A low-carbon evaluation framework for regional power systems

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With the escalating challenges of climate change and the imperative for carbon neutrality, evaluating the carbon footprint of regional power systems becomes crucial. To address this issue, a low-carbon evaluation framework for regional power systems is developed. First, this study identifies the fundamental requirements that the index system for the low-carbon power system should follow and specifies the general direction for the index system's creation. Second, an evaluation model for carbon reduction ability is proposed by considering generation side, grid side and load side of the power system. Then, a comparative evaluation model for the carbon reduction capability of multi-regional power systems is proposed to spatiotemporally compare the carbon reduction capability of different power systems. Next, a quantification method for the weights of low-carbon evaluation indicators is established based on the power system simulation of multi-scenario scheduling and index sensitivity analysis method. Finally, a low-carbon comprehensive score for regional power systems is created by combining the evaluation results of the system's carbon reduction capacity with index weights. The practical research results in a region of Zhejiang province in China demonstrate that the proposed model can provide a reasonable and feasible evaluation plan for the low-carbon construction of regional power systems.

KEYWORDS

regional power system, low-carbon evaluation, index system, economy dispatch, carbon accounting

1 Introduction

In recent years, the continuously increasing emissions of greenhouse gases have intensified global climate change, attracting widespread attention from countries around the world (Kweku et al., 2018). As a major carbon emitter, China officially proposed in 2020 the strategic goals of "striving to achieve carbon peak by 2030 and carbon neutrality by 2060", known as the "double carbon" targets. Looking at the composition of China's carbon emissions, about 50% comes from the electric industry (Liu, 2016). Therefore, control-ling carbon emissions in the electric industry and promoting the low-carbon transformation of energy and electricity are of significant importance and impact for China to achieve the 'dual carbon' targets at an early date. Against this backdrop, the construction of new power systems is progressing vigorously (Han et al., 2020). However, how to quantitatively evaluate the low-carbon level of

power systems, to guide government poli-cy-making and corporate investment decisions, remains to be thoroughly studied.

Clarifying the key low-carbon technologies in the power system is the foundation for evaluating the low-carbon level of the power system. Currently, the power system mainly implements carbon reduction and emission reduction measures in three aspects: generation, grid, and load (Liu, 2016). The generation side is a critical aspect for implementing carbon reduction. The main carbon reduction technologies on the generation side include: 1) Enhancing the grid-connected power generation capabilities of clean and renewable energy sources, such as wind energy, hydrogen energy, solar energy, etc (Shen et al., 2020; Hoang et al., 2021; He et al., 2022). 2) Improving the energy efficiency of thermal power generation (Chen et al., 2020). 3) Devel-oping end-of-pipe "decarbonization technologies", such as carbon dioxide capture (Gao et al., 2020). 4) Optimizing electricity generation in smart microgrids with renewable sources and emission reduction (Ghiasi et al., 2021). The grid side, referring to the transmission and distribution network, mainly reduces emissions through: 1) Reducing transmission and distribution line losses (Impram et al., 2020). 2) Enhancing the grid's capacity to accommodate renewable energy sources by increasing energy storage facilities and optimizing grid dispatch (Zhang et al., 2021a; Zhang et al., 2021b). 3) Exploring the evolution of smart grids towards the Internet of Energy (IoE) (Ghiasi et al., 2023). The load side features a variety of emission reduction methods. From the perspective of load side, the main approaches include: 1) Guiding electricity consumers to actively participate in load side response, optimizing consumer electricity usage behaviors (Yang et al., 2022; Ruan et al., 2023). 2) Advancing and popularizing energy-saving technologies to enhance the energy efficiency of electrical appliances (Zhao et al., 2021).

Currently, there is extensive research on the assessment of low-carbon development levels for each aspect of generation, grid, and load. 1) For the generation side, Ref (Wen et al., 2018) proposes a quantitative analysis approach for assessing China's power sector transition strategy based on a dynamic simulation model, which translates the transition target of non-fossil energy generation in 2030 into a series of plausible pathways. Ref (Pehl et al., 2017) integrates prospective life-cycle assessment with global integrated energy–economy–land-use–climate modelling to explore life-cycle emissions of future low-carbon power supply systems and implications for technology choice. Ref (Oğuz and Şentürk, 2019), based on the concept of life cycle assessment and life cycle cost, studies the carbon emission payback for photovoltaic and wind power generation on Bozcaada Island, All scenarios are compared by considering different impact categories such as global warming potential (GWP), acidification potential (AP), and eutrophication potential (EP), which revealed that Life Cycle Assessment (LCA) and Life Cycle Cost Analysis (LCCA) are useful and practical tools that help to determine drawbacks and benefits of different renewable energy systems considering their long-term environmental and economic impacts. 2) For the grid side, Ref (Clegg and Mancarella, 2019) presents a novel integrated electricity-heat-gas transmission network model, and analyzes the low carbon technology. DC power flow modelling is coupled with steady-state gas network energy and transportation cost optimization to

assess gas-electricity price interactions. Ref (Liu et al., 2021) proposes a feasible and comprehensive evaluation index system of operation benefits. an index-based evaluation criterion is established to evaluate the operation benefits on reliability level, intelligence level, power marketization level, economic benefits, environmental benefits, and social benefits. Ref (Wen et al., 2019) mainly discusses the method of calculating the comprehensive benefit considering the load characteristics. Based on the method of involving Analytic Hierarchy Process and Entropy Weight, a new concept called investment entropy is pointed out to measure the relationship between benefit and investment structure. 3) The methods for assessing the low-carbon benefits on the load side mainly revolve around energy efficiency. Typical examples include using energy efficiency indicators, such as Power Usage Effectiveness for data centers (PUE), Cooling Load Factor for air conditioning (CLF), and Renewable Energy Ratio (RER) (Long et al., 2022).

All these methods assess the low-carbon level of individual elements within the 'generation, grid, and load' system of the power system, lacking a certain comprehensiveness and making it difficult to jointly use them for a comprehensive evaluation of the low-carbon level of the power system. To conduct a comprehensive assessment of the low-carbon level of the power system, Ref (Chen et al., 2016) introduces a three-stage Data Envelopment Analysis (DEA) model on the basis of eliminating the environmental factors and builds an evaluation system for low-carbon benefits in line with the characteristics of the national smart grids. Ref (Zhou et al., 2012) reveal the possible low-carbon benefits from different sectors. The tested factors include demand-side management, smart grid technologies, low-carbon generation technologies, utilization of low-carbon energy and low-carbon power dispatch. Corresponding evaluation methods are then proposed to analyze the low-carbon benefits from different sources quantitatively. Ref (Li et al., 2023) proposes that the operating costs of the distribution network can be reduced through complementary optimization of source-grid-load-storage (SGLS), which can promote full consumption of the distributed energy resources with high penetration and contribute to the development of low carbon economy. With that, the low carbon efficiency evaluation index system for SGLS is proposed, which con-siders four dimensions including source side, gird side, load side as well as storage side. However, these studies did not fully consider the potential emission reduction benefits of new features of the power system, such as grid energy storage and adjustable load, making it difficult to accurately assess their low-carbon levels. Also, these assessment indicators cannot perform bi-directional temporal and spatial comparative analysis for power grids with different topological structures, lacking flexibility and robustness.

