

Article

Coordinated Planning of Source–Grid–Load–Storage Systems Considering Dual-Dimensional Evaluation of Load Carbon Emission Characteristics and Regulation Potential

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Abstract

Driven by “dual-carbon” targets, the large-scale integration of high-penetration distributed generation (DG) exacerbates peak-shaving pressures and supply–demand mismatches in regional power grids. Conventional planning methods often rely on spatial node homogeneity assumptions, failing to exploit the collaborative potential of flexible demand-side resources. To address this limitation, this paper proposes a coordinated source–grid–load–storage planning method guided by a “load carbon emission characteristics–regulation potential” dual-dimensional assessment. First, demand-side nodal attributes are quantitatively evaluated across two dimensions. A hybrid weighting framework fusing the Fuzzy Analytic Hierarchy Process (FAHP) and an improved CRITIC method is introduced to identify four typical characterized nodal clusters, generating a spatial priority list for resource allocation. Second, targeting the minimization of the full life-cycle net present value cost, a Mixed Integer Quadratic Programming (MIQP) model for coordinated source–grid–load–storage planning is constructed. By embedding the priority list into spatial placement decisions, DGs and energy storage systems are strategically guided to preferentially aggregate at high marginal-value nodes. Finally, simulations on an IEEE 30-node regional power grid demonstrate that the proposed method enhances peak-shaving and valley-filling capabilities by 33.1% and 39.83%, respectively, while elevating the comprehensive system load factor from 0.84 to 0.86. These numerical results validate the superiority of the proposed framework in preventing spatial resource misallocation and achieving a profound synergy between low-carbon performance and global economic efficiency.



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1. Introduction

The strategic planning of new-type power systems serves as a cornerstone for achieving carbon peak and carbon neutrality goals, which requires the holistic coordination of generation, grid, load, and storage resources, underpinned by intensive

source–grid–load–storage interactions [1,2]. With the large-scale integration of high-penetration distributed generation (DG), significant operational challenges have emerged regarding grid security and stability. As a flexible regulatory asset, battery energy storage systems (BESS) can effectively shift load profiles across both spatial and temporal horizons, while demand-side response programs can further elevate system flexibility through active grid interactions. Crucially, given that responsive characteristics exhibit distinct spatial heterogeneity across various network nodes, deeply mining demand-side adjustable capabilities—and subsequently executing the coordinated planning of utility-scale storage and DGs—can effectively mitigate renewable-induced supply–demand mismatches, thereby optimizing energy storage sizing and minimizing global capital expenditures. Consequently, approaching the problem from the nodal load perspective to incorporate load carbon emission behaviors and regulation potentials, and subsequently constructing a coordinated source–grid–load–storage planning framework, is of paramount significance for fostering the low-cost, low-carbon, and highly reliable operation of regional power grids [3].

Substantial research has been dedicated to low-carbon power system planning, with some scholars investigating low-carbon-economic coordinated planning from the perspective of energy storage allocation [4]. Specifically, Ref. [5] determines energy storage sizing and siting based on network loss sensitivity and proposes a low-carbon regional power grid planning method that incorporates the fuzzy control of on-load tap changers. Ref. [6] introduces a low-carbon economic dispatch strategy for integrated power systems driven by the substitution effects of carbon taxes and carbon trading. By integrating the Monte Carlo method, LSTM, and the Grey Wolf Optimizer to handle carbon price uncertainties and load forecasting, this approach achieves simultaneous optimization of system carbon emissions and the investment payback period. Furthermore, Ref. [7] establishes a distributed low-carbon economic dispatch model incorporating electro-thermal energy storage systems. It utilizes a stepped carbon trading mechanism to guide a multi-agent master-slave game, effectively curtailing greenhouse gas emissions while significantly enhancing the cycling depth of energy storage charging and discharging. Although these studies successfully improve the economic viability of low-carbon grid operations, they overlook the collaborative synergies between adjustable loads and the source–grid–storage components during operational phases, thereby failing to fully unlock the flexibility potential inherent on the demand side. To address this limitation, recent studies have begun incorporating demand-side proactivity into low-carbon power system planning. Ref. [8] proposes an integrated demand response trading mechanism to foster coordinated, low-carbon scheduling between the generation and demand sides of integrated energy systems. Ref. [9] presents a coordinated cooling, heating, electricity, and gas optimization model for integrated energy systems based on a stepped carbon trading (LCT) mechanism and multi-energy demand response (MDR). Additionally, Ref. [10] embeds policy mandates into generation expansion planning models as constraints while comprehensively factoring in demand-side management. Despite their contributions, these low-carbon planning studies predominantly rely on system-level aggregate carbon accounting paradigms. They neglect the dynamic spatial distribution of demand-side carbon responsibility allocation as carbon intensities vary across the network via power flow transmission [11]. This neglect ultimately leads to an insufficient exploitation of the collaborative source–grid–load–storage potential in electricity–carbon interactions.

To promote electricity–carbon synergy, recent studies have leveraged Carbon Emission Flow (CEF) theory and carbon emission responsibility allocation mechanisms to shift carbon accountability from the generation side to the consumer side, thereby enhancing the demand-side low-carbon-economic synergy [12,13]. Specifically, Ref. [14] employs the nodal carbon intensity as a key guidance signal and applies the Shapley value method to fairly and rationally allocate carbon responsibility among load aggregators, successfully stimulating energy conservation and emission reduction across the system. Ref. [15] traces demand-side carbon responsibilities by incorporating the dynamic impacts of off-design device characteristics on system carbon flow calculations. Ref. [16] develops a dynamic carbon intensity framework to incentivize demand-side responses. However, these studies primarily focus on the impacts of carbon emission flows on the power system while overlooking the intrinsic regulation potential of responsive loads. This limitation biases coordinated source–grid–load–storage planning strategies toward prioritizing carbon reduction for economic gain, failing to effectively leverage demand-side flexible resources. Accurate quantitative evaluation of demand-side resources remains a vital prerequisite for their deep exploitation and effective utilization [17]. To this end, Ref. [18] extrapolates the response characteristics of large-capacity customer groups based on small-sample demand response data. Ref. [19] comprehensively reviews the research status of demand response (DR) potential assessment across four dimensions: the categories of DR potential, evaluation spatial-temporal horizons, and methodological frameworks. Currently, baseline-load-based demand response mechanisms demonstrate unique advantages in supporting large-scale applications and standardized routine scheduling [20,21]. Ref. [22] proposes a large-scale demand response implementation method anchored by consumer baseline loads. By constructing a shared energy storage allocation model aimed at social welfare maximization and introducing a Vickrey–Clarke–Groves (VCG) market clearing strategy, it achieves a synergistic upgrade in demand-side flexibility and energy storage economic efficiency. Ref. [23] presents a two-stage framework for prosumer communities participating in incentive-based demand response based on consumer baseline loads; it utilizes the convex-concave procedure algorithm to optimize community energy management for cost–benefit balancing and introduces the Owen value method to realize equitable internal cost-sharing. Furthermore, Ref. [24] introduces a multi-timescale joint day-ahead and intra-day demand response strategy utilizing multi-timescale uncertainty profiles of baseline loads and renewable energy. Ref. [25] targets full-time demand response based on baseline loads to fully unleash demand-side proactivity, upon which an energy storage configuration model is established to significantly enhance system flexibility. Despite these advancements, the aforementioned Ref. relies on a single mechanism—either carbon emission responsibility or regulation potential—to foster electricity–carbon synergy, thereby ignoring the spatial heterogeneity of different nodal loads across both carbon responsibilities and regulatory capacities. Guiding regional power grid planning from a singular dimension inevitably fails to facilitate the multi-dimensional triad synergy of a low-carbon, secure, and economic system. At present, research investigating the joint planning of DG and ESS based on a comprehensive consideration of heterogeneous nodal characteristics to achieve a low-carbon, secure, and economic operation of regional power grids remains sparse.

This paper approaches the problem from the nodal load perspective, introducing evaluation metrics that measure load carbon emission characteristics and regulation potentials to construct a coordinated source–grid–load–storage planning model based on this dual-dimensional framework:

- (1) Construction of a “Load Carbon Emission Characteristic–Regulation Potential” Dual-Dimensional Comprehensive Evaluation Framework: This paper establishes a dual-

dimensional evaluation system to orthogonally decouple nodes across two distinct dimensions: load carbon emission characteristics and load regulation potentials. By quantifying the decarbonization urgency and regulatory flexibility of each node, four categories of typically characterized nodal clusters are identified.

- (2) Implementation of an FAHP–Improved CRITIC Hybrid Weighting Method: To enhance the reference value of the evaluation results, a hybrid weighting method combining the Fuzzy Analytic Hierarchy Process (FAHP) and an improved CRITIC approach is adopted. This framework effectively fuses subjective policy orientations with objective data regularities to determine planning priority rankings, thereby providing a rigorous mathematical foundation for identifying the optimal location and sequencing of resource deployment.
- (3) Development of a Characterization Priority-Guided Coordinated Source–Grid–Load–Storage Planning Model: A Mixed Integer Quadratic Programming (MIQP) model is proposed for coordinated source–grid–load–storage planning. By translating the dual-dimensional evaluation results into spatial sitting and capacity-guiding constraints within the mathematical model, distributed flexibility resources are strategically directed toward high marginal-value nodes, successfully achieving the tripartite coordinated operation of security, low-carbon emissions, and economic efficiency in the power system.

2. Load Carbon Emission Characteristics—Regulation Potential Evaluation Index System

2.1. Load Carbon Emission Characteristics

The load carbon emission characteristic is a comprehensive evaluation attribute rooted in user electricity consumption behaviors, characterizing the temporal coupling relationship between the nodal net load and the nodal carbon intensity. Specifically, the nodal net load curve is defined as the temporal difference between the nodal real-time load profile and the real-time DG output profile. By executing carbon emission flow (CEF) calculations for each period, the chronological nodal carbon intensity curve is derived. To comprehensively quantify the spatial span and morphological similarity between these curves, a time-series-based morphological feature analysis is utilized to decompose the sequential profiles into discrete feature points and localized line segments, which are jointly evaluated alongside the spatial distances among nodes and the corresponding volatility trends of the line segments [26].

As illustrated in Figure 1, specific indices—namely the distance-based low-carbon degree and the trend-based low-carbon proximity—are established to strictly measure the geometric distance and trend similarity between the net load profile and the carbon intensity curve [27]. Structurally, the load carbon emission characteristics are distinctively quantified by four sub-indices: Nodal Carbon Emissions, which describes the total mass of carbon emissions generated by the load within a specified sampling horizon; Distance-based Low-carbon Degree, which quantifies the geometric distance between corresponding sampling points of the net load and carbon intensity curves; Trend-based Low-carbon Degree, which characterizes the morphological variations and slope discrepancies between the two temporal curves; and Low-carbon Electricity Penetration Rate, which evaluates the ratio of the cumulative net load during intervals where the variation trends of the net load and carbon intensity curves are completely opposite to the total net load volume. The rigorous mathematical formulations and exhaustive computational procedures for these four indices are detailed in Equations (A1)–(A18) of Appendix A.

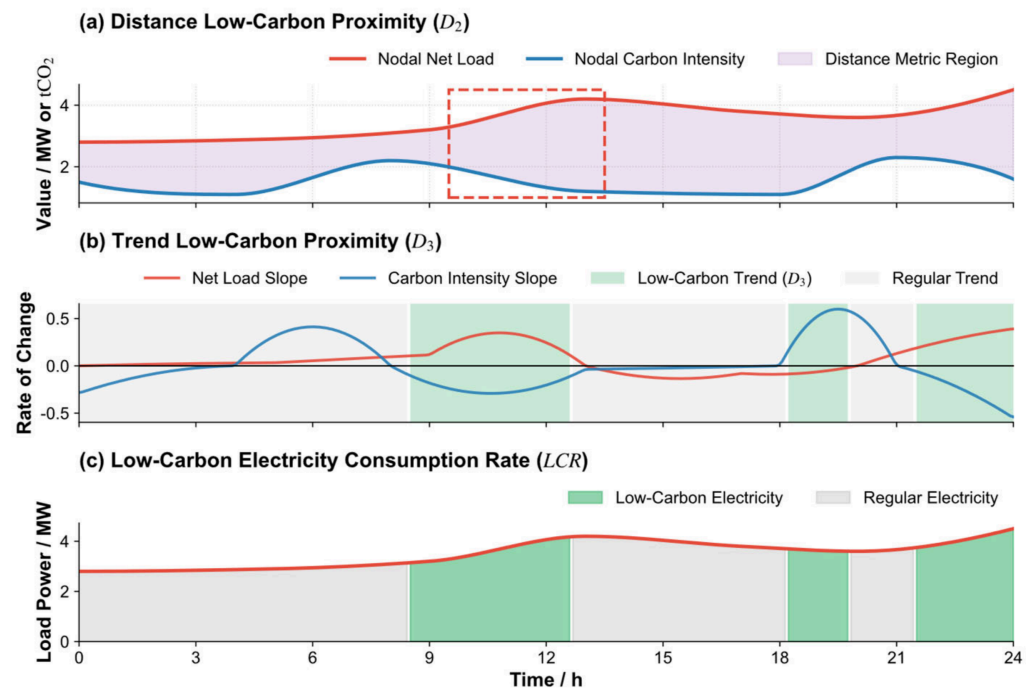


Figure 1. Distance low carbon, trend low carbon and low carbon electricity consumption rate schematic diagram. (a) Distance low-carbon proximity (D_2); (b) Trend low-carbon proximity (D_3); (c) Low-carbon electricity consumption rate (LCR).

2.2. Load Regulation Potential Characteristics

The load regulation potential is utilized to evaluate the interactive capabilities and flexible responsiveness of demand-side flexibility resources. Drawing upon the evaluation framework established [28], and given that conventional calculation methodologies rely heavily on historical, field-proven demand response execution datasets, this paper proposes advanced proxy indices derived from the outputs of the operational optimization model to reflect the potential execution profiles of various loads from a system-level scheduling perspective. Structurally, the comprehensive metrics encompass the modified task completion proxy index and the task timeliness proxy index, which successfully circumvent data dependencies while maintaining physical rigor. The mathematical formulations for these two newly proposed proxy indices are established in Equations (1) and (2), respectively, whereas the detailed formulations and computational pipelines for the remaining auxiliary indicators within this potential assessment dimension are expanded in Equations (A19)–(A42) of Appendix A:

1) Task completion proxy index

To circumvent the dependency on actual task assignment datasets, this study integrates the capacity assessment philosophy commonly used in system demand response scheduling [29], constructing the task completion proxy index based on the theoretical response results optimized and output by the Customer Directrix Line (CDL) baseline model [20]:

$$s_{31,i} = \frac{\sum_t |\Delta P_{i,t}^{resp}|}{\sum_t P_{i,t}^{DR_cap}} \quad (1)$$

where $\Delta P_{i,t}^{resp}$ denotes the actual load response capacity executed by node i within the optimization model at time period t , and $P_{i,t}^{DR_cap}$ signifies the corresponding theoretical upper bound of the adjustable regulation capacity for that node. This index characterizes

the task completion performance from the perspective of potential release rates; a value closer to 1 indicates that the node has fully unleashed its flexible regulation potential under the guidance of pricing signals.

