{t,s}^{D,e}$ represent charging and discharging power, respectively, and $\eta^{C,e}$ and $\eta^{D,e}$ are charging and discharging efficiencies.

The charging and discharging power are limited by

$$0 \leq P_{t,s}^{C,e} \leq P^{C,emax} \quad (50)$$

$$0 \leq p_{t,s}^{D,e} \leq p^{D,emax} \quad (51)$$

where $p^{C,emax}$ and $p^{D,emax}$ denote the maximum charging and discharging power of the EES, respectively.

Since the EES capacity is obtained via leasing, the stored energy is constrained by the leased capacity:

$$0 \leq S_{t,s}^e \leq S_{e,s}^{rent} \quad (52)$$

where $S_{e,s}^{rent}$ denotes the day-ahead leased capacity of EES.

To avoid end-of-horizon bias, the initial and terminal states are constrained as

$$S_{0,s}^e = S_{T,s}^e \quad (53)$$

where T denotes the final time period of the scheduling horizon.

3.3.5. Other Energy Storage Constraints

(1) Thermal Energy Storage Constraints

Thermal energy storage is used to shift heat across time periods. Its energy balance is given by

$$S_{t,s}^h = S_{t-1,s}^h + \eta^{C,h} p_{t,s}^{C,h} - \frac{1}{\eta^{D,h}} p_{t,s}^{D,h} \quad (54)$$

where $S_{t,s}^h$ denotes stored thermal energy, $p_{t,s}^{C,h}$ and $p_{t,s}^{D,h}$ denote heat charging and discharging power; $\eta^{C,h}$ and $\eta^{D,h}$ represent charging and discharging efficiencies.

The operational limits are

$$0 \leq p_{t,s}^{C,h} \leq p^{C,hmax} \quad (55)$$

$$0 \leq p_{t,s}^{D,h} \leq p^{D,hmax} \quad (56)$$

$$0 \leq S_{t,s}^h \leq S^{h,max} \quad (57)$$

where $p^{C,hmax}$ and $p^{D,hmax}$ denote the maximum heat charging and discharging power of the thermal energy storage, respectively, and $S^{h,max}$ represents the upper limit of thermal storage capacity.

The terminal constraint is

$$S_{0,s}^h = S_{T,s}^h \quad (58)$$

(2) Hydrogen Storage Constraints

Hydrogen storage is used to store the hydrogen produced during the electrolysis process, enabling inter-temporal conversion from electrical energy to chemical energy. Its operation is constrained by hydrogen storage capacity and injection/withdrawal rate limits.

The hydrogen storage balance is expressed as

$$S_{t,s}^{H_2} = S_{t-1,s}^{H_2} + H_{t,s}^{in} - H_{t,s}^{out} \quad (59)$$

where $S_{t,s}^{H_2}$ denotes the stored hydrogen at time t under scenario s , $H_{t,s}^{in}$ and $H_{t,s}^{out}$ represent hydrogen inflow and outflow, respectively.

The operational constraints are given by

$$0 \leq H_{t,s}^{in} \leq H^{in,max} \quad (60)$$

$$0 \leq H_{t,s}^{out} \leq H^{out,max} \quad (61)$$

$$0 \leq S_{t,s}^{H_2} \leq S^{H_2,max} \quad (62)$$

where $H^{in,max}$ and $H^{out,max}$ denote the maximum hydrogen injection and withdrawal rates, and $S^{H_2,max}$ is the hydrogen storage capacity limit.

The terminal condition is

$$S_{0,s}^{H_2} = S_{T,s}^{H_2} \quad (63)$$

(3) Ammonia Storage Constraints

Ammonia not only serves as an energy carrier participating in system dispatch, but also exhibits energy storage characteristics. Its storage and consumption processes must satisfy material balance and capacity constraints.

The ammonia storage balance is expressed as

$$S_{t,s}^{NH_3} = S_{t-1,s}^{NH_3} + A_{t,s}^{in} - A_{t,s}^{out} \quad (64)$$

where $S_{t,s}^{NH_3}$ denotes the stored ammonia, $A_{t,s}^{in}$ and $A_{t,s}^{out}$ represent ammonia inflow and outflow, respectively.

The limits are defined as

$$0 \leq A_{t,s}^{in} \leq A^{in,max} \quad (65)$$

$$0 \leq A_{t,s}^{out} \leq A^{out,max} \quad (66)$$

$$0 \leq S_{t,s}^{NH_3} \leq S^{NH_3,max} \quad (67)$$

where $A^{in,max}$ and $A^{out,max}$ denote maximum ammonia injection and withdrawal rates, and $S^{NH_3,max}$ is the ammonia storage capacity limit.

The boundary condition is

$$S_{0,s}^{NH_3} = S_{T,s}^{NH_3} \quad (68)$$

3.4. Model Solution

The integrated energy system optimization model proposed in this study adopts a two-layer structure. The lower layer is a multi-period mixed-integer optimization model that considers ammonia co-firing constraints, electricity–heat coupling, and energy storage operation constraints. The upper layer optimizes the leasing capacity of EES. Since only a single capacity decision variable is involved in the leasing mode, the upper-layer problem can be formulated as a one-dimensional continuous optimization problem.

3.4.1. Analysis of the Problem Structure

Let c_1 denote the leasing capacity of EES, with a range of $[c_1^{min}, c_1^{max}]$. Given c_1 , the lower-level scheduling model yields the system's optimal operation cost $C_{op}(c_1)$ over the planning horizon. Moreover, the leasing cost is a linear function of c_1 , expressed as $C_{rent}(c_1)$. Thus, the upper-level optimization problem can be formulated as:

$$\min_{c_1} F(c_1) = C_{op}(c_1) + C_{rent}(c_1) \quad (69)$$

Analysis of the system's operational behavior shows that when the capacity is too small, the system's flexibility is insufficient, curtailment of wind and solar power increases, and the carbon emission cost increases. Conversely, when the capacity is excessively large, the leasing cost increases, whereas the reduction in operating cost is marginal. Therefore, the total cost function $F(c_1)$ exhibits a unimodal trend within the feasible range. Accordingly, the capacity optimization problem can be formulated as a one-dimensional unimodal continuous optimization problem.

3.4.2. GSS Algorithm

For the one-dimensional minimization of a unimodal function, the GSS algorithm is employed to optimize the capacity. The method requires no gradient information and iteratively approaches the optimal solution by interval reduction. The procedure is stable and computationally efficient.

Let the initial search interval be $[c_1^{min}, c_1^{max}]$, and the golden section ratio be λ :

$$\lambda = \frac{\sqrt{5} - 1}{2} \quad (70)$$

Two internal test points, x_1 and x_2 , are constructed within the interval:

$$x_1 = c_1^{max} - \lambda(c_1^{max} - c_1^{min}) \quad x_2 = c_1^{min} + \lambda(c_1^{max} - c_1^{min}) \quad (71)$$

The objective function values $F(x_1)$ and $F(x_2)$ are evaluated at these points. If $F(x_1) < F(x_2)$, the optimal solution lies in the interval $[c_1^{min}, x_2]$, otherwise, it lies in $[x_1, c_1^{max}]$. The interval is iteratively reduced until the desired accuracy is achieved, yielding the optimal capacity.