To address these issues, this paper proposes a low-carbon evaluation system suit-able for regional power grids. By comprehensively considering the generation side, grid side, and load side, a dynamic low-carbon evaluation system for quantifying the improvement effects of regional power systems and comparing the construction of multiple regional power systems over time and space, along with its calculation methods, has been established. Additionally, the paper, combining multi-scenario analysis, economy dispatch simulation, and sensitivity analysis, obtains more accurate and comprehensive changes in the carbon emissions of the power system. Using the entropy weight
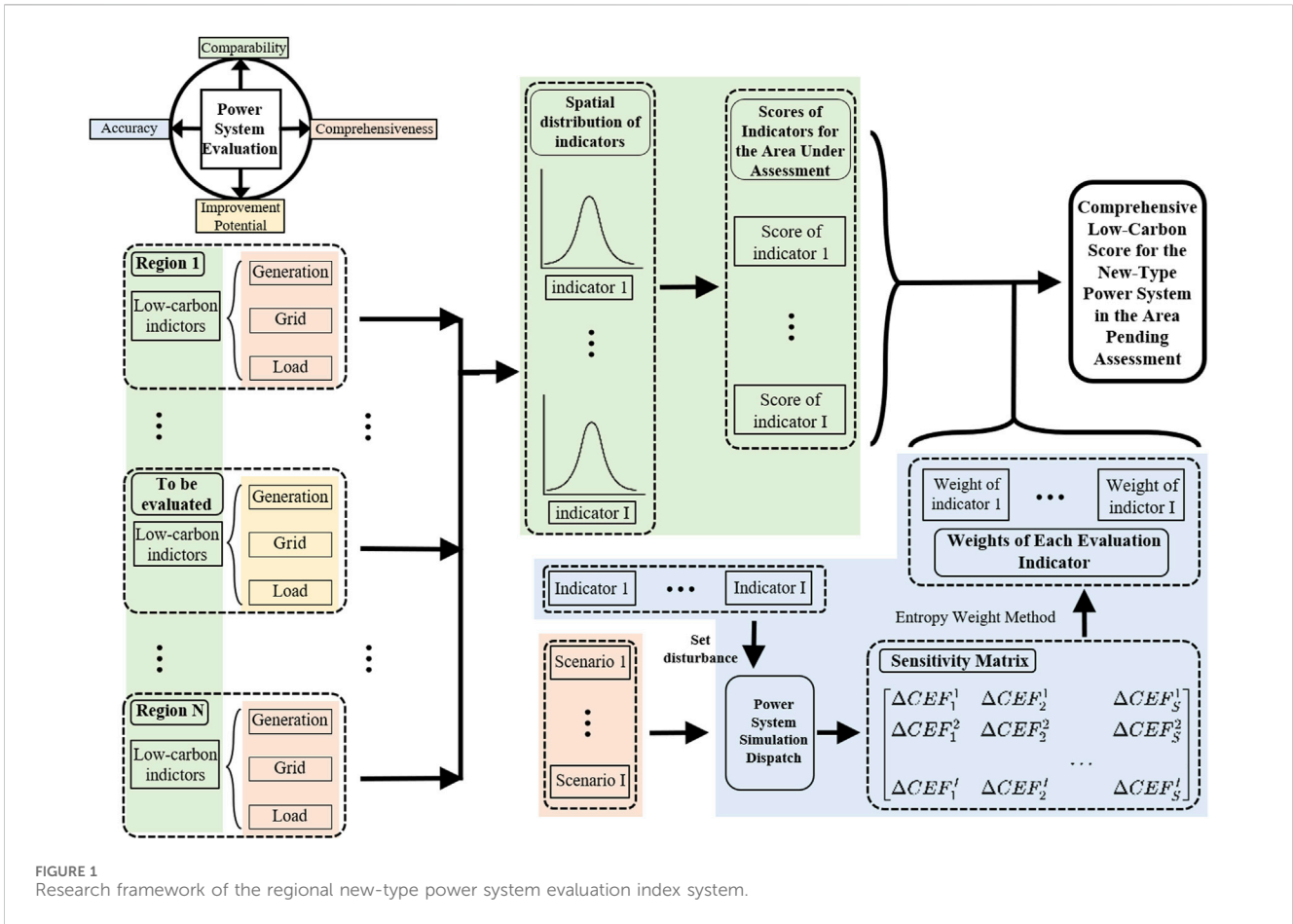
FIGURE 1
Research framework of the regional new-type power system evaluation index system.

method, the coupling impacts of each segment of the power system are incorporated into the indicator system through the weights of various indicators. An example analysis of a regional power system in Zhejiang, China, verifies the comprehensiveness and feasibility of the proposed indicators.

2 Framework for the low-carbon assessment system of regional power systems

When assessing the low-carbon level of power systems, it is necessary to ensure that the indicator system is comprehensive, accurate, improvable, and comparable.

- Comprehensiveness. The comprehensiveness of the indicator system means that the proposed low-carbon indicator system for power systems should cover the carbon reduction performance assessment of key technologies in all aspects of the power system as much as possible, without omitting important technical details.
- Accuracy. The accuracy of the indicator system refers to the calculation results of the proposed low-carbon indicator system for power systems accurately reflecting the significant role of each key link in the power system in reducing carbon emissions.

- Improvability and Comparability. The improvability and comparability of the indicator system emphasize the role of the proposed low-carbon indicator system in the vertical self-comparison of regional power systems and the horizontal comparison among multiple regional power systems."

Based on the four essential characteristics that the indicator system should possess, the paper proposes a research framework for the low-carbon evaluation system of regional power systems (Figure 1). From the perspective of comprehensiveness, the paper assesses the power system from its basic components, namely, generation, grid, and load - the three key links, and reflects the coupling relationships between these basic components of the power system through multi-scenario analysis, achieving a comprehensive evaluation of the low-carbon effectiveness of both the local and overall power system. From the perspective of accuracy, on one hand, the paper deeply studies the carbon reduction logic of key technologies in each segment, providing calculation methods for each indicator. On the other hand, the evaluation system uses an economy dispatch model to reflect the quantitative impact of indicators, incorporating the weights of each indicator into the calculation, thereby achieving an accurate assessment of the low-carbon effectiveness of each segment of the power system. At the same time, the calculation results of various indicators at different times can serve as a basis for the vertical self-comparison of regional power systems, reflecting the improvability of the indicator system.

Lastly, based on the distribution of multi-regional indicators, the evaluation scores for comparing various indicators of the region being assessed are measured, providing a basis for the horizontal comparison of regional power systems, reflecting the comparability of the indicator system.