2) Task timeliness proxy index

To counteract the temporal supply–demand imbalance triggered by large-scale renewable energy grid integration, this paper utilizes the concentration of load response capacity during system peak net-load periods to characterize its timeliness, thereby quantifying the temporal value of flexibility resources [30]:

$$s_{32,i} = \frac{\sum_{t \in T_{sys_peak}} |\Delta P_{i,t}^{resp}|}{\sum_t |\Delta P_{i,t}^{resp}|} \quad (2)$$

where T_{sys_peak} represents the set of time periods exhibiting the highest system net load. This index highlights the temporal concentration of response behaviors; a higher ratio demonstrates that the regulation behaviors of the target node are more precisely aligned with the system's most critical peak-shaving demands.

3. Comprehensive Evaluation Methodology

3.1. Subjective Weighting of First-Level Indices Based on FAHP

The Fuzzy Analytic Hierarchy Process (FAHP) is deployed to determine the subjective weights of the first-level evaluation indices [31]. Initially, a fuzzy complementary judgment matrix $A = (a_{ij})_{n \times n}$ is constructed, which strictly satisfies the mathematical conditions of $a_{ij} \in [0, 1]$ and $a_{ij} + a_{ji} = 1$. The subjective weight vector w' is then derived by solving the maximum eigenvalue of the judgment matrix along with its corresponding eigenvector:

$$Aw' = \lambda_{\max} w' \quad (3)$$

Subsequently, the obtained eigenvector is normalized to yield the definitive subjective weight set for the first-level evaluation indices: $W_1 = \{w_1, w_2, w_3, w_4\}$.

3.2. Objective Weighting of Second-Level Indices Based on CRITIC

The Criteria Importance Through Intercriteria Correlation (CRITIC) method determines objective weights based on the contrast intensity and conflicting character of the evaluation indices, thereby effectively mining the internal fluctuation patterns embedded in the data. Initially, the raw data matrix undergoes forward scaling and deviation normalization to yield the dimensionless standardized matrix X^* . Where x_{ij}^* signifies the normalized data element of the j -th index at the i -th node within the matrix, the definitive computational steps for the objective weights are established as follows:

1) Standard deviation

$$\sigma_j = \sqrt{\frac{1}{m-1} \sum_{i=1}^m (x_{ij}^* - \bar{x}_j^*)^2} \quad (4)$$

where a larger σ_j indicates a more pronounced variance of this index across different nodes, thereby signifying a higher volume of discriminative information embedded within it; m represents the total number of nodes participating in the assessment, and $\bar{x}_j^*$ denotes the sample mean of the j -th normalized index.

2) Correlation coefficient

$$R_j = \sum_{k=1}^n (1 - r_{jk}) \quad (5)$$

where r_{jk} denotes the Pearson correlation coefficient between index j and index k . A smaller value of R_j indicates a weaker linear correlation between the two indices, which effectively avoids information redundancy among the evaluation indicators.

3) Quantity of information and weights

Defining $C_j = \sigma_j \cdot R_j$ as the quantity of information contained within the j -th second-level index, its normalized objective weight is formulated as follows:

$$w_j^{critic} = \frac{C_j}{\sum_{k=1}^n C_k} \quad (6)$$

where n represents the total number of second-level evaluation indices.

Critically, relying on a singular data feature configuration from raw electricity consumption data may inadvertently induce weight distortion due to data anomalies or highly homogeneous node characteristics. For instance, specific inactive or boundary nodes exhibit highly uniform behavioral profiles during certain intervals. This spatial homogeneity drives the localized standard deviation to zero or the cross-correlation coefficient to unity. Within the conventional CRITIC algorithm, such extreme data distributions inevitably trigger numerical ill-conditioning during matrix inversions or normalizations, leading to severe mathematical weight distortions. To fortify the mathematical robustness of the global evaluation system under massive heterogeneous datasets, this paper introduces a robust smoothing factor α ($\alpha \in [0, 1]$) to implement a linear weighting smoothing mechanism that couples the raw CRITIC weights with equal-weight benchmarks:

$$w_j^{final} = (1 - \alpha) \cdot w_j^{critic} + \alpha \cdot \frac{1}{N} \quad (7)$$

Rather than functioning as a subjective artifact, this robust smoothing factor regularizes the objective data discrepancies and eliminates numerical pathology. It guarantees that pivotal localized user behavioral profiles are never neglected or numerically obliterated under extreme sample distributions.

3.3. Combination Weighting and Comprehensive Scoring

By executing a hierarchical decomposition process, the subjective weights of the first-level indices $W1$ are cascaded to their corresponding second-level indicators. Consequently, the global comprehensive weight for each individual second-level index j (denoted as ω_j) is derived as follows:

$$\omega_j = w_{k(j)} \cdot w_j^{final} \quad (8)$$

Ultimately, the global comprehensive evaluation score for each individual node is aggregated and calculated as follows:

$$S_i = \sum_j \omega_j \cdot x_{ij}^* \quad (9)$$

where $w_{k(j)}$ denotes the subjective weight of the first-level index k to which the j -th second-level indicator belongs.

Based on these scores, a spatial priority ranking for carbon emission characteristics Ω_{DG}^{prio} , which governs the optimal siting of distributed generations, and a dedicated priority sequencing for regulation potential Ω_{ES}^{prio} , which guides the prospective placement of energy storage systems, are simultaneously generated.

4. Mathematical Model for Source–Grid–Load–Storage Collaborative Planning

This section constructs a Mixed-Integer Quadratic Programming (MIQP) model for the coordinated planning of source–grid–load–storage systems, as illustrated in Figure 2. To remedy the limitations of conventional planning paradigms that solely chase financial metrics, the proposed optimization framework not only pursues global life-cycle economic optimality but also establishes rigorous physical tracking constraints to strategically guide flexibility resources toward nodes exhibiting the highest marginal value. Consequently, this mathematical coupling successfully achieves a profound techno-economic synergy within the spatial allocation process.

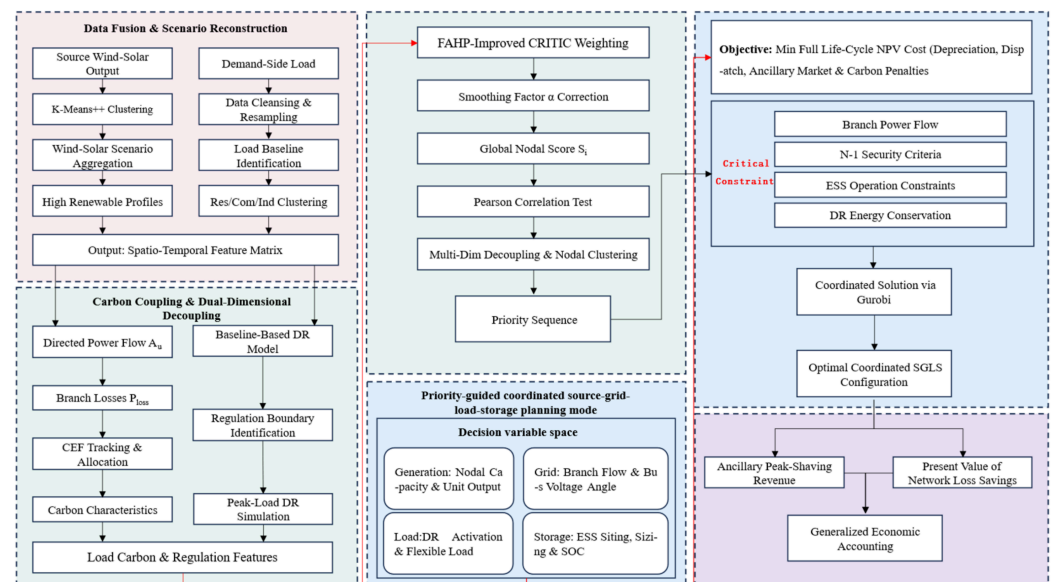


Figure 2. Coordinated SGLS planning framework considering dual-dimensional evaluation of load carbon emissions and regulation potential.

4.1. Objective Function

The objective of this model is to minimize the total life-cycle net present value (NPV) cost of the system throughout the entire planning horizon Y :

$$\min F = C_{inv}^{sys} + \sum_{y=1}^Y \frac{C_{op}^{sys} + C_{carbon}}{(1+r)^y} \quad (10)$$

where F signifies the global life-cycle net present value (NPV) cost of the system; C_{op}^{sys} , C_{inv}^{sys} , and C_{carbon} denote the initial investment cost, the annualized operational cost, and the annualized carbon emission cost, respectively. r represents the discount rate, and y indicates the specific planning year.

1) Investment cost

The initial investment cost C_{inv}^{sys} comprises the upfront capital expenditures for distributed generations, energy storage systems, and centralized generation units.

$$C_{inv}^{sys} = \sum_{i \in \Omega_N} (c_{inv}^{DG} Q_i^{DG} + c_{inv}^{ES} Q_i^{ES} + c_{fix}^{ES} y_i^{ES}) + C_{inv}^G \quad (11)$$

where Ω_N denotes the set of system nodes; Q_i^{DG} and Q_i^{ES} represent the continuous decision variables signifying the installed planning capacities of distributed generations and energy storage systems at node i , respectively. $y_i^{ES} \in \{0, 1\}$ is a binary decision variable designated for ESS sitting, where $y_i^{ES} = 1$ indicates the deployment of an ES system at node i , and 0 otherwise. c_{inv}^{DG} and c_{inv}^{ES} signify the unit capacity investment costs of DG and ES systems, respectively; c_{fix}^{ES} represents the fixed construction cost of a single ES station, and C_{inv}^G denotes the fixed investment asset cost of centralized thermal generation units.

2) System operational cost

The system operational cost C_{op}^{sys} is derived via an annualized extrapolation based on representative typical daily profiles. It comprehensive encompasses the fuel and start–stop costs of centralized thermal units, operation and maintenance expenditures for distributed generations, life-cycle degradation penalties for energy storage systems, demand response compensations, and penalties associated with wind and solar curtailments.

$$C_{op}^{sys} = N_{days} \sum_{t \in T} (C_{gen,t} + C_{node,t}) + C_{start/stop} \quad (12)$$

$$C_{gen,t} = \sum_{g \in \Omega_G} (a_g u_{g,t} + b_g P_{g,t} + c_g P_{g,t}^2) \quad (13)$$

$$C_{node,t} = \sum_{i \in \Omega_N} \left[c_{op}^{DG} P_{i,t}^{DG} + \frac{c_{cycle}^{ES}}{2} (P_{i,t}^{ch} + P_{i,t}^{dis}) + c_{DR} (P_{i,t}^{DR+} + P_{i,t}^{DR-}) + \lambda_{curt} P_{i,t}^{curt} \right] \quad (14)$$

where N_{days} denotes the total number of operating days per year; T represents the set of dispatch time intervals within a typical day, and Ω_G signifies the set of centralized thermal generation units. For the thermal power sector: $u_{g,t}$ is a binary decision variable indicating the start–stop status of thermal unit g at time t ; $P_{g,t}$ represents the active power output of the unit; a_g , b_g , and c_g denote the constant, linear, and quadratic cost coefficients of the thermal fuel consumption characteristics, respectively; and $C_{start/stop}$ signifies the annualized total start–stop cost of the thermal units. For the node-level operation: c_{op}^{DG} represents the unit operation and maintenance cost coefficient of distributed generations; $P_{i,t}^{DG}$ is the actual power output of the DG; $P_{i,t}^{ch}$ and $P_{i,t}^{dis}$ signify the charging and discharging powers of the energy storage systems, respectively; c_{cycle}^{ES} represents the economic degradation cost coefficient associated with ES cycle-life loss; $P_{i,t}^{DR\pm}$ indicates the flexible capacity variation under demand response (DR) programs; λ_{curt} denotes the unit penalty factor for renewable energy curtailment; and $P_{i,t}^{curt}$ represents the actual wind or solar power curtailment at node i at time t .

3) Carbon Emission Penalty Cost

$$C_{carbon} = p_{CO2} \cdot \max\{0, E_{total} - E_{quota}\} \quad (15)$$

$$E_{total} = N_{days} \Delta t \sum_{t \in T} \left(\sum_g \mu_g P_{g,t} + \sum_i \mu_{DG} P_{i,t}^{DG} \right) \quad (16)$$

where p_{CO2} is the carbon price; E_{total} is the total annual carbon emissions of the system; E_{quota} is the annual free carbon allowance; Δt is the scheduling time interval; μ_g , μ_{DG} are the carbon emission intensity factors of thermal power and DG, respectively.

4.2. Constraints

(1) Guidance constraints formulated based on dual-dimensional assessment

Guided by the spatial priority rankings Ω_{DG}^{prio} and Ω_{ES}^{prio} , these tactical constraints mathematically enforce the physical deployment of system flexibility resources into critical nodes that exhibit prominent comprehensive assessment scores.

$$\sum_{i \in \text{Top}_K(\Omega_{DG}^{prio})} Q_i^{DG} \geq \alpha_{share}^{DG} \sum_{i \in \Omega_N} Q_i^{DG} \quad (17)$$

$$\sum_{i \in \text{Top}_K(\Omega_{ES}^{prio})} Q_i^{ES} \geq \alpha_{share}^{ES} \sum_{i \in \Omega_N} Q_i^{ES} \quad (18)$$

where Top_K denotes the set manipulation operator designated to extract the top- K nodes from the spatial priority rankings; The setting of the K -value in this paper introduces an offline calibration mechanism based on baseline scenario capacity estimation. First, the unconstrained baseline planning model is utilized to roughly estimate the system's global total configured capacity. Subsequently, in conjunction with the predefined core-region capacity coverage ratio, a capacity cumulative search is performed along the descending spatial priority list to scientifically determine the number of core-region nodes K , thereby ensuring that the guided resources precisely lean toward high marginal-value nodes. α_{share}^{DG} and α_{share}^{ES} represent the predefined core-region capacity coverage ratios for distributed generations and energy storage systems, respectively.

(2) Tactical investment and construction logic constraints

$$\sum_{i \in \Omega_N} y_i^{ES} \leq N_{ES}^{max}, C_{inv}^{sys} \leq C_{max}^{budget} \quad (19)$$

where Q_{min}^{site} and Q_{max}^{site} denote the lower and upper capacity boundaries for a single energy storage station, respectively; N_{ES}^{max} represents the maximum allowable number of ES stations to be deployed across the entire system; and C_{max}^{budget} signifies the global upper limit for the total investment budget.

