

Article

Low-Carbon Robust Planning for PIEs with Multi-Time-Scale Uncertainties and Elastic DR Regulation

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Abstract

With the widespread application of park integrated energy systems (PIEs), challenges of multi-energy coupling, high investment costs, and multi-type uncertainties have become increasingly prominent. Existing research often employs typical scenario generation or robust optimization for short-term uncertainties but struggles with long-term load growth uncertainties and fails to fully utilize the flexibility of demand-side resources during the planning phase. This paper proposes a robust planning method for PIEs considering dynamic demand response and multi-timescale uncertainties. First, an energy flow framework encompassing cooling, heating, electricity, gas, and hydrogen is constructed. To overcome the limitations of traditional fixed-boundary DR, a dynamic elastic DR mechanism featuring transferable, substitutable, and curtailable types is established. Transferable demand boundaries are defined by a price–demand elasticity matrix, and actual responses are dynamically adjusted in synergy with system power balance conditions for optimal configuration. Second, multivariate dynamic time warping and hierarchical clustering algorithms derive typical daily scenarios accounting for short-term uncertainties. Finally, information gap decision theory characterizes long-term load growth uncertainty, constructing a robust planning model addressing both timescales. Case studies show that flexible resources and demand response reduce lifecycle cost by 55.24% and carbon emissions by 47.75%. The proposed demand response method further cuts costs by 153,800 yuan and emissions by 11.36%. The robust planning method synergistically addresses multi-timescale uncertainties, ensuring economy while maximizing resilience to uncertain fluctuations.

Keywords: demand response; robust planning; uncertainty; IGDT; MDTW



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1. Introduction

With the transformation of the global energy structure and the advancement of dual carbon goals, the traditional single-energy supply model struggles to satisfy the complex energy demands of urbanization [1]. Integrated energy parks, as modern multi-energy complementary systems incorporating flexible resources, have attracted extensive attention for their potential to optimize resource allocation, enhance energy utilization efficiency, and reduce carbon emissions, thereby serving as a vital pathway toward sustainable development [2–4].

In recent years, demand response (DR) has emerged as a key flexibility management tool in power systems, with increasing research focused on its application at the park level. Studies have developed various integrated demand response models for parks, incorporating distributed resources such as photovoltaics, electrical/thermal/cold storage, and time-of-use pricing incentives [5,6]. Other works have proposed price-based and substitution-based DR mechanisms using elasticity matrices or considering user-side energy conversion [7,8], as well as dual-objective optimization frameworks that integrate comprehensive DR [9]. Additional efforts have explored DR coordination with dynamic pricing [10], seasonal storage impacts on flexibility [11], and user comfort constraints via thermodynamic modeling [5]. Most existing approaches rely on price elasticity matrices to quantify DR, which suits operational dispatch under price signals but falls short in park-level planning. In planning phases, DR must account not only for price variations but also for system supply conditions to avoid over-sizing equipment capacity solely to meet extreme imbalances. Thus, incorporating dynamic demand-side response into coordinated planning remains essential.

For collaborative planning of park integrated energy systems (PIESs), bi-level models have been widely adopted to optimize energy station siting, capacity configuration, network layout, and multi-energy flows (electricity–heat–gas), balancing investment costs with economic, environmental, and reliability objectives [12–15]. Other studies have addressed distributed generation with intelligent storage [16] or hybrid renewable–CHP–thermal storage systems using stochastic optimization [17]. Uncertainty handling in PIES planning primarily involves typical scenario generation or robust optimization. Typical scenarios mitigate deterministic limitations and computational burdens of probabilistic methods [18–20], often using Latin hypercube sampling [21], spectral clustering for seasonal profiles [22], or Gaussian kernel density estimation combined with clustering [23]. However, conventional clustering usually treats source and load profiles independently before combination, overlooking their temporal correlations. Robust optimization approaches employ box-type uncertainty sets [24], distributed robust models for resilience under extreme events [25], or interval-based methods for multi-stakeholder planning [26]. While these address short-term source-load uncertainties effectively, lifecycle PIES planning must also manage long-term load growth uncertainties, as overly conservative assumptions can significantly inflate costs.

Therefore, this study proposes a robust PIES planning method that integrates dynamic DR regulation and multi-timescale uncertainty. The main scientific novelties and contributions of this paper are summarized as follows:

- (1) A dynamic elastic demand response mechanism is proposed to overcome the limitations of traditional fixed-boundary DR. By coupling price–demand elasticity with the actual system power balance, transferable boundaries are dynamically adjusted during the planning phase, preventing equipment over-sizing and unlocking greater economic and decarbonization potentials.
- (2) A multi-timescale uncertainty management framework is established. It uniquely combines the multivariate dynamic time warping (MDTW) algorithm to preserve multi-energy source-load temporal correlations for short-term fluctuations with information gap decision theory (IGDT) to robustly hedge against long-term load growth uncertainty without requiring prior probability distributions.
- (3) A comprehensive collaborative planning model for PIESs is constructed, embedding a deep coupling of hydrogen systems and generalized multi-energy storage (electricity, heat, cold, gas, and hydrogen). This model systematically quantifies the synergistic effects of these flexible resources on full lifecycle costs and zero-carbon targets.

2. Park Integrated Energy System Overview

PIESs exhibit unique advantages in multi-energy complementarity and mutual support due to their core feature of energy coupling [27]. This study focuses on the planning of a PIES encompassing electricity, heat, gas, cooling, and hydrogen, with its structure shown in Figure 1. The system's energy input comprises wind and photovoltaic generation, supported by the upstream power grid and gas network. Key conversion devices include CHP units, electric chillers (ER), gas boilers (GBs), and absorption chillers (ACs). A CCHP subsystem, formed by coordinating CHP units and ACs, achieves efficient cascaded energy utilization. Furthermore, a two-stage power-to-gas technology—involving electrolysis (EL), hydrogen methanation (MR), and hydrogen fuel cells (HFCs)—enhances overall conversion efficiency and environmental performance. The system integrates multiple energy storage types (ES, HS, GS, H₂S, IS, and WS) and an electric vehicle charging station (EV) to improve operational flexibility and reliability.

