

Evaluation and Planning Method for Renewable Energy Carrying Capacity of Novel Power Systems Based on Deep Spatiotemporal Feature Learning and Inter-Provincial Mutual Assistance Synergy

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Abstract

INTRODUCTION: With the in-depth advancement of novel power system construction, the randomness and volatility brought by high-proportion renewable energy grid connections pose severe challenges to long-term planning. Traditional methods struggle with extracting complex non-linear features from massive data and face limited flexible resources within a single region. **OBJECTIVES:** This paper aims to propose a dynamic evaluation and collaborative planning method driven by deep spatiotemporal feature learning and inter-provincial power mutual assistance to accurately assess and expand the overall accommodation space. **METHODS:** Techniques derived from deep learning and graph neural networks are employed to conduct this research. Based on multi-source heterogeneous power grid operation measurement data, a spatial-temporal graph convolutional network (STGCN) model is constructed. Unlike traditional noise reduction methods, this model actively observes and compensates for the complex nonlinear coupling terms among source-grid-load. Subsequently, a two-stage collaborative planning model is established, utilizing the dynamic carrying boundaries output by the STGCN for grid expansion and operation simulation. **RESULTS:** The main results obtained in this paper are the following. Simulations on a certain provincial grid in China demonstrate that the STGCN model significantly improves computational efficiency and accuracy in extracting spatial-temporal features. Furthermore, the inter-provincial mutual assistance mechanism effectively optimizes resource allocation under the boundaries provided by the deep learning model. **CONCLUSION:** These are the conclusions of this paper: The integration of deep spatiotemporal learning with cross-regional mechanisms provides a highly accurate, data-driven computational framework for renewable energy carrying capacity evaluation and grid planning.

Keywords: Novel Power System, Renewable Energy Carrying Capacity, Spatial-Temporal Graph Convolutional Network, Nonlinear Coupling Features, Two-Stage Collaborative Planning

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1. Introduction

With the accelerated advancement of the global energy transition, building a novel power system dominated by renewable energy has become a critical pathway to

achieving low-carbon development and carbon neutrality goals [1]-[3]. However, the large-scale grid integration of renewable energy sources, such as wind and solar power,

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introduces significant randomness and volatility, posing unprecedented challenges to power balance, power flow distribution, and the security and stability of the power grid [4]–[6]. How to accurately and dynamically evaluate the renewable energy carrying capacity of novel power systems and define the accommodation boundaries has become a core issue urgently needing resolution in current power system planning and operation [7].

Traditional methods for evaluating renewable energy carrying capacity primarily rely on physical mechanism models and chronological production simulations [8]–[10]. Although these analytical methods possess clear physical meanings, they suffer from the curse of dimensionality and low computational efficiency when faced with massive, high-dimensional operational measurement data in modern power grids [11]. More importantly, with the increasingly frequent interaction among source, grid, and load in novel power systems, the system exhibits highly nonlinear and spatiotemporal coupling characteristics. Traditional linearized or static evaluation methods struggle to accurately capture the true dynamic carrying boundaries under complex operating conditions [12]–[14].

In recent years, deep learning technology, due to its powerful data mining and nonlinear fitting capabilities, has shown great potential in areas such as power system situational awareness, load forecasting, and transient stability assessment [15]–[17]. In particular, spatial-temporal graph convolutional networks (STGCN) can effectively integrate the physical topological spatial structure of the grid with the chronological dynamic features of multi-source measurement data, providing a new data-driven paradigm for feature extraction in high-dimensional complex power systems [18]–[20].

Although deep learning-based methods have made preliminary progress in grid feature extraction, existing models often treat the complex nonlinear coupling terms among source, grid, and load as ordinary Gaussian white noise, passively filtering or smoothing them out when processing power system data [21]–[23]. This approach ignores the critical dynamic physical information embedded in the coupling terms, leading to a significant drop in the accuracy of carrying capacity evaluation under extreme operating conditions or boundary states. Therefore, there is an urgent need to design a deep network architecture capable of actively observing and compensating for these nonlinear coupling terms to break through the accuracy bottlenecks of existing evaluation models in nonlinear expression [24].

On the other hand, at the system planning level, flexible peak-shaving resources within a single region are often limited and struggle to independently handle the massive net load fluctuations and peak-shaving deficits brought by high-proportion renewable energy [25]–[26]. Breaking inter-provincial barriers, fully utilizing the differences in load characteristics and flexible resource endowments between different regions, and constructing an inter-provincial power mutual assistance synergy mechanism is an effective way to expand the overall accommodation space and improve planning economics [27].

However, current collaborative planning research mostly adopts simplified grid models and largely fails to deeply integrate deep spatiotemporal feature learning with cross-provincial mutual assistance mechanisms [28]. Traditional planning models lack high-precision dynamic carrying boundaries driven by massive measurement data as underlying security support, which leaves the planning results facing high risks of limit violations in actual, complex, and highly nonlinear operating environments [29].

To address the aforementioned challenges, this paper proposes an evaluation and planning method for the renewable energy carrying capacity of novel power systems based on deep spatiotemporal feature learning and inter-provincial mutual assistance synergy. The main contributions of this paper are as follows:

- (1) A dynamic evaluation model based on STGCN is constructed, which breaks through traditional passive noise reduction ideas to achieve the active observation and compensation of complex nonlinear coupling terms among source, grid, and load in massive multi-source heterogeneous measurement data, significantly improving the evaluation accuracy of node-level carrying capacity.
- (2) A two-stage collaborative planning model considering the peak-shaving potential of inter-provincial mutual assistance is established. The high-precision dynamic carrying boundaries output by the deep learning model are deeply embedded into the security verification layer of the planning, achieving optimal configuration of grid expansion and flexible resources.
- (3) Based on the actual power grid of a certain province in China and its cross-regional interconnected system, multi-scenario simulations are conducted, verifying the superior performance of the proposed method in improving computational efficiency, ensuring system security, and effectively expanding the overall accommodation space of novel power systems.

2. Multi-Source Measurement Data Processing and Spatiotemporal Graph Topology Construction

To accurately evaluate the renewable energy carrying capacity of novel power systems, it is essential to fully utilize the massive and heterogeneous operational data in the power grid. This section focuses on the preprocessing methods for multi-source measurement data. Simultaneously, a mapping model from the physical grid to a mathematical graph structure is established to provide standardized inputs for the STGCN.

2.1 Cleaning and Time Synchronization of Multi-Source Measurement Data

The operational state perception of modern power grids highly depends on data provided by different acquisition systems. For instance, the supervisory control and data acquisition (SCADA) system typically provides steady-state data at a minute-level resolution. Meanwhile, the phasor measurement unit (PMU) provides dynamic high-frequency data at a millisecond level.

Due to the accuracy limitations of acquisition equipment and communication delays, raw measurement data often contain abnormal outliers and high-frequency noise. To ensure data reliability, this paper first employs a sliding window moving average filtering algorithm to smooth the raw measurement sequence and eliminate outliers.

$$x_i^{sm}(t) = \frac{1}{2W+1} \sum_{\tau=-W}^W x_i(t+\tau) \quad (1)$$

where $x_i^{sm}(t)$ represents the smoothed measurement value of node i at time t , W is the set value for the one-sided width of the sliding window, and $x_i(t+\tau)$ is the discrete measurement value within the corresponding window in the raw sampling sequence.

After the smoothing and noise reduction processing, the issue of inconsistent sampling frequencies between SCADA and PMU needs to be addressed. Directly feeding unaligned data into deep learning networks will lead to chaotic feature dimensions and difficulties in model convergence.