In order to achieve the requirements above, it necessitates the assessment of various resources of the electric power system (including generation side, grid side, and load side). What's more, it requires considering the electric power system as an integrated whole, taking into account the role of different resources in the operation of the electric power system and evaluating the overall operational outcomes. The research framework is shown in Figure 1, the paper will specifically elaborate on the proposed indicator system and its calculation methods, and how it works in the power system. By combining the individual and the holistic perspectives can an accurate assessment of the various resources of the electric power system be formed.

3 Low-carbon assessment indicator system for regional power systems

3.1 Assessment model for carbon reduction capability on the generation side

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

Excluding minor greenhouse gas emissions from electrical equipment such as circuit breakers, the direct carbon emissions of the power system primarily originate from the fuel combustion process on the generation side. Therefore, the low-carbon level of the power system on the generation side is directly linked to the proportion of clean energy generation within that power system. Consequently, we define the 'clean generation contribution degree', K^{G}, and use the average proportion of regional clean energy generation to assess the carbon reduction capability of the generation side.

$$K^{\mathrm{G}} = \frac{1}{T}\sum_{t=1}^{T}\frac{E_t^{\mathrm{Clean}}}{E_t^{\mathrm{G}}} \tag{1}$$

where, T is the total number of sampling points. E_t^{Clean} represents the clean energy generation within the region during the time t (as shown in Equation 2). E_t^{G} represents the total power generation in the region during the time t.

$$E_t^{\mathrm{Clean}} = \int_{\Delta t} P^{\mathrm{Clean}} dt \tag{2}$$

$$E_t^{\mathrm{G}} = \int_{\Delta t} P^{\mathrm{G}} \mathrm{dt} \tag{3}$$

In equations (2) and (3), Δt represents the length of the time interval, P^{Clean} and P^{G} represent the clean energy power and total power. Ideally, the time interval Δt should approach infinitesimally small values to measure the contribution of regional clean energy generation power to the total regional generation power over a past period. Considering the universality of the indicator and the

practical difficulty in data acquisition, the calculation can choose a suitable time interval length Δt based on the actual frequency of the data obtained, using Equation 1 to assess the absolute level of low carbon on the generation side. It should be noted that when making horizontal comparisons between regions, it is important to ensure that the time interval length Δt selected for the calculation of indicators is the same, to ensure the comparability of the evaluation results. The above discussion about the length of the time interval Δt is also applicable to the calculation of low-carbon level assessment indicators for the grid side and load side, and will not be reiterated later.

3.2 Assessment model for carbon reduction capability on the grid side

On the grid side, reducing carbon emissions involves actively adapting to the generation characteristics of clean energy sources, timely storing clean electricity, shifting electricity demand, and utilizing the flexibility resources of electricity to adjust the power supply-demand curve, thereby maximizing the output of clean energy. Therefore, the carbon reduction capability of the grid side in advanced power systems mainly depends on two aspects. Firstly, it is necessary to measure whether the power system has the appropriate electrical infrastructure for carbon reduction and emission reduction, specifically, whether the power system has sufficient flexibility resources to meet the needs of low-carbon dispatching of the grid. Secondly, the effectiveness of the low-carbon regulation of the power system must be assessed, that is, whether the existing resources of the power system can be reasonably used to adjust the supply-demand relationship, maximizing the grid-connected clean energy. Accordingly, two indicators need to be defined on the grid side to assess the carbon reduction capability from the perspectives of electrical infrastructure configuration and grid regulation effectiveness.

In the dispatching process, the scheduling of flexibility resources is primarily influenced by the power consumption of rigid loads with poor flexibility and high uncertainty, as well as the power output from wind and photovoltaic generation in the power system. Therefore, to measure the sufficiency of flexibility resource allocation in meeting the demands of low-carbon dispatching in the grid, a 'flexibility resource allocation rate' is defined. This involves comparing the maximum adjustable capacity of flexibility resources over a period of time with the maximum value of the absolute sum of the power consumption of rigid loads and the power output from wind and photovoltaic generation over the same period. The specific calculation formula is as shown in Equation 4.

$$K^{\mathrm{Flex}} = \frac{\max_t \left| P_t^{\mathrm{Flex}} \right|}{\max_t \left(\left| P_t^{\mathrm{L}} \right| + \left| P_t^{\mathrm{W}} \right| + \left| P_t^{\mathrm{PV}} \right| \right)} \tag{4}$$

where P_t^{Flex} represents the adjustable capacity of flexibility resources on the grid side during the time period t, mainly including the adjustable capacity of grid-side energy storage and pumped-storage power stations. $P_t^{\mathrm{L}}, P_t^{\mathrm{W}}, P_t^{\mathrm{PV}}$ are respectively the power consumption of rigid loads, wind power generation, and photovoltaic power generation during the time period t.

One of the challenges in achieving low-carbon power systems is the real-time supply-demand balance characteristic of the power

system, that is, not only ensuring that the generation side is sufficiently clean but also ensuring that the load side can instantaneously consume the produced clean energy. In the power system, the dispatch center located on the grid side can use flexibility resources to adjust the supply-demand relationship through real-time dispatching, actively adapting to the changes in the clean energy generation curve on the generation side, thereby maximizing the grid-connected clean energy. Accordingly, the clean power supply-demand matching degree $K^{\text{CleanMatch}}$ is defined to assess the matching level between clean power supply and power demand in the power system, thus measuring the low-carbon regulation effect of the grid. The specific calculation formula is as shown in Equation 5.

$$K^{\text{CleanMatch}} = \frac{1}{T}\sum_{t=1}^{T} r\left(\frac{E_t^{\text{Clean}}}{E_t^{\text{Load}}}\right) \qquad (5)$$

Where E_t^{Load} represents the regional load electricity consumption within the region during the period t (as shown in Equation 6), and $r(\cdot)$ is a reward-penalty function, defined as in Equation 7.

$$E_t^{\text{Load}} = \int_{\Delta t} P^{\text{Load}} dt \qquad (6)$$

$$r(x) = \begin{cases} x, 0 \le x \le 1 \\ -\dfrac{2}{2C^{\text{tol}}-1}x + \dfrac{2C^{\text{tol}}+1}{2C^{\text{tol}}-1}, 1 < x \le 2C^{\text{tol}} \\ -1, x > 2C^{\text{tol}} \end{cases} \qquad (7)$$

The setting of the reward-penalty function is based on the following principles: When the ratio of clean electricity to regional load demand is less than 1, meaning the supply of clean electricity is insufficient to meet regional load demand, it encourages the generation of more clean power or the reduction of regional load demand. In this case, the closer the ratio is to 1, the higher the score obtained. When the ratio equals 1, meaning the supply of clean electricity perfectly matches the regional load demand, the power system achieves the optimal low-carbon operational effect, and the score obtained is the highest, being 1. When the ratio further increases, meaning the supply of clean electricity exceeds the regional load demand, necessitating the export of clean electricity to other regions, it is beneficial for the clean production of electricity in other regions within a certain range. However, when the ratio reaches a certain multiple (denoted by C^{tol} in the paper), such outward export negatively impacts the overall stability and safety of the power grid. Therefore, when the ratio is greater than 1 but less than C^{tol}, the score accordingly decreases; at the ratio equal to C^{tol}, the score is 0, and continuing to increase the ratio results in negative scores; to prevent excessive penalties, when the ratio further increases and reaches $2C^{\text{tol}}$, the score obtained is fixed at −1.