(3) Power flow and network security constraints

1) Node power balance logic

$$\sum_{l \in \Omega_L(i)} P_{l,t} = P_{i,t}^g + P_{i,t}^{DG} + (P_{i,t}^{dis} - P_{i,t}^{ch}) + (P_{i,t}^{ren} - P_{i,t}^{curt}) - P_{i,t}^{eff,load} \quad (20)$$

where $P_{i,t}^g$ denotes the power output of the centralized thermal generation unit located at node i ; $P_{i,t}^{ren}$ represents the available renewable energy power at node i ; $P_{i,t}^{eff,load}$ signifies the effective responsive load profile after demand response adjustments; $P_{i,t}^{eff,load}$ indicates the set of transmission lines connected to node i ; and $P_{l,t}$ represents the power flow transferred on transmission line l .

2) Formulation and thermal transfer capacity limits of network power flows

$$P_{l,t} = \frac{\theta_{i,t} - \theta_{j,t}}{x_l}, |P_{l,t}| \leq P_l^{max}, \forall l = (i, j) \quad (21)$$

where $\theta_{i,t}$ and $\theta_{j,t}$ denote the voltage phase angles at node i and node j , respectively; x_l represents the operational reactance value of transmission line l ; and P_l^{max} signifies the predefined thermal stability transfer capacity limit of the transmission line.

- (4) Distributed generation output profile and grid hosting capacity constraints
 1) Distributed generation operational output limitations

$$0 \leq P_{i,t}^{DG} \leq Q_i^{DG} \cdot \eta_{i,t}^{\text{profile}} \quad (22)$$

- 2) Nodal hosting capacity and penetration security boundaries for distributed generations

To eliminate operational vulnerabilities within weakly connected network clusters, such as feeder-end nodes where excessive renewable penetration significantly elevates the risk of local reverse power flows and line congestion, the maximum potential active power injection from distributed generations at an individual node is strictly capped by a predefined percentage $\eta_{i,t}^{\text{profile}}$ of its localized peak load demand:

$$Q_i^{DG} \cdot \max_t(\eta_{i,t}^{\text{profile}}) \leq \beta_{\text{hosting}} \cdot P_i^{\text{peak}} \quad (23)$$

where $\eta_{i,t}^{\text{profile}}$ signifies the normalized power output profile (bounded between 0 and 1) of the distributed generations at node i at time t ; P_i^{peak} denotes the annualized peak value of the original localized load at node i ; and β_{hosting} represents the maximum allowable penetration threshold coefficient. Physically, this constraint effectively mitigates the technical vulnerabilities associated with high photovoltaic (PV) penetration at light-load nodes.

- (5) Operational and dynamic state constraints for energy storage systems

The mathematical model leverages a continuous state variable $SOC_{i,t}$ to explicitly perform the chronological tracking of the state-of-charge profiles for energy storage systems, while simultaneously enforcing a cyclic energy conservation boundary across the entire scheduling horizon.

- 1) State-of-charge dynamic state-transition formulation:

$$SOC_{i,t+1} = SOC_{i,t} + \left(\eta_{ch} P_{i,t}^{ch} - \frac{P_{i,t}^{dis}}{\eta_{dis}} \right) \Delta t \quad (24)$$

- 2) State-of-charge limits and initial-terminal balance:

$$0 \leq SOC_{i,t} \leq Q_i^{ES}, \quad SOC_{i,0} = SOC_{i,T} = \sigma_{init} Q_i^{ES} \quad (25)$$

- 3) Charging and discharging power constraints:

$$0 \leq P_{i,t}^{ch} \leq \gamma_{rate} Q_i^{ES}, \quad 0 \leq P_{i,t}^{dis} \leq \gamma_{rate} Q_i^{ES} \quad (26)$$

where $SOC_{i,t}$ signifies the stored energy of the energy storage system at time t ; η_{ch} and η_{dis} denote the charging and discharging efficiencies, respectively; σ_{init} represents the initially configured state-of-charge; and γ_{rate} is the energy-to-power ratio coefficient, reflecting the distinction between power-oriented and energy-oriented energy storage systems. Given that the objective function has already accounted for the economic degradation cost associated with energy storage cycle-life loss, the optimization solver will spontaneously avoid the uneconomical behavior of simultaneous charging and discharging, thereby effectively enhancing the computational efficiency of the model.

- (6) Demand response balance constraints

The model adopts a shiftable load strategy to strictly enforce the conservation of total load energy throughout the daily scheduling horizon, thereby preventing the optimization from misinterpreting load curtailment as load regulation.

$$0 \leq P_{i,t}^{\text{DR}\pm} \leq \epsilon_{\text{DR}} P_{i,t}^{\text{load}}, \sum_{t \in T} P_{i,t}^{\text{DR}+} = \sum_{t \in T} P_{i,t}^{\text{DR}-} \quad (27)$$

where ϵ_{DR} signifies the maximum allowable load regulation ratio at the node; and $P_{i,t}^{\text{load}}$ represents the original base load at node i at time t . This constraint ensures that the peak-shaving and valley-filling effect is a genuine temporal shifting of energy rather than a net loss of energy consumption.

(7) System-level N-1 security and adequacy constraints

To guarantee system adequacy under high penetration of renewable energy and prevent system instability triggered by sudden photovoltaic (PV) drops, the model introduces dynamic spinning reserve constraints. It requires that at any given time t , the maximum available supply capacity of the system must cover the load demand while reserving sufficient spinning capacity to withstand the largest contingency of a single generation unit:

$$P_{\text{sys},t}^{\text{avail}} \geq \sum_{i \in \Omega_N} P_{\text{load},t}^{\text{eff},i} + P_{g,\text{biggest}}^{\text{max}} \quad (28)$$

$$P_{\text{sys},t}^{\text{avail}} = \sum_{g \in \Omega_C} P_g^{\text{max}} u_{g,t} + \sum_{i \in \Omega_N} Q_i^{\text{DG}} \eta_{i,t}^{\text{profile}} + \sum_{i \in \Omega_N} \gamma_{\text{rate}} Q_i^{\text{ES}} + P_{\text{ren},t}^{\text{base}} \quad (29)$$

where P_g^{max} is the rated maximum power output of thermal generation unit g ; $P_{\text{sys},t}^{\text{avail}}$ represents the total available supply capacity of the system; $P_{g,\text{biggest}}^{\text{max}}$ denotes the rated capacity of the largest single unit within the system, representing the N-1 reserve standard; and $P_{\text{ren},t}^{\text{base}}$ signifies the power output of other uncontrollable baseline generation sources within the system.

4.3. Generalized Comprehensive Economic Assessment Model for the System

To comprehensively and quantitatively evaluate the techno-economic benefits of the coordinated source–grid–load–storage planning scheme, a generalized comprehensive economic assessment model for the system is constructed in this paper [32].

$$G - \text{CNPVC} = C_{\text{NPV}} - R_{\text{flex}} - R_{\text{loss}} \quad (30)$$

where C_{NPV} signifies the traditional full life-cycle net present value cost; R_{flex} denotes the auxiliary peak-shaving revenue of the energy storage system; and R_{loss} represents the discounted economic benefit from network loss reduction brought by the smoothing of the load profile. The aforementioned dynamic revenues are all converted to the beginning of the planning period via the Present Value Interest Factor of Annuity (PVIFA):

$$\text{PVIFA} = \frac{1 - (1 + r)^y}{r} \quad (31)$$

With the development and refinement of ancillary service markets such as deep peak-shaving in power systems, energy storage systems obtain revenues by providing auxiliary peak-shaving services. The calculation formulation for the energy storage auxiliary peak-shaving revenue R_{flex} is expressed as

$$R_{\text{flex}} = \text{PVIFA} \times \left[\frac{(\Delta P_{\text{peak}} + \Delta P_{\text{valley}}) \times}{t_h \times N_{\text{days}} \times c_{\text{flex}}} \right] \quad (32)$$

where ΔP_{peak} and ΔP_{valley} denote the peak-shaving and valley-filling powers, respectively; t_h represents the daily effective response duration; and c_{flex} is the unit capacity compensation price within the ancillary service market.

A classical network loss empirical evaluation model based on the load factor is introduced to address the lack of non-linear network loss tracking during the planning stage. By calculating the difference in the total system electrical energy losses before and after optimization ΔE_{loss} , the economic benefits brought by the improvement of the grid operational state are quantified:

$$\Delta E_{loss} = E_{loss}^{base} - E_{loss}^{opt} \quad (33)$$

$$R_{loss} = PVIFA \times \Delta E_{loss} \times c_{grid} \quad (34)$$

where c_{grid} is the benchmark electricity price for network loss conversion; and E_{loss}^{base} and E_{loss}^{opt} represent the annual total system network loss energy (MWh) of the baseline scheme and the optimization scheme, respectively, the specific calculation of which relies on the equivalent peak load and loss factor of the system:

$$E_{loss} = P_{loss_peak} \times 8760 \times F_{ls} \quad (35)$$

$$P_{loss_peak} = P_{peak_load} \times \lambda_{loss} \quad (36)$$

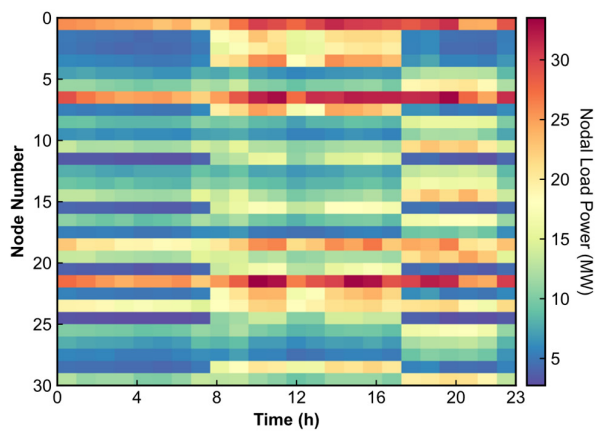
$$F_{ls} = a \cdot f + (1 - a) \cdot f^2 \quad (37)$$

where P_{loss_peak} is the peak network loss power of the system; P_{peak_load} denotes the equivalent rated peak load of the system; λ_{loss} represents the boundary of the peak network loss rate, which is set to 0.06 in this paper; F_{ls} is the loss factor; f signifies the annual load factor of the system; and a is the empirical coefficient.

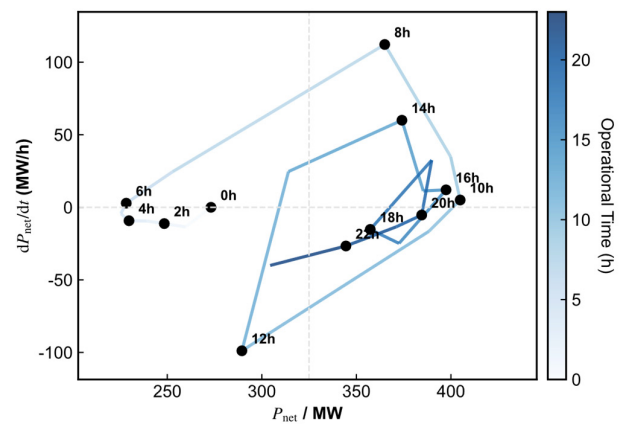
5. Case Studies

5.1. Case Study Parameters

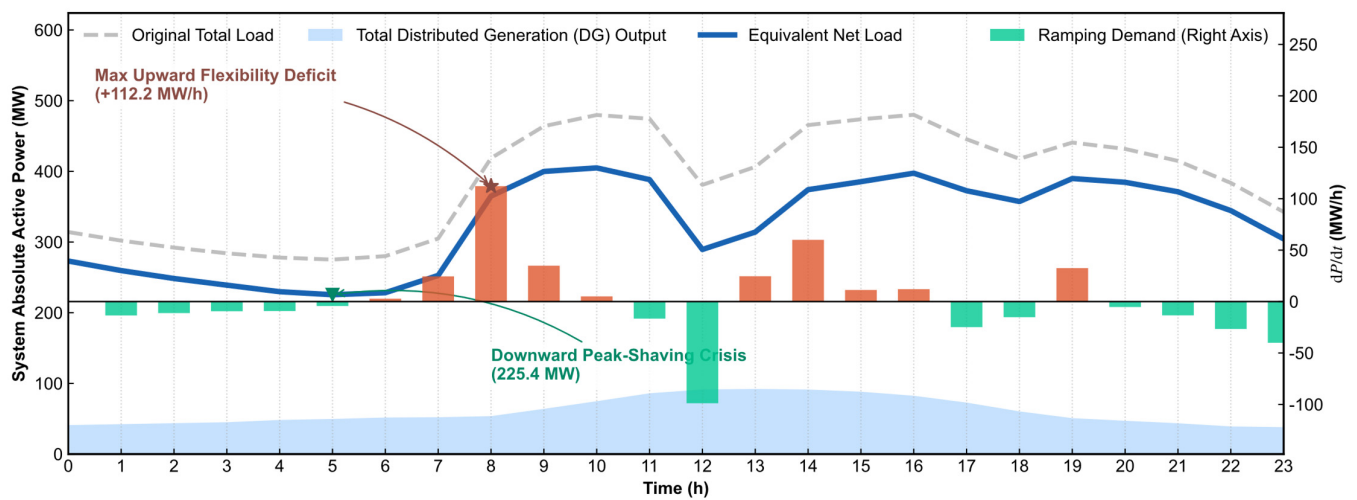
The simulation in this study is performed on the IEEE 30-bus test system. The system comprises 6 thermal generation units with a total capacity of 600 MW. To emphasize the distinct differences in load regulation potential across various nodes, the demand-side data has been reconstructed to reflect the chronological characteristics of individual node loads. The load and wind-solar output data are derived from actual field measurements in a specific region; the original profiles are cleansed and aggregated to generate high-penetration renewable output curves, as illustrated in Figure 3c. Concurrently, to emulate the spatio-temporal heterogeneity of nodal loads in actual power grids, a $\pm 5\%$ random perturbation is superimposed onto the baseline curves. The resulting nodal load profiles are presented in Figure 3a. The rated peak load is 480 MW, the planning horizon is set to 15 years, and the discount rate is fixed at 8%. The techno-economic parameters for the distributed generation (DG), energy storage systems (ESS), and main grid interactions are summarized in Table 1. The model is implemented in Python 3.12.7 and solved using the Gurobi 12.0.3 solver. For the IEEE 30-bus system, the decision variables primarily comprise nodal voltage phase angles, branch power flows, active power outputs of conventional generators and distributed generation, energy storage charging/discharging powers and state-of-charge (SOC) dynamics, as well as binary/integer variables representing the siting selection states of energy storage and demand response. Under a MIPGap tolerance of 0.1%, the model comprises approximately 8163 variables (including 492 integer/binary variables alongside continuous variables) and 11,204 constraints, achieving a computation time of approximately 3.45 s.