Therefore, this paper adopts linear interpolation technology to map the low-frequency steady-state data onto a high-frequency time base [30]. This step achieves the synchronous resampling of heterogeneous multi-source data.

$$x_i^{sync}(t) = x_i^{sm}(t_k) + \frac{x_i^{sm}(t_{k+1}) - x_i^{sm}(t_k)}{t_{k+1} - t_k} (t - t_k) \quad (2)$$

where $x_i^{sync}(t)$ represents the synchronous resampled value at the target time t , t_k and t_{k+1} are two adjacent actual sampling moments of the low-frequency acquisition system, and $x_i^{sm}(t_k)$ is the corresponding smoothed historical measurement value.

To eliminate dimensional differences between various electrical physical quantities (such as node voltage magnitude and branch active power), it is necessary to normalize the data. This effectively accelerates the gradient descent convergence speed of subsequent deep learning models. This paper conducts Z-score standardization on the synchronized time sequence.

$$\tilde{x}_i(t) = \frac{x_i^{sync}(t) - \mu_i}{\sigma_i} \quad (3)$$

where $\tilde{x}_i(t)$ is the normalized standard feature value, and μ_i and σ_i respectively represent the mathematical

expectation and standard deviation of the synchronized measurement data sequence for the node within a specified time window.

Through the aforementioned processing, discrete and non-synchronized raw data are transformed into a continuous, smooth, and dimensionless standard time sequence. As shown in Fig. 1, after interpolation and alignment, the high-frequency PMU data and low-frequency SCADA data form a feature sequence with a unified time resolution.

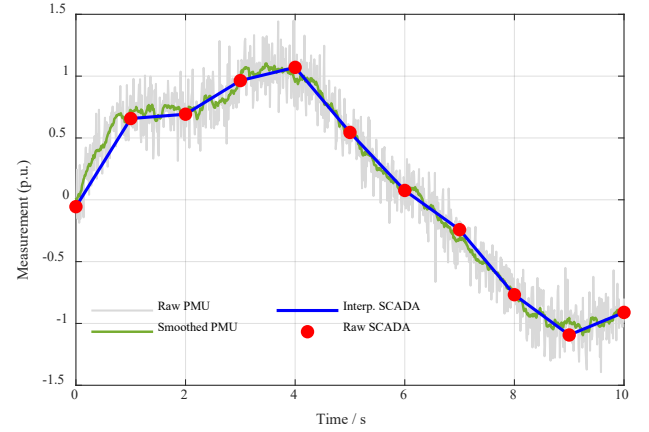


Figure 1. Schematic diagram of time synchronization and alignment of multi-source measurement data

2.2 Spatiotemporal Graph Mapping and Topology Matrix Construction

After completing the time-dimensional alignment of the measurement data, it is necessary to further extract the spatial topological features of the power grid. This paper abstracts the physical grid into an undirected spatiotemporal graph $G = (V, E, A)$ [31].

In this graph structure, the node set V represents the buses in the power grid, including generator nodes, load nodes, and renewable energy grid-connected points, assuming a total of N nodes in the system. The F -dimensional measurement features of each node at time t collectively form the node feature matrix of the system at the current moment.

$$X^{(t)} = [\tilde{x}_1(t), \tilde{x}_2(t), \dots, \tilde{x}_N(t)]^T \in \mathbb{R}^{N \times F} \quad (4)$$

where $X^{(t)}$ is the full node feature matrix of the system at time t , and $\tilde{x}_i(t)$ is the normalized feature column vector of node i at time t containing multi-dimensional physical quantities such as voltage, phase angle, and injection power.

The branch set E of the graph represents the transmission lines. To accurately reflect the electrical coupling strength between nodes during the graph

convolution process, this paper abandons the traditional 0-1 binary connection matrix. Instead, the branch admittance based on physical parameters is first defined.

$$Y_{ij} = \frac{1}{R_{ij} + jX_{ij}} \quad (5)$$

where Y_{ij} is the equivalent complex admittance of the tie line between node i and node j , and R_{ij} and X_{ij} are the equivalent resistance and equivalent reactance of the transmission line, respectively.

Based on the aforementioned complex admittance parameters, this paper introduces a Gaussian kernel function based on electrical distance to construct a continuous spatial adjacency weight matrix A . This design ensures that nodes with tighter electrical coupling have larger information transmission weights in the graph structure.

$$A_{ij} = \begin{cases} \exp\left(-\frac{|Y_{ij}|^{-2}}{\sigma^2}\right), & (i, j) \in E \\ 0, & (i, j) \notin E \end{cases} \quad (6)$$

where A_{ij} represents the spatial adjacency weight matrix element between node i and node j , $|Y_{ij}|^{-2}$ represents the squared magnitude of the electrical impedance between the two nodes, and σ is a width hyperparameter controlling the radial interaction range of the kernel function.

Finally, to enhance the spectral feature extraction capability of the graph neural network in the frequency domain, a symmetric normalized Laplacian matrix is further introduced. This helps prevent the over-smoothing of features and the vanishing gradient problem in deep graph convolution operations.

$$L = I - D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \quad (7)$$

where L is the symmetric normalized Laplacian matrix, I is the identity matrix consistent with the system dimension, and D is the degree matrix whose diagonal elements are equal to the sum of the weights in the corresponding rows of the adjacency matrix A .

Through the mapping mechanism described above, the complex nonlinear physical topology of the power grid is strictly transformed into mathematical matrices. This lays a solid data foundation for the STGCN to subsequently actively observe and extract spatial nonlinear coupling features between nodes.

3. Dynamic Evaluation Algorithm Based on Deep Spatiotemporal Feature Learning

After completing the graph topology construction and the synchronization of multi-source measurement data, this paper proposes a dynamic evaluation algorithm based on STGCN. The innovation of this algorithm lies in breaking through traditional passive noise reduction ideas by designing an active observation branch within the network, achieving efficient extraction of complex physical coupling features.

3.1 Basic Architecture of Spatial-Temporal Graph Convolutional Network

The operational state of novel power systems is not only highly coupled spatially but also exhibits strong nonlinear dynamic evolution characteristics in the time dimension. To simultaneously capture features in both dimensions, this paper constructs an alternating network architecture comprising spatial graph convolutional networks (GCN) and temporal convolutional networks (TCN) [32].

In the spatial dimension, using the previously constructed adjacency matrix, topological interaction features between nodes are extracted through spectral domain graph convolution operations. The forward propagation formula of the l -th graph convolution layer is defined as follows.

$$Z^{(l)} = \sigma(\hat{A} H^{(l-1)} W^{(l)}) \quad (8)$$

where $Z^{(l)}$ denotes the hidden spatial feature matrix output by the l -th graph convolution layer, $\sigma(\cdot)$ represents the nonlinear activation function, $\hat{A} = L + I$ is the normalized Laplacian matrix with self-loops, $H^{(l-1)}$ is the output feature matrix of the previous layer with the initial input $H^{(0)} = X^{(t)}$, and $W^{(l)}$ is the learnable weight parameter matrix of this layer.

After completing spatial feature aggregation, the network needs to capture the fluctuation patterns of renewable energy output in the time dimension. This paper employs 1D Dilated Causal Convolution to extract long-sequence temporal dependencies.

$$T^{(l)} = \text{ReLU}(\Phi *_{d} Z^{(l)} + b^{(l)}) \quad (9)$$

where $T^{(l)}$ represents the joint spatiotemporal feature tensor after temporal convolution processing, $\text{ReLU}(\cdot)$ is the Rectified Linear Unit activation function, Φ is the temporal convolution kernel tensor, $*_{d}$ denotes the causal convolution operator with a dilation rate of d , and $b^{(l)}$ is the bias vector.