3.3 Assessment model for carbon reduction capability on the load side

On the load side, the method to reduce carbon emissions in the power system is similar to that on the grid side, which involves changing the demand curve through the adjustment of elastic loads (such as electric vehicles), actively adapting to the changes in the clean energy generation curve, thus maximizing the grid-connected clean energy volume and achieving the goal of reducing carbon emissions in the power system. Additionally, on the load side, the purchase of green electricity can provide economic incentives for the low-carbon transformation of the power system. Therefore, it is necessary to examine the proportion of green electricity consumption in power consumption to assess the low-carbon level of the load side of the power system. In summary, to measure the carbon reduction capability on the load side, two indicators are proposed: the elastic load allocation rate K^{Elastic} and the green electricity consumption proportion K^{Green}, with their specific formulas as shown in Equations 8, 9.

$$K^{\text{Elastic}} = \frac{\max_t P_t^{\text{Elastic}}}{\max_t P_t^{\text{Load}}} \qquad (8)$$

$$K^{\text{Green}} = \frac{E^{\text{Green}}}{E^{\text{Power}}} \qquad (9)$$

In Equation 8, P_t^{Elastic} represents the adjustable capacity of elastic loads during the time period. In Equation 9, E^{Green} represents the annual green electricity consumption in the region, and E^{Power} represents the total annual electricity consumption in the region.

3.4 Summary for requirements of the low-carbon assessment indicator system

To elucidate the criteria for assessment with precision, we enumerate all the parameters requisite for the model evaluation as depicted in Table 1.

It can be observed that the parameters required for the model include various operational state parameters of the electric power system, primarily operational power generation and energy consumption. These parameters have been extensively documented in the operation of electric power systems and can be adeptly adapted to meet the computational demands of the evaluation model. However, there are still a key point that need to be emphasized.

The point is the normalization of the time interval. It is imperative to underscore that when conducting horizontal comparisons across regions, the uniformity of the time interval length selected for the computation of indicators is essential to ensure the comparability of the evaluation outcomes. This stipulation stems from the fact that the sampling time intervals for different parameters vary. In practical applications, 1 min, 15 min, or 1 h are common sampling frequencies.

3.5 Comparative assessment model for carbon reduction capability in multi-regional advanced power systems

To enable the comparison of carbon reduction capabilities across multiple regional power systems, this paper employs the maximum likelihood estimation method to generate regional data sample distribution functions $f(x|\theta)$, where x, θ respectively represent regional indicator samples and parameters to be estimated. These parameters are shown in section 3.1–3.3. They

TABLE 1 Data required for the assessment.

Parameters	Description of parameters
K^G	Clean generation contribution degree
E_t^{Clean}	Clean energy generation within the region
E_t^G	Total energy generation within the region
P^{Clean}	Clean energy power generation
P^G	Total power generation
K^{Flex}	Flexibility resource allocation rate
P_t^{Flex}	Adjustable capacity of flexibility resources on the grid side during the time period
P_t^L	Power consumption of rigid loads
P_t^W	Wind power generation
P_t^{PV}	Photovoltaic power generation
$K^{CleanMatch}$	Clean power supply-demand matching degree
E_t^{Load}	Regional load electricity consumption within the region
P^{Load}	Regional load power consumption
$K^{Elastic}$	Elastic load allocation rate
K^{Green}	Green electricity consumption proportion
E^{Green}	Annual green electricity consumption in the region
E^{Power}	Total annual electricity consumption in the region
$P_t^{Elastic}$	Adjustable capacity of elastic loads

show the spatial-temporal characteristics of energy generation and consumption. After obtaining the estimated parameters, the relative score K_i of the regional indicator i in the obtained distribution can be given based on the position of the regional indicator in the distribution (as shown in Equation 10). According to the properties and definitions of probability, the range of values for the relative score K_i is [0, 100].

$$K_i = 100\sigma^i \int_{-\inf}^{K^i} f(x|\theta)dx \qquad (10)$$

Specifically, given the vector of evaluation values for the absolute indicator i of each region, $X^i = [x_1, \ldots, x_n], i \in I$, with the suppose that the indicator satisfies standard normal distribution. $\mu^i, (\sigma^i)^2$ are to be estimated. Construct the likelihood function as shown in Equation 11.

$$L(\mu, \sigma^2 | x) = \Pi_{i=1}^n \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x_i - \mu)^2}{2\sigma^2}} \qquad (11)$$

After taking the logarithm, the derivative with respect to the parameters to be estimated should be zero (as shown in Equation 12), and solving this gives the relationship between the parameters to be estimated and the sample x (as shown in Equation 13).

Finally, the relative score of the regional indicator for the assessed region is obtained based on the position of the assessed regional indicator K_i in the distribution (as shown in Equation 14).

$$\begin{cases} \dfrac{d}{d\mu} \ln L(\mu, \sigma^2) \bigg| x = \dfrac{1}{\sigma^2} \sum_{i=1}^n (x_i - \mu) = 0 \\ \dfrac{d}{d\sigma} \ln L(\mu, \sigma^2) \bigg| x = -\dfrac{n}{\sigma} + \dfrac{2}{\sigma^3} \sum_{i=1}^n (x_i - \mu)^2 = 0 \end{cases} \qquad (12)$$

$$\begin{cases} \mu = \dfrac{1}{N} \sum_{i=1}^n x_i \\ \sigma^2 = \dfrac{1}{n} \sum_{i=1}^n (x_i - \mu)^2 \end{cases} \qquad (13)$$

$$K_i = \frac{100}{\sqrt{2\pi}\sigma^i} \int_{-\inf}^{K^i} e^{-\frac{(x-\mu^i)^2}{2\sigma^{i2}}} dx \qquad (14)$$