(a) Spatiotemporal Evolution Heatmap of Nodal Baseline Load



(b) Phase-Plane Trajectory of Net Load System Dynamics



(c) Chronological Supply-Demand Profile and Flexibility Deficit Analysis with High Non-Carbon Penetration

Figure 3. Spatio-temporal net load dynamics and flexibility deficits. (a) Spatiotemporal evolution heatmap of nodal baseline load; (b) Phase-plane trajectory of net load system dynamics; (c) Chronological supply–demand profile and flexibility deficit analysis with high non-carbon penetration.

Table 1. Techno-economic parameters for distributed generation, energy storage systems, and main grid interactions.

Parameter Category	Item/Symbol	Value	Unit	Description
System Planning	Planning horizon	15	yr	Project life cycle
	Discount rate	8	%	Used for NPC calculation
	Carbon allowance	500,000	tCO ₂ /yr	Annual free allowance
Distributed Generation	Capital cost	4,000,000	RMB/MW	Wind/PV units
	O&M cost	15	RMB/MWh	Operational cost
	Lifetime	20	yr	Asset lifetime
	Annual utilization hours	2200	h	LCOE calculation reference
Energy Storage System	Unit capacity cost	900,000	RMB/MWh	Capital cost per unit capacity
	Fixed cost	200,000	RMB/station	Fixed construction cost
	Max system capacity	200	MW	System-level upper limit
	Cycle-life cost	80	RMB/MWh	Degradation cost
Grid & Carbon	Efficiency	0.93	%	Charging/discharging efficiency
	Carbon penalty	200	RMB/tCO ₂	Excess emission price

Figure 3 illustrates the temporal variations in the system's original load, equivalent net load, and net load ramping requirements over a 24-h operational cycle. Due to the spatio-temporal fluctuations of high-penetration wind and solar renewable power outputs, each parameter exhibits significant divergence over time. For the original total load, it escalates to a maximum value of 480 MW around 10:00 and 16:00, respectively. After superimposing the high-penetration wind and photovoltaic (PV) outputs, the system's equivalent net load profile undergoes a substantial transformation. Particularly during the late-night to early-morning period, the net load drops to its daily minimum of 225.4 MW at 05:00, driven by high wind power outputs coinciding with the system's off-peak demand hours. Regarding the system's ramping requirements, they are predominantly dictated by the net load behavior; the ramping demand remains relatively flat during the night and noon periods, whereas during the morning peak hours—especially around 08:00—the system experiences a pronounced positive ramping demand peaking at +112.2 MW/h, triggered by the rapid escalation of the net load. Overall, the integration of a high proportion of zero-carbon power sources causes a shift in the system's supply–demand balance boundaries, deepening the daytime net load troughs and intensifying the downward peak-shaving pressure at night.

Figure 3c depicts the absolute variations in system net load and ramping rates in the absence of flexibility resources such as energy storage or demand response. It can be observed that at 05:00, the downward peak-shaving pressure is severe, where the aggregate minimum technical output of the 6 thermal units stands at 210 MW. The equivalent net load of 225.4 MW at this moment implies that the system's downward peak-shaving margin has been compressed to a mere 15.4 MW. Any further increase in wind power generation would inevitably introduce the risk of wind curtailment or frequency fluctuations. Conversely, at 08:00, the hourly load increase exceeds 110 MW while nocturnal wind power output simultaneously experiences a phase-out reduction, resulting in the maximum upward flexibility deficit for the system, with the hourly ramping rate reaching +112.2 MW/h. Relying solely on an isolated conventional thermal generation cluster to mitigate such high-frequency, large-amplitude net load shocks presents significant regulatory limitations.

To comprehensively account for the operational state of the system, this paper further introduces the dynamic phase-plane method in Figure 3b to analyze supply–demand characteristics. The horizontal axis represents the net load magnitude, while the vertical axis represents the net load ramping rate. Based on the node-level load distribution results shown in Figure 3a, the baseline load exhibits distinct spatial heterogeneity and chronological clustering. Mapping these dynamics onto the phase-plane diagram reveals that the system's operational state points display a wide-amplitude dynamic evolution trajectory between low net load levels and high positive ramping rates. This characteristic underscores that the existing system still suffers from notable dynamic regulation limitations in smoothing supply–demand volatility. Therefore, the coordinated allocation of energy storage systems within the planning framework is of paramount importance for comprehensively enhancing overall system flexibility.

5.2. Load Carbon Emission Characteristic Metrics

Figure 4 illustrates the profiles of carbon intensity and load carbon emission characteristics across various nodes in the regional power grid within a 24-h cycle under the baseline scenario, where no distributed generation or energy storage systems are deployed. Due to the non-linear interactions of the network topology and the power-flow carbon allocation mechanism, the carbon responsibilities borne by individual nodes exhibit distinct variations. Nodes 7 and 12 display high daily average carbon intensities, with mean values of 0.503 tCO₂/MWh and 0.444 tCO₂/MWh, respectively, which manifest as dark, high-carbon

bands in the graph. Conversely, the carbon intensities of nodes 5 and 8 remain at zero. This condition arises due to the constraints of network topology boundaries and chronological dispatch states, where no actual active power injection or transmission occurs at these specific nodes during certain periods, resulting in a zero-power-flux state.

Spatiotemporal Carbon Intensity Matrix & Normalized Multi-dimensional Features

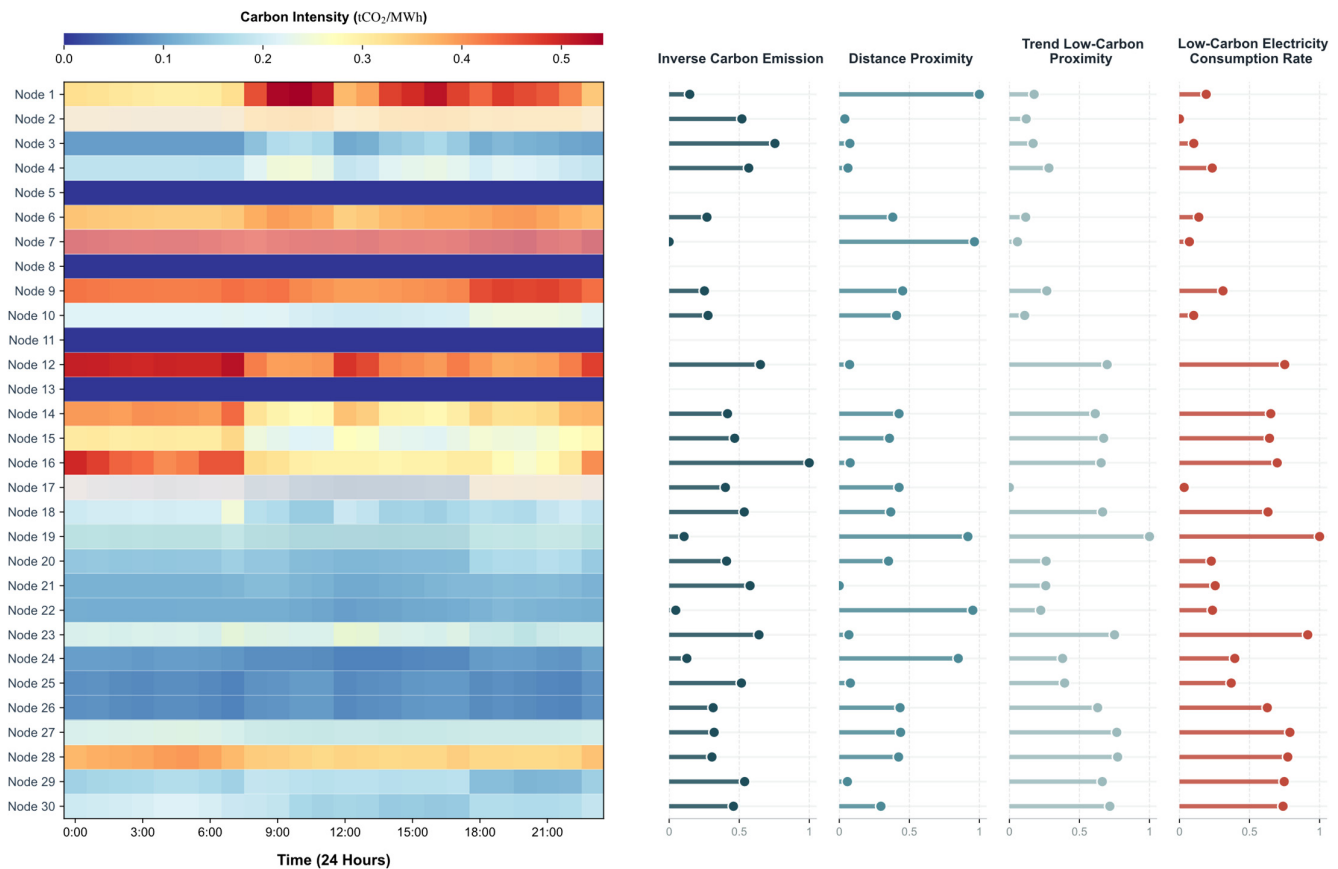


Figure 4. Spatio-temporal carbon intensity and load carbon emission profiles in the regional power grid.

Nodal electricity carbon emissions are predominantly dictated by the scale of the baseline load and the network topology. In contrast, dynamic coupling metrics—such as trend low-carbon proximity and low-carbon electricity utilization rate—reflect the phase-matching alignment between the peak-valley morphology of the load curve and the evolutionary cycle of the system's carbon intensity. In this paper, the carbon emission behavior characteristics of individual nodes under the baseline scenario are quantitatively evaluated using four metrics: electricity carbon emissions, distance low-carbon proximity, trend low-carbon proximity, and low-carbon electricity utilization rate.

Specifically, node 16 exhibits an electricity carbon emission value of 3.08, yet its trend low-carbon proximity is only 0.292. This divergence indicates a pronounced chronological mismatch between the peak demand periods of this node and the low-carbon intervals of the system. On the contrary, node 19 registers an electricity carbon emission value of 1.44, while its trend low-carbon proximity and low-carbon electricity utilization rate reach 0.858 and 0.841, respectively, both ranking among the highest in the network. The electrical consumption behavior of this node demonstrates high chronological consistency with the distributed generation output profiles.

In summary, traditional assumptions of homogeneous loads overlook the inherent differences in carbon emission behaviors among distinct nodes. By extracting these explicit load carbon emission characteristic metrics, this paper successfully achieves an effective quantification of the carbon emission features unique to each node.

5.3. Load Regulation Potential Metrics

Figure 5 displays the regulation potential characteristics of various nodes, which manifest distinct variations across the feature space. The node group represented by nodes 24, 7, 1, and 22 exhibits the highest load density and profile stability levels, with their annual maximum utilization hours all exceeding 7300 h; specifically, node 24 reaches a peak value of 7621 h, while maintaining its load volatility rate within the 0.10 to 0.11 interval. This dataset demonstrates that nodes 24, 7, 1, and 22 possess regulation characteristics characterized by large capacity and high stability.

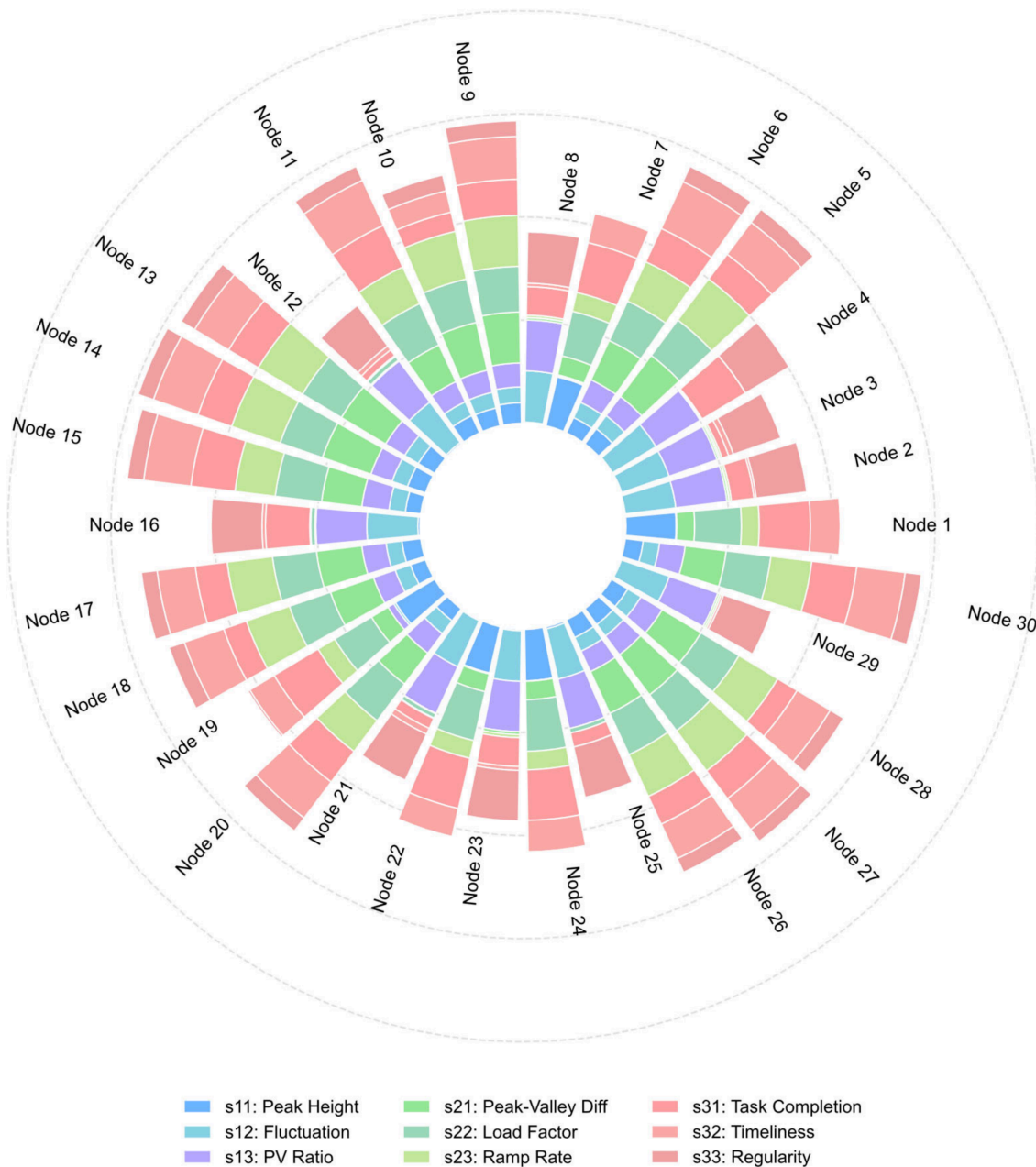


Figure 5. Load regulation potential metrics.