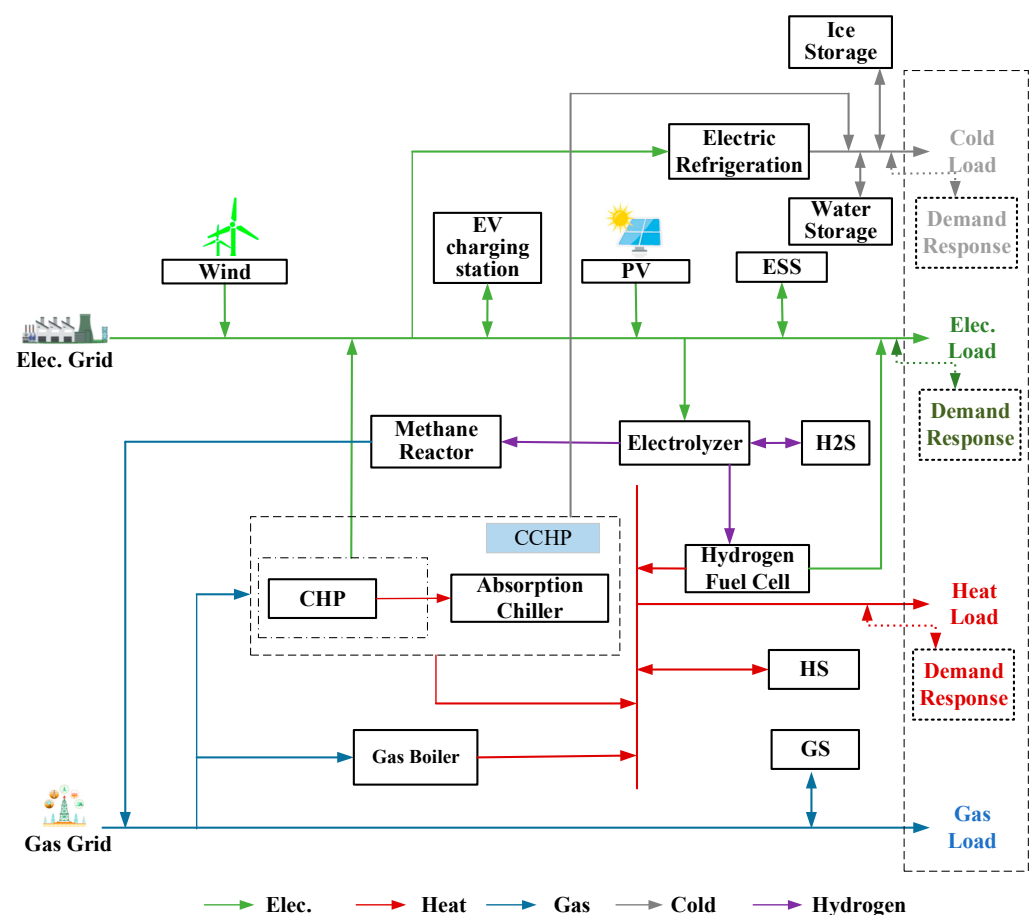


Figure 1. Structural diagram of the PIES. The dashed box in the figure represents elements of the same type.

3. Methods

3.1. Extraction of Typical Scenarios for Source-Load Profiles

This study employs the MDTW algorithm and hierarchical clustering to extract typical scenarios that account for the temporal correlation characteristics of source-load profiles. Unlike traditional independent clustering that may overlook the stochastic probability of multi-energy concurrent peaks, the MDTW algorithm aligns time series through dynamic programming, calculates the minimum path distance using Euclidean distance, and forms a comprehensive multi-dimensional distance through weighting. By treating the electrical, thermal, cooling, and gas loads as a holistic tensor, MDTW effectively preserves the actual

stochastic characteristics, including extreme cases where consumers consume maximum energy across several energy channels simultaneously.

Let the original dataset be denoted as $\Phi \in \mathbf{R}^{8760 \times 6}$, containing annual hourly data for six categories: wind power (W), photovoltaic generation (PV), electrical load, thermal load, gas load, and cooling load. The original data are restructured into a three-dimensional tensor Ψ . Normalization is applied to each energy type.

$$\begin{cases} \Psi = f_{\text{reshape}}(\Phi) \in \mathbf{R}^{365 \times 24 \times 6}, \\ x_{n,d,t,k} = \frac{x_{k,d,t} - \min(\Psi_{d,t,k})}{\max(\Psi_{d,t,k}) - \min(\Psi_{d,t,k})}, \end{cases} \quad (1)$$

where f_{reshape} is the matrix reconstruction function; $x_{d,t,k}$ is the actual value of the k -th energy type at day d and time t ; $x_{n,d,t,k}$ is the normalized value of the k -th energy type at day d and time t ; $k \in \{1, \dots, 6\}$ is the index of energy type; $\Psi_{d,t,k}$ are the three-dimensional tensor Ψ scalar elements within.

For the multi-dimensional time series $\mathbf{A}$ and $\mathbf{B}$ spanning two days, the multivariate distance is defined as follows.

$$\begin{cases} D_{\text{MDTW}}(\mathbf{A}, \mathbf{B}) = \sum_{k=1}^6 w_k D_{\text{DTW}}(\mathbf{a}_k, \mathbf{b}_k) \\ w_k = \frac{1 - H_k}{\sum_{k=1}^6 (1 - H_k)}, H_k = - \sum_{d=1}^{365} p_{d,k} \ln p_{d,k} \end{cases} \quad (2)$$

$$\begin{cases} \Delta(a_{t_1,k}, b_{t_2,k}) = |a_{t_1,k} - b_{t_2,k}| \\ D_{\text{DTW}}(a_{t_1,k}, b_{t_2,k}) = \Delta(a_{t_1,k}, b_{t_2,k}) + \min\{D_{\text{DTW}}(a_{t_1-1,k}, b_{t_2,k}), \\ D_{\text{DTW}}(a_{t_1,k}, b_{t_2-1,k}), D_{\text{DTW}}(a_{t_1-1,k}, b_{t_2-1,k})\} \\ D_{\text{MDTW}}(\mathbf{a}_k, \mathbf{b}_k) = \sum_{t_1, t_2 \in T_d} D_{\text{DTW}}(a_{t_1,k}, b_{t_2,k}) \end{cases} \quad (3)$$

where w_k is the weighting coefficient for energy types, determined by the entropy weight method; a_k and b_k are the time series (vectors) of the k -th energy type data for days a and b , respectively; $a_{t_1,k}$ is the element in $\mathbf{a}_k$ (value at time t_1), and $b_{t_2,k}$ is the element in $\mathbf{b}_k$ (value at time t_2); $D_{\text{DTW}}(\cdot)$ is the DTW distance calculation formula; H_k is the time-series information entropy; $p_{d,k}$ is the time-series probability distribution; $\Delta(a_{t_1,k}, b_{t_2,k})$ is the actual distance; T_d is the set of time points over a 24 h day.

Hierarchical clustering minimizes the within-cluster sum of squared distances Γ . The scenario nearest the cluster center is selected: Construct the Distance Matrix $\mathbf{M} \in \mathbf{R}$.

$$\begin{cases} \Gamma = \sum_{c=1}^C \sum_{\Psi_d \in S_c} D_{\text{MDTW}}^2(\Psi_d, \mu_c) \\ \mu_c = \frac{1}{N_c} \sum_{\Psi_d \in S_c} \Psi_d \\ m_{d_1, d_2} = D_{\text{MDTW}}(\Psi_{d_1}, \Psi_{d_2}), \forall d_1, d_2 \in \{1, \dots, 365\} \end{cases} \quad (4)$$

where C is the preset number of clusters; Ψ_d is the two-dimensional data vector; μ_c is the centroid of the c -th cluster; N_c is the number of data points.

3.2. A Robust Planning Model for PIESs Considering Uncertainty and DR

A robust planning model for PIESs considering uncertainty and DR is illustrated in Figure 2. First, based on historical source-load data, MDTW algorithm quantifies the comprehensive distance among electricity, heat, gas, and cooling time-series curves. Hierarchical clustering then extracts typical daily scenarios to characterize short-term uncertainties from renewable output and load fluctuations. Second, a park-level planning model minimizes total lifecycle cost. It incorporates a dynamic DR mechanism based

on a price elasticity matrix, with constraints for energy conversion equipment, storage capacity, renewable penetration, and low-carbon targets, optimizing both configuration and operation. Finally, to address long-term load growth uncertainty, IGDT constructs a two-layer robust optimization framework. Building on the short-term model's solution, a box-type uncertainty set quantifies load growth boundaries, enabling dynamic capacity adjustments. This yields a robust configuration plan, accommodating both short- and long-term uncertainties.