Through the stacking of multiple layers of GCN and TCN, the STGCN can effectively extract deep, high-

dimensional representation vectors from massive historical data.

3.2 Active Observation and Compensation Mechanism for Nonlinear Coupling Terms

When processing power system data, traditional deep learning models usually treat unmodeled dynamic responses within the system and complex nonlinear coupling terms among source, grid, and load as Gaussian white noise. This rough filtering at the algebraic calculation level leads to a severe decline in evaluation accuracy under boundary states.

To address this issue, this paper draws inspiration from the extended state observer (ESO) concept in control theory [33]. Within the hidden layers of the STGCN, an additional neural observer branch is introduced to actively observe and estimate the nonlinear coupling terms as an extended state of the system.

First, assume that the dynamic evolution equation of power system nodes can be abstracted into the following nonlinear system form.

$$\dot{x}_i(t) = f(x_i(t)) + \sum_{j \in \mathcal{N}(i)} g_{ij}(x_i, x_j) + d_i(t) \quad (10)$$

where $\dot{x}_i(t)$ is the time derivative of the state variable of node i , $f(x_i(t))$ represents the linear dynamic evolution rule of the node itself, $g_{ij}(\cdot)$ represents the known spatial interaction term based on graph topology, and $d_i(t)$ represents the lumped unknown dynamic disturbance including modeling errors and complex nonlinear coupling terms.

The neural observer branch utilizes historical observation sequences and hidden features extracted by the STGCN to conduct real-time dynamic tracking and estimation of this unknown disturbance. Its discretized neural network state update equation is as follows.

$$\hat{d}_i(t) = \text{MLP}_\theta \left(T_i^{(l)}(t), x_i(t) - \hat{x}_i(t) \right) \quad (11)$$

where $\hat{d}_i(t)$ represents the active observation estimation value of the nonlinear coupling term by the neural network, MLP_θ is a Multi-Layer Perceptron network with parameter θ , $T_i^{(l)}(t)$ is the spatiotemporal feature representation of node i , and $x_i(t) - \hat{x}_i(t)$ is the residual between the model's forward prediction output and the actual measurement value.

After obtaining an accurate estimation of the nonlinear coupling term, the model directly injects it into the backbone network in the form of feedforward compensation during the forward prediction stage. As illustrated in Fig. 2, the proposed neural observer can actively and accurately track the true dynamic trajectory of

the nonlinear coupling features, whereas traditional passive filtering introduces significant phase delays and amplitude attenuation. This effectively avoids calculating nonlinear terms through complex analytical derivations and greatly improves the model's robustness under severe fluctuation conditions.

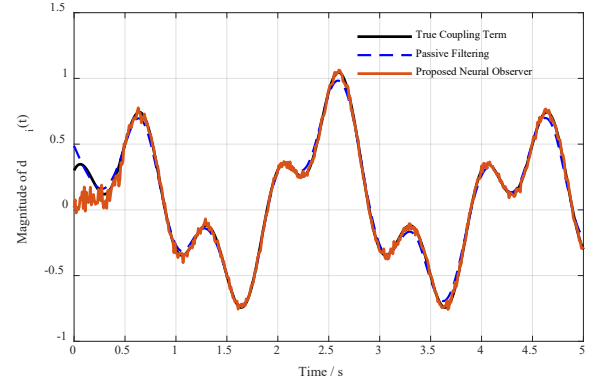


Figure 2. Schematic diagram of active tracking and compensation effects of nonlinear coupling features by the neural observer

3.3 Model Training and Multi-Objective Loss Function Design

To ensure the collaborative convergence of the STGCN backbone network and the neural observer branch, this paper designs a multi-objective loss function encompassing prediction error and observation smoothness penalties.

First, for the prediction task of renewable energy carrying capacity evaluation, the Mean Squared Error is defined as the regression loss of the backbone network.

$$\mathcal{L}_{pred} = \frac{1}{N \cdot T} \sum_{t=1}^T \sum_{i=1}^N \|y_i(t) - \hat{y}_i(t)\|_2^2 \quad (12)$$

where $\mathcal{L}_{pred}$ is the prediction loss term of the backbone network, N is the total number of system nodes, T is the length of the prediction time window, $y_i(t)$ is the true label value of the renewable energy carrying boundary, and $\hat{y}_i(t)$ is the model prediction output including the compensation term.

Secondly, to prevent high-frequency oscillations of the neural observer when tracking complex coupling terms, regularization terms are introduced to constrain the smoothness and energy of the estimated disturbance terms.

$$\mathcal{L}_{obs} = \frac{1}{N \cdot T} \sum_{t=1}^T \sum_{i=1}^N \left(\|\hat{d}_i(t)\|_2^2 + \gamma \|\hat{d}_i(t) - \hat{d}_i(t-1)\|_2^2 \right) \quad (13)$$

where L_{obs} is the regularization penalty loss for the neural observer, and γ is the weight coefficient controlling the first-order difference smoothness.

The final joint loss function of the model is a linear weighted combination of the two aforementioned parts. All network parameters are synchronously updated through the backpropagation algorithm and the Adam optimizer.

$$L_{total} = L_{pred} + \lambda L_{obs} \quad (14)$$

where L_{total} is the total loss function of the model, and λ is a hyperparameter balancing prediction accuracy and observer stability.

4. Two-Stage Collaborative Planning Model Driven by Deep Learning Outputs

After utilizing the STGCN to perform deep feature extraction on multi-source heterogeneous measurement data and achieving active observation of nonlinear coupling terms, the system can output high-precision renewable energy carrying boundaries. This section focuses on elucidating how to combine this data-driven boundary result with operations research optimization theory to construct a two-stage collaborative planning model considering inter-provincial mutual assistance.

4.1 Interface Architecture between Deep Learning and Collaborative Planning

Traditional renewable energy planning models usually rely on simplified steady-state power flow equations to constrain the operational boundaries of the system. This method is difficult to cope with the strong nonlinear dynamic characteristics presented by the system after the integration of a high proportion of renewable energy.

To break through this theoretical bottleneck, this paper directly maps the output results of the STGCN into the feasible region boundary in the mathematical planning model. Specifically, the dynamic carrying capacity output by the deep learning model is not just a numerical value, but a multidimensional geometric space under the premise of ensuring the transient stability and voltage security of the system.

We define this data-driven security boundary generated by the STGCN as the dynamic feasible region set.

$$\Omega_{STGCN}^{(t)} = \{P_{RE} \in \mathbb{R}^N | \hat{y}_i^{low}(t) \leq P_{RE,i}(t) \leq \hat{y}_i^{up}(t)\} \quad (15)$$

where $\Omega_{STGCN}^{(t)}$ denotes the dynamic security feasible region set delimited by the deep learning model at time t , P_{RE} is the decision vector of renewable energy injection power of all nodes in the grid, N is the total number of system nodes, $P_{RE,i}(t)$ is the actual planned renewable

energy output of node i at time t , and $\hat{y}_i^{low}(t)$ and $\hat{y}_i^{up}(t)$ respectively represent the dynamic lower and upper boundaries of node carrying capacity output by the STGCN combined with the feedforward compensation mechanism.