Furthermore, nodes 10 and 20 exhibit annual maximum utilization hours within the 5200 to 5400 interval, but present a relatively high load volatility rate of 0.28, indicating that their flexibility potential stems primarily from the chronological discreteness of consumption behaviors.

At the response execution performance level, the divergence in metric values among nodes further reflects the underlying tiers of their regulation endowment. Specifically, the task completion rates for nodes 1, 22, and 24 are all greater than 0.93, ensuring reliable execution of dispatch commands. Conversely, that of node 10 is merely 0.78. This contrast demonstrates that even when regulatable capacity is available, a substantial response performance gap of nearly 20% in execution efficiency still exists among different nodes.

Notably, node 19 stands out with highly prominent high-potential characteristics, registering an annual maximum utilization hours of 7226 and a task completion rate of 0.94, making it one of the few critical nodes in the network that simultaneously balances scale effects with response accuracy.

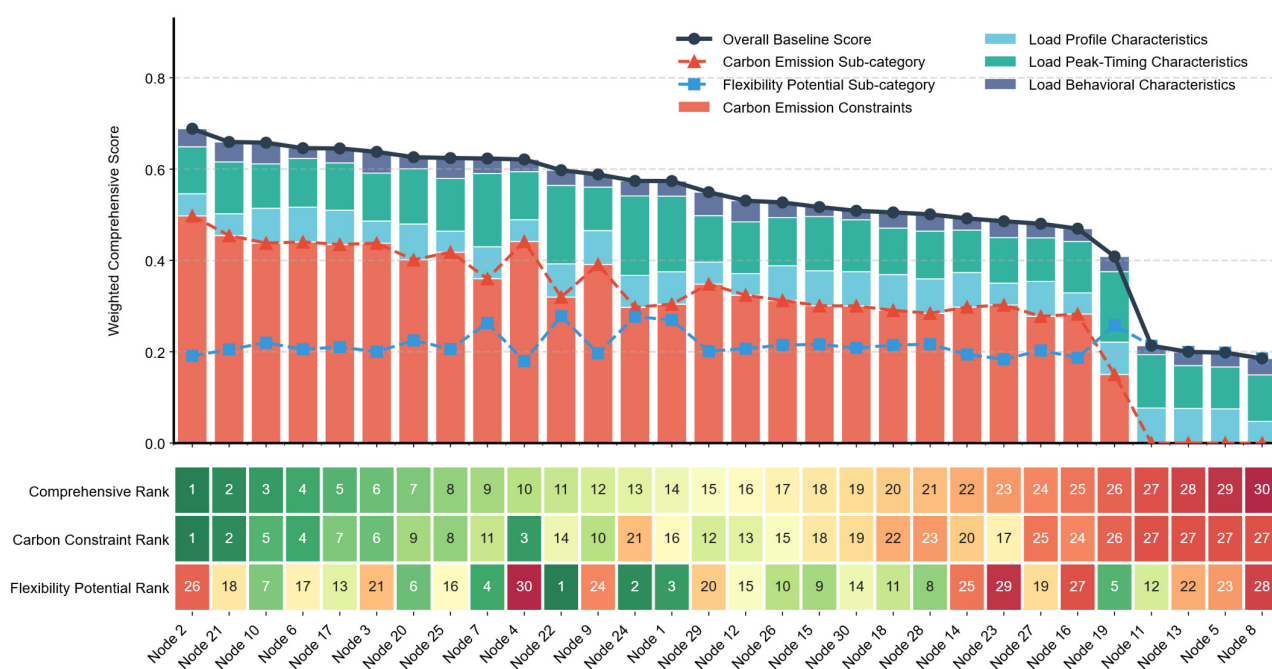
In summary, the accurate quantification of metric differences within high-potential node groups provided by this evaluation system delivers vital data support for the subsequent differentiated guidance of resource allocation in coordinated source–grid–load–storage planning, successfully preventing the misallocation of regulatory resources into nodes that exhibit “high potential but low reliability”.

5.4. Comprehensive Evaluation

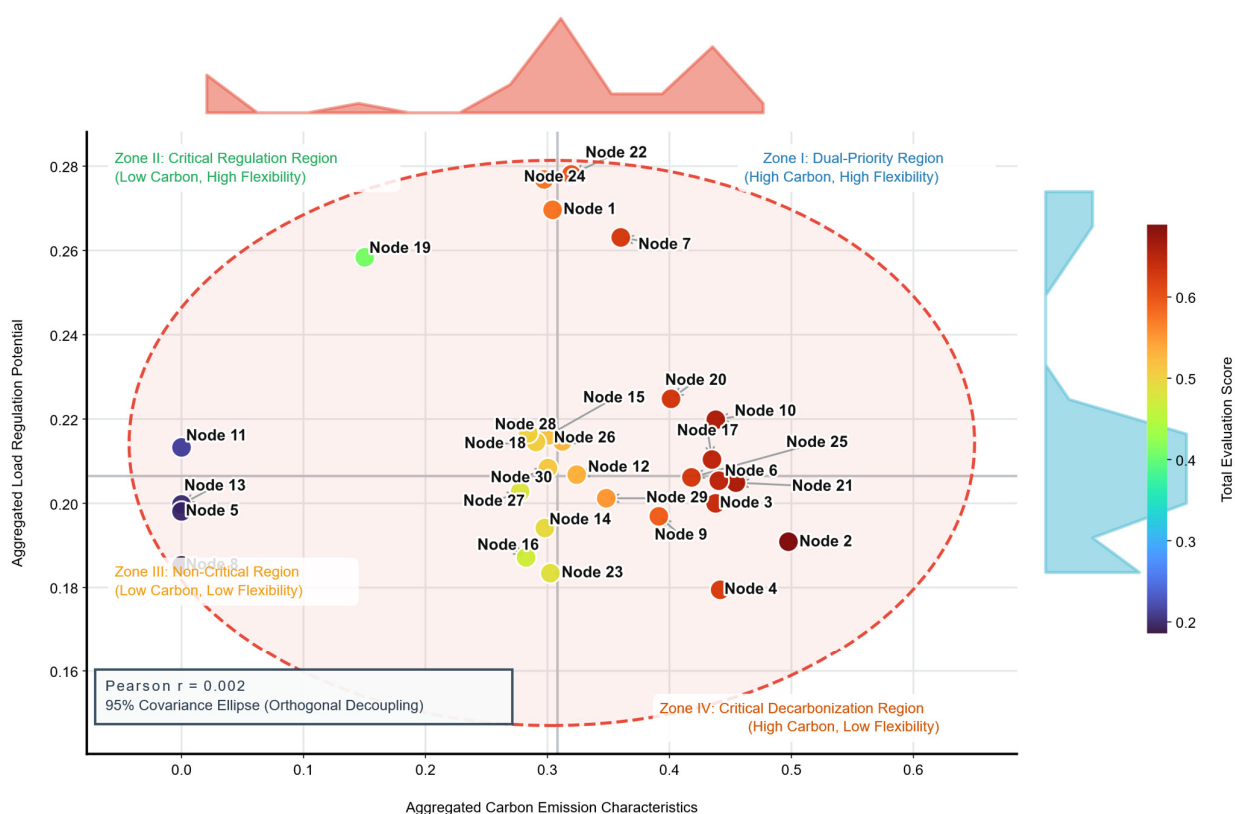
Based on the FAHP-improved CRITIC hybrid weighting evaluation system, Figure 6 illustrates the two-dimensional scores of the 30 regional power grid nodes across their load carbon emissions and regulation potential characteristics. The nodes exhibit a highly discrete distribution trend within the two-dimensional space, showing no conventional diagonal clustering effect. According to the Pearson correlation coefficient analysis, the computed correlation coefficient between the two datasets is merely $r = 0.002$ with a p -value of 0.99, demonstrating that the two dimensions are statistically almost completely uncorrelated. That is, nodes with high carbon emission characteristics do not necessarily possess stronger flexible regulation capabilities, and vice versa.

In light of this, this paper divides the two-dimensional feature space into four quadrants using the median values of each metric as the benchmark boundaries: Zone I: High Carbon-High Potential Dual-Priority Region; Zone II: Low Carbon-High Potential Critical Regulation Region; Zone III: Low Carbon-Low Potential Non-Critical Region; Zone IV: High Carbon-Low Potential Critical Decarbonization Region.

In summary, traditional single-dimensional evaluation paradigms frequently overlook the true spatial distribution mismatch between demand-side carbon responsibilities and regulation capabilities. The dual-dimensional assessment established in this paper achieves an accurate quantification of the global nodal endowment boundaries. In the subsequent coordinated source–grid–load–storage planning, these characteristic zones will be utilized to provide differentiated allocation guidance. This guides flexible regulation resources to aggregate toward high-potential nodes such as Zone I and Zone II, thereby avoiding the spatial misallocation of flexibility resources and harmonizing the low-carbon emission, economic efficiency, and operational security of the power grid.



(a) Nodal Multi-Dimensional Score Aggregation and Ranking Comparison



(b) Strategic Zoning and 95% Covariance Confidence Ellipse Test

Figure 6. Dual-dimensional evaluation results based on FAHP-improved CRITIC hybrid weighting method. (a) Nodal multi-dimensional score aggregation and ranking comparison; (b) Strategic zoning and 95% covariance confidence ellipse test.

5.5. Planning Results

To verify the effectiveness of the proposed model considering the dual-dimensional evaluation of load carbon emissions and regulation potential, comparative experiments are conducted under three resource allocation modes under different strategies in a high-penetration wind-solar output scenario:

Strategy 1: Taking the minimization of total cost in traditional planning methods as the optimization objective, this strategy disregards the distinct characteristics of individual nodes and simulates the disordered optimization results without priority constraints.

Strategy 2: Adopting a sub-strategy planning method that incorporates distinct nodal characteristics, this strategy introduces the evaluated node sequence into the planning model as constraints. It utilizes a capacity-guiding mechanism to ensure that flexibility resources are preferentially allocated to high-potential nodes.

As shown in Table 2 and Figure 7, the selection of resource allocation modes and planning strategies exerts a profound impact on the system's techno-economic indicators. Under single-resource allocation configurations, the ESS-only mode yields a generalized comprehensive cost of 9.39 billion RMB and carbon emissions of 2.5297 million tons, both of which mark the extreme upper bounds among all test scenarios. Conversely, in the DG-only configuration, the system suffers from a critical lack of bi-directional regulation functionality, resulting in zero peak-shaving and valley-filling capacities. Under the coordinated source-storage allocation scenario, compared with the conventional Strategy 1, the proposed Strategy 2 achieves a 1.08% reduction in generalized comprehensive cost, despite a marginal 3.18% increase in total carbon emissions. Crucially, however, the peak-shaving and valley-filling capabilities under this strategy are substantially enhanced by 33.1%, with the actual regulation depths reaching 24.05 MW and 20.01 MW, respectively.

Table 2. Source-grid-load-storage planning results.

Resource Allocation Mode	Strategy	Total Cost (10 ⁸ RMB)	Annual CO ₂ (10 ⁴ t)	Load Factor	PS/VF Cap. (MW)
DG-Only	1	89.78	218.24	0.83	0/0
	2	88.00	228.78	0.81	0/0
ESS-Only	1	93.90	252.97	0.83	13.84/10.97
	2	93.90	252.97	0.83	13.84/10.97
Coordinated (DG+ES)	1	89.37	220.77	0.84	18.07/14.31
	2	88.40	227.80	0.86	24.05/20.01

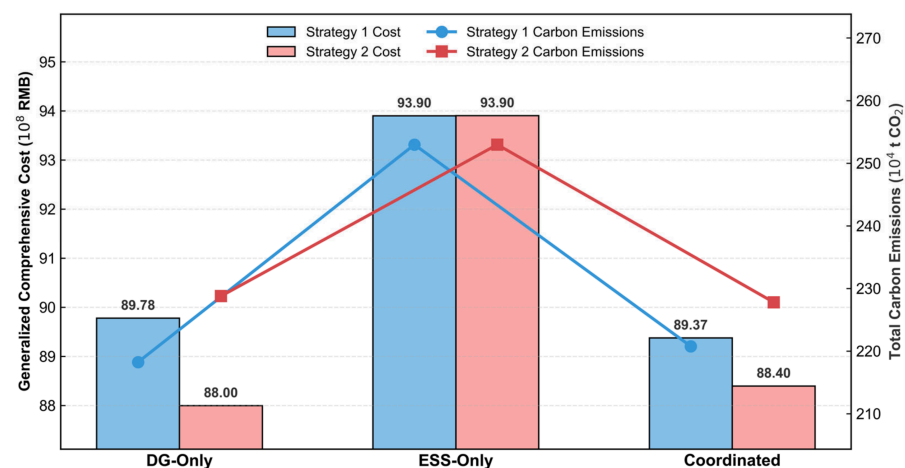


Figure 7. Cost and carbon emission analysis across different scenarios under Strategies 1 and 2.

The evolutionary trajectory of these data underscores that isolated DG-only or ESS-only configurations exhibit distinct performance bottlenecks, failing to simultaneously satisfy the rigorous economic and flexibility requirements of modern regional power grids. In contrast, when energy storage and distributed generation are jointly deployed, Strategy 2 demonstrates a conspicuous asymmetric trade-off advantage: it secures a massive expansion in system regulation depth and an upgrade in global generalized economic efficiency at the expense of a negligible increment in carbon emissions. This strategy successfully realizes multi-dimensional improvements in system security, flexibility, and economic viability while maintaining a fundamentally stable low-carbon emission profile.

The underlying driving force behind this feature decoupling and performance leap lies in the fact that Strategy 2 broadens the spatial precision of resource allocation as well as the boundaries of economic valuation. The conventional Strategy 1 easily triggers the disordered expansion of distributed generation, frequently culminating in redundant investments. Conversely, anchored by the evaluation models of load carbon emission characteristics and regulation potential, Strategy 2 effectively curbs the chaotic proliferation of distributed generation at low-value nodes. The capital thus salvaged is strategically redirected into energy storage deployment at high-potential critical nodes. Through operational economics, this reallocated capacity is translated into 117 million RMB of revenue within the ancillary service market. Furthermore, through the deep coordination of source and storage resources, the comprehensive system load factor is elevated to 0.86, effectively smoothing power flow fluctuations and capturing an additional 8 million RMB in network loss reduction benefits.

In summary, for modern regional power grids characterized by high-penetration wind-solar integration, the dual-dimensional feature evaluation-based coordinated source-grid-load-storage planning proposed in this study delivers an effective methodology to prevent the spatial misallocation of resources. By achieving highly accurate spatial targeting, this framework overcomes the conventional planning paradigm's inherent limitations of over-emphasizing capital investment while neglecting regulatory flexibility. Consequently, it maximizes generalized economic benefits while rigorously safeguarding localized regulation adequacy and global system security.