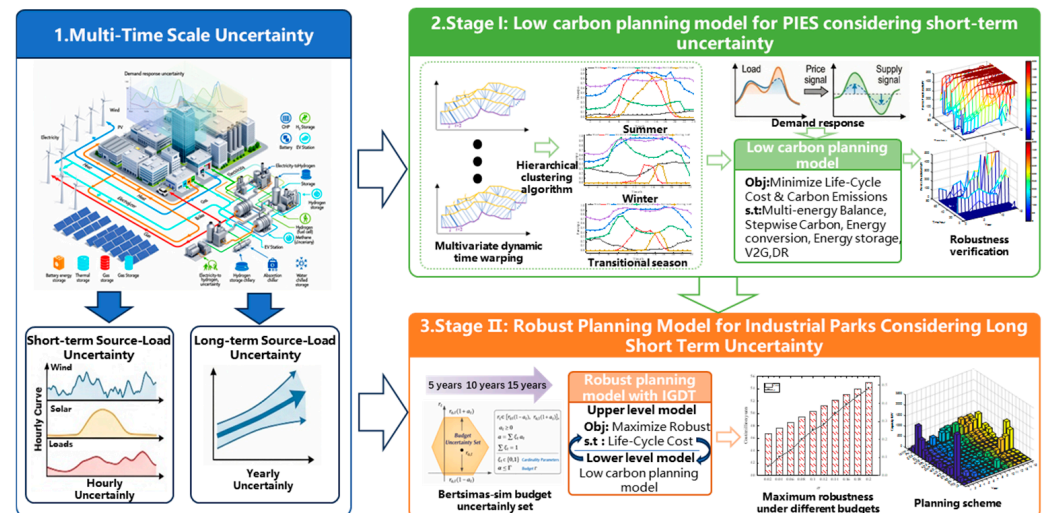


Figure 2. Robust planning model considering uncertainty and DR. The arrows in Figure 1 represent the direction of power, the orange line represents the flow of thermal power, the red line represents the flow of electrical power, the deep blue sign represents the flow of electricity, the light blue line represents water, and the green line represents the flow of hydrogen power.

3.2.1. Free Carbon Emission Allowance Trading Model

Carbon emission costs in PIEs are calculated based on tradable emissions after deducting free allowances allocated via a baseline method [28]. For the park-level integrated energy system proposed in this paper, carbon emissions mainly originate from three sources: externally purchased electricity $P_{e,buy,t}$, CHP, and GB.

$$\begin{cases} E'_{p,t} = K'_h(P_{h,CHP,t} + \varphi P_{e,CHP,t} + P_{h,GB,t}) + K'_e P_{e,buy,t} \\ E_{p,t} = K_h(P_{h,CHP,t} + \varphi P_{e,CHP,t} + P_{h,GB,t}) + K_e P_{e,buy,t} \\ E_0 = \sum_{t=1}^T (E_{p,t} - E'_{p,t}) \\ C_C = c_C E_0 \end{cases}, \quad (5)$$

where K'_h and K'_e are the carbon emission intensities per unit of electricity and heat; $P_{e,CHP,t}$ and $P_{h,CHP,t}$ are the electrical and thermal power outputs of the CHP; φ is the electricity-to-heat conversion coefficient; $P_{h,GB,t}$ is the thermal power of GB; K_e and K_h are the corresponding free allocation quotas; $E_{p,t}$ is the actual carbon emissions; E_0 is the tradable carbon emissions; C_C is the carbon emission cost; c_C is the benchmark price.

3.2.2. Demand Response Modeling

Existing research often models DR as a single price-driven reaction using a price elasticity matrix [29]. For park-level planning, considering load growth and supply variations, focusing solely on price fails to capture actual energy supply conditions. A holistic view is needed to avoid redundant planning from extreme power imbalances. This study dynamically adjusts transferable loads via system optimization. The transferable load from the price–demand elasticity matrix sets the upper boundary per interval, while the model

determines the actual value. Electrical and thermal DR are treated similarly. Price-based electrical DR includes transferable and curtailable loads.

$$\left\{ \begin{array}{l} e_{t,j} = \frac{\Delta P_{el,t}^c}{P_{load,t}^e \frac{\Delta \delta_{e,j}}{\delta_{e,j}}} \\ 0 \leq P_{sl,t}^e \leq P_{sl,t,0}^e \left(\sum_{j=1}^{T_{day}} e_{sl,t,j} \frac{\Delta \delta_{e,j}}{\delta_{e,j}} \right), e_{sl,t,j} > 0 \\ P_{sl,t,0}^e \left(\sum_{j=1}^{T_{day}} e_{sl,t,j} \frac{\Delta \delta_{e,j}}{\delta_{e,j}} \right) \leq P_{sl,t}^e \leq 0, e_{sl,t,j} < 0 \\ \sum_{t=1}^{T_{day}} P_{sl,t}^e = 0, P_{al,t}^e = P_{al,t,0}^e \left(\sum_{j=1}^{T_{day}} e_{al,t,j} \frac{\Delta \delta_{e,j}}{\delta_{e,j}} \right) \end{array} \right. , \quad (6)$$

where $e_{i,j}$ is the flexible electrical load coefficient. When t equals the first moment of period j , $e_{t,j}$ (self-elasticity) and $e_{t,j}$ (cross-elasticity) coefficients are from paper [30]. $P_{load,t}^e$ represents the original electrical load; $\Delta P_{el,t}^c$ represents the price-responsive electrical load adjustment; $\Delta \delta_{e,j}$ and $\delta_{e,j}$ are the change and benchmark electricity selling price in period j ; $P_{al,t}^e$ represents the curtailable electrical load; $P_{sl,t}^e$ represents the transferable electrical load; $P_{al,t,0}^e$ and $P_{sl,t,0}^e$ are their maximums; cross- and self-elasticity coefficients form matrices E_{sl} and E_{al} , respectively, considering a single day. $e_{sl,t,j}$ and $e_{al,t,j}$ are their scalar elements; T_{day} is the number of time intervals in a day.

Electrical–thermal substitutable DR constraints:

$$\left\{ \begin{array}{l} 0 \leq P_{rl,t}^{phe} \leq \mu_{rl}^e P_{el,t} \\ 0 \leq P_{rl,t}^{peh} \leq \mu_{rl}^h P_{hl,t} \\ P_{el,t} = P_{load,t}^e + P_{sl,t}^e + P_{al,t}^e - P_{rl,t}^{phe} + \varepsilon_{eh} P_{rl,t}^{peh} + \varepsilon_{ec} P_{rl,t}^{pec} \end{array} \right. \quad (7)$$

where $P_{el,t}$ is the post-DR electrical load; $P_{rl,t}^{phe}$ and $P_{rl,t}^{peh}$ are electrical-to-thermal and thermal-to-electrical substitution; $P_{rl,t}^{pec}$ is electrical-to-cooling substitution; ε_{eh} and ε_{ec} are substitution coefficients; μ_{rl}^e and μ_{rl}^h are proportional limits for substitutable electrical/thermal loads.

Cooling load DR includes curtailable and substitutable loads:

$$\left\{ \begin{array}{l} -\mu_{al}^c P_{load,t}^c \leq P_{al,t}^c \leq 0 \\ 0 \leq P_{rl,t}^{pec} \leq \mu_{rl}^c P_{cl,t} \\ P_{cl,t} = P_{load,t}^c + P_{al,t}^c - P_{rl,t}^{pec} \end{array} \right. , \quad (8)$$

where μ_{al}^c is the curtailable coefficient; $P_{al,t}^c$ is the curtailable cooling load; μ_{rl}^c is the substitutable cooling load limit; $P_{cl,t}$ represents the cooling load power after DR; $P_{load,t}^c$ represents the original cooling load.