3.6 Comprehensive assessment of regional advanced power systems

After obtaining the low-carbon scores for each indicator of the regional power system, the paper proposes obtaining a comprehensive low-carbon score K^{compre} for the regional power system through the weighted sum of the low-carbon scores of each indicator, with the specific formula as shown in Equation 15.
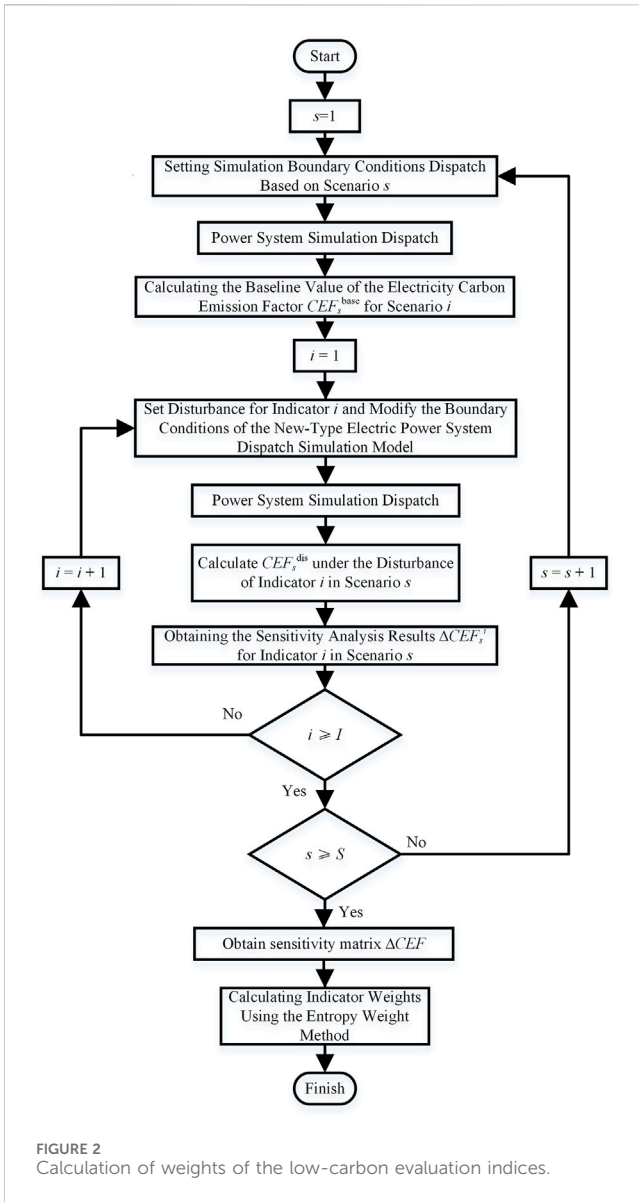
$$K^{compre} = \sum_{i=1}^I w_i K_i \qquad (15)$$

FIGURE 2
Calculation of weights of the low-carbon evaluation indices.

In Equation 15, w_i represents the corresponding weight for indicator i. The method for calculating these weights will be specifically elaborated in the next chapter.

4 Quantification method for low-carbon assessment indicator weights based on multi-scenario analysis

4.1 Framework for the quantification method of low-carbon assessment indicator weights

Obviously, the low-carbon level of the power system is related to the current state of development in each aspect of generation, grid, and load within the power system, and there exists a certain coupling relationship between these aspects. Thus, it is not feasible to determine the overall low-carbon

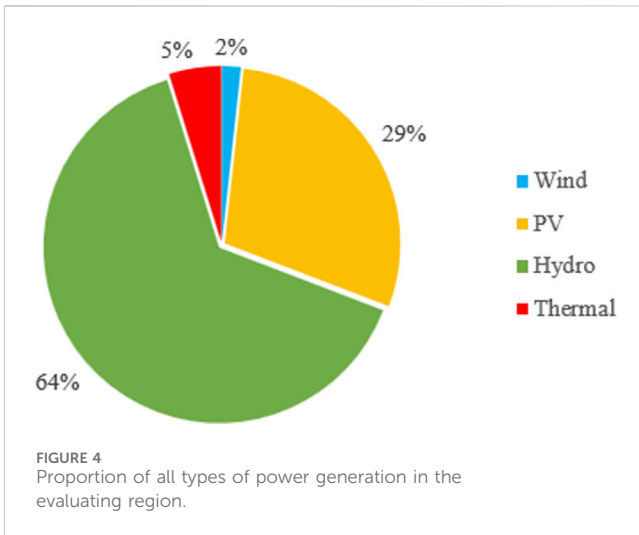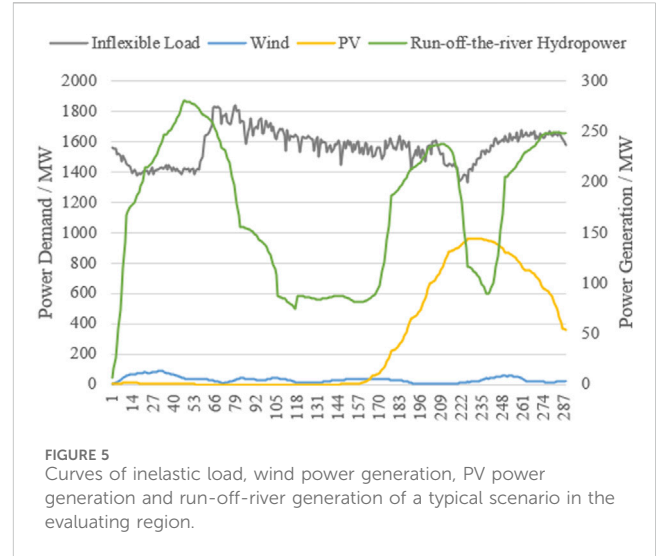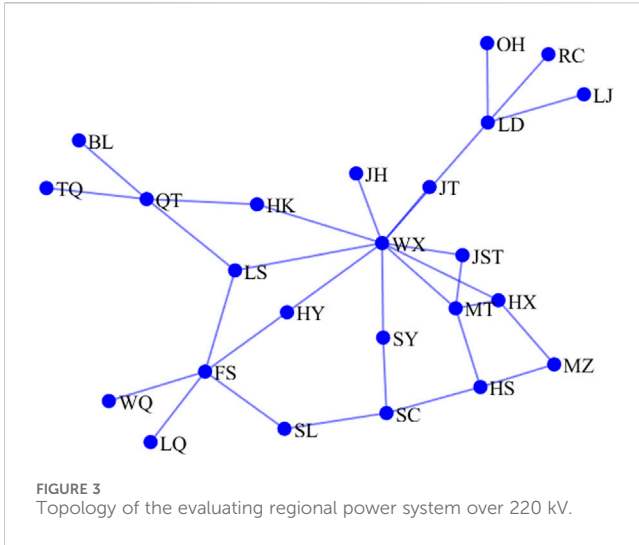TABLE 2 Electricity production and consumption of year 2022 of the evaluating region.

Categories	Annual statistical electricity/MWh
Wind power generation	13.95
Photovoltaic power generation	94.84
Hydroelectric power generation	670.74
Thermal power generation	87.34
Total electricity consumption	1325.94

level of the power system by evaluating a single aspect in isolation. To better reflect the overall low-carbon level of the power system in the indicator system, it is necessary to determine the weights of each indicator, thereby obtaining a comprehensive low-carbon evaluation result for the regional power system. When selecting weights, they should objectively reflect the dynamic impact of variations in each indicator on the overall low-carbon level of the power system. Indicators with more dramatic impacts on the low-carbon level should be assigned greater weights, thereby highlighting the key technologies that the power system should focus on for achieving low-carbon goals and guiding the low-carbon development of the power system.