5.6. Comparative Analysis of Different Strategies Under Coordinated Configuration

As illustrated by Table 3 and the power flow heatmap in Figure 8, the configuration topology and operational states of the regional power grid under different strategies can be visually distinct. In Strategy 1, the installed capacity of distributed generation (DG) reaches 116.06 MW and is highly dispersed across 8 nodes, while the energy storage system (ESS) capacity stands at 38.85 MW and is concentrated in only 4 nodes. Conversely, Strategy 2 streamlines the DG capacity to 90 MW, centrally deploying it across 6 nodes, while substantially expanding the ESS capacity to 60 MW distributed across 6 nodes. Furthermore, during the peak hours from 08:00 to 21:00, the main backbone of the network under Strategy 1—including lines 37 to 41—exhibits pronounced heavy-load (congestion) characteristics. Upon the implementation of Strategy 2, it is conspicuous that the dark, heavily loaded zones in the heatmap are significantly reduced. The global power flow distribution tends to be more balanced, which effectively suppresses the violation of transmission power limits across critical lines. Quantitatively, under Strategy 1, lines 37 to 41 suffer from heavy-load congestion (loading exceeding 85%) for a cumulative duration of 6.5 h during a typical day, whereas Strategy 2 curtails this congestion window by 78.2%, while concurrently dropping the system-wide peak network losses by 14.6%, directly demonstrating enhanced spatial operational relief.

Table 3. DG and ESS configurations under different strategies.

Strategy	DG Planned Nodes	Total DG Configured Capacity (MW)	ESS Planned Nodes	Total ESS Configured Capacity (MW)
1	14, 20, 21, 22, 24, 25, 27, 28	116.06	1, 14, 19, 24	38.85
2	2, 3, 4, 21, 22, 24	90	1, 22, 23, 24, 26, 30	60

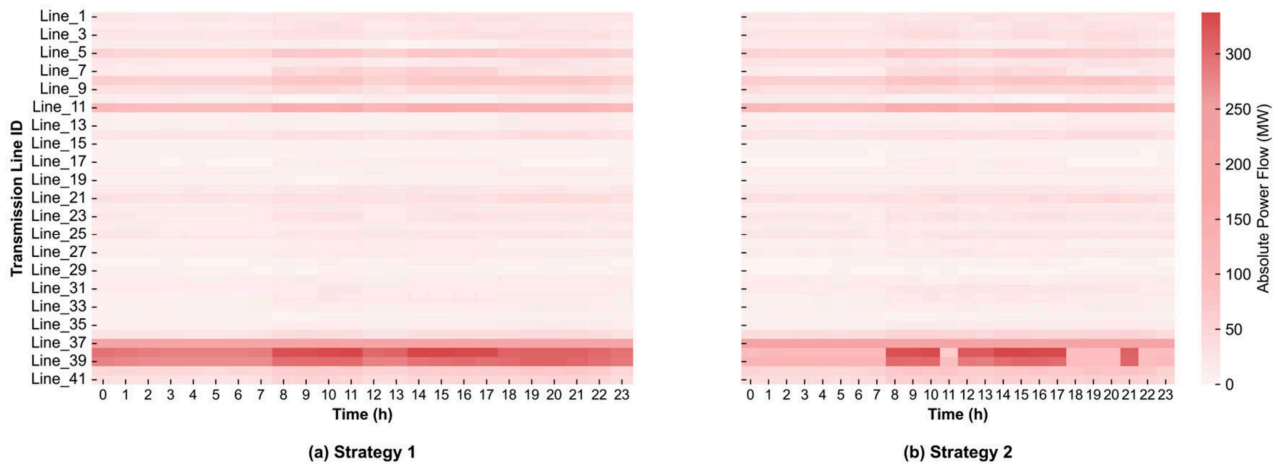


Figure 8. Congestion heatmap of line power flows under coordinated configuration. (a) Strategy 1; (b) Strategy 2.

The underlying planning philosophy of the system has fundamentally shifted from crude, investment-driven cost reduction toward high-precision, efficiency-oriented optimization. While Strategy 1 achieves a lower average power supply cost through the chaotic, large-scale integration of low-marginal-cost generation, it suffers from severe tidal power flow effects due to deficient operational flexibility. Conversely, Strategy 2 eliminates redundant power source capacities and centrally deploys large-scale energy storage. This establishes a lean configuration paradigm that seamlessly harmonizes high-quality decarbonization with deep flexibility, effectively mitigating the spatial transmission stress across the regional power grid from a global perspective.

The profound mechanism driving this spatial configuration restructuring and power flow smoothing lies in the fact that Strategy 2 achieves highly accurate target guidance based on the dual-dimensional nodal characteristics. On one hand, distributed generation is strategically concentrated at high-carbon baseline nodes (e.g., Nodes 2 and 21) to maximize the system’s decarbonization efficiency. On the other hand, energy storage capital is directed into flexible hub nodes with prominent regulation potential (e.g., Nodes 22, 24, and 1). This characterization-guided spatial allocation enables large-scale energy storage systems to suppress and absorb the intermittent fluctuations of distributed generation locally. By performing chronological energy shifts via localized peak-shaving and valley-filling, this configuration successfully prevents surplus power from backfeeding over long distances into the main backbone network due to source–load spatio-temporal mismatches, thereby eliminating line congestion at the structural topology level.

Crucially, as indexed in Figure 6 and Table 3, a minor portion of the resources optimized by Strategy 2 do not purely aggregate within the high-carbon high-potential quadrant (Zone I), but are instead strategically diverted into Zone II or Zone IV. This spatial dispersion represents the core physical essence of grid optimization rather than a tactical flaw. While the dual-dimensional evaluation scores provide essential prior signals for

resource placement, the ultimate allocation is rigorously governed by a multi-constrained MIQP framework incorporating line thermal transfer limits (Constraint 22), nodal power-angle balances (Constraint 21), and localized hosting capacity boundaries (Constraint 24). Forcing the entirety of DGs and ESSs into the narrow cluster of Zone I nodes would inevitably saturate local hosting capabilities, triggering severe reverse power feedback and local voltage violations.

Further analysis indicates that the power balance paradigms across individual nodes exhibit pronounced divergence, as illustrated in Figure 9. Nodes 2, 3, and 4, which are configured exclusively with distributed generation, experience severe daytime net load deep troughs; notably, Node 21 continuously backfeeds power to the main grid during the peak hours of photovoltaic (PV) generation. Conversely, Nodes 22 and 24, equipped with large-capacity energy storage, demonstrate superior autonomy and localized regulation capabilities. Their intra-day net load fluctuations are substantially smoothed, effectively mitigating the chronological shocks induced by the intermittent output of local renewable energy sources. Exploring the profound mechanism behind these heterogeneous scheduling behaviors, it fundamentally arises from the dual-dimensional feature space guidance mechanism that reshapes the power flow evolution logic of the regional power grid. On one hand, DGs are strategically allocated to nodes with high load carbon emission scores; on the other hand, energy storage resources are centrally deployed at flexible hub nodes with abundant regulation potential. In actual operation, when daytime PV generation peaks and causes localized power surpluses, the ESSs at the hub nodes dynamically switch to charging mode to realize localized consumption of surplus power. Conversely, during the evening peak, as PV output subsides and system load escalates, the ESSs flexibly transition to a power-support mode for peak discharging, working in tandem with the demand response mechanism to achieve comprehensive peak-shaving and valley-filling.

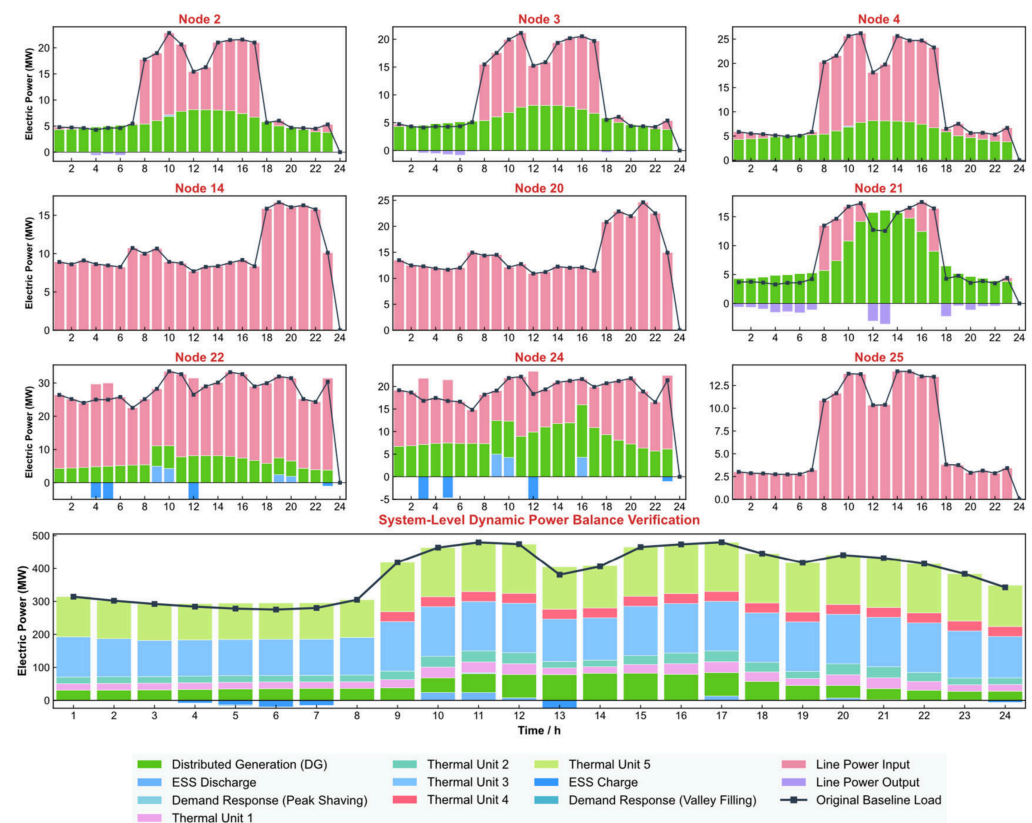


Figure 9. Typical node-level and system-level full spatio-temporal dynamic power balance.

In summary, the coordinated source–grid–load–storage scheduling strategy proposed in this paper successfully unlocks the flexibility margins of high-potential nodes. While rigorously safeguarding the real-time dynamic power balance at both global and nodal levels, it significantly enhances the localized consumption efficiency of clean energy.

5.7. Discussion

After comparing with guidance planning based on single-dimensional metrics, the relevant performance outcomes are systematically interpreted. Although prior studies established a planning architecture governed by load carbon emission attributes [27], and some literature focuses primarily on temporal regulation capability [28], the case study results indicate that treating these two attributes separately constrains spatial resource allocation. The dual-dimensional integration proposed in this paper is not intended to invalidate single-metric methodologies, but rather to simultaneously capture nodal carbon urgency and operational flexibility, thereby facilitating multi-dimensional spatial resource optimization.

Although the results of this study demonstrate the effectiveness and economic advantages of the proposed dual-dimensional characterization-guided planning framework, several practical issues still warrant discussion. At present, the model employs a deterministic typical scenario to evaluate the spatial coordination between demand-side characteristics and resource allocation. This design is primarily intended to validate the core innovation of this study, namely how nodal carbon emission urgency and operational regulation potential interact to guide optimal siting under distinct spatial characteristics. While real-world distribution networks inevitably encounter short-term stochastic fluctuations in renewable output and load profiles, the deterministic framework still provides a clear and manageable analytical basis for identifying the regularities of spatial resource allocation. Incorporating advanced uncertainty management methods to address such operational volatility represents our next step for future research. Furthermore, the modest computational scale and rapid convergence demonstrated in the IEEE 30-bus case study illustrate the favorable structural scalability of the proposed framework, offering a valuable analytical reference for future extension to larger-scale power systems.

6. Conclusions

To facilitate the effective utilization of demand-side flexibility resources and ensure efficient investment in the planning process of regional power grids while fully incorporating the impacts of source–load uncertainties and the collaborative carbon reduction and regulatory capabilities of diverse resources, this paper proposes a coordinated source–grid–load–storage planning method guided by a “load carbon emission characteristics–regulation potential” dual-dimensional assessment. The main conclusions drawn are as follows:

- (1) This paper establishes a dual-dimensional quantitative evaluation framework for demand-side characteristics, indicating a weak correlation between the carbon emission attributes of node loads and their dynamic regulation potential. Conducting a dual-dimensional comprehensive assessment based on these findings enables a more accurate demarcation of node characteristic boundaries, thereby assisting in mitigating the spatio-temporal mismatch risks of flexibility resources at both the topological deployment and chronological scheduling levels.
- (2) The proposed dual-dimensional characterization-guided planning strategy achieves controlled generalized comprehensive costs throughout the life cycle and directs investments toward high-potential hub nodes. Compared with conventional homogenized planning, the system’s peak-shaving and valley-filling capabilities are altered,

and the system's comprehensive load factor is adjusted accordingly. Furthermore, by accounting for operational revenues from ancillary services and network loss reduction, the strategy balances the initial investment requirements, achieving a coordinated integration among system security, flexibility, and economic indicators.

- (3) The spatial configuration framework developed in this study coordinates the internal power flow evolution within the regional power grid. Siting flexible resources at nodes with high regulation potential alleviates heavy-loading and congestion phenomena along lines induced by the high-penetration integration of wind and solar power. Consequently, this maintains the secure operational boundaries of the regional power grid and supports power flow stability.

The coordinated source–grid–load–storage planning method proposed in this paper demonstrates the critical role of node-level dual-dimensional feature guidance in optimizing the spatial layout of system resources and promoting clean energy consumption, offering a novel planning paradigm for modern regional power grids. However, this study does not delve into the impacts of multi-agent game-theoretical behaviors on the coordinated planning framework. Future research could expand the source–load interaction response models from the perspective of multi-agent trading within coupled carbon-electricity markets, further enhancing the comprehensive benefits for all source–grid–load–storage stakeholders and system operational reliability under complex market environments.

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Abbreviations

The following abbreviations are used in this manuscript:

DG	Distributed Generation
BESS	Battery Energy Storage Systems
CEF	Carbon Emission Flow
VCG	Vickrey–Clarke–Groves
DR	Demand Response
CDL	Customer Directrix Line

FAHP	Fuzzy Analytic Hierarchy Process
CRITIC	Criteria Importance Through Intercriteria Correlation
MIQP	Mixed-Integer Quadratic Programming
NPV	Net Present Value
PVIFA	Present Value Interest Factor of Annuity
ESS	Energy Storage Systems
SGLS	Source–Grid–Load–Storage

Appendix A

Appendix A.1. Load Carbon Emission Characteristic Model

In the carbon emission flow calculation, each generator serves as the sole carbon emission source in the system. A carbon emission flow calculation method based on the power-flow distribution matrix is adopted to accurately decompose the generator active power into various nodal loads, branch powers, and losses. By combining the real-time carbon emissions of the generators with their power decomposition results, the carbon emission flow of the power system is calculated. This calculation method is widely applicable to power systems of different scales and configurations.