3.2.3. Park-Level Planning Model Considering Short-Term Uncertainties

Objective Function

Total cost includes investment (INV), operation (OP), maintenance (MA), and carbon trading (CT), minus electrical storage revenue (ESR):

$$\left\{ \begin{array}{l} \min F = \min \left[\sum_{n=1}^N (1+\tau)^{1-n} C_{INV,n} + \sum_{n=1}^N (1+\tau)^{-n} (C_{OP,n} + C_{main,n} + C_{C,n} - F_{ES,n}) \right] \\ C_{INV,n} = \sum_{i \in \phi} \{ (1 - \varepsilon_i) O_{inv,i} \times [(1 - f_{i,n}) P_{max,i,n} + f_{i,n} S_{max,i,n}] \} \\ C_{OP,n} = \sum_{T_s \in D_{day}} \sum_{t \in T_s} [O_{e,t} (P_{e,buy,t,n} + \Delta P_{el,t,n}) + O_{g,t} P_{g,buy,t,n} + O_{wp} P_{wp,cut,t,n}] \\ C_{main,n} = \sum_{T_s \in D_{day}} \sum_{t \in T_s} \sum_{i \in \phi} O_{p,i} P_{i,t,n}, C_{C,n} = \sum_{T_s \in T_{day}} \sum_{t \in T_s} O_C (E_{p,t,n} - E'_{p,t,n}) \\ F_{ES,n} = \sum_{T_s \in T_{day}} \sum_{t \in T_s} O_{e,t} (P_{ES,t,n}^{dis} - P_{ES,t,n}^{cha}) \end{array} \right. , \quad (9)$$

where $C_{INV,n}$, $C_{OP,n}$, $C_{main,n}$, and $C_{C,n}$ are INV, OP, MA, and CT in year n ; $F_{ES,n}$ represents the ESR; τ is the discount rate; ϕ is the set of planned equipment; T_s is the time period of the s -th type of a typical day; D_{day} is the set of typical days; ε_i is the residual value coefficient of the i -th equipment; $O_{inv,i}$ is the unit investment cost; $P_{max,i,n}$ and $S_{max,i,n}$ are the planned power capacity and planned energy storage capacity; $f_{i,n}$ is a Boolean variable, where a value of 1 indicates that the i -th equipment is of the energy storage type; $O_{e,t}$ and $O_{g,t}$ are the unit electricity purchase cost and unit gas purchase; O_{wp} is the unit cost of curtailed wind and solar power; $O_{p,i}$ is the unit operational cost; O_C is the unit carbon emission cost; $P_{e,buy,t,n}$ is the purchased electrical power; $\Delta P_{el,t,n}$ is the demand response adjustment for electrical load; $P_{g,buy,t,n}$ is the purchased gas power; $P_{wp,cut,t,n}$ is the curtailed wind and solar power; $P_{i,t,n}$ is the output power; $E_{p,t,n}$ and $E'_{p,t,n}$ are the actual carbon emissions and carbon quota; $P_{ES,t,n}^{dis}$ and $P_{ES,t,n}^{cha}$ are ES discharge/charge power.

Constraint Conditions

(a) Power balance constraint.

$$\begin{cases} P_{W,t} + P_{PV,t} + P_{e,buy,t} + P_{e,HFC,t} + P_{e,CHP,t} + P_{e,EL,t}^{dis} + P_{e,ES,t}^{dis} = P_{el,t} + P_{e,ES,t}^{cha} + P_{e,EV,t}^{cha} + P_{e,EL,t} + P_{e,ER,t} \\ P_{h,CHP,t} + P_{h,GB,t} + P_{h,HFC,t} + P_{h,HS,t}^{dis} = P_{hl,t} + P_{h,HS,t}^{cha} + P_{h,AC,t} \\ P_{c,ER,t} + P_{c,AC,t} + P_{c,WS,t}^{dis} + P_{c,IS,t}^{dis} = P_{cl,t} + P_{c,WS,t}^{cha} + P_{c,IS,t}^{cha} \\ P_{g,buy,t} + P_{g,MR,t} + P_{g,GS,t}^{dis} = P_{gl,t} + P_{g,GS,t}^{cha} + P_{g,GB,t} + P_{g,CHP,t} \\ P_{H2,EL,t} + P_{H2,HS,t}^{dis} = P_{H2,MR,t} + P_{H2,HFC,t} + P_{H2,HS,t}^{cha} \end{cases}, \quad (10)$$

where $P_{W,t}$ and $P_{PV,t}$ are W/PV power; $P_{e,HFC,t}$, $P_{e,CHP,t}$, $P_{e,EL,t}$, and $P_{e,ER,t}$ are HFC, CHP, EL, and ER power; $P_{e,ES,t}^{dis}$ and $P_{e,ES,t}^{cha}$ are EV discharge/charge power; $P_{e,ES,t}^{dis}$ and $P_{e,ES,t}^{cha}$ are ES discharge/charge power; $P_{e,buy,max}$ is the limit on purchased electrical power. $P_{h,CHP,t}$, $P_{h,GB,t}$, $P_{h,HFC,t}$ and $P_{h,AC,t}$ are CHP, GB, HFC, and AC heat, respectively; $P_{hl,t}$ is post-DR thermal load; $P_{h,HS,t}^{dis}$ and $P_{h,HS,t}^{cha}$ are HS discharge/charge power; $P_{c,ER,t}$ and $P_{c,AC,t}$ are ER/AC cooling; $P_{c,WS,t}^{cha}$, $P_{c,WS,t}^{dis}$, $P_{c,IS,t}^{cha}$ and $P_{c,IS,t}^{dis}$ are WS/IS charge/discharge power. $P_{g,MR,t}$, $P_{g,GB,t}$, and $P_{g,CHP,t}$ are MR, GB, and CHP gas; $P_{gl,t}$ is gas load; $P_{g,GS,t}^{cha}$ and $P_{g,GS,t}^{dis}$ are GS charge/discharge power; $P_{g,buy,max}$ is the limit on purchased gas power. $P_{H2,EL,t}$ is EL hydrogen production power; $P_{H2,MR,t}$ and $P_{H2,HFC,t}$ are MR/HFC consumption power; $P_{H2,HS,t}^{cha}$ and $P_{H2,HS,t}^{dis}$ are H2S charge/discharge power.

(b) Energy conversion equipment constraints.

$$\begin{cases} P_{out,i}(t) = \eta_i P_{in,i}(t) \\ 0 \leq P_{in,i}(t) \leq P_{i,max} \end{cases}, \quad (11)$$

where i denotes equipment (EL, MR, HFC, GB, CHP, ER, and AC); $P_{i,max}$ is output upper limit; η_i is efficiency.

(c) Energy storage constraints.