Considering the comprehensiveness and accuracy of the indicator system, the paper proposes a method for determining indicator weights based on economy dispatch, the entropy weight method, and multi-scenario sensitivity analysis. This method relies on the economy dispatch model to accurately reflect the coupled impact of key technologies in each segment on the carbon reduction effectiveness of the power system. The carbon emission level of the regional power system under simulation dispatch is obtained by calculating the electricity carbon emission factor (as shown in Eq. (16)), where CE_t represents the carbon emissions of the regional power system during the period t.

$$CEF = \frac{1}{T} \sum_{t=1}^{T} \frac{CE_t}{E_{\text{Load}}^t} \tag{16}$$

The weight calculation method is illustrated in Figure 2. Firstly, based on the typical daily data of the power system, S typical scenarios are set as boundary conditions for the economy dispatch model. The simulation is run to obtain the electricity carbon emission factor CEF_s^{base} for the scenario s, which serves as the baseline carbon emission level for the scenario s, where $s = 1, \ldots, S$. Then, in each scenario, a small perturbation is applied to indicator i to change the boundary conditions of the simulation model (specific perturbation settings are shown in Table 2). The simulation is rerun to obtain the electricity carbon emission factor $CEF_{s,i}^{\text{dis}}$ after the disturbance of indicator i, thus determining the difference ΔCEF_s^i from the baseline carbon emission level CEF_s^{base} of the scenario. After obtaining the disturbance differences of all indicators across the set of scenarios, a sensitivity matrix ΔCEF is formed, and the entropy weight method is used to calculate the weights, ultimately yielding the weights $w_i, i \in I$.

FIGURE 3
Topology of the evaluating regional power system over 220 kV.

FIGURE 5
Curves of inelastic load, wind power generation, PV power generation and run-off-river generation of a typical scenario in the evaluating region.

FIGURE 4
Proportion of all types of power generation in the evaluating region.

4.2 Indicator weight calculation model based on the entropy weight method

The specific steps for using the entropy weight method to analyze the perturbation matrix to obtain the weights of each indicator are as follows:

(1) Normalize the sensitivity matrix $\Delta CEF = [\Delta CEF_s^i]^{I \times S}$ to obtain the normalized sensitivity matrix $M = [m_s^i]^{I \times S}$ (as shown in Equation 17).

$$m_s^i = \frac{\Delta CEF_s^i - \min_s(\Delta CEF^i)}{\max_s(\Delta CEF^i) - \min_s(\Delta CEF^i)} \quad (17)$$

(2) Normalize the standardized sensitivity matrix M to obtain the normalized sensitivity matrix $Z = [z_s^i]^{I \times S}$.

$$z_s^i = \frac{m_s^i}{\sum\limits_{i=1}^{S} m_s^i} \quad (18)$$

(3) Calculate the information entropy e_i for each indicator (as shown in equation (19))

$$e^i = -\frac{1}{\ln I} \sum_{i=1}^{I} z_s^i \ln z_s^i \quad (19)$$

(4) Determine the weights w^i for each indicator based on the information entropy (as shown in Equation 20)

$$w^i = \frac{1 - e^i}{\sum\limits_{i=1}^{I} e^i} \quad (20)$$

4.3 Power system dispatch simulation model

To simulate the real operation of the power system, the paper establishes a security-constrained economic dispatch optimization model, which achieves economy dispatch by solving the optimal power flow distribution. The specific modeling is shown in Equations 21–32. The objective function of the optimization model is to minimize dispatch costs, including the generation cost of power units and the call cost of adjustable loads. During operation, it is necessary to ensure real-time balance between power supply and electricity demand (as shown in Equation 22), where the power supply includes the generation power $P_{g,t}^{\mathrm{G}}$ of power units and the discharging power $P_{j,t}^{\mathrm{ESS,dis}}$ of new energy storage, while the electricity demand includes rigid load $P_{d,t}^{\mathrm{L}}$, adjustable load $P_{l,t}^{\mathrm{Elastic}}$, and the charging power $P_{j,t}^{\mathrm{ESS,cha}}$ of new energy storage. For each power unit, it is essential to ensure that the generation power does not exceed the capacity limit and ramping constraints (as shown in Equations 23, 24. The power flow $P_{b,t}^{\mathrm{transimission}}$ of each line is obtained using the direct current power flow model (as shown in Equation 25), where FF is the line power transfer factor, and the line flow should not exceed the steady-state capacity limit of the line (as shown in Equation 26)."

TABLE 3 Evaluation results of the low-carbon level of the regional power system.

Indictors	Carbon reduction capability assessment	Spatial characteristics parameters of indicator distribution		Scores of each indicator	Scenarios sensitivity analysis				Indicator weights
		μ	σ		Scenario 1	Scenario 2	Scenario 3	Scenario 4	
Clean Generation Contribution Degree	0.866	0.300	0.258	98.58	0.80	0.66	0.56	0.60	0.1978
Flexibility Resource Allocation Rate	0.0834	0.0448	0.0868	67.17	5.55	5.55	5.55	5.55	0.2007
Clean Power Supply-Demand Matching Degree	0.588	0.304	0.259	86.28	−4.85	−4.83	−4.55	−4.29	0.2003
Proportion of Adjustable Loads	0.03	0.0303	0.0201	49.36	11.10	10.78	10.41	10.20	0.2005
Green Electricity Consumption Proportion	0.0011	3.17×10^{-4}	5.53×10^{-4}	93.25	5.55	5.55	5.55	5.55	0.2007

$$\text{Minimize} \sum_{t \in T, g \in G} C\left(P_{g,t}^{\text{G}}\right) + \sum_{t \in T, l \in L} C\left(P_{l,t}^{\text{Elastic}}\right) \tag{21}$$

$$\sum_{g \in G} P_{g,t}^{\text{G}} + \sum_{j \in J} \alpha_{j,t}^{\text{dis}} P_{j,t}^{\text{ESS,dis}} = \sum_{d \in D} P_{d,t}^{\text{L}} + \sum_{l \in L} P_{l,t}^{\text{Elastic}} + \sum_{j \in J} \beta_{j,t}^{\text{cha}} P_{j,t}^{\text{ESS,cha}} \tag{22}$$

$$\underline{P_g^{\text{G}}} \leq P_{g,t}^{\text{G}} \leq \overline{P_g^{\text{G}}} \tag{23}$$

$$\underline{\Delta P_g^{\text{G}}} \leq P_{g,t}^{\text{G}} - P_{g,t-1}^{\text{G}} \leq \overline{\Delta P_g^{\text{G}}} \tag{24}$$

$$P_{b,t}^{\text{transmission}} = \sum_{g} F_{b,g} P_{g,t}^{\text{G}} + \sum_{j} F_{b,j} \alpha_{j,t}^{\text{dis}} P_{j,t}^{\text{ESS,dis}} - \sum_{j} F_{b,j} \beta_{j,t}^{\text{cha}} P_{j,t}^{\text{ESS,cha}} - \sum_{d} F_{b,d} P_{d,t}^{\text{L}} - \sum_{l} F_{b,l} P_{l,t}^{\text{L}} \tag{25}$$

$$\underline{P_b^{\text{transmission}}} \leq P_{b,t}^{\text{transmission}} \leq \overline{P_b^{\text{transmission}}} \tag{26}$$