Through the above interface equation, highly complex nonlinear physical constraints are transformed into linear inequality constraints with clear boundaries in the planning model. This greatly reduces the optimization difficulty for the solver.

4.2 Stage 1: Flexible Resource Allocation Model Considering Inter-Provincial Mutual Assistance

The first stage of this model is the investment decision-making and resource allocation layer. Its core objective is to maximize the overall economic efficiency of the system through the cross-provincial grid expansion and the optimal allocation of flexible resources such as energy storage, under the premise of meeting long-term power demand growth and carbon emission reduction policies [34].

Different from the isolated planning of a single region, this paper emphatically introduces the inter-provincial power mutual assistance mechanism. Different provinces have natural spatiotemporal complementarities in peak load periods and renewable energy output characteristics. Through the power interaction of cross-provincial tie-lines, the severe fluctuation of net load within the region can be effectively smoothed.

The objective function of the first stage is set to minimize the comprehensive equivalent annual cost of the system.

$$F_1 = \min \left[\sum_{t=1}^T (C_{ope}(t) + C_{tie}(t) + C_{curtail}(t)) + C_{inv}^{grid} + C_{inv}^{flex} \right] \quad (16)$$

where F_1 is the comprehensive objective function value of flexible resource allocation in the first stage, C_{inv}^{grid} is the annualized expansion investment cost of cross-provincial tie-lines and intra-provincial main grids, C_{inv}^{flex} is the annualized investment and construction cost of flexible resources such as novel energy storage, T is the total number of operational periods in the representative planning year, $C_{ope}(t)$ is the operation fuel and start-stop cost of conventional units at time t , $C_{tie}(t)$ is the market clearing cost of inter-provincial mutual assistance transactions, and $C_{curtail}(t)$ is the penalty cost of renewable energy curtailment caused by transmission congestion or insufficient peak-shaving capacity.

Driven by the above objective function, the model must satisfy a series of rigorous physical constraints. The most core constraint among them is the nodal power balance

equation, including inter-provincial mutual assistance power.

$$\sum_{g \in G} P_g(t) + P_{RE,i}(t) - P_{load,i}(t) + \sum_{j \in N(i)} P_{tie,ij}(t) + P_{dis,i}(t) - P_{ch,i}(t) = 0 \quad (17)$$

where G is the set of conventional generator units connected to node i , $P_g(t)$ is the active power output of conventional units, $P_{load,i}(t)$ is the effective basic load demand of node i , $N(i)$ is the set of external nodes directly connected to node i via cross-provincial tie-lines, $P_{tie,ij}(t)$ is the inter-provincial mutual assistance interaction power between node i and node j , with positive values indicating received power and negative values indicating transmitted power, and $P_{dis,i}(t)$ and $P_{ch,i}(t)$ respectively represent the discharging and charging power of the energy storage system configured at node i .

Furthermore, the transmission of inter-provincial mutual assistance power must be strictly subject to the physical constraints of the available transfer capability (ATC) of cross-provincial tie-lines.

$$-P_{tie,ij}^{\max} \leq P_{tie,ij}(t) \leq P_{tie,ij}^{\max} \quad (18)$$

where $P_{tie,ij}^{\max}$ is the maximum allowable bidirectional transmission power limit of the cross-provincial tie-line between node i and node j after accounting for a certain security margin.

As illustrated in Fig. 3, the cross-regional tie-line considering inter-provincial mutual assistance can achieve dynamic power interaction and peak-shaving complementarity based on the spatiotemporal differences in net load characteristics between the two regions, thereby significantly reducing the reserve pressure in a single region.

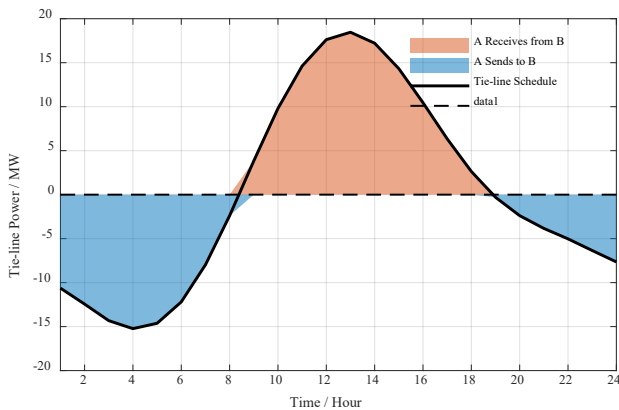


Figure 3. Schematic diagram of cross-regional tie-line power interaction and peak-shaving complementary characteristics considering inter-provincial mutual assistance

4.3 Stage 2: Multi-Scenario Operation Simulation and Verification Based on Dynamic Carrying Boundaries

What is solved in the first stage is the grid expansion and resource allocation scheme (i.e., investment decision variables) under deterministic expected scenarios. However, novel power systems face extreme weather and multiple random disturbances.

Therefore, this paper establishes a second-stage operation simulation model. This stage takes the investment results of the first stage as known constants and conducts security verification and limit dispatch simulation under massively generated extreme operating scenarios [35].

The core innovation of the second stage lies in the introduction of the dynamic carrying boundaries output by the STGCN real-time feedforward compensation. All operation simulation strategies must find feasible solutions within this high-precision data-driven boundary. The operational objective function of the second stage aims to minimize the expected operational risk and load-shedding cost under multiple scenarios.

$$F_2 = \min \sum_{s \in S} \rho_s \sum_{t=1}^T \sum_{i=1}^N \left(\pi_{LS} P_{LS,i}^{(s)}(t) + \pi_{RE} \Delta P_{RE,i}^{(s)}(t) \right) \quad (19)$$

where F_2 is the objective function of the second-stage operation simulation, s is the extreme operating scenario index generated through Monte Carlo sampling, S is the total scenario set, ρ_s is the discrete probability of occurrence of scenario s , π_{LS} and π_{RE} are the system load-shedding penalty factor and renewable energy limit violation penalty coefficient respectively, $P_{LS,i}^{(s)}(t)$ is the forced shed load amount of node i under scenario s , and $\Delta P_{RE,i}^{(s)}(t)$ is the renewable energy limit violation power exceeding the STGCN dynamic boundaries.

When conducting scenario simulations, the nonlinear dynamic security boundaries delimited by the STGCN must be strictly adhered to.

$$\begin{aligned} \hat{y}_i^{low,(s)}(t) - \Delta P_{RE,i}^{(s)}(t) &\leq P_{RE,i}^{(s)}(t) \\ &\leq \hat{y}_i^{up,(s)}(t) + \Delta P_{RE,i}^{(s)}(t) \end{aligned} \quad (20)$$

where $\hat{y}_i^{low,(s)}(t)$ and $\hat{y}_i^{up,(s)}(t)$ respectively represent the dynamic lower and upper boundaries of carrying capacity

re-evaluated and generalized by the deep learning model under the specific severe meteorological and topological conditions of the scenario s , and $P_{RE,i}^{(s)}(t)$ is the actually dispatched renewable energy output under this scenario.