To mathematically account for the various types of energy storage devices presented in Figure 1, a unified mathematical model is constructed for all six storage types (ES, HS, GS, H2S, WS, and IS). This model restricts the capacity state and charging/discharging power boundaries, and prevents simultaneous charging and discharging for each storage unit:

$$\begin{cases} S_{i,t} = S_{i,t-1} + \eta_i^{cha} P_{i,t}^{cha} \Delta t - P_{i,t}^{dis} \Delta t / \eta_i^{dis} \\ S_{i,min} \leq S_{i,t} \leq S_{i,max} \\ 0 \leq B_{i,t}^{cha} + B_{i,t}^{dis} \leq 1 \\ 0 \leq P_{i,t}^{cha} \leq B_{i,t}^{cha} P_{i,max}^{cha} \\ 0 \leq P_{i,t}^{dis} \leq B_{i,t}^{dis} P_{i,max}^{dis} \end{cases}, \quad (12)$$

where $i \in \Omega$, Ω is the comprehensive storage set encompassing all energy storage types; $S_{i,t}$ is capacity; $P_{i,t}^{\text{cha}}$ and $P_{i,t}^{\text{dis}}$ are charge/discharge power; $P_{i,\max}^{\text{cha}}$ and $P_{i,\max}^{\text{dis}}$ are max single power; $B_{i,t}^{\text{cha}}$ and $B_{i,t}^{\text{dis}}$ are binary state variables; η_i^{cha} and η_i^{dis} are efficiencies; $S_{i,\min}$ and $S_{i,\max}$ are capacity limits.

- (d) Electric vehicle charging station (EV) constraints. Aggregating individual EV capabilities into a unified cluster model [31].

$$\begin{cases} 0 \leq P_{\text{EV},t}^{\text{dis}} \leq A_t^{\text{dis}} W_{\text{EV}} \\ 0 \leq P_{\text{EV},t}^{\text{cha}} \leq A_t^{\text{cha}} W_{\text{EV}} \\ 0 \leq P_{\text{EV},t}^{\text{dis}} + P_{\text{EV},t}^{\text{cha}} \leq W_{\text{EV}} \end{cases}, \quad (13)$$

where A_t^{dis} and A_t^{cha} are max discharge/charge ratios; W_{EV} is capacity.

- (e) Renewable energy generation constraints.

$$\begin{cases} 0 \leq P_{\text{W},t} \leq P_{\text{W},\max} \\ 0 \leq P_{\text{PV},t} \leq P_{\text{PV},\max} \end{cases}, \quad (14)$$

where $P_{\text{W},\max}$, $P_{\text{PV},\max}$ are max outputs.

- (f) Low-carbon planning constraints.

$$\begin{cases} E_{0,x} \geq E_{0,x-1} \\ E_{0,y+1} \leq (1-v)E_{0,y}, \quad y \geq x \\ E_{0,\text{year}} \leq 0 \end{cases}, \quad (15)$$

where $E_{0,x}$, $E_{0,y}$, and $E_{0,\text{year}}$ are tradable carbon emissions in peak year, year y , and final year.

3.2.4. Robust Planning Model for PIEs Considering Long-Term and Short-Term Uncertainties

Load growth uncertainty critically impacts system robustness. Information gap decision theory (IGDT) serves as a non-probabilistic modeling method, quantifying parameter deviations through “information gaps” without assuming probability distributions. Its robust framework employs a bi-level optimization that co-optimizes equipment capacity while determining the maximum allowable deviation threshold for load growth rates, thereby mitigating supply risks from unexpectedly high growth. The system lifecycle is divided into three stages, with the baseline load growth rates expressed as:

$$r_{0,t} = [r_{0,1}, r_{0,2}, r_{0,3}], \quad (16)$$

Actual rate uncertainty set:

$$\begin{cases} r_t \in [r_{0,t}(1-a_t), r_{0,t}(1+a_t)], \quad a_t \geq 0 \\ \alpha = \sum_t \xi_t a_t \\ \sum_t \xi_t = 1 \end{cases}, \quad (17)$$

where a_t is uncertain range; ξ_t is uncertain range; α represents the weighted uncertainty range, reflecting the system's ability to mitigate uncertainty risks, referred to as the robustness coefficient.

The robust planning model for park-level systems considering both long-term and short-term uncertainties is characterized as follows:

$$\begin{cases} \max \alpha \\ s.t. \max F \leq F_0(1 + \sigma) \\ r_t \in [r_{0,t}(1 - a_t), r_{0,t}(1 + a_t)] \\ \text{Equations (10) to (17)} \end{cases} \quad (18)$$

where F represents the cost considering both uncertainties; F_0 is the minimum cost considering short-term uncertainties; σ is the acceptable cost increase coefficient.

4. Results and Discussion

A case study of a park in Guangdong uses historical data. This study aims to construct an integrated energy functional system for this park, with a planning horizon of 15 years to achieve zero carbon emissions. The MDTW algorithm and hierarchical clustering are applied to identify three typical daily load profiles (summer: 92 days; winter: 91; transition: 182). Typical daily load profiles are shown in Figure 3.

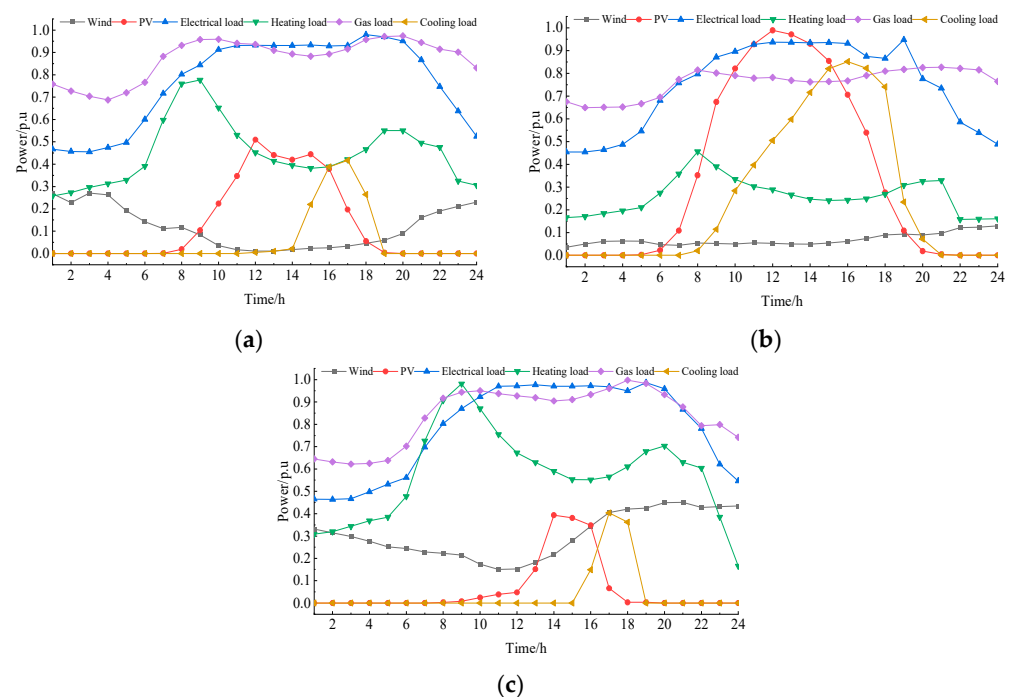


Figure 3. Per-unit value curves of source-load profiles on typical days. (a) Typical day in transitional season; (b) Typical day in summer; (c) Typical day in winter.

Specifically, the electric load starts at a peak of 220 kW and grows at 10% per year in Years 1–5, 7% per year in Years 6–10, and 6% per year in Years 11–15. The thermal load, gas load, and cooling load follow the same growth pattern, with initial peak values of 500 kW, 260 kW, and 500 kW, respectively, and identical annual growth rates of 10%, 7%, and 6% across the three corresponding phases. Discount rate: 0.08. Storage SOC bounds: 30% start/end. Carbon: base price 80 CNY/t, electricity emission factor 1.09 t/MWh, heat 0.102 t/GJ, free quota for electricity 0.728 t/MWh, heat 0.065 t/GJ, electricity-to-heat conversion 1.66. Time-of-use pricing: off-peak (00:00–08:00) 0.324 CNY/kWh, peak (10:00–12:00, 14:00–19:00) 1.353 CNY/kWh, flat 0.807 CNY/kWh. Gas: 3.5 CNY/m³. Curtailment cost: 0.2 CNY/kWh. Equipment parameters are shown in Table 1.