It should be noted that the applicability of the GSS algorithm relies on the unimodal property of the objective function. In this study, the leasing price of energy storage is assumed to be constant. Under this assumption, the total cost function remains smooth and unimodal, which ensures the effectiveness of the GSS method. However, if more complex pricing schemes are considered, such as non-linear or time-varying leasing prices (e.g., time-of-use or demand-dependent pricing), the total cost function may become non-unimodal with multiple local optima. In such cases, the GSS algorithm may fail to identify the global optimum. To address such scenarios, more advanced optimization methods, such as global optimization techniques or heuristic algorithms, may be required. This will be explored in future work.

3.4.3. Model Solution Procedure

The solution procedure of the model is illustrated in Figure 3.

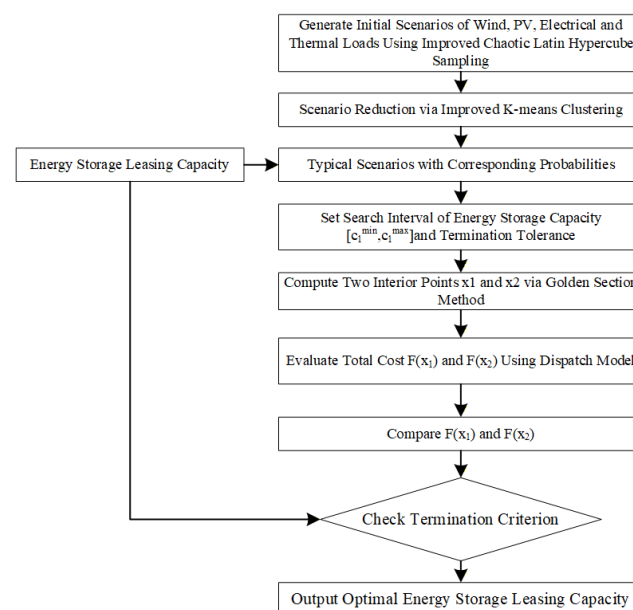


Figure 3. Flowchart of the energy storage capacity optimization framework.

First, stochastic scenarios of wind power, PV power, and electrical and thermal loads are generated using the C-LHS method. These scenarios are then reduced through an improved K-means clustering algorithm to obtain representative scenarios and their associated probability distributions. Subsequently, a coupled model of capacity optimization and operational scheduling is established. The feasible interval and termination accuracy for the EES leasing capacity are set, and two test points are generated within the interval according to the golden section ratio. The lower-level scheduling model is invoked to evaluate the system's operational cost at each point. Based on the total costs at the two points, the capacity search interval is updated, and the optimization is performed by iteratively narrowing the interval. The iteration terminates when the interval width satisfies the accuracy requirement, yielding the optimal EES leasing capacity and the corresponding system scheduling plan.

4. Case Analysis

4.1. System Composition and Parameters

The system considered in this study comprises one wind power plant, one PV power plant, one CHP unit, one water electrolysis unit, one power-to-ammonia unit, one hydrogen fuel cell system, one electric boiler, and four types of energy storage devices. The initial number of scenarios is set to 1000, and 10 typical scenarios are obtained. The typical source-load scenarios considering prediction errors are shown in Figure 4. The probabilities of the typical scenarios are presented in Table 1, and the main parameters of each unit are listed in Table 2 [25].

Table 1. Probability of typical scenarios.

Scenario ID	Probability	Scenario ID	Probability
1	0.0671	6	0.0553
2	0.0448	7	0.1097
3	0.2187	8	0.0512
4	0.1273	9	0.0942
5	0.1484	10	0.0834

Table 2. The main parameters of each unit.

Parameter	Value	Parameter	Value
$h_{H_2}/(\text{MW}\cdot\text{h}/\text{t})$	37.87	η_e^{FC}	0.4
$h_{N_2}/(\text{MW}\cdot\text{h}/\text{t})$	0.8	η_h^{FC}	0.35
$h_{NH_3}/(\text{MW}\cdot\text{h}/\text{t})$	11.49	η^c	0.95
η^{H_2}	0.85	η^d	0.95
η^{NH_3}	0.85	$c_{coal}/(\text{CNY}/\text{t})$	1000
$\sigma/(\text{MW}\cdot\text{h}/\text{t})$	1.6044	$c^{wt}/(\text{CNY}/\text{kW}\cdot\text{h})$	0.03
η^{EB}	0.8	$c^{pv}/(\text{CNY}/\text{kW}\cdot\text{h})$	0.04
$c^e/(\text{CNY}/\text{t})$	100	$c^{ab}/(\text{CNY}/\text{kW}\cdot\text{h})$	0.15
$a \times 10^{-5}/(\text{t}\cdot\text{MW}^{-2}\cdot\text{h}^{-1})$	7.58799	$b \times 10^{-6}/(\text{t}\cdot\text{MW}^{-2}\cdot\text{h}^{-1})$	2.716019
$c/(\text{t}\cdot\text{h}^{-1})$	18.82248	cv	0.23