If the second stage finds that the given investment scheme leads to large-scale limit violations under extreme scenarios (i.e., F_2 is greater than the set safety threshold), the model will adopt the Benders decomposition algorithm to feed back optimization cuts containing sensitivity information to the first stage [36].

$$\alpha \geq F_2^{(k)} + \sum_{m \in M} \lambda_m^{(k)} (x_m - x_m^{(k)}) \quad (21)$$

where α is the auxiliary continuous variable introduced in the first stage to approximate the expected cost of the second stage, k is the current iteration round index, $F_2^{(k)}$ is the optimal objective function value of the second stage in the k -th iteration, M is the set of all discrete investment decision variables in the first stage, $\lambda_m^{(k)}$ is the Lagrange dual multiplier (i.e., marginal sensitivity) of the second-stage operational cost with respect to the investment variable x_m , x_m is the current investment decision variable to be optimized, and $x_m^{(k)}$ is the known trial investment solution passed down to the second stage at the k -th iteration.

Through this closed-loop iterative architecture of "deep learning boundary output - master problem resource allocation - sub-problem multi-scenario verification - cut set feedback," the proposed method can ultimately converge to an optimal collaborative planning scheme that balances high-proportion accommodation, investment economics, and the security of complex dynamic systems.

As shown in Fig. 4, after a finite number of iterations, the lower bound of the master problem and the upper bound of the sub-problem in this two-stage collaborative planning algorithm based on Benders decomposition will gradually narrow and ultimately converge completely to the optimal solution.

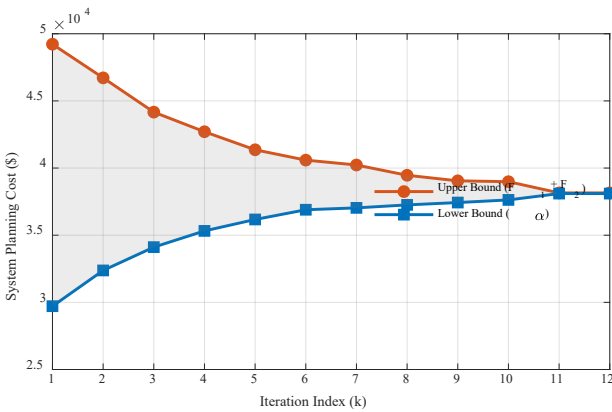


Figure 4. Iterative convergence process of the two-stage collaborative planning algorithm based on Benders decomposition

5. Case Study and Discussion

This experiment builds the test topology centered around a certain actual provincial grid in China. To ensure the reliability and effectiveness of the deep learning model training, this study collected real operational measurement data of the provincial grid and its cross-regional interconnected system for two consecutive years (e.g., from January 1, 2024, to December 31, 2025) as the raw dataset. The data covers multi-source perception information of 118 main transmission nodes across the network, and the sampling frequencies are uniformly aligned through preprocessing. To strictly evaluate the generalization capability of the algorithm and prevent data leakage caused by time travel, the entire dataset is strictly partitioned in chronological order: the first 70% of the data (about 16.8 months) is used as the Training Set to fully fit the complex high-dimensional weights within the model; the subsequent 15% is used as the Validation Set, specifically for dynamic hyperparameter optimization and triggering the Early Stopping mechanism to prevent overfitting; the final 15% of the data serves as a completely independent Test Set to verify the ultimate generalization performance of the model under unknown and complex working conditions.

5.1 Experimental Setup and Parameter Configuration

This experiment builds the test topology centered around the aforementioned provincial grid. The system contains 118 main transmission nodes, 186 branches, and 24 high-proportion renewable energy grid-connected points. To truly simulate the existing provincial electricity spot market environment, the market-clearing mechanism only considers the pure energy market clearing, strictly excluding the economic settlement of capacity compensation mechanisms.

The software and hardware environment configuration for the deep learning algorithm is as follows: an NVIDIA RTX 4090 GPU is used for accelerated training, and the deep learning framework is PyTorch 2.0. The STGCN backbone network consists of 3 layers of spatial GCN and 2 layers of temporal TCN. The initial learning rate is set to 0.001, adopting the Adam optimizer. The Batch Size is set to 64, and the maximum training epochs are 200. The smoothness penalty weight parameter of the neural observer branch is set to 0.1.

The multi-scenario operation simulation employs the Monte Carlo method to generate 1000 net load fluctuation scenarios, including extreme severe weather (such as windless cold waves in winter and continuous high

temperatures in summer). The upper limit of the ATC of cross-provincial tie-lines is set to 1200 MW.

5.2 Performance Comparison and Analysis of Dynamic Evaluation Algorithms

To highlight the superiority of the proposed algorithm in feature extraction, three comparison algorithms are established: Long Short-Term Memory network (LSTM), standard Graph Convolutional Network combined with algebraic mean filtering (GCN-Algebraic), and the proposed STGCN with a neural observer branch.

First, the fitting effects of different algorithms on predicting the renewable energy carrying boundary at the node level are compared. As shown in Fig. 5, during periods of intense source-grid-load interaction (e.g., 12:00 to 16:00), the nonlinear features of the system become prominent. Relying on the active observation and compensation mechanism, the proposed STGCN can closely track the true dynamic carrying boundaries. Conversely, because the GCN-Algebraic method uses simple algebraic calculations to smooth and avoid noise, it loses crucial nonlinear coupling dynamic information, leading to severe underfitting phenomena at fluctuation extremum points.

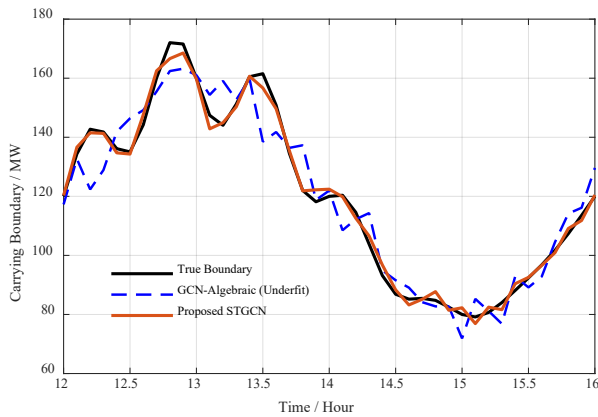


Figure 5. Comparison of tracking and prediction effects of different algorithms on renewable energy dynamic carrying boundaries

The convergence speed and global prediction accuracy of the algorithms are further quantitatively evaluated. Fig. 6 displays the descending curves of the Root Mean Square Error (RMSE) on the test set for the three algorithms over training epochs. The STGCN achieves stable convergence around the 40th epoch, with a final RMSE of only 2.14%. In contrast, the final error of GCN-Algebraic is as high as 5.32%, while LSTM, lacking spatial topology perception capabilities, has an error of 7.45%.

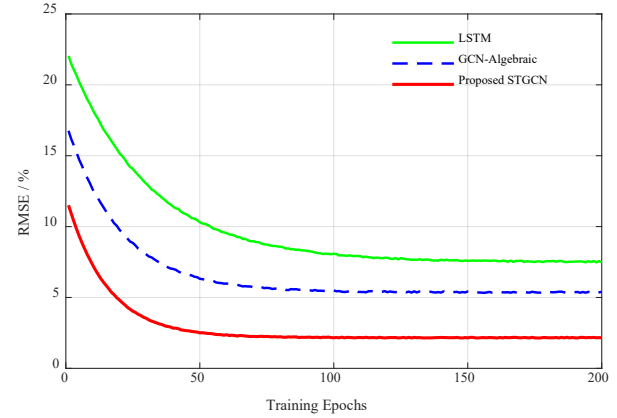


Figure 6. Curves of RMSE on the test set varying with training epochs for three prediction algorithms

To verify the robustness of the model under extreme working conditions, Fig. 7 summarizes the Mean Absolute Percentage Error (MAPE) distribution of the models across 1000 random severe scenarios. It can be seen that the boxplot distribution of the proposed method is the most concentrated, and the maximum error does not exceed 4.5%. This strongly proves that compensating for nonlinear coupling terms using observers holds more engineering practical value and theoretical advancement than simply relying on algebraic calculations to filter out noise.