For the constructed low-carbon planning model, five scenarios are first considered for simulation comparison, where flexible resources refer to various types of energy storage devices and electric vehicle charging stations. Both Scenario 3 and Scenario 4 incorporate demand-side response but differ in their modeling approaches: Scenario 3 models demand-

side response based on the method from reference [7], primarily adjusting transferable demand response according to price signals; Scenario 4 employs the modeling method proposed in this paper, regulating transferable demand response under the synergistic influence of price signals and other multi-type flexible resources. Scenarios 1–4 adopt a source-load temporal correlation clustering method based on the MDTW algorithm. Scenario 5 considers both generalized flexible resources and demand-side response but does not account for source-load temporal correlations. The MILP model is solved using YALMIP R20230622 with the Gurobi 11.0 solver on MATLAB R2020b.

Table 1. Parameters of various pieces of equipment to be planned.

Abbreviation	MA/(¥/kWh)	INV/(¥/kW)	Conversion Efficiency
W	0.03	5000	-
PV	0.026	3000	-
ES	0.01	2250	0.95
EL	0.03	800	0.87
HFC	0.04	5000	0.5 (Electricity), 0.4 (Heat)
MR	0.05	3000	0.6
H2S	0.02	1450	0.95
CHP	0.03	1200	0.4 (Electricity), 0.5 (Heat)
GB	0.03	500	0.95
HS	0.013	1500	0.95
GS	0.011	1800	0.95
ER	0.01	750	0.5
AC	0.014	1200	0.4
EV	0.03	3100	0.95
WS	0.01	800	0.85
IS	0.012	1000	0.9

The planning results for equipment capacity are summarized in Table 2 and Figure 4. The synergy between generalized flexible resources (ES, EV, etc.) and DR significantly optimizes the system configuration. Introducing flexibility resources (Scenario 2) reduces W and PV capacity by 92.7% and 75.3%, respectively, and cuts the total investment cost by 58.4% compared to the baseline without flexibility (Scenario 1). The addition of DR (Scenarios 3 and 4) generally leads to a decrease in planned storage capacity, indicating DR can partially substitute for storage regulation. The hydrogen system (EL, HFC, MR, and H2S) acts as a crucial coupling bridge. H2S capacity increases substantially in Scenarios 3 and 5. In Scenario 3, the fixed-boundary DR, which only responds to price, fails to coordinate coupled electrical-thermal load fluctuations, inadvertently increasing hydrogen system volatility and necessitating more H2S (1335.8 kW). In Scenario 5, independent clustering decouples the temporal characteristics of different loads, weakening the basis for synergistic optimization and forcing the H2 system to bear additional conversion fluctuation pressure, resulting in the highest H2S capacity (2810.7 kW). In contrast, Scenario 4's proposed adjustable DR, combined with correlation clustering, optimally coordinates responses with system conditions, requiring only 367.9 kW of H2S.

Figure 4 illustrates the capacity expansion trajectory. Scenario 1 requires a massive deployment of W/PV in the final year to meet the zero-carbon target due to a lack of storage for renewable fluctuation mitigation. Conversely, Scenario 4 deploys flexibility resources early (Year 1) to smooth investment and relies on increased HS and GS capacity in the final year to reduce emissions, demonstrating how temporal energy shifting supports decarbonization and reduces peak supply equipment needs. The total lifecycle cost analysis (Table 3) reveals that flexibility resources dramatically improve economic performance. Scenario 2's total cost is 44.7010 M¥, a 53.96% reduction from Scenario 1 (97.0946 M¥), primarily due to a 58.4% drop in investment cost. The proposed DR method (Scenario 4)

further optimizes the total cost to 43.4595 M¥, saving 0.1538 M¥ compared to the fixed-boundary DR method (Scenario 3), while also reducing system carbon emissions by 11.36%. Overall, Scenario 4 achieves a 55.24% cost reduction and a 47.75% emission reduction compared to Scenario 1, highlighting the combined economic and low-carbon benefits of coordinated flexibility and DR. Scenario 5 yields the highest ES revenue due to greater system supply pressure from independent clustering.

Table 2. New capacity of equipment in each scenario.

Equipment		Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
W		20,185.9	1487.3	1756.3	1676.9	1405.3
PV		11,596.6	2861.4	2378.8	2538.9	2588.3
EL		3403.7	2459.3	2215.6	2269.7	2238.2
HFC		2941.3	1755.2	1595.7	1702.5	1608.9
MR		609.7	400.0	340.3	373.4	308.1
CHP		299.5	136.5	139.4	131.1	131.6
GB		90.0	261.7	281.4	281.5	259.4
ER		894.7	824.7	717.0	789.8	810.9
AC		363.3	158.9	162.5	156.5	267.9
Generalized Flexible Resources	ES	/	1293.1	1105.1	1140.8	1276.0
	H2S	/	527.3	1335.8	367.9	2810.7
	HS	/	1585.9	1968.1	1495.3	1901.2
	GS	/	1949.8	1186.1	1726.9	403.8
	EV	/	2500.0	2500.0	2500.0	2500.0
	WS	/	847.5	1111.1	1111.1	1063.8
	IS	/	527.3	0.0	0.0	94.5

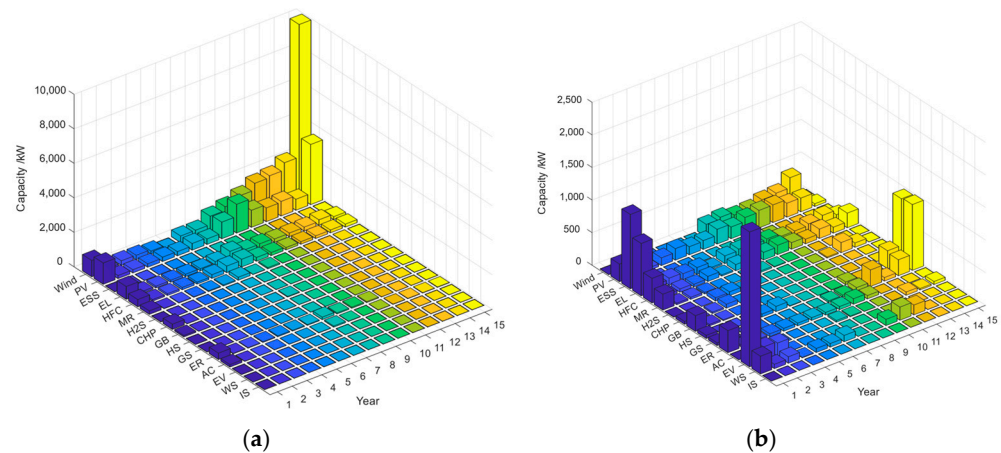


Figure 4. Scenario 1 and Scenario 4 equipment new capacity distribution. (a) Scenario 1; (b) Scenario 4. The colors in the picture represent the change of year, gradually increasing from blue to yellow.

Table 3. Planning results of each scenario.