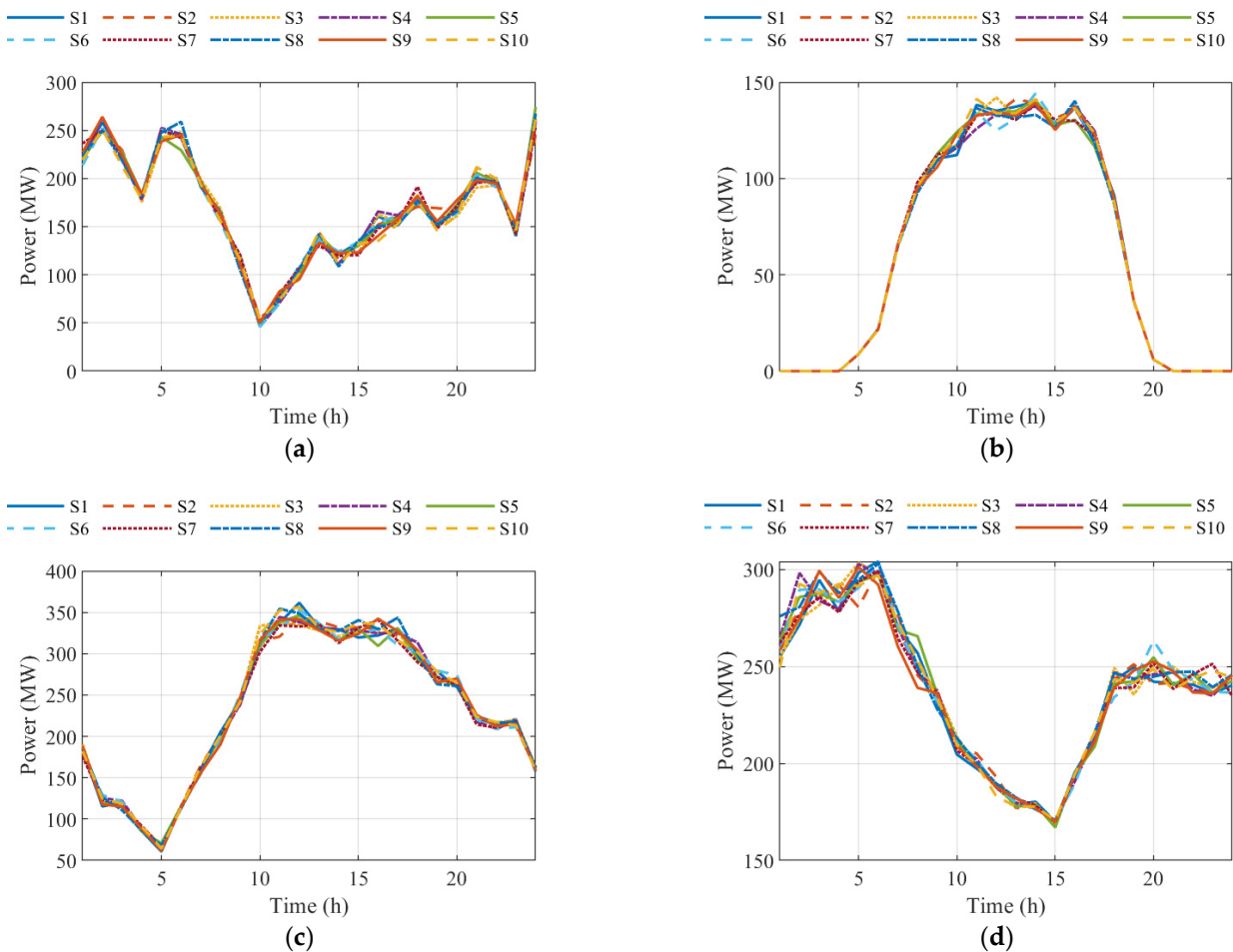


Figure 4. Typical scenario of source load considering prediction error; (a) Wind Power Scenarios Considering Errors; (b) PV Power Scenarios Considering Errors; (c) Electric Load Scenarios Considering Errors; (d) Heat Load Scenarios Considering Errors.

4.2. Effectiveness Analysis of Stochastic Scenario Generation

This study employs a stochastic sampling method to perform optimization analysis on wind and PV scenarios. To improve computational accuracy, a large number of random scenario samples must be generated. To evaluate the computational performance of the C-LHS method, a comparative analysis is conducted against the conventional LHS approach.

Figure 5 shows the variation of computing time for the two sampling methods under different sample sizes. As shown in the figure, when the number of samples reaches 1000, the computing time of the conventional LHS method increases sharply, whereas that of the C-LHS grows at a much slower rate. For a comprehensive performance comparison, a representative sample size is selected. As shown in Figure 6, when the number of samples reaches approximately 800, the similarity of the scenario sets generated by the two methods to the actual distribution stabilizes at a high level, indicating that further increasing the number of samples provides little additional benefit for scenario representativeness. Therefore, selecting a sample size of 1000 is of representative significance: this size ensures sufficient accuracy of the scenario set while clearly demonstrating the computational efficiency advantages of the improved algorithm. Figure 7 further presents the comparison of the two methods on four key indicators at a sample size of 1000.

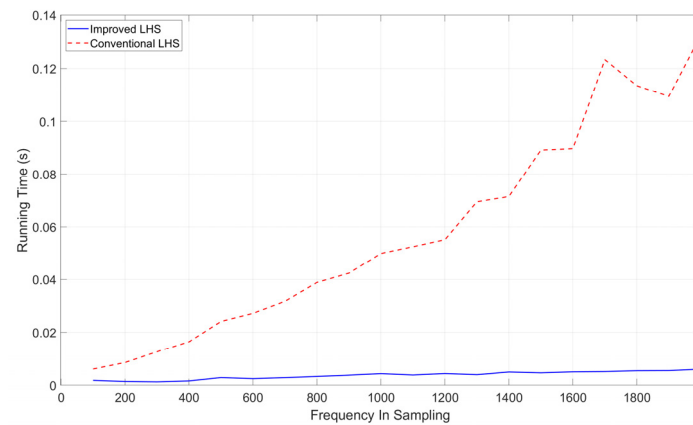


Figure 5. Analysis of computational efficiency under different sampling algorithms.

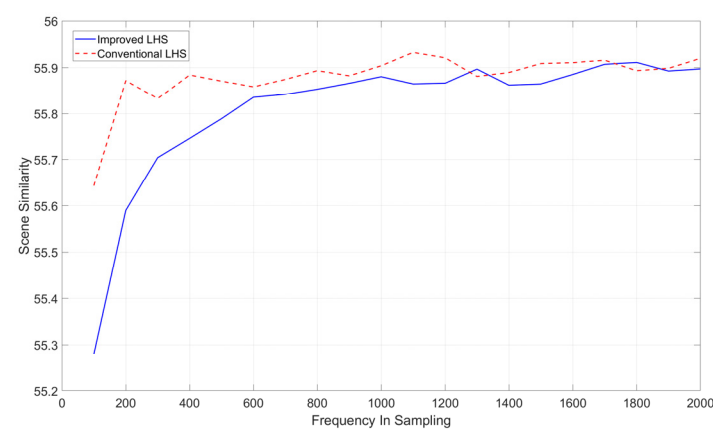


Figure 6. Analysis of Scene similarity under different sampling algorithms.

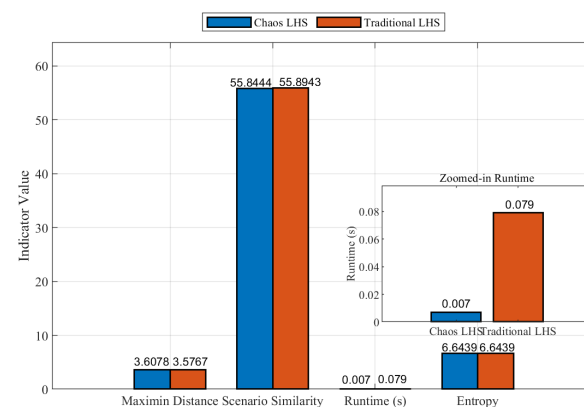


Figure 7. Comparison of the four key indicators under different sampling algorithms.

As shown in Figure 7, when the sample size is set to 1000, the C-LHS method achieves performance comparable to that of the conventional LHS in key metrics, including maximum and minimum distance, scenario similarity, and entropy, while requiring less computational time. This result is consistent with the trends shown in Figures 5 and 6, further confirming the computational efficiency advantage of the C-LHS method while maintaining sampling quality.

4.3. Construction of Comparative Cases and Scheduling Analysis

To verify the effectiveness of this study, the system is divided into five cases for analysis:

Case 1: without heat storage, electric boiler, or ammonia co-firing.

Case 2: with ammonia co-firing only.

Case 3: with heat storage and electric boiler only.

Case 4: with heat storage, electric boiler, and ammonia co-firing.

Case 5: with heat storage, electric boiler, and ammonia co-firing, and with optimization of the day-ahead lease capacity of EES.

The optimization results for the five cases are obtained under the typical scenarios and summarized in Table 3.

Table 3. Comparison of costs and carbon emissions of different schemes.