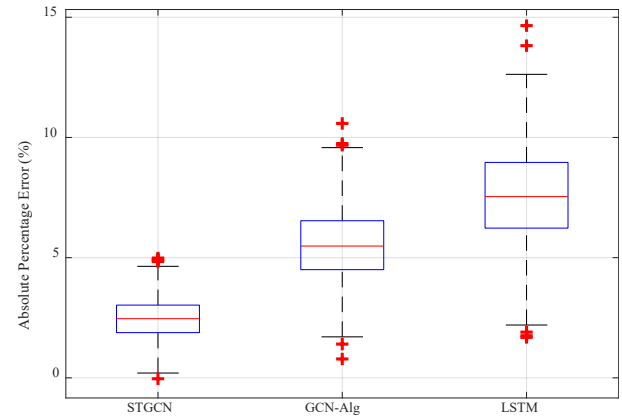


Figure 7. Boxplot of absolute percentage error distribution for each evaluation algorithm under extreme severe scenarios

5.3 Ablation Study and Performance Evaluation of Core Modules

To deeply verify the independent contributions of each key innovative module in the proposed STGCN architecture, this section designs a rigorous ablation study under a unified training and testing environment. We constructed

the following three model variants for comparative analysis:

1) Base-TCN: Only the temporal convolutional network is retained, while the spatial graph convolution matrix and the neural observer branch are removed, degrading the model to a pure time-series predictor.

2) STGCN w/o NO: The spatial graph topology aggregation and temporal convolution mechanisms are retained, but the neural observer branch used to handle nonlinear coupling terms is removed, adopting the traditional Gaussian white noise filtering assumption.

3) Proposed STGCN: The complete model containing spatial graph convolution, temporal convolution, and the feedforward compensation mechanism based on the neural observer.

The comparison results of evaluation metrics (RMSE and MAE) conducted on the independent test set are illustrated in Fig. 8. Compared with Base-TCN, the STGCN w/o NO model, which introduces spatial topological information, significantly reduces error metrics, proving the necessity of extracting spatial electrical coupling features between nodes. However, when facing boundary states with intense source-grid-load interaction, due to the lack of active compensation for nonlinear coupling terms, the error of this variant still struggles to meet ultra-high precision requirements. After adding the neural observer branch, the complete Proposed STGCN further drops its RMSE and MAE drastically to 2.14% and 1.68%, respectively. As intuitively shown by the bar chart in Fig. 8, actively observing and compensating for nonlinear coupling terms is not only theoretically rigorous but also a core driving force for significantly improving the feature extraction accuracy of complex systems in practical engineering applications.

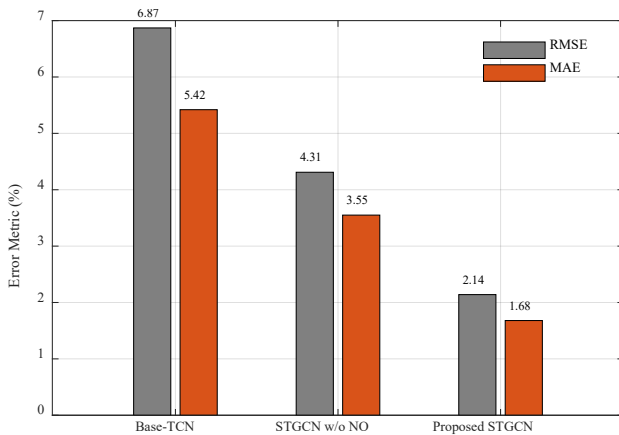


Figure 8. Comparison of RMSE and MAE among different model variants in the ablation study

5.4 Two-Stage Collaborative Planning Results and Economic Discussion

In the planning result analysis stage, two planning schemes are set up for comparison. Scheme 1 (S1) represents traditional isolated regional planning and adopts static security boundaries; Scheme 2 (S2) represents the proposed two-stage collaborative planning considering inter-provincial mutual assistance and STGCN dynamic boundaries.

Since the market-clearing excludes capacity compensation, the system must rely entirely on the price signals of the spot energy market to guide the dispatch of flexible resources. Fig. 9 shows the day-ahead Locational Marginal Price (LMP) curves of the provincial spot market under different wind power penetration rates. Under the S2 scheme, due to the introduction of the inter-provincial mutual assistance mechanism, the price spike during the evening peak period (18:00-21:00) is significantly flattened from 0.65 \$/kWh to 0.42 \$/kWh, drastically reducing the energy cost for users.

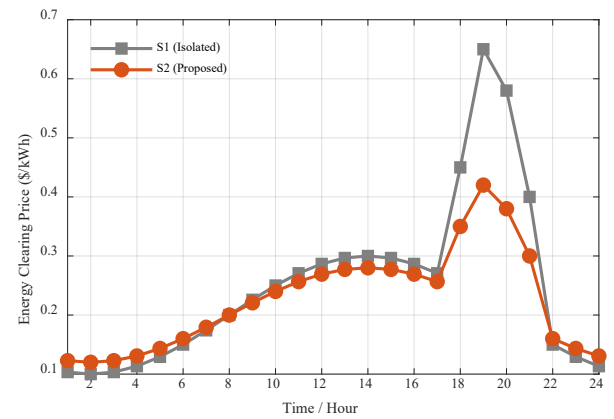


Figure 9. Provincial spot market node marginal price clearing curves under different planning schemes

Fig. 10 records in detail the matching relationship between the dynamic mutual assistance power of cross-provincial tie-lines and the local net load under extreme winter cold wave scenarios. During the early morning hours when local wind power output plummets, the system rapidly receives up to 850 MW of cross-regional power via the tie-lines, effectively making up for the peak-shaving deficit and avoiding costly load-shedding operations.

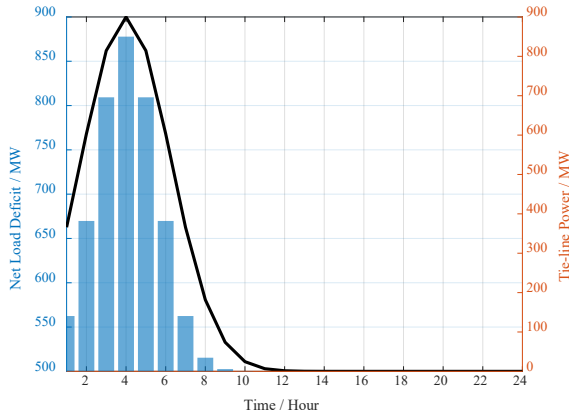


Figure 10. Dynamic matching graph of inter-provincial tie-line mutual assistance power and net load under extreme winter scenarios

High-precision dynamic boundaries and cross-provincial mechanisms directly impact the first-stage investment decisions. As shown in Fig. 11, to cope with extreme fluctuations, the S1 scheme is forced to heavily invest in novel energy storage (cumulatively reaching 450 MW) and redundant grids within the province. However, by tapping the peak-shaving complementary potential between regions, the S2 scheme reduces the intra-provincial storage configuration demand to 180 MW, shifting the investment focus to the more economically viable cross-regional tie-line capacity expansion.