Scenario	Total (M¥)	INV (M¥)	OP (M¥)	MA (M¥)	CT (M¥)	ESR (M¥)	E _{p,t} (t)
1	97.09	75.28	14.00	7.66	0.16	0.00	91.15
2	44.70	31.34	9.05	6.86	0.08	2.63	48.96
3	43.61	29.93	9.20	6.64	0.09	2.24	53.72
4	43.46	29.95	9.04	6.68	0.08	2.29	47.62
5	44.38	30.37	9.91	6.64	0.09	2.62	53.18

Furthermore, a detailed breakdown of the full lifecycle cost components demonstrates the operational superiority of the proposed method. Compared to the baseline (Scenario 1), Scenario 4 significantly reduces operation costs (OP) from 14.00 M¥ to 9.04 M¥ and maintenance costs (MA) from 7.66 M¥ to 6.68 M¥, as the flexible DR mechanism shifts peak

loads to periods of high renewable generation, reducing reliance on costly purchased energy and equipment wear. Additionally, the coordinated utilization of energy storage in Scenario 4 generates 2.29 M¥ in electrical storage revenue (ESR), a benefit entirely absent in the non-flexible baseline, thereby further offsetting the total lifecycle cost.

A direct comparison between Scenario 4 (correlation clustering) and Scenario 5 (independent clustering) underscores the value of capturing source-load temporal correlations. Scenario 4's total cost is 0.922 M¥ lower, with 0.419 M¥ lower investment and 0.870 M¥ lower operational cost, indicating that Scenario 5's less economically viable plan faces greater supply pressure. As shown in Figure 5, while both methods capture general trends, the independently clustered profiles in Scenario 5 show slightly higher renewable output during peaks and a mismatch between electrical and thermal load peaks, leading to increased ES (+135 kW) and H2S (+2443 kW) capacity but decreased GS capacity (Table 2). This validates that correlation clustering enhances planning economy and low-carbon performance, albeit with a trade-off in slightly reduced storage capacity and system flexibility.

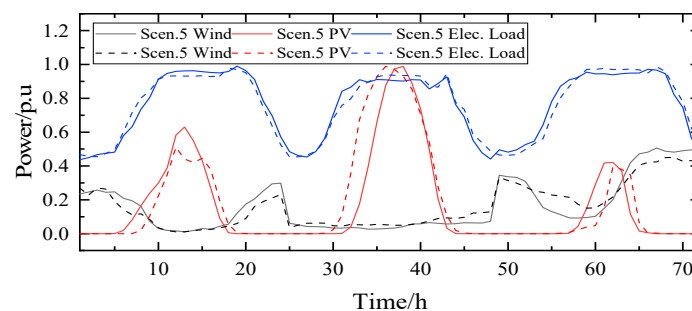


Figure 5. Comparison of source-load curves between Scenario 4 and Scenario 5.

To verify robustness under the short-term uncertainty model, the typical daily profiles with the highest weighted seasonal loads from each of the three seasons are selected as boundary conditions. This specific selection aims to test the system's capability to withstand extreme stochastic scenarios where maximum energy consumption occurs across multiple energy channels simultaneously. Economic optimization simulations are performed for Scenario 4 and Scenario 5 (see Figure 6). Purchased gas power distributions are similar in both scenarios, with increasing periods hitting the maximum limit and rising total volumes over the years. Over the full lifecycle: Scenario 5—gas purchase at limit 37.59% of time; electricity 0.277%; Scenario 4—gas 34.722%; electricity 0.556%. Compared to Scenario 5, Scenario 4 reduces the gas limit proportion by 2.87 percentage points, improving robustness to some extent, while the slight 0.279 percentage point increase in electricity limit proportion has negligible overall impact.

Flexibility resources alone (Scenario 2) reduce emissions by 46.3% versus Scenario 1. The proposed DR method (Scenario 4) achieves the lowest cumulative emissions (4762.04 t), 11.4% lower than the fixed-boundary DR (Scenario 3). Emission composition analysis (Figure 7) confirms that Scenario 3 leads to higher emissions from electricity purchases, GB, and CHP over the first six years. Scenario 4's dynamic DR (Figure 8) more precisely shifts loads to periods of high renewable output, unlike Scenario 3, which may reduce peak load during high-renewable hours. The proposed method, by dynamically coupling demand-side response with power balance and optimizing electrical/thermal load transfers according to actual conditions, more accurately shifts loads to high-renewable low-carbon periods, effectively reducing overall system carbon emission intensity.

Using the short-term uncertainty optimal cost as baseline, the budget is gradually expanded to determine the maximum achievable robustness coefficient under different cost increases (equal weighting across three stages). Results are shown in Figure 9.

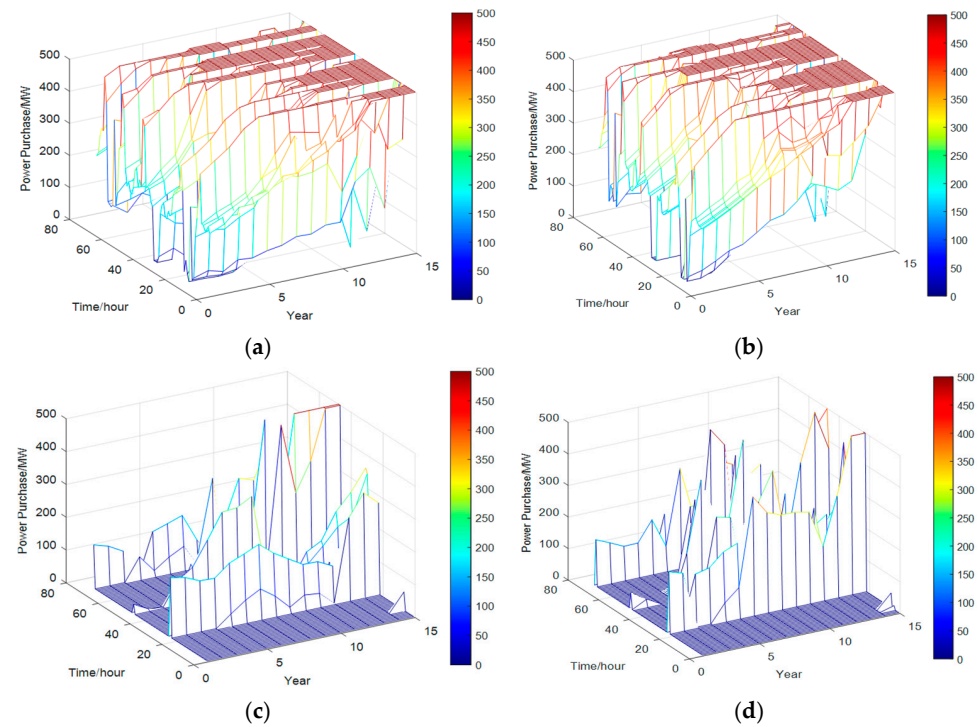


Figure 6. Scenario 4 and Scenario 5 purchase power distribution. (a) Scenario 4 gas purchasing power; (b) Scenario 5 gas purchasing power; (c) Scenario 4 purchased electricity power; (d) Scenario 5 purchased electricity power.