Case	Total Cost (10 ⁴ CNY)	CHP Operating Cost (10 ⁴ CNY)	Carbon Emission Cost (10 ⁴ CNY)	Wind & Solar Curtailment Cost (10 ⁴ CNY)	Wind & Solar Operation Cost (10 ⁴ CNY)	Environmental Cost (10 ⁴ CNY)	Equipment O&M Cost (10 ⁴ CNY)	Energy Storage Cost (10 ⁴ CNY)	Carbon Emissions (10 ³ t CO ₂)
1	157.73	49.27	9.06	49.26	15.58	0.62	29.84	4.10	1.27
2	127.34	45.26	8.03	26.43	16.79	0.57	26.16	4.12	1.16
3	117.54	49.27	9.06	11.93	17.53	0.62	24.83	4.30	1.27
4	103.45	45.14	8.00	0	18.14	0.57	27.29	4.32	1.16
5	101.22	45.50	8.08	0	18.14	0.57	27.27	1.69	1.17

From Table 3, the comparison of the five cases under typical scenarios shows the following. Compared with Case 1, Case 2 achieves reductions of 8.13% in the operating cost of the cogeneration unit, 11.37% in carbon emission cost, 46.35% in wind and solar curtailment cost, and 19.27% in total cost, indicating that introducing ammonia co-firing enhances wind and solar power utilization and reduces system coal consumption. Compared with Case 1, Case 3 reduces wind and solar curtailment cost by 75.78% and total cost by 25.48%, showing that the addition of thermal storage and electric boiler devices can further improve wind and solar power utilization and operational economy. Compared with Case 3, Case 4 reduces the operating cost of the cogeneration unit by 8.38%, carbon emission cost by 11.7%, wind and solar curtailment cost by 100%, and total cost by 11.99%, outperforming the linear sum of Cases 2 and 3. This demonstrates that introducing ammonia co-firing in a system equipped with heat storage and electric boiler devices can further enhance wind and solar power utilization and reduce system coal consumption. Compared with Case 4, Case 5 shows reductions of 60.87% in energy storage cost and 2.1% in total cost, indicating that optimizing the day-ahead lease capacity of EES can lower both energy storage costs and the overall operating cost of the system.

4.4. Impact Analysis of Ammonia Co-Firing Technology in the CHP Unit

The coal consumption cost and carbon emission cost of a CHP unit are important indicators of the system's clean energy use. Lower coal consumption and carbon emissions indicate higher energy utilization efficiency of the unit, which not only improves the system's cleanliness but also reduces greenhouse gas emissions and other environmental pollutants, thereby contributing positively to environmental quality.

From Table 3, it can be seen that compared with Case 1, the operating cost of the CHP unit in Case 2 has decreased by 8.13%, and the carbon emission cost has decreased by 11.37%, indicating that introducing ammonia co-firing can effectively reduce coal consumption and carbon emissions. The electricity output and coal consumption of the CHP units in Cases 1 and 2 are shown in Figure 8.

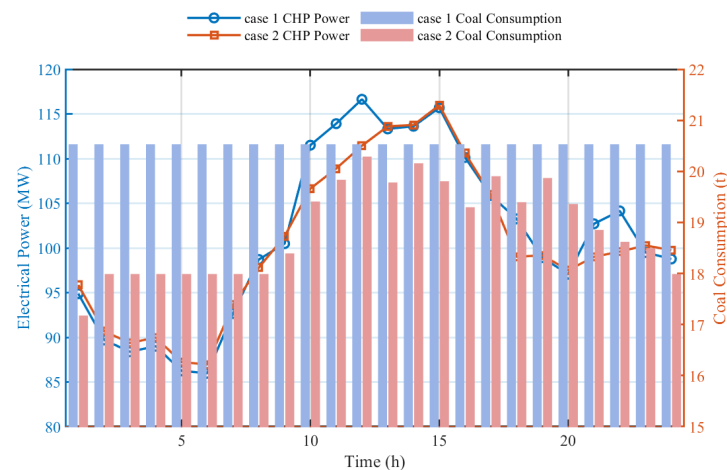


Figure 8. Electrical power and coal consumption for CHP output.

As shown in Figure 8, after introducing ammonia co-firing in Case 2, the electricity output of the CHP unit is similar to that of Case 1 in most periods, while the coal consumption is reduced. During the off-peak electricity period from 0:00 to 8:00, the coal consumption in Case 2 is significantly lower than in Case 1. The thermal scheduling results of the CHP units in Cases 1 and 2 are shown in Figure 9.

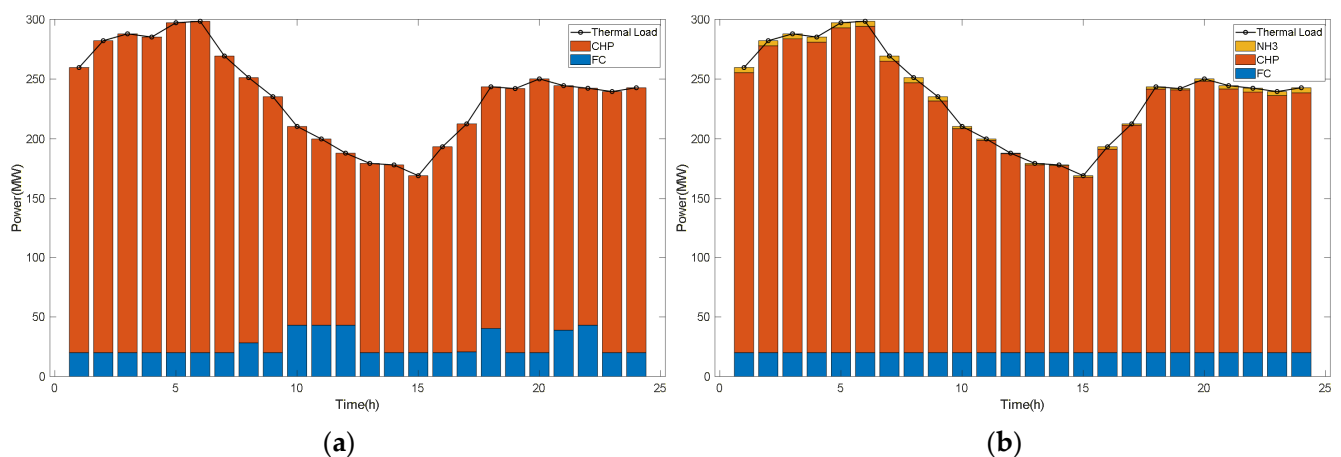


Figure 9. Thermal dispatch results. (a) Case 1; (b) Case 2.

As can be seen from the comparison in Figure 9, the heat released during the ammonia synthesis process can effectively supplement the system's thermal load demand, thereby reducing heating energy consumption and enhancing system operational flexibility.

4.5. Impact of Thermal–Electric Decoupling of the CHP Unit with Thermal Energy Storage and Electric Boiler on Wind and PV Power Accommodation

To analyze the impact of enhanced thermoelectric decoupling capability on wind and PV energy accommodation after the installation of thermal storage tanks and electric boilers, Case 1 and Case 3 are selected for comparative analysis. The corresponding wind and PV accommodation results are illustrated in Figure 10a,b.