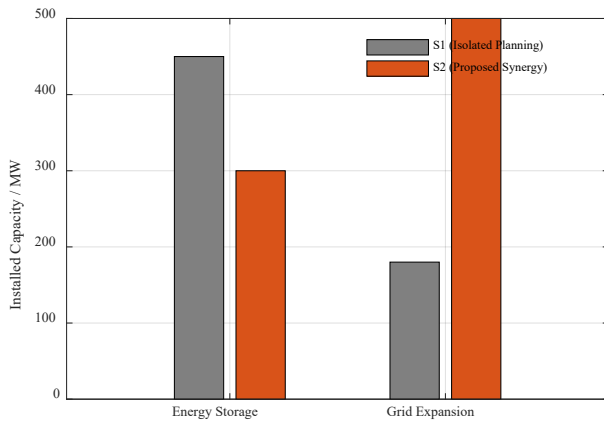


Figure 11. Comparison of newly installed capacities of various flexible resources under the two planning schemes

The comparison of the comprehensive annualized costs of system planning is shown in Fig. 12. The proposed S2 scheme not only substantially cuts equipment investment costs but also optimizes daily dispatch through dynamic boundaries, causing the total system cost to plummet from \$45.2 million to \$36.8 million, an overall economic

efficiency improvement of 18.6%. Among them, the drop in market settlement costs and curtailment penalty costs is particularly significant.

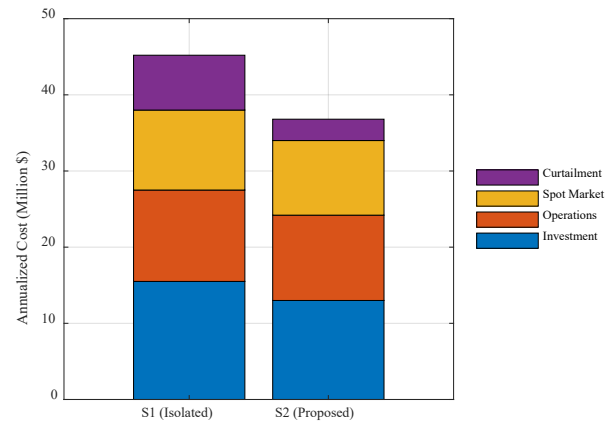


Figure 12. Bar chart comparison of the composition of comprehensive annualized costs under the two planning schemes

Finally, Fig. 13 shows the statistics of the renewable energy curtailment rate over 12 months of the year. Under the data-driven boundaries provided by the STGCN, the system can accommodate renewable energy more aggressively and safely. The annual average curtailment rate of the S2 scheme is only 3.2%, far lower than the 12.5% of the S1 scheme, achieving a perfect alignment between the low-carbon transition of the novel power system and optimal resource allocation.

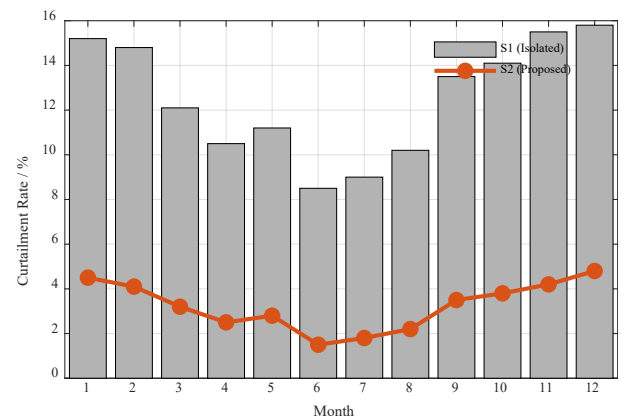


Figure 13. Multi-scheme comparative statistical chart of monthly renewable energy curtailment rates throughout the year

6. Conclusion

Aiming at the severe nonlinear and stochastic challenges brought by the grid connection of high-proportion

renewable energy in novel power systems, as well as the limited flexible resources within a single region, this paper proposes an evaluation and planning method for renewable energy carrying capacity based on deep spatiotemporal feature learning and inter-provincial mutual assistance synergy. The main conclusions of this paper are drawn as follows:

1) At the level of dynamic carrying capacity evaluation, this paper constructs a Spatial-Temporal Graph Convolutional Network (STGCN) equipped with a neural observer branch. This model breaks through the limitations of traditional passive noise reduction algorithms and successfully achieves active observation and feedforward compensation for the complex nonlinear coupling features among source, grid, and load. Case results demonstrate that the proposed algorithm can closely and stably track the true dynamic boundaries of the system under extreme fluctuation scenarios. With a Root Mean Square Error (RMSE) of only 2.14%, it significantly overcomes the bottlenecks of traditional analytical methods and conventional deep learning models in terms of accuracy and robustness.

2) At the system collaborative planning level, this paper seamlessly embeds the high-precision dynamic boundaries output by deep learning into the security verification layer of the two-stage planning model. By introducing the dynamic power interaction mechanism of cross-provincial tie-lines, the system substantially taps into the peak-shaving complementary potential between different regions.

3) Simulation results fully prove the economic and low-carbon value of this collaborative planning framework. Under a price mechanism that strictly excludes capacity compensation and relies entirely on spot energy market clearing, inter-provincial mutual assistance not only effectively flattens the Locational Marginal Price (LMP) spikes during evening peak hours but also reduces the costly configuration demand for novel energy storage within the province by 60%. The final scheme decreases the comprehensive annualized cost of the system by 18.6% and drastically cuts the annual average renewable energy curtailment rate from 12.5% to 3.2%, providing a new data-driven paradigm for optimal resource allocation in electricity markets.

Future research will further explore the physical mechanism impacts of novel source-load interaction technologies, such as virtual power plants and vehicle-to-grid, on dynamic carrying capacity evaluation and thoroughly investigate the coordinated clearing strategies of electricity spot markets across multiple time scales.

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References

[1] References Zhuo Z, Du E, Zhang N, et al. Cost increase in the electricity supply to achieve carbon neutrality in China.