(1) Formulation of Power-Flow Distribution Matrix and Generator Power Allocation

For a power system encompassing n nodes, the mathematical relationship between the generator power at each node and the total power flux flowing through each node represented by the power-flow distribution matrix A_u is established as follows:

$$A_u P = P_G \quad (A1)$$

where $P_G \in R^{n \times 1}$ is the vector composed of the generator active power at each node; $P = [P_1 P_2 \cdots P_n]^T$ is the vector composed of the power flux flowing through each node; $A_u \in R^{n \times n}$ is the power-flow distribution matrix, the elements of which are calculated according to the following formula:

$$(A_u)_{ij} = \begin{cases} 1, & i = j \\ -\frac{|P_j|}{P_i}, & i \in S_j, j = 1, 2, \dots, n \\ 0, & \text{otherwise} \end{cases} \quad (A2)$$

where $(A_u)_{ji}$ denotes the element located at the j -th row and i -th column within the matrix A_u ; P_{ji} represents the active power flow transmitted on the branch j - i , with the direction defined from node j to i ; P_i signifies the active power flux flowing through node i ; S_j represents the set of nodes directly connected to node j where the active power flow is directed toward node j .

By utilizing the power-flow distribution matrix, the active power paths from individual generators to various branches and loads can be quantified, thereby realizing generator power allocation.

1) Active power drawn by nodal loads from generators.

Based on the power-flow distribution matrix, the load P_{lk} at node k is expressed as the sum of contributions from various generators as follows:

$$P_{lk} = \frac{P_{lk}}{P_k} P_k = \frac{P_{lk}}{P_k} e_k^T P = \frac{P_{lk}}{P_k} e_k^T A_u^{-1} P_G \quad (A3)$$

where P_k denotes the power flux flowing through node k ; $e_k \in R^{n \times 1}$ represents a column vector where the k -th component is equal to 1 and all other components are 0.

The active power component $P_{lk,Gi}$ drawn by the load at node k from the generator at node i can be expressed as:

$$P_{lk,Gi} = \frac{P_{lk} P_{Gi}}{P_k} e_k^T A_u^{-1} e_i \quad (A4)$$

where P_{Gi} signifies the active power output of the generator located at node i ; $e_i \in R^{n \times 1}$ represents a column vector where the i -th component is equal to 1 and all other components are 0.

2) Active power drawn by transmission branches from generators.

Assuming that the active power flow on transmission branch k - j is directed from node k to node j , the transmitted branch power P_{kj} is supported by the upstream generator power of node k , which is calculated as follows:

$$P_{kj} = \frac{P_{kj}}{P_k} P_k = \frac{P_{kj}}{P_k} e_k^T P = \frac{P_{kj}}{P_k} e_k^T A_u^{-1} P_G \quad (A5)$$

3) Network power loss allocation borne by generators.

The active power transmission loss P_{kj}^{loss} on branch k - j is shared by the upstream generator power of node k , which is calculated as follows:

$$P_{\text{loss}} = \frac{P_k^{\text{loss}}}{P_k} P_k = \frac{P_k^{\text{loss}}}{P_k} e_k^T P = \frac{P_k^{\text{loss}}}{P_k} e_k^T A_u^{-1} P_G \quad (A6)$$

(2) Basic Operational Parameters of Carbon Emission Flow Theory

1) Carbon Flow Rate

The carbon flow rate represents the total mass of equivalent carbon emissions flowing through a transmission branch or a specific node per unit time, expressed in $\text{tCO}_2/(\text{MW} \cdot \text{h})$. Taking the transmission branch k - j within an n -node system as an illustrative example, its branch carbon flow rate R_{kj} can be expressed as

$$R_{ij} = \frac{P_{ij}}{P_k} e_k^T A_u^{-1} \text{diag}(P_G) E_G \quad (A7)$$

where P_{kj} is the active power flow transmitted on branch k - j ; P_k is the total active power flux flowing through node k ; $e_k \in R^{n \times 1}$ is a column vector where the k -th component is equal to 1 and all other components are 0; $A_u \in R^{n \times n}$ is the power-flow distribution matrix; $P_G \in R^{n \times 1}$ is the vector composed of the generator active power at each node; $\text{diag}(P_G)$ represents the operator that transforms a column vector into a diagonal matrix; and $E_G \in R^{n \times 1}$ is the vector composed of the carbon emission intensities of individual generation units.

2) Branch Carbon Flow Density

The branch carbon flow density signifies the equivalent generation-side carbon emissions associated with a unit of electrical energy transmitted over a specific line, which is derived from the ratio of the branch carbon flow rate to its corresponding active power flow, expressed in $\text{tCO}_2/(\text{MW} \cdot \text{h})$. The carbon flow density ρ_{kj} of branch k - can be expressed as

$$\rho_g = \frac{R_g}{P_g} \quad (A8)$$

3) Nodal Carbon Intensity

The nodal carbon intensity characterizes the equivalent generation-side carbon emissions induced per unit of electrical energy consumed at a specific node. It is calculated as the ratio of the aggregate carbon flow rates entering the node via transmission lines to the total power flux flowing through that node, expressed in $\text{tCO}_2/(\text{MW}\cdot\text{h})$. The nodal carbon intensity $I_{\text{NCEL},j}$ of node j can be expressed as

$$I_{\text{NCEL},j} = \sum_{k \in S_j} (R_g - R_g^{\text{loss}}) / P_j \quad (\text{A9})$$

where S_j is the set of upstream nodes directly connected to node j ; R_g^{loss} represents the carbon flow rate associated with the network losses on transmission branch $k-j$; and P_j signifies the total active power flux flowing through node j .

(3) Quantitative Model for Carbon Emission Characteristics of Nodal Loads

The actual carbon emissions of a node are jointly determined by the nodal carbon intensity and the nodal net load. The nodal net load curve is derived by subtracting the real-time distributed generation (DG) output from the real-time load of the specific node, representing the actual electrical energy drawn from the grid. The nodal carbon intensity curve is calculated using the carbon emission flow theory at each time interval, characterizing the real-time carbon emissions per unit of electrical energy consumed at that node. By optimizing the net load curve to shift consumption away from high carbon-intensity periods toward low carbon-intensity periods, carbon reduction can be achieved while maintaining total energy consumption constant. Therefore, the relationship between the net load curve and the carbon intensity curve dictates the carbon emission profile of the load.

Leveraging the concepts of calculus, this paper decomposes the sequential curves into a series of discrete points and line segments. The physical distance between points and the structural trends between line segments are utilized to characterize the proximity and shape similarity between these sequential curves. Consequently, the metrics of distance-based low-carbon degree and trend-based low-carbon degree are proposed to evaluate the closeness and trend similarity between the net load curve and the carbon intensity curve. On this basis, and customized to the specific problem investigated herein, the total electrical carbon emissions and the low-carbon electricity utilization rate are incorporated to provide a more comprehensive quantification of the carbon emission characteristics of the load.

When calculating the carbon emission characteristics of the loads within each active distribution network under the regional power grid, it is essential to ensure that the sampling frequency of the load curves across all distribution networks is identical and capable of accurately capturing the variation characteristics of these load profiles. Specifically, the sampling frequency must exceed twice the fluctuation frequency of the load curves. To guarantee the accuracy, stability, and applicability of the resulting planning decisions, typical load curves and renewable energy output curves that effectively describe their respective operational characteristics are utilized to perform the nodal net load calculations. Subsequently, the nodal carbon intensities are calculated after fully incorporating the variations in generation carbon emission intensities and topological structure changes within the regional power grid.

1) Nodal Carbon Emissions

The electrical carbon emission metric is employed to describe the total amount of carbon emissions generated by the load within a specified sampling horizon. It is defined as the reciprocal of the sum of the products of the nodal net load, the normalized nodal carbon intensity, and the time interval between adjacent sampling points. A higher value

of this metric indicates lower carbon emissions. The electrical carbon emission metric of node i can be expressed as

$$d'_{1,i} = \frac{1}{\sum_{n=1}^N c_{i,n} u_{i,n} \Delta t} \quad (\text{A10})$$

where $d'_{1,i}$ represents the electrical carbon emission metric of node i ; N denotes the total number of sampling points within the sampling horizon; $c_{i,n}$ is the normalized nodal carbon intensity of node i at the n -th sampling point; $u_{i,n}$ signifies the normalized nodal net load of node i at the n -th sampling point; and Δt denotes the value of the time interval between adjacent sampling points under the current sampling frequency.

2) Distance-Based Low-Carbon Degree

The distance-based low-carbon degree is utilized to describe the distance between corresponding sampling points of the nodal net load curve and the nodal carbon intensity curve within a specified sampling horizon. A larger distance between the two corresponding points of the nodal net load curve and the nodal carbon intensity curve at the same sampling point results in a greater distance-based low-carbon degree. The distance-based low-carbon degree of node i is composed of the sum incremental change and the product incremental change at each sampling point, where the sum incremental change and product incremental change are, respectively expressed as

$$r_{1,i} = \frac{\sum_{n=1}^N e^{\left| \frac{u_{i,n} + c_{i,n}}{2} - c_{i,n} \right|}}{N} \quad (\text{A11})$$

$$r_{2,i} = \frac{\sum_{n=1}^N e^{\left| \sqrt{u_{i,n} c_{i,n}} - c_{i,n} \right|}}{N} \quad (\text{A12})$$

where $r_{1,i}$ represents the sum incremental change in node i ; and $r_{2,i}$ is the product incremental change in node i .

Based on the sum incremental change and product incremental change, the distance-based low-carbon degree of node i can be calculated as

$$d_{2,i} = \varphi_1 r_{1,i} + (1 - \varphi_1) r_{2,i} \quad (\text{A13})$$

where $d_{2,i}$ represents the distance-based low-carbon degree of node i ; φ_1 denotes the weight coefficient, which is generally taken as 0.5.

3) Trend-Based Low-Carbon Degree

The trend-based low-carbon degree is employed to describe the difference in variation trends between the nodal net load curve and the nodal carbon intensity curve. To further distinguish the carbon emission variations caused by load characteristics, the trend-based low-carbon degree is positive where the variation trends of the nodal net load curve and the nodal carbon intensity curve are opposite, and negative with its reciprocal taken when they are identical. Within the sampling horizon, when the variation trends of the nodal net load curve and the nodal carbon intensity curve are opposite and the difference between their slopes is larger, the trend-based low-carbon degree becomes greater, indicating a more low-carbon profile of the load carbon emission characteristics. The trend-based low-carbon degree of node i is expressed as

$$d_{3,i} = \frac{\sum_{n \in N'} e^{|c'_{i,n} - u'_{i,n}|} + \sum_{n \in N''} -e^{-|c'_{i,n} - u'_{i,n}|}}{N - 1} \quad (\text{A14})$$

$$\begin{cases} N' \in N(c'_{i,n} \times u'_{i,n} < 0) \\ N'' \in N(c'_{i,n} \times u'_{i,n} \geq 0) \end{cases} \quad (\text{A15})$$

$$c'_{i,n} = \frac{c_{i,n+1} - c_{i,n}}{\Delta t} \quad (\text{A16})$$

$$u'_{i,n} = \frac{u_{i,n+1} - u_{i,n}}{\Delta t} \quad (\text{A17})$$

where $d_{3,i}$ represents the trend-based low-carbon degree of node i ; $c'_{i,n}$ is the slope of the carbon intensity curve of node i at the n -th sampling point; $u'_{i,n}$ is the slope of the net load curve of node i at the n -th sampling point; the slopes are calculated across $N-1$ intervals; N' denotes the set of sampling intervals where the variation trends of the nodal net load curve and the nodal carbon intensity curve are opposite; N'' denotes the set of sampling intervals where the variation trends of the nodal net load curve and the nodal carbon intensity curve are identical; $c_{i,n+1}$ is the normalized nodal carbon intensity of node i at the $(n+1)$ -th sampling point; and $u_{i,n+1}$ signifies the normalized net load of node i at the $(n+1)$ -th sampling point.

4) Low-Carbon Electricity Utilization Rate

The low-carbon electricity utilization rate is employed to describe the ratio of the cumulative net load during the intervals where the variation trends of the nodal net load curve and the nodal carbon intensity curve are opposite to the total net load within the sampling horizon. A larger net load volume during the periods characterized by opposite variation trends between the nodal net load and nodal carbon intensity curves results in a higher low-carbon electricity utilization rate, indicating a more low-carbon profile of the load carbon emission characteristics. The low-carbon electricity utilization rate of node i can be expressed as

$$d_{4j} = \frac{\sum_{n \in N'} u_{i,n}}{\sum_{n=1}^N u_{i,n}} \quad (\text{A18})$$

where d_{4j} represents the low-carbon electricity utilization rate of node i .

Appendix A.2. Indirect Energy Storage Model and Core Parameters Based on Customer Directrix Line (CDL)

The high-penetration integration of renewable energy sources has significantly weakened the regulation capabilities on the generation side, creating an urgent need to tap into the flexible loads on the demand side as indirect energy storage to participate in source–load–storage interactive operations. The crux of establishing indirect energy storage lies in determining the system's Customer Directrix Line (CDL). From the perspective of the power grid side, this paper issues a unified CDL tailored for regional flexible loads to assist the grid in peak shaving and mitigate renewable energy curtailment. Subsequently, load clusters operate as indirect energy storage to respond to this CDL. To objectively characterize the geometric profiles of the load curves, a per-unit normalization preprocessing of the load curves must first be executed.

Appendix A.2.1. Data Preprocessing Methodology

To objectively characterize the geometric profiles of the load curves, a per-unit normalization preprocessing of the load curves must be executed, utilizing the formula formulated below. Let $l_{R,i,t}$ denote the active power value of the i -th flexible load during time interval t . The total electrical energy consumption $a_{R,i}$ within the entire scheduling horizon T is expressed as:

$$a_{R,i} = \sum_{t=1}^T l_{R,i,t} \quad (\text{A19})$$

Using $a_{R,i}$ as the base value to normalize $l_{R,i,t}$, the per-unit formulation is defined as follows:

$$l_{R,i,t}^* = \frac{l_{R,i,t}}{a_{R,i}} \quad (\text{A20})$$

where $l_{R,i,t}^*$ represents the normalized per-unit value of the i -th flexible load.