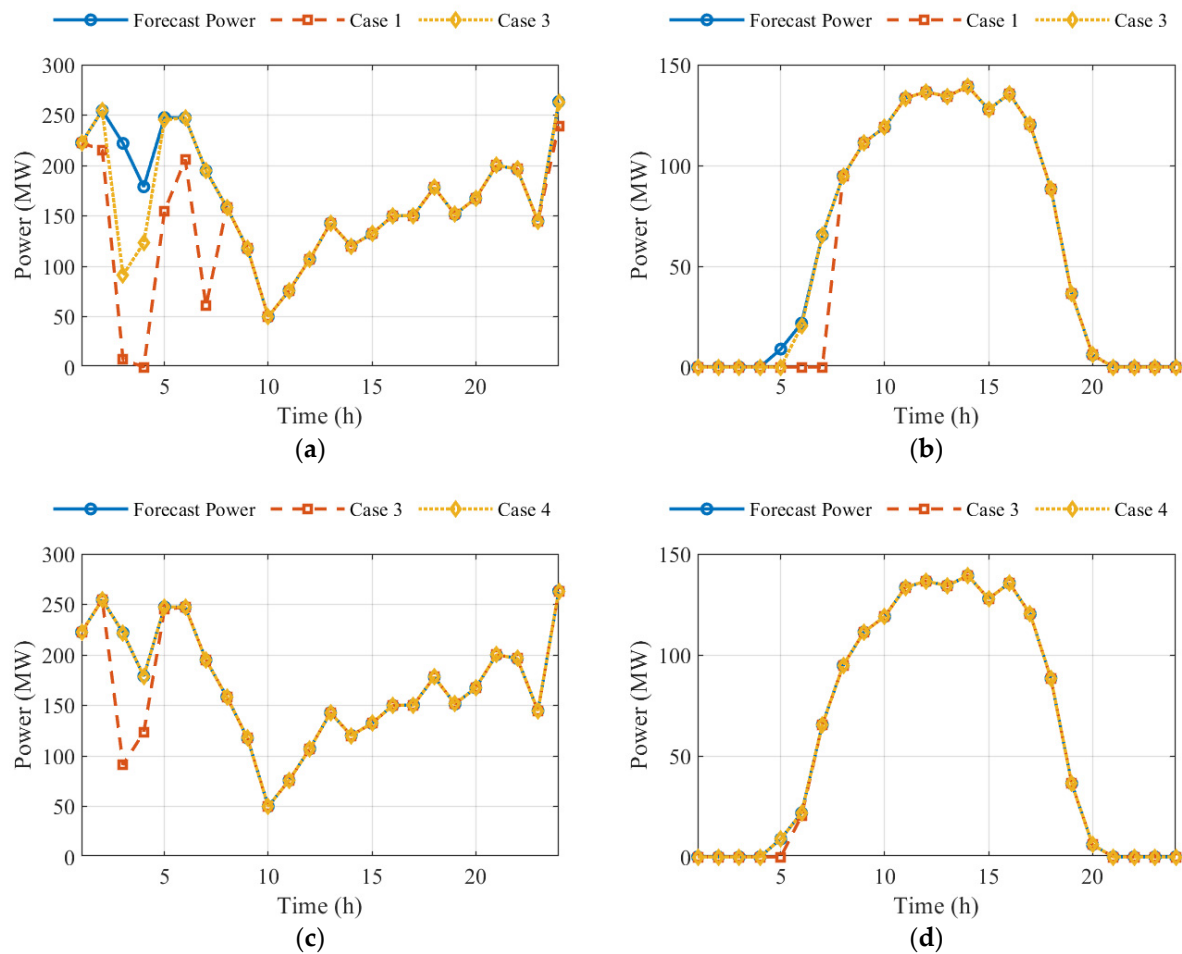


Figure 10. Forecasted Wind and PV Power and Corresponding Wind and PV Accommodation under Different Schemes. (a) Wind Accommodation: Case 1 vs. Case 3; (b) PV Accommodation: Case 1 vs. Case 3; (c) Wind Accommodation: Case 3 vs. Case 4; (d) PV Accommodation: Case 3 vs. Case 4.

As shown in Figure 10a, in Case 1 without thermal storage and electric boiler installations, the CHP unit is constrained by heat supply requirements and must maintain a relatively high minimum forced electrical output during off-peak electricity demand periods. This operational constraint limits system flexibility. Consequently, significant wind power curtailment occurs during the low-demand period from 2:00 to 7:00. Meanwhile, during the PV ramp-up period between 4:00 and 7:00, photovoltaic accommodation is restricted due to the minimum output limitation of the CHP unit, leading to notable PV curtailment.

In contrast, after introducing thermal storage tanks and electric boilers in Case 3, the coupling relationship between heat supply and power generation is effectively alleviated. The thermal storage device absorbs surplus heat during periods of excess electricity, while the electric boiler utilizes off-peak electricity to supplement heat demand. As a result, the minimum forced electrical output of the CHP unit is significantly reduced. Figure 10a,b show that, under identical wind and solar generation conditions, wind curtailment during 2:00–7:00 is substantially mitigated in Case 3, and PV curtailment during 4:00–7:00 is markedly reduced.

From an overall performance perspective, the combined wind and solar curtailment rate decreases from 14.79% in the original configuration to 3.58% after the installation of thermal storage and electric boiler systems. These results demonstrate that thermoelectric decoupling achieved through thermal storage and electric boiler integration effectively

enhances renewable energy accommodation capability, thereby providing strong support for high renewable penetration operation.

4.6. Impact of Introducing Ammonia Co-Firing in the System with Thermal Energy Storage and Electric Boiler on Wind and PV Power Accommodation

Building upon the previous analysis of the effects of thermal storage and electric boiler installations on wind and PV power accommodation, this section further investigates the impact of introducing ammonia co-firing technology on renewable energy utilization. To this end, Case 3 and Case 4 are selected for comparative analysis. The corresponding wind and PV output profiles are illustrated in Figure 10c,d, respectively.

As shown in Figure 10c, although both schemes are equipped with thermal storage and electric boiler systems, Case 3 still experiences wind curtailment during certain periods. This phenomenon is particularly evident when electrical demand is relatively low while renewable generation remains high, indicating that system flexibility is still constrained despite partial thermoelectric decoupling.

In contrast, after the introduction of ammonia co-firing in Case 4, the operational flexibility of the CHP unit is further enhanced. The restriction on wind power output is alleviated, and the wind curtailment level exhibits a noticeable reduction compared with Case 3.

A similar trend can be observed for photovoltaic generation. As illustrated in Figure 10d, Case 4 demonstrates improved PV accommodation capability during periods of rapid output increase and peak generation. With ammonia co-firing incorporated, the system maintains heat supply requirements while further relaxing constraints on power-side output, thereby enabling more effective absorption of PV energy and reducing curtailment.

Overall, the results indicate that, beyond the initial thermoelectric decoupling achieved through thermal storage and electric boiler deployment, the integration of ammonia co-firing technology further enhances system flexibility and renewable adaptability. Consequently, wind and photovoltaic accommodation levels are continuously improved. These findings suggest that ammonia co-firing not only contributes to carbon emission reduction but also plays a positive role in improving overall system operational performance under high renewable penetration.

4.7. Comparative Analysis Under Uncertain Scenarios

In actual operation, wind and PV power outputs exhibit significant forecasting errors, and scheduling optimization based solely on deterministic forecasts may fail to reflect the system's performance under real operating conditions. To evaluate the adaptability of the proposed scheduling strategy under uncertainty, stochastic operational scenarios are constructed based on wind and solar forecast errors, and multi-scenario re-simulations are performed using the C-LHS method.