Specifically, the economy dispatch model also considers the physical constraints of new grid-connected entities such as adjustable loads and new types of energy storage. The adjustment power of the adjustable load must not exceed its maximum adjustable capacity in period t (as shown in Equation 27). The adjustment power of the new energy storage must not exceed its maximum adjustable power (as shown in Equations (28), (29)), and the state of charge of the new energy storage must be maintained within a safe range (as shown in Equation 31), where E_j^{ESS} represents the maximum capacity of the new energy storage j. Finally, the new energy storage cannot be in both charging and discharging states simultaneously, hence 0-1 integer variables $\alpha_{j,t}^{\text{dis}}, \beta_{j,t}^{\text{cha}} \in \{0, 1\}$ are defined to represent the charging and discharging states of the storage, and it is restricted to be in only one of these states at a time (as shown in Equation 32).

$$\underline{P_l^{\text{Elastic}}} \leq P_{l,t}^{\text{Elastic}} \leq \overline{P_l^{\text{Elastic}}} \tag{27}$$

$$\underline{P_j^{\text{ESS,dis}}} \leq P_{j,t}^{\text{ESS,dis}} \leq \overline{P_j^{\text{ESS,dis}}} \tag{28}$$

$$\underline{P_j^{\text{ESS,cha}}} \leq P_{j,t}^{\text{ESS,cha}} \leq \overline{P_j^{\text{ESS,cha}}} \tag{29}$$

$$SOC_{j,t} = SOC_{j,t-1} + \frac{1}{E_j^{\text{ESS}}} \left(\beta_{j,t}^{\text{cha}} \eta^{\text{cha}} P_{j,t}^{\text{ESS,cha}} - \alpha_{j,t}^{\text{dis}} \frac{P_{j,t}^{\text{ESS,dis}}}{\eta^{\text{dis}}} \right) \tag{30}$$

$$\underline{SOC_j} \leq SOC_{j,t} \leq \overline{SOC_j} \tag{31}$$

$$\alpha_{j,t}^{\text{dis}} + \beta_{j,t}^{\text{cha}} \leq 1 \tag{32}$$

The economy dispatch model established above is actually a mixed-integer linear programming problem, hence it can be solved quickly and accurately using commercial solvers.

5 Case study analysis

5.1 Set up

The paper conducted an empirical study of the proposed assessment system on a regional power system in Zhejiang Province, China. Figure 3 shows the topology of the 220 kV and above power grid in this region. The production and consumption of electricity in the region for the year 2022 are shown in Table 2. It is evident that the proportion of clean energy generation is significant

TABLE 4 Settings of sensitivity analysis of the low-carbon evaluation of the regional power system.

Indictors	Description of indicator settings
Clean Generation Contribution Degree	The power output of clean energy sources is increased by 1% during each time period
Flexibility Resource Allocation Rate	The installed capacity of flexibility resources on the grid side is increased by 1% of the region's maximum daily electricity consumption
Clean Power Supply-Demand Matching Degree	The installed capacity of flexibility resources on the grid side is increased by 1% of the region's maximum daily electricity consumption
Proportion of Adjustable Loads	The proportion of adjustable loads is increased by 1%
Green Electricity Consumption Proportion	The clean energy generation in each time period increases by 1% of the electricity consumption in each time period

in this area, but the total generation is less than the regional electricity consumption, necessitating reliance on external power supply to achieve a balance of power supply and demand. The installed capacity of various types of power generation within the region is shown in Figure 4. From the perspective of installed capacity, clean energy accounts for 95% of the total installed capacity in the region, indicating a high level of clean power generation; among the clean energy sources, hydropower (including run-of-the-river and pumped-storage power stations) has the largest installed capacity, accounting for 64% of the total capacity in the region and is the main power generation resource in the area.

The paper selected 96 h (four typical days) of operation states of the power system in this region, divided into four scenarios to form a set of economy dispatch scenarios. The four scenarios are high-demand and low-demand scenarios for both summer and winter, which is commonly used in electrical power system engineering practice. These four scenarios reflect the typical characteristics of the power system operation in the region, fully demonstrating its changing patterns. The frequency of the economy dispatch is 5 minutes per instance, meaning each scenario includes 288 operating points. Figure 5 shows the rigid load curve for one of the scenarios (24 h) as well as the generation curves for wind, solar, and run-of-the-river hydropower resources. In actual operation, the output of wind and solar resources, as well as the run-of-the-river hydropower stations, are treated as negative rigid loads and do not participate in generation dispatch. To achieve regional power supply and demand balance, the regional external interconnection lines are treated as power generation units (hereinafter referred to as external power supply), with the generation capacity of the external power supply being the sum of the upper limits of the transmission line capacities. According to the actual situation of the region, the upper limit of adjustable loads is set at 3% of the real-time rigid load. In calculating dispatch costs, the local types of power units are priced according to grid electricity prices to determine dispatch costs, external power supply is priced according to the average price of medium- and long-term electricity trading in the region, and the dispatch cost for adjustable loads is based on the compensation unit price for adjustable loads in Zhejiang Province.

5.2 Low-carbon assessment results of the regional power system

Based on publicly available data, the paper calculated the results of the indicator system for 31 regions in China and the region under assessment. Due to space limitations, the article only shows the fitted distribution parameters obtained from the calculations of various indicators for 32 regions and the scores of each assessment indicator for the region under assessment (Table 3). According to the results, this region scored relatively high in terms of clean generation contribution degree, clean power supply-demand matching degree, and the proportion of green electricity consumption, all exceeding 85. Even the relatively lower score in the proportion of adjustable load reached the national average. The assessment results of various indicators for this region are favorable. Moreover, the results of each indicator can serve as a basis for longitudinal comparison within the region, providing a clear illustration of the dynamic changes in local indicators over time and highlighting the construction status of the regional power system, thus facilitating improvements and enhancements in the low-carbon level of the power system. It should be noted that due to the statistical frequency of the existing data, the paper used annual statistical data for horizontal comparisons. However, provided that the frequency of data from different regions is consistent, readers can use higher-frequency data for more precise horizontal comparisons.