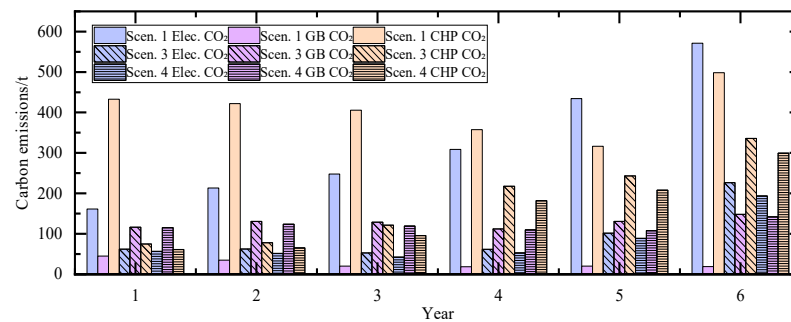


Figure 7. The distribution of carbon emissions in each scenario in the first 6 years.

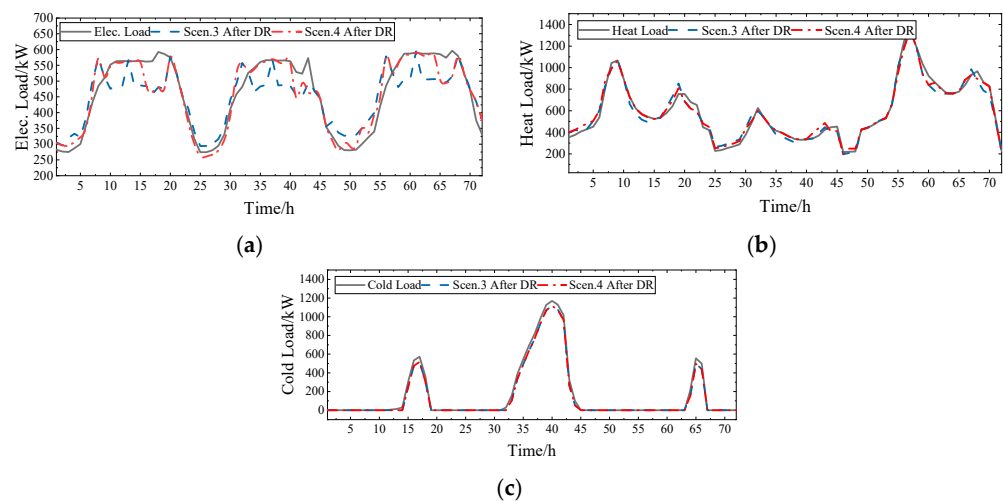


Figure 8. Scenario 3 and Scenario 4 load demand-side response. (a) Electrical load; (b) Thermal load; (c) Cooling load.

The robustness coefficient correlates positively with total lifecycle cost. At 20% cost increase, the coefficient reaches 0.483, meaning that the system can withstand load growth rates up to 48.3% above baseline. From 14% to 20% cost increase, the coefficient rises from 0.345 to 0.483, with each 1% cost increment yielding 0.047 improvement (near-linear). From 2% to 12%, each 1% increment yields 0.049 gain, indicating slightly diminishing marginal returns in robustness enhancement per unit cost. Figure 10 illustrates the structural differences in optimal equipment capacity configuration when transitioning from a model considering only short-term uncertainty (Figure 10a) to one encompassing combined long-term and short-term uncertainties (Figure 10b) at a 0.2 cost increase coefficient. This comparison indicates how the system proactively adjusts its sizing strategy to hedge against unpredictable long-term load growth. Compared to Scenario 4, W and PV capacity increases by a total of 59% annually to meet demand. Overall energy storage capacity rises by 18%. EL, HFC, and MR capacities increase by 27.9%, 22.2%, and 56.3%, respectively—all surpassing the cost growth rate. This highlights that the hydrogen system, combined with electrical storage, effectively accommodates renewable peaks and converts surplus to gas, mitigating heating/gas shortages under purchased gas power constraints. The optimal configuration mode under these multi-timescale uncertainties is found through the proposed IGDT bi-level optimization framework. Specifically, decision-makers first define an acceptable cost increment budget (e.g., $\sigma = 0.2$, representing a 20% cost increase tolerance based on their specific risk aversion). The model then automatically balances the investment and operational constraints to solve for the optimal equipment sizing that maximizes the system's robustness (i.e., the maximum tolerable load growth deviation α), thereby yielding the exact optimal configuration mode presented in Figure 10b.

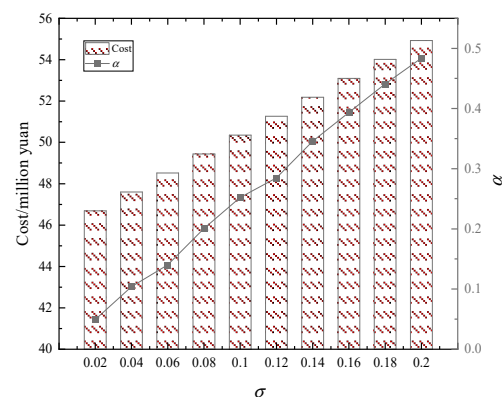


Figure 9. Variation in system cost and robustness coefficient.

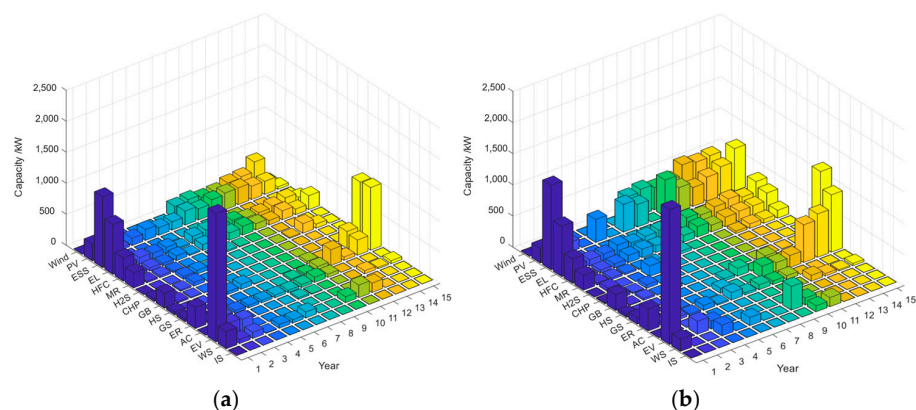


Figure 10. Scenario 1 and Scenario 4 equipment new capacity distribution. (a) Short-term uncertainty; (b) Long-term and short-term uncertainties. The colors in the picture represent the change of year, gradually increasing from blue to yellow.

5. Conclusions

This study uses MDTW with hierarchical clustering to extract typical scenarios capturing short-term source-load uncertainties and integrates IGDT for long-term load growth uncertainty, achieving balance among economic efficiency, low-carbon performance, and robustness. Key conclusions: The proposed scenario method, considering source-load temporal correlation, outperforms traditional clustering by enhancing economic and low-carbon benefits while preserving robustness. Flexible resources and demand response reduce lifecycle cost by 55.24% and carbon emissions by 47.75% without compromising safety. The demand response approach, accounting for price incentives and actual park energy supply to optimize transferable loads, lowers lifecycle cost by 153,800 CNY and emissions by 11.36% compared to existing methods. Overall, the multi-timescale robust PIES planning effectively manages short- and long-term uncertainties, ensuring economic viability and maximum resilience to fluctuations.

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Abbreviations

The following abbreviations are used in this manuscript:

CCHP	Combined cooling, heating and power
CHP	Combined heat and power
DTW	Dynamic time warping
ESR	Electrical storage revenue
HFC	Hydrogen fuel cell
IGDT	Information gap decision theory
INV	Investment cost
MDTW	Multivariate dynamic time warping
MILP	Mixed-integer linear programming

PIES	Park integrated energy system
SOC	State of charge

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