Specifically, $\pm 10\%$ random perturbations are introduced to the wind and PV forecast curves to generate 50 stochastic operational scenarios. For each scenario, re-scheduling calculations are performed for Case 1 and Case 5. The operational cost, carbon emissions, and renewable power utilization are then collected for all scenarios to evaluate the stability and economic performance of different scheduling strategies under stochastic fluctuations. Table 4 presents the statistical results of the two cases across the 50 stochastic scenarios.

Table 4. Comparison of Indicators Between Two Plans.

	Case 1	Case 5
Average Cost (10^4 CNY)	155.6	101.05
Cost Std. Dev. (10^4 CNY)	2.47	0.78
Worst Cost (10^4 CNY)	160.61	103.44
Optimal Cost (10^4 CNY)	149.88	100.12
Carbon Emission Cost (10^4 CNY)	9.06	8.05
Wind Power Utilization (%)	82.28	99.91
PV Utilization (%)	93.46	99.62
Cost Variation Coefficient	0.0159	0.0078

From an economic perspective, the average operational cost of Case 5 under the stochastic scenarios is 101.05×10^4 CNY, representing a reduction of approximately 35.05% compared with 155.6×10^4 CNY for Case 1. This indicates that the proposed strategy still exhibits a significant cost advantage under uncertain conditions. Meanwhile, the standard deviation of the operational cost in Case 5 is 0.78×10^4 CNY, a decrease of approximately 68.26% compared with 2.47×10^4 CNY for Case 1, demonstrating a substantially reduced sensitivity to wind and solar power fluctuations.

Furthermore, the system operational stability is evaluated using the coefficient of variation (defined as the ratio of the standard deviation to the mean). The coefficient of variation for Case 5 is 0.0078, compared with 0.0159 for Case 1, representing a reduction of approximately 50.9%. This indicates that the proposed scheduling strategy provides higher stability and stronger robustness against disturbances under stochastic operational scenarios.

In terms of risk performance under extreme scenarios, the worst-case operational cost of Case 5 is 103.44×10^4 CNY, representing a reduction of approximately 35% compared with 160.61×10^4 CNY for Case 1. This demonstrates that under adverse wind and solar power output conditions, the proposed method can still maintain superior operational performance, indicating strong risk resilience.

In terms of low-carbon operation, the average carbon emission cost of Case 5 is 8.05×10^4 CNY, representing a reduction of approximately 11.1% compared with 9.06×10^4 CNY for Case 1. Meanwhile, regarding renewable power utilization, the wind and PV absorption rates in Case 5 increase to 99.91% and 99.62%, respectively, which are significantly higher than those in Case 1.

In summary, under stochastic operational scenarios considering the uncertainty of wind and solar power output, the proposed scheduling strategy not only demonstrates a clear advantage in terms of average operational cost, but also exhibits superior performance in operational stability, risk resilience under extreme scenarios, carbon reduction, and renewable power utilization. These results fully validate its operational stability and economic efficiency under uncertain conditions.

4.8. Sensitivity Analysis

4.8.1. Sensitivity Analysis of Energy Storage Leasing Price

To investigate the economic impact of EES leasing, a sensitivity analysis on the leasing price is conducted. The leasing price is varied within a predefined range, and the corresponding optimal leasing capacity and renewable energy curtailment cost are evaluated, as shown in Figure 11a,b.

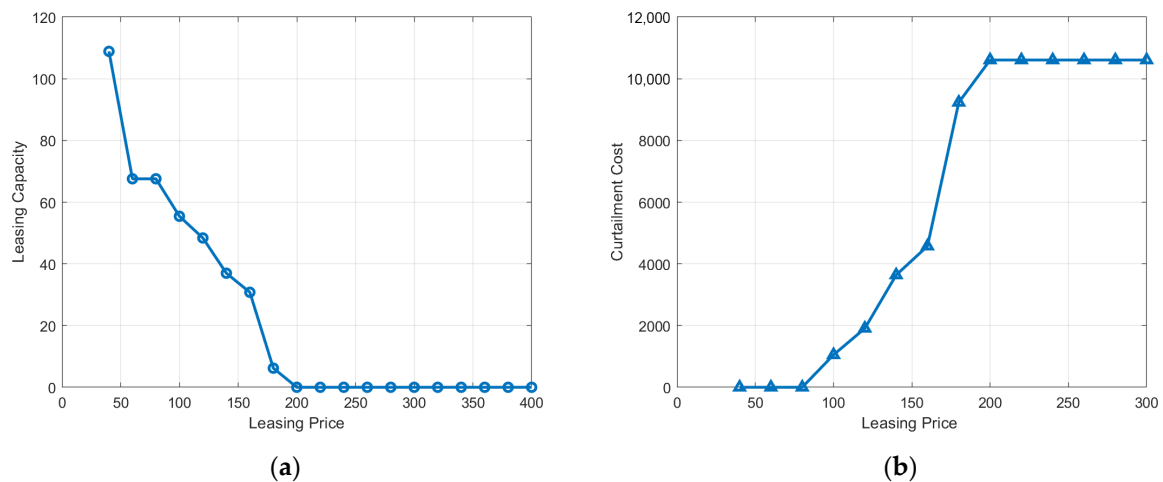


Figure 11. Sensitivity analysis of EES leasing price. (a) Leasing Price vs. Capacity; (b) Leasing Price vs. Curtailment Cost.

Figure 11a illustrates the relationship between leasing price and optimal leasing capacity. When the leasing price is low, the system tends to lease a larger storage capacity, as the marginal benefit of reducing renewable energy curtailment exceeds the leasing cost. As the leasing price increases, the optimal leasing capacity gradually decreases, indicating a reduction in the economic attractiveness of storage leasing. When the leasing price exceeds a critical threshold (approximately 200), the optimal leasing capacity drops to zero. Beyond this threshold, leasing energy storage becomes economically unfavorable compared to curtailing excess renewable energy.

Figure 11b shows the variation of renewable energy curtailment cost with respect to the leasing price. At low leasing prices, the curtailment cost is close to zero, indicating that sufficient storage capacity can effectively absorb renewable energy. However, as the leasing price increases and the leasing capacity decreases, the system gradually loses its ability to fully utilize renewable energy, leading to a sharp increase in curtailment cost. When the leasing capacity becomes zero, the curtailment cost stabilizes at a high level, suggesting that the system can only rely on its inherent flexibility.

Overall, the results reveal a clear trade-off between leasing cost and curtailment loss. A moderate leasing price can effectively reduce renewable energy curtailment and lower total system cost, while excessively high leasing prices suppress storage participation and increase curtailment. The identified price threshold provides a useful reference for determining economically viable leasing prices in practical applications.

4.8.2. Sensitivity Analysis of the Heat Recovery Allocation Coefficient

To further investigate the impact of CHP operational characteristics on the performance of the integrated energy system, a sensitivity analysis of the heat recovery allocation coefficient is conducted. In this study, this parameter is represented by the slope of the feasible operating region of the CHP unit, denoted as c_v . It characterizes the coupling relationship between power output and heat output, and thus reflects the thermoelectric coupling strength of the unit.