Then, considering the minimization of the total cost—which comprises the grid-side peak-shaving operational cost, the renewable energy curtailment cost, and a regularization term—the grid operator issues the CDL. The objective function is formulated as follows:

$$\begin{aligned} \min C_{\text{CDL}} = & \sum_{t=t_{\text{st}}}^{t_{\text{end}}} \sum_{g=1}^{N_G} \left[(a_g + b_g P_{g,t} + c_g P_{g,t}^2) + c_{\text{st}} x_{g,t} + c_{\text{sh}} y_{g,t} \right] + \sum_{t=1}^T \sum_{n=1}^{N_{\text{DG}}} c_{\text{cut}} P_{\text{cut},n,t} \\ & + \gamma \sum_{t=1}^T \left[\left(\sum_{i=1}^{N_R} l_{R,i,t}^* - L_{\text{CDL},t}^* \right)^2 + \left(\bar{L}_{\text{CDL}} - L_{\text{CDL},t}^* \right)^2 \right] \end{aligned} \quad (\text{A21})$$

where t_{st} , t_{end} denote the start and end times of the peak-shaving period, respectively; N_G is the total number of thermal power units; a_g, b_g, c_g represents the fuel cost function coefficient of the g -th thermal power unit; $P_{g,t}$ is the active power output of the g -th thermal power unit during time interval t ; $c_{\text{st}}, c_{\text{sh}}$ are the start-up and shut-down costs of the thermal power units, respectively; $x_{g,t}, y_{g,t}$ represent the start-up and shut-down status binary variables (or actions) of the g -th thermal power unit during time interval t , respectively; T is the total number of time intervals in a day, which is taken as $T = 24$ in this paper; N_{DG} is the total number of renewable energy units; c_{cut} signifies the penalty coefficient for renewable energy curtailment; $P_{\text{cut},n_{\text{DG}},t}$ represents the curtailed power of the n_{DG} renewable energy unit during time interval t ; γ is the load divergence coefficient; N_R represents the total number of flexible load clusters; $\bar{L}_{\text{CDL}}, L_{\text{CDL},t}^*$ denote the normalized mean value of the unified CDL and the normalized power value of the unified CDL during time interval t , respectively; $l_{R,i,t}^*$ is the normalized per-unit value of the i -th flexible load cluster during time interval t . It should be noted that in the regularization term, the former component is introduced to facilitate the tracking performance of the flexible loads, while the latter component is utilized to smooth the CDL profile. The value of γ ranges from 1 to 1000 to keep its order of magnitude consistent with the other operational costs. Concurrently, the operational constraints of the indirect energy storage model encompass demand line constraints, power balance constraints, thermal unit output limits, thermal unit start-up/shut-down constraints, thermal unit ramping limits, and renewable energy curtailment constraints, among others. The detailed mathematical formulations are presented below:

Appendix A.2.2. Remaining Operational Constraints for the Flexible Load Regulation Potential Model

(1) Baseline/Demand Line Constraints

As an integral component of indirect energy storage, the flexible loads must ensure that the total daily electrical energy consumption remains invariant:

$$\begin{cases} \sum_{t=1}^T L_{\text{CDL},t}^* = 1 \\ 0 \leq L_{\text{CDL},t}^* \leq 1 \end{cases} \quad (\text{A22})$$

where $L_{\text{CDL},t}^*$ represents the unified CDL issued by the system during time interval t .

(2) Power Balance Constraints

After the flexible loads respond to the issued CDL, the real-time active power balance of the power system must be strictly satisfied at each time interval:

$$\sum_{g=1}^{N_G} P_{g,t} + \sum_{n=1}^{N_{DG}} (P_{n,t} - P_{\text{cut},n,t}) = \sum_{n_b=1}^{N_B} P_{\text{load},n_b,t} + \sum_{i=1}^{N_R} P_{R,i,t} \quad (\text{A23})$$

$$P_{R,i,t} = a_{R,i} (l'_{R,i,t} - l^*_{R,i,t}) \quad (\text{A24})$$

where $P_{n_{DG},t}$ is the forecasted active power output of the n_{DG} renewable energy unit during time interval t ; N_B represents the total number of loads; $P_{\text{load},n_b,t}$ is the forecasted power consumption of the n_b load during time interval t ; $P_{R,i,t}$ denotes the equivalent indirect energy storage power of the i -th flexible load cluster during time interval t ; $l'_{R,i,t}$ represents the normalized per-unit value of the i -th flexible load cluster after implementing the demand response during time interval t , where $L^*_{\text{CDL},t} = l'_{R,i,t}$ under the condition of full response; and $a_{R,i}$ is the total daily electrical energy consumption of the i -th flexible load cluster.

(3) Thermal Unit Output Constraints.

$$u_{g,t} P_g^{\min} \leq P_{g,t} \leq u_{g,t} P_g^{\max} \quad (\text{A25})$$

where $u_{g,t}$ denote the operational status of the g -th thermal power unit during time interval t , where a value of 1 indicates that the unit is in an online/on status, and a value of 0 indicates that the unit is in an offline/off status; $P_g^{\min}$ and $P_g^{\max}$ represent the minimum and maximum active power output limits of the g -th thermal power unit, respectively.

(4) Thermal Unit Start-up and Shut-down Constraints.

$$\begin{cases} x_{g,t} - y_{g,t} = u_{g,t} - u_{g,t-1} \\ x_{g,t} + y_{g,t} \leq 1 \end{cases} \quad (\text{A26})$$

where $x_{g,t}$ and $y_{g,t}$ represent the operational status actions of the g -th thermal power unit during time interval t , respectively, where a value of 1 indicates a start-up and a shut-down action of the unit, respectively, and a value of 0 represents no start-up and no shut-down action of the thermal power unit, respectively.

(5) Thermal Unit Ramp-Rate Constraints.

$$-D_g \Delta t \leq P_{g,t} - P_{g,t-1} \leq D_g \Delta t \quad (\text{A27})$$

where D_g represents the ramp-rate power limit of the g -th thermal power unit.

(6) Renewable Energy Curtailment Constraints.

$$P_{\text{cut},n_{DG},t} \leq P_{n_{DG},t} \quad (\text{A28})$$

Appendix A.2.3. CDL-Based Indirect Energy Storage Core Parameters and Incentive Mechanisms

To fully characterize the “energy storage-like” properties of indirect energy storage, based on the aforementioned model, this paper further describes the core parameters, which comprise four parts: charging/discharging power, rated charging/discharging power, rated capacity, and state of charge (SOC). The detailed conversion formulas are as follows:

(1) Core Parameter Conversion Formulas for Indirect Energy Storage

1) Charging and Discharging Power

After the load clusters respond to the issued CDL, the condition $P_{R,i,t} > 0$ represents the charging state of the indirect energy storage, which is equivalent to $P_{char,i,t}^R$. Conversely, the condition $P_{R,i,t} < 0$ denotes the discharging state of the indirect energy storage, which is equivalent to $P_{disc,i,t}^R$. The real-time charging and discharging power of the indirect energy storage at each time interval is defined as:

$$\begin{cases} P_{char,i,t}^R = |P_{R,i,t}|, & P_{R,i,t} > 0 \\ P_{disc,i,t}^R = -|P_{R,i,t}|, & P_{R,i,t} < 0 \end{cases} \quad (A29)$$

2) Rated Charging and Discharging Power

The rated charging and discharging power can characterize the upper output limits of the indirect energy storage. The upper charging and discharging limits are determined by the maximum difference between the daily energy consumption multiplied by the CDL and $l_{R,i,t}^*$, whereas the lower limit corresponds to the scenario where the loads completely do not respond to the CDL, which yields:

$$\bar{P}_{R,i} = \max\{P_{R,i,t}\} \quad (A30)$$

where $\bar{P}_{R,i}$ is the rated power of the i -th indirect energy storage.

Then, the upper and lower limits constraint for the charging and discharging power of the i -th indirect energy storage at time interval t is expressed as:

$$0 \leq P_{R,i,t} \leq \bar{P}_{R,i} \quad (A31)$$

3) Rated Capacity

For indirect energy storage, its rated capacity depends on the sum of the maximum regulatable power of the flexible load clusters at that time interval, which is manifested as the power difference when the load curve completely responds to the CDL.

$$\bar{S}_{R,i} = \max\{a_{R,i,t} | L_{CDL,t}^* - l_{R,i,t}^* |\} \quad (A32)$$

4) State of Charge (SOC)

The SOC of indirect energy storage can be defined as the ratio of the remaining response capacity of the flexible loads at that time interval to the rated capacity, and the specific formula is as follows:

$$S_{R,i,t} = \frac{\bar{S}_{R,i} - P_{R,i,t}}{\bar{S}_{R,i}} \quad (A33)$$

When the indirect energy storage responds, the system operator provides incentives to the load aggregators based on the similarity between the flexible loads and the CDL curve as well as the responded power. The incentive mechanisms are as follows.

$$\begin{cases} c_{R,i} = \sum_{t=1}^T (P_{char,i,t}^R - P_{disc,i,t}^R) \beta \varepsilon_{R,i}, & \varepsilon_{R,i} \geq 0.8 \\ c_{R,i} = 0, & \varepsilon_{R,i} < 0.8 \end{cases} \quad (A34)$$

$$\varepsilon_{R,i} = 1 - \sqrt{\sum_{t=1}^T (L_{CDL,t}^* - l_{R,i,t}^*)^2} \quad (A35)$$

where β is the incentive price, which is set to 1500 Yuan/MW in this paper; $l'_{R,i,t}$ is the normalized per-unit value of the i -th flexible load cluster at time interval t after implementing the response; $\varepsilon_{R,i}$ denotes the similarity coefficient between the i -th load cluster and the CDL. The higher the similarity between the flexible load and the CDL, the greater the incentive received by the load aggregator, and no incentive is granted if the similarity is less than the threshold. In this paper, it is assumed that the flexible loads are completely rational and capable of fully responding to the CDL. During the response intervals, $L_{CDL,t}^* = l'_{R,i,t}$, which leads to $\varepsilon_{R,i,t} = 1$; during the non-response intervals, $\varepsilon_{R,i,t} = 1 - \sqrt{\left(L_{CDL,t}^* - l'_{R,i,t}\right)^2}$, making the indirect energy storage incentive term linear and applicable to different types of flexible loads.

Appendix A.3. Flexible Load Regulation Potential Evaluation Methodology

To enable load aggregators to reasonably evaluate indirect energy storage resources, establish indirect energy storage models for flexible load clusters with differentiated regulation potentials, and orderly participate in energy storage system (ESS) planning, this paper proposes a load potential evaluation framework across three dimensions: load curve characteristics, load peak-shaving characteristics, and load behavior characteristics.

Appendix A.3.1. Load Curve Characteristics s_1

The load curve characteristics s_1 are used to evaluate the potential of the load to adjust its own curve shape. A larger s_1 indicates a wider load regulation range. It includes three indicators: the annual maximum utilization hours s_{11} , the load volatility rate s_{12} , and the load peak-valley difference rate s_{13} . The specific expressions are as follows.

The annual maximum utilization hours s_{11} denotes the equivalent number of hours required for the load to continuously operate at its maximum load level to consume the entire year's electrical energy. A larger s_{11} indicates a greater potential of the load acting as a flexible load, and the specific formula is as follows:

$$s_{11} = \frac{Q_{\text{year}}}{P_{\text{year,max}}} \quad (\text{A36})$$

where Q_{year} is the annual electricity consumption; $P_{\text{year,max}}$ is the maximum power consumption of the load.

The load volatility rate s_{12} reflects the dispersion degree of the load on a temporal scale. A more dispersed load electricity consumption implies a stronger potential for peak-shifting, which translates to a greater potential of the load acting as a flexible load. The specific formula is as follows:

$$s_{12} = \frac{\sigma_{\text{load}}}{\mu_{\text{load}}} \quad (\text{A37})$$

where σ_{load} and μ_{load} are the standard deviation and the mean value of the typical daily load curve, respectively.

The peak-valley difference rate refers to the proportion of the difference between the maximum and minimum loads of a typical daily load curve to the maximum load. The specific formula is shown as follows:

$$s_{13} = \frac{(P_{\text{load,max}} - P_{\text{load,min}})}{P_{\text{load,max}}} \quad (\text{A38})$$

where $P_{\text{load,max}}$ and $P_{\text{load,min}}$ are the maximum load and minimum load of the typical daily load curve, respectively.

Appendix A.3.2. Load Peak-Shaving Characteristics s_2

The load peak-shaving characteristics s_2 are used to evaluate the contribution degree of the load's electricity consumption to the system peak load. The calculation formulas for each indicator are as follows.

The peak-time load difference coefficient s_{21} reflects the contribution degree of users to driving the formation of the entire grid's peak load. The calculation formula is:

$$s_{21} = \bar{P}_{\text{load}, t_{\text{peak}}} - \bar{P}_{\text{load}} \quad (\text{A39})$$

where $\bar{P}_{\text{load}, t_{\text{peak}}}$ is the average value of the load during peak periods; $\bar{P}_{\text{load}}$ is the daily average value of the load.

The load peak-shaving correlation coefficient s_{22} is used to measure the consistency degree between the user load curve and the system load curve. A larger s_{22} indicates a lower degree of consistency, which implies a smaller potential for indirect energy storage. The calculation formula is:

$$s_{22} = \frac{\sum_{t=1}^T (P_{\text{load}, t} - \bar{P}_{\text{load}}) (P_{\text{sys}, t} - \bar{P}_{\text{sys}})}{\sqrt{\sum_{t=1}^T (P_{\text{sys}, t} - \bar{P}_{\text{sys}})^2}} \quad (\text{A40})$$

where $P_{\text{load}, t}$ is the active power value of the load during time interval t ; $P_{\text{sys}, t}$ is the active power value of the system during time interval t ; $\bar{P}_{\text{sys}}$ is the average active power value of the system.

The load peak ratio s_{23} is used to measure the ratio of the peak-period load to the total daily load. A larger s_{23} indicates a greater regulation potential of the load during peak periods. The calculation formula is:

$$s_{23} = \frac{\sum_{t=t_{\text{st}}}^{t_{\text{end}}} P_{\text{load}, t}}{\sum_{t=1}^T P_{\text{load}, t}} \quad (\text{A41})$$

Appendix A.3.3. Load Behavior Characteristics s_3

The load behavior characteristics s_3 are used to evaluate the responsiveness of the load to the unified CDL of the grid. It includes three indicators: the task completion degree s_{31} , the task completion timeliness s_{32} , and the electricity consumption regularity coefficient s_{33} . The specific expression for the electricity consumption regularity coefficient is as follows.

A smaller electricity consumption regularity coefficient s_{33} indicates a smoother load curve, implying that this type of user has a more regular electricity consumption pattern that is not easily changed; therefore, the potential for indirect energy storage is smaller. The specific formula is shown as follows:

$$s_{33} = \frac{1}{\left(-\sum_{t=1}^T P'_{\text{load}, t} \ln P'_{\text{load}, t} \right)} \quad (\text{A42})$$

where $P'_{\text{load}, t}$ is the per-unit value of the load during time interval t .

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