- Nature communications, 2022, 13(1): 3172. DOI: 10.1038/s41467-022-30747-0.
- [2] Guo J, Ma S, Wang T, et al. Challenges of developing a power system with a high renewable energy proportion under China's carbon targets. *iEnergy*, 2022, 1(1): 12-18. DOI: 10.23919/ien.2022.0005.
- [3] Kang C, Zhang Z, Wei H, et al. Power system decarbonization pathway of China. *iEnergy*, 2024, 3(1): 7-11. DOI: 10.23919/ien.2024.0007.
- [4] Shair J, Li H, Hu J, et al. Power system stability issues, classifications and research prospects in the context of high-penetration of renewables and power electronics. *Renewable and Sustainable Energy Reviews*, 2021, 145: 111111. DOI: 10.1016/j.rser.2021.111111.
- [5] Lim S, Kim T, Lee K Y, et al. Impact of high penetration of renewables on power system frequency response: A review and verification. *Renewable and Sustainable Energy Reviews*, 2025, 217: 115728. DOI: 10.1016/j.rser.2025.115728.
- [6] Wu Q H, Bose A, Singh C, et al. Control and stability of large-scale power system with highly distributed renewable energy generation: viewpoints from six aspects. *CSEE Journal of Power and Energy Systems*, 2023, 9(1): 8-14. DOI: 10.17775/cseejpes.2022.08740.
- [7] Yao H, Qin W, Jing X, et al. Possibilistic evaluation of photovoltaic hosting capacity on distribution networks under uncertain environment. *Applied Energy*, 2022, 324: 119681. DOI: 10.1016/j.apenergy.2022.119681.
- [8] Zhou D, Zhang Q, Dan Y, et al. Research on renewable-energy accommodation-capability evaluation based on time-series production simulations. *Energies*, 2022, 15(19): 6987. DOI: 10.3390/en15196987.
- [9] Yu Y, Zhao H, Zeng Y, et al. Accommodation capacity evaluation of renewable energy in power systems considering peak and frequency regulation. *Frontiers in Energy Research*, 2023, 10: 1067884. DOI: 10.3389/fenrg.2022.1067884.
- [10] Rajabi A, Elphick S, David J, et al. Innovative approaches for assessing and enhancing the hosting capacity of PV-rich distribution networks: An Australian perspective. *Renewable and Sustainable Energy Reviews*, 2022, 161: 112365. DOI: 10.1016/j.rser.2022.112365.
- [11] Mousa H H H, Mahmoud K, Lehtonen M. A comprehensive review on recent developments of hosting capacity estimation and optimization for active distribution networks. *IEEE Access*, 2024, 12: 18545-18593. DOI: 10.1109/access.2024.3359431.
- [12] Fu X, Wu X, Zhang C, et al. Planning of distributed renewable energy systems under uncertainty based on statistical machine learning. *Protection and Control of Modern Power Systems*, 2022, 7(4): 1-27. DOI: 10.1186/s41601-022-00262-x.
- [13] Xiang Y, Li L, Li R, et al. Design flexible renewable energy penetrated power system to address long-run and short-run interactive inference. *The Innovation Energy*, 2024, 1(3). DOI: 10.59717/j.xinn-energy.2024.100042.
- [14] Huang H, Lin Y, Zhou Y, et al. Data-driven modeling of power system dynamics: Challenges, state of the art, and future work. *iEnergy*, 2023, 2(3): 200-221. DOI: 10.23919/ien.2023.0023.
- [15] Yeji L, Minjae S, Kyungnam P, et al. Power system decision making in the age of deep learning: A comprehensive review. *Energies*, 2025, 18(18): 4867. DOI: 10.3390/en18184867.
- [16] Wei C, Pi D, Ping M, et al. Short-term load forecasting using spatial-temporal embedding graph neural network. *Electric*

- power systems research, 2023, 225: 109873. DOI: 10.1016/j.epr.2023.109873.
- [17] Zhang D, Yang Y, Shen B, et al. Transient stability assessment in power systems: A spatiotemporal graph convolutional network approach with graph simplification. *Energies*, 2024, 17(20): 5095. DOI: 10.3390/en17205095.
- [18] Zhang T, Jiao W, Yu J, et al. Short-term residential load forecasting framework based on spatial-temporal fusion adaptive gated graph convolution networks. *IEEE Transactions on Neural Networks and Learning Systems*, 2025. DOI: 10.1109/tnnls.2025.3551778.
- [19] Huang B, Wang J. Applications of physics-informed neural networks in power systems-a review. *IEEE Transactions on Power Systems*, 2022, 38(1): 572-588. DOI: 10.1109/tpwrs.2022.3162473.
- [20] Ngo Q H, Nguyen B L H, Vu T V, et al. Physics-informed graphical neural network for power system state estimation. *Applied Energy*, 2024, 358: 122602. DOI: 10.1016/j.apenergy.2023.122602.
- [21] Zhao N, You F. Sustainable power systems operations under renewable energy induced disjunctive uncertainties via machine learning-based robust optimization. *Renewable and sustainable energy reviews*, 2022, 161: 112428. DOI: 10.1016/j.rser.2022.112428.
- [22] Stiasny J, Misyris G S, Chatzivasileiadis S. Physics-informed neural networks for non-linear system identification for power system dynamics[C]//2021 IEEE Madrid PowerTech. IEEE, 2021: 1-6. DOI: 10.1109/powertech46648.2021.9495063.
- [23] Lu G, Bu S. Online Power System Dynamic Security Assessment: A GNN-FNO Approach Learning From Multisource Spatial-Temporal Data. *IEEE Transactions on Industrial Informatics*, 2025. DOI: 10.1109/tii.2025.3576847.
- [24] Cao D, Zhao J, Hu W, et al. Physics-informed graphical learning and Bayesian averaging for robust distribution state estimation. *IEEE Transactions on Power Systems*, 2023, 39(2): 2879-2892. DOI: 10.1109/tpwrs.2023.3282413.
- [25] Chen X, Zhou W. Support carbon neutrality target—Which flexible power source is the best option for China? *Energy*, 2023, 285: 128682. DOI: 10.1016/j.energy.2023.128682.
- [26] Guerra K, Haro P, Gutiérrez R E, et al. Facing the high share of variable renewable energy in the power system: Flexibility and stability requirements. *Applied Energy*, 2022, 310: 118561. DOI: 10.1016/j.apenergy.2022.118561.
- [27] Liu J, Jiang B, Tang Z, et al. Coordinated planning of interconnected multi-regional power systems considering large-scale energy storage systems, transmission expansion, and carbon emission quota trading. *CSEE Journal of Power and Energy Systems*, 2025, 11(2): 490-502. DOI: 10.17775/cseejpes.2023.06230.
- [28] Moradi-Sepahvand M, Amraee T. Secure expansion of energy storage and transmission lines considering bundling option under renewable penetration. *Applied Energy*, 2023, 347: 121414. DOI: 10.1016/j.apenergy.2023.121414.
- [29] Bertozzi O, Ooi G A, Aftab M A, et al. Data-driven planning of mixed-generation power systems: Towards 100% RES-based grids. *International Journal of Electrical Power & Energy Systems*, 2025, 172: 111207. DOI: 10.1016/j.ijepes.2025.111207.
- [30] Cheng G, Lin Y, Abur A, et al. A survey of power system state estimation using multiple data sources: PMUs, SCADA, AMI, and beyond. *IEEE Transactions on Smart Grid*, 2023, 15(1): 1129-1151. DOI: 10.1109/tsg.2023.3286401.
- [31] Wu H, Xu Z, Wang M. Unrolled spatiotemporal graph convolutional network for distribution system state estimation and forecasting. *IEEE Transactions on Sustainable Energy*, 2022, 14(1): 297-308. DOI: 10.1109/tste.2022.3211706.
- [32] Simeunović J, Schubnel B, Alet P J, et al. Spatio-temporal graph neural networks for multi-site PV power forecasting. *IEEE Transactions on Sustainable Energy*, 2021, 13(2): 1210-1220. DOI: 10.1109/tste.2021.3125200.
- [33] Zhu Y, Dong Z, Cheng Z, et al. Neural network extended state-observer for energy system monitoring. *Energy*, 2023, 263: 125736. DOI: 10.1016/j.energy.2022.125736.
- [34] Borozan S, Giannelos S, Falugi P, et al. Machine learning-enhanced benders decomposition approach for the multi-stage stochastic transmission expansion planning problem. *Electric Power Systems Research*, 2024, 237: 110985. DOI: 10.1016/j.epr.2024.110985.
- [35] Huang W, Hu B, Shao C, et al. Power system reliability evaluation based on sequential Monte Carlo simulation considering multiple failure modes of components. *Journal of Modern Power Systems and Clean Energy*, 2024, 13(1): 202-214. DOI: 10.35833/mpce.2023.000939.
- [36] Göke L, Schmidt F, Kendziorowski M. Stabilized Benders decomposition for energy planning under climate uncertainty. *European Journal of Operational Research*, 2024, 316(1): 183-199. DOI: 10.1016/j.ejor.2024.01.016.