Specifically, a larger c_v indicates stronger thermoelectric coupling, meaning that a higher power output is required to satisfy a given heat demand. This effectively increases the minimum technical power output of the CHP unit and reduces its operational flexibility. In contrast, a smaller c_v corresponds to enhanced decoupling capability, which is beneficial for system regulation and renewable energy integration.

According to the literature in [10], a reference value of $c_v = 0.23$ is adopted, corresponding to a typical operating condition. However, in practical applications, the value of c_v is not constant and may vary with operating conditions such as load level, heat demand, and control strategies. Therefore, to comprehensively evaluate its impact, c_v is varied within the range of 0.16–0.30 around the reference value, and a sensitivity analysis is performed.

Figure 12a illustrates the variation of the total system cost with respect to c_v . It can be observed that the total cost exhibits a non-monotonic trend: as c_v increases from 0.16 to approximately 0.23, the total cost decreases significantly; however, when c_v further increases to 0.30, the total cost rises slightly. This indicates that an optimal operating region exists around $c_v \approx 0.23$.

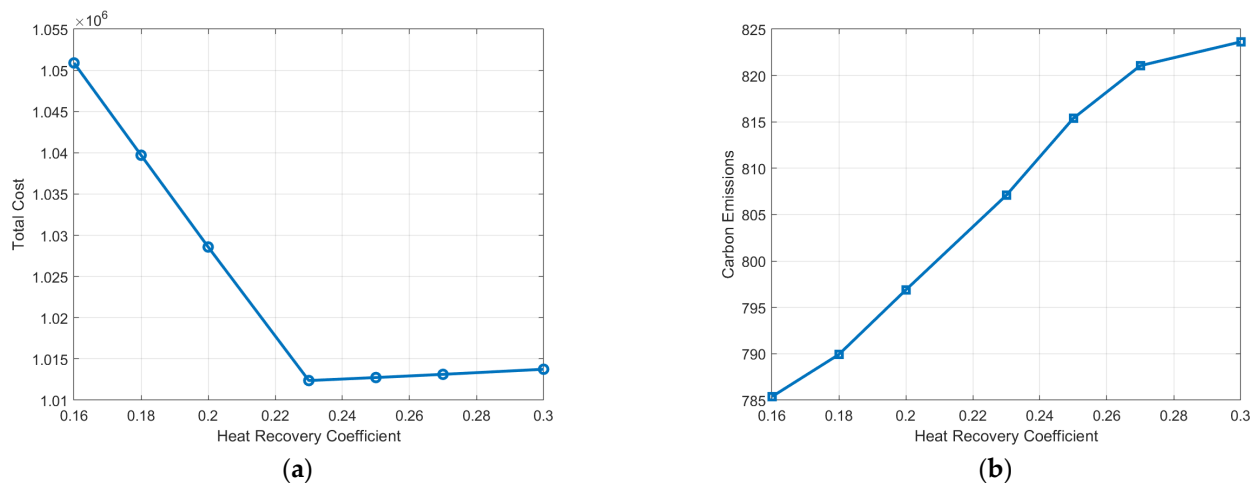


Figure 12. Sensitivity analysis results of the heat recovery allocation coefficient. (a) Impact of Heat Recovery Coefficient on Cost; (b) Impact of Heat Recovery Coefficient on Emissions.

From a mechanistic perspective, when c_v is relatively small, the CHP unit has strong decoupling capability but relatively low heat utilization efficiency, which may lead to increased operation of auxiliary heating units and higher system costs. At moderate values of c_v (around 0.23), a favorable balance is achieved between heat utilization efficiency and operational flexibility, resulting in the lowest system cost. When c_v becomes larger, the strengthened thermoelectric coupling raises the minimum power output of the CHP unit under heat demand constraints, thereby limiting renewable energy accommodation and increasing reliance on fossil-fuel-based generation, which in turn leads to higher system costs.

Figure 12b shows the corresponding carbon emissions. It can be seen that carbon emissions increase monotonically with c_v . This is because stronger thermoelectric coupling reduces system flexibility and restricts the integration of renewable energy, resulting in higher output from conventional fossil-fuel units and thus increased emissions.

Overall, the results indicate that the heat recovery allocation coefficient c_v is a key parameter affecting the operational flexibility of CHP units and the overall system performance. Lower c_v values improve decoupling capability and facilitate renewable energy utilization but may reduce heat utilization efficiency, while higher c_v values strengthen coupling and constrain system flexibility. Therefore, in practical applications, c_v should be carefully selected according to specific operating conditions to achieve a balance between economic performance and environmental impact.

It is also noteworthy that the reference value ($c_v = 0.23$) reported in the literature is close to the optimal region identified in this study, which indirectly validates the rationality of the selected parameter.

5. Conclusions

To address the challenges of increased uncertainty and insufficient flexibility in integrated energy systems with high renewable penetration, this paper develops a stochastic day-ahead scheduling framework integrating uncertainty scenario modeling, thermoelectric decoupling, ammonia co-firing, and EES capacity leasing optimization. Through coordinated multi-mechanism optimization, the proposed approach simultaneously enhances economic performance, low-carbon operation, and system stability. The main conclusions are summarized as follows:

1. The proposed C-LHS method combined with an improved K-means clustering algorithm enhances the efficiency of scenario generation and reduction while preserving scenario representativeness and distribution consistency. The approach provides reliable technical support for stochastic scheduling of integrated energy systems.
2. By integrating thermal energy storage and electric boilers, the conventional heat-led constraint of CHP units is effectively relaxed, improving electrical-side flexibility. The introduction of ammonia co-firing further optimizes the fuel structure and reduces carbon intensity, while heat recovery from ammonia synthesis enhances thermal-side regulation capability. The coordinated operation of these mechanisms improves renewable energy accommodation and overall operational efficiency, demonstrating synergistic effects.
3. This study treats EES capacity as a day-ahead leasing decision variable. A unimodal capacity optimization model is formulated and solved using the Golden Section Search algorithm, achieving a balance between computational efficiency, cost, and operational flexibility. The results indicate that the proposed mechanism not only reduces energy storage costs and overall system operating costs, but also enhances its stability and resilience under renewable energy output fluctuations.

Although the direct economic benefits observed in this study are relatively limited, the value of the proposed EES leasing framework should not be evaluated solely based on short-term cost reduction. The proposed approach enhances system flexibility, improves renewable energy accommodation, and alleviates operational constraints of conventional units, which are critical for integrated energy systems with high renewable penetration. Moreover, the leasing optimization is implemented at the scheduling level and does not introduce significant additional computational burden. Therefore, its implementation complexity is considered acceptable in relation to the operational benefits achieved. With the increasing penetration of renewable energy, the economic value of flexible resources such as shared energy storage is expected to become more prominent.

Author Contributions: Conceptualization, B.F. and Z.W.; methodology, Z.W.; software, Z.W.; validation, B.F. and Z.W.; formal analysis, Z.W.; investigation, B.F.; resources, B.F.; data curation, Z.W.; writing—original draft preparation, Z.W.; writing—review and editing, B.F. and Z.W.; visualization, Z.W.; supervision, B.F.; project administration, B.F.; funding acquisition, B.F. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Key Research and Development Program of the Hubei Province of China, grant number 2023BAB209.

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Zhang, Q.; Li, G.; Chen, X.; Yang, A.; Zhu, K. Enhancing Renewable Energy Integration via Robust Multi-Energy Dispatch: A Wind–PV–Hydrogen Storage Case Study with Spatiotemporal Uncertainty Quantification. *Energies* **2025**, *18*, 4498. [[CrossRef](#)]

2. Liu, M.; Wang, S.; Zhao, Y.; Tang, H.; Yan, J. Heat–power decoupling technologies for coal-fired CHP plants: Operation flexibility and thermodynamic performance. *Energy* **2019**, *188*, 116074. [\[CrossRef\]](#)
3. Yang, J.; Zeng, L.; He, K.; Gong, Y.; Zhang, Z.; Chen, K. Optimization of the joint operation of an electricity–heat–hydrogen–gas multi-energy system containing hybrid energy storage and power-to-gas–combined heat and power. *Energies* **2024**, *17*, 3144. [\[CrossRef\]](#)
4. Chen, H.; Wu, H.; Kan, T.; Zhang, J.; Li, H. Low-carbon economic dispatch of integrated energy system containing electric hydrogen production based on VMD-GRU short-term wind power prediction. *Int. J. Electr. Power Energy Syst.* **2023**, *154*, 109420. [\[CrossRef\]](#)
5. Faisal, S.; Gao, C. A comprehensive review of integrated energy systems considering power-to-gas technology. *Energies* **2024**, *17*, 4551. [\[CrossRef\]](#)
6. Zeng, X.; Zhang, W.; Wang, X. Optimal Configuration of Regional Integrated Energy System After Taking Into Account Multiple Uncertainties and the Participation of Concentrating Solar Power Plants. *High Volt. Eng.* **2023**, *49*, 353–363. (In Chinese)
7. Wang, J.; Wei, Z.; Zhang, Y.; Ma, Z.; Sun, G.; Zang, H.; Chen, S. Multi-objective optional day-ahead dispatching for regional integrated energy system considering uncertainty. *Power Syst. Technol.* **2018**, *42*, 3496–3503. (In Chinese)
8. Hao, J.; Guo, X.; Li, Y.; Wu, T. Uncertain scheduling of the power system based on wasserstein distributionally robust optimization and improved differential evolution algorithm. *Energies* **2024**, *17*, 3846. [\[CrossRef\]](#)
9. Li, M.; Miao, S.; Li, J.; Ye, C.; Yi, B. Optimal allocation of energy storage system in PV micro grid considering uncertainty of demand response. *Power Syst. Prot. Control* **2018**, *46*, 69–77. (In Chinese)
10. Yi, L.; Shi, Q. A wind power consumption model of CHP with thermal energy storage based on demand response. *Acta Energiæ Solaris Sin.* **2021**, *42*, 90–96. (In Chinese)
11. Chen, Y.; Ma, Y.; Zheng, G.; Sun, Z.; Chen, D.; Gao, Y. Coordinated planning of thermo-electrolytic coupling for multiple CHP units considering demand response. *Power Syst. Technol.* **2022**, *46*, 3821–3830. (In Chinese)
12. Zhang, S.; Gu, W.; Zhang, X.-P.; Lu, H.; Lu, S.; Ding, S.; Wang, J.; Zhao, S. Steady-state security region of integrated energy system considering thermal dynamics. *IEEE Trans. Power Syst.* **2023**, *39*, 4138–4153. [\[CrossRef\]](#)
13. Han, Z.; Li, Z.; Zhang, W.; Liu, K.; Dong, H.; Yuan, T. Economic operation strategy of hydrogen integrated energy system considering uncertainty of photovoltaic output power. *Electr. Power Autom. Equip.* **2021**, *41*, 99–106. (In Chinese)
14. Lin, L.; Zheng, X.Y.; Zhou, L.W. Wind-PV-thermal-storage multi-energy complementary optimal dispatching based on hydrogen gas turbine. *Power Syst. Technol.* **2022**, *46*, 3007–3016. (In Chinese)
15. Liang, J.P.; Zhang, G.H.; Li, F.T.; Xie, C.; Wang, T. Low-carbon optimal scheduling of integrated energy system considering hydrogen energy storage, ammonia production and carbon capture. *Electr. Power Autom. Equip.* **2024**, *44*, 16–23. (In Chinese)
16. Ma, R.; Chen, J.; Zhao, J.C.; Zhang, H.W.; Sun, M. Multi-objective optimization for capacity of non-grid-connected wind/hydrogen hybrid power system. *Acta Energiæ Solaris Sin.* **2019**, *40*, 422–429. (In Chinese)
17. Yuan, T.; Li, G.; Zhang, Z.; Zhang, L.; Cai, G.; Mei, S. Optimal modeling on equipment investment planning of wind power-hydrogen energy storage and coal chemical pluripotent coupling system. *Trans. China Electrotech. Soc.* **2016**, *31*, 21–30. (In Chinese)
18. Li, S.; Deng, N.; Yan, S.; Liu, L.; Peng, S.; Peng, X. Optimal configuration optimization of PV energy storage microgrid using improved ant colony dynamic programming. *Acta Energiæ Solaris Sin.* **2023**, *44*, 468–476. (In Chinese)
19. Hu, Z.; Jiang, W.; Zhang, L.; Yang, X.; Zou, Y.; Wang, K. Optimal allocation of hydrogen storage capacity based on improved cat swarm optimization. *Electr. Power* **2023**, *56*, 33. (In Chinese)
20. Finnah, B.; Gönsch, J.; Ziel, F. Integrated day-ahead and intraday self-schedule bidding for energy storage systems using approximate dynamic programming. *Eur. J. Oper. Res.* **2022**, *301*, 726–746. [\[CrossRef\]](#)
21. Li, Q.; Jang, X.; Zhang, J.Z. Business Models for Large-Scale Energy Storage Systems to Participate in Electricity Spot Market. *J. Shanghai Jiao Tong Univ.* **2023**, *57*, 1543–1558. (In Chinese)
22. Huang, C.; Zhang, H.; Song, Y.; Wang, L.; Ahmad, T.; Luo, X. Demand response for industrial micro-grid considering photovoltaic power uncertainty and battery operational cost. *IEEE Trans. Smart Grid* **2021**, *12*, 3043–3055. [\[CrossRef\]](#)
23. Xu, J.; Hi, Z.; Xu, Y. Research progress and prospect of ammonia cofiring in utility coal-fired boiler. *Huazhong Keji Daxue Xuebao* **2022**, *50*, 55–65. (In Chinese)
24. Zhao, S.; Peng, J.; Ge, R.; Wu, S.; Zeng, K.; Huang, H.; Yang, K.; Sun, Z. Research progress on selective catalytic reduction (SCR) catalysts for NO_x removal from coal-fired flue gas. *Fuel Process. Technol.* **2022**, *236*, 107432. [\[CrossRef\]](#)
25. Yuan, W.; Chen, L.; Wang, C.; Wang, Z. Bi-level optimal scheduling of power-to-ammonia coupling wind-photovoltaic-thermal integrated energy system based on ammonia energy storage technology. *Proc. CSEE* **2023**, *43*, 6992–7003. (In Chinese)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.