After obtaining the low-carbon scores for each indicator, to perform a comprehensive low-carbon evaluation of the regional power system, it is necessary to calculate the weights of each indicator using the proposed weight calculation method. First, the power system simulation scenario set is run to obtain the baseline carbon emission data for each scenario. Then, the operating boundary conditions of the power system in each scenario are changed according to the perturbation settings for each indicator in Table 4, and the economy dispatch is conducted multiple times, resulting in the electricity carbon emission factor after the perturbation of each indicator in each scenario, thus forming a sensitivity matrix. The sensitivity is set to be 1%. Considering that the operational conditions of the power system are unlikely to undergo significant changes in a short period, it is reasonable to conduct this value. Finally, the entropy weight method is used to calculate the weights of each indicator, with the results shown in Table 3. It can be seen that due to the high degree of cleanliness in the region's power generation, further increases in the clean generation contribution degree have a smaller impact on the low-carbon level of the power system. For this regional power system, variations in flexibility resources (including grid side and load side flexibility resources) have a greater impact on the low-carbon level of the power system, and the corresponding indicator weights are also larger. This indicates that the indicator weights

calculated by the proposed method are consistent with the actual situation.

6 Conclusion

To assess the low-carbon effectiveness of complex engineering in regional power systems, this paper designs a comprehensive low-carbon evaluation system for regional power systems, considering comprehensiveness, accuracy, comparability, and improvability. From the perspective of comprehensiveness, the system first establishes assessment models for the carbon reduction capabilities of the generation side, grid side, and load side of regional power systems. By accurately reflecting the carbon reduction capabilities of each segment through the assessment models, it provides a basis for longitudinal self-improvement of the regional power systems, achieving accuracy and improvability of the indicators. Subsequently, considering the comparability between regions, a comparative assessment model for carbon reduction capabilities of multi-regional power systems is proposed, enabling a spatial dynamic comparison of carbon reduction capabilities of regional power systems. Finally, further considering the coupling relationships among various segments of the power system, a quantification method for the weights of low-carbon evaluation indicators is proposed based on economy dispatch under multiple scenarios and sensitivity analysis of indicators. Combining the comparative assessment results of regional power systems' carbon reduction capabilities and the weights of indicators, a comprehensive low-carbon score for regional power systems is formed, accurately assessing the overall low-carbon level of the target regional power system. Furthermore, this evaluation system plays a crucial role in steering the strategic planning and sustainable development of regional power systems towards a low-carbon future. It not only assesses the current low-carbon level but also identifies areas for potential improvement, thereby guiding policy-making and investment decisions in energy infrastructure.

The empirical study results in a certain region of Zhejiang, China, demonstrate that the low-carbon assessment system proposed in the paper can comprehensively evaluate the carbon reduction capability construction of regional power systems, providing a reasonable and feasible assessment scheme for the low-carbon construction of regional power systems. Beyond the specific indicators designed in the article, more importantly, the paper also provides the design rationale and calculation methods for the regional power system assessment indicator system, offering a research framework for the refinement of low-carbon indicator systems in the future.

Data availability statement

The data analyzed in this study is subject to the following licenses/restrictions: The dataset is not public. Requests to access these datasets should be directed to huanxinliao@link.cuhk.edu.cn.

Author contributions

JY: Conceptualization, Writing–review and editing. HZ: Conceptualization, Writing–review and editing. HH: Conceptualization, Writing–review and editing. XH: Conceptualization, Writing–review and editing. XW: Conceptualization, Writing–review and editing. YQ: Conceptualization, Writing–review and editing. HL: Writing–original draft, Writing–review and editing. YZ: Writing–review and editing.

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Conflict of interest

Authors JY, HZ, HH, XH, XW, and YQ were employed by State Grid Zhejiang Lishui Electric Power Company, Ltd.

Authors HL and YZ were employed by Hangzhou Guodian Power Technology Development Company, Ltd.

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References

Chen, S., Liu, P., and Li, Z. (2020). Low carbon transition pathway of power sector with high penetration of renewable energy. *Renew. Sustain. Energy Rev.* 130, 109985. doi:10.1016/j.rser.2020.109985

Chen, Y., Li, S., Lu, S., Yang, L., and Fan, S. (2016). "Evaluation of low-carbon benefits of smart grids based on a three-stage DEA model," in International Conference on Smart Grid and Clean Energy Technologies, Chengdu, China (ICSGCE), 145–149.

Clegg, S., and Mancarella, P. (2019). Integrated electricity-heat-gas modelling and assessment, with applications to the Great Britain system. Part II: transmission network

analysis and low carbon technology and resilience case studies. *Energy* 184, 191–203. doi:10.1016/j.energy.2018.02.078

Gao, W., Liang, S., Wang, R., Jiang, Q., Zhang, Y., Zheng, Q., et al. (2020). Industrial carbon dioxide capture and utilization: state of the art and future challenges. *Chem. Soc. Rev.* 49 (23), 8584–8686. doi:10.1039/d0cs00025f

Ghiasi, M., Niknam, T., Dehghani, M., Siano, P., Haes Alhelou, H., and Al-Hinai, A. (2021). Optimal multi-operation energy management in smart microgrids in the presence of RESs based on multi-objective improved DE algorithm: cost-emission based optimization. *Appl. Sci.* 11 (8), 3661. doi:10.3390/app11083661

Ghiasi, M., Wang, Z., Mehrandezh, M., Jalilian, S., and Ghadimi, N. (2023). Evolution of smart grids towards the Internet of energy: concept and essential components for deep decarbonisation. *IET Smart Grid* 6 (1), 86–102. doi:10.1049/stg2.12095

Han, X., Qiu, J., Sun, L., Shen, W., Ma, Y., and Yuan, D. (2020). Low-carbon energy policy analysis based on power energy system modeling. *Energy Convers. Econ.* 1, 34–44. doi:10.1049/enc2.12005

He, B., Zhao, H., Liang, G., Zhao, J., Qiu, J., and Dong, Z. Y. (2022). Ensemble-based Deep Reinforcement Learning for robust cooperative wind farm control. *Int. J. Electr. Power & Energy Syst.* 143, 108406. doi:10.1016/j.ijepes.2022.108406

Hoang, A. T., Pham, V. V., and Nguyen, X. P. (2021). Integrating renewable sources into energy system for smart city as a sagacious strategy towards clean and sustainable process. *J. Clean. Prod.* 305, 127161. doi:10.1016/j.jclepro.2021.127161

Impram, S., Nese, S. V., and Oral, B. (2020). Challenges of renewable energy penetration on power system flexibility: a survey. *Energy Strategy Rev.* 31, 100539. doi:10.1016/j.esr.2020.100539

Kweku, D. W., Bismark, O., Maxwell, A., Desmond, K., Danso, K., Oti-Mensah, E., et al. (2018). Greenhouse effect: greenhouse gases and their impact on global warming. *J. Sci. Res. Rep.* 17 (6), 1–9. doi:10.9734/jsrr/2017/39630

Li, Y., Zhang, T., Xiang, T., and Wang, T. (2023). "Low carbon efficiency evaluation index system for source-grid-load-storage complementary optimization," in 5th Asia Energy and Electrical Engineering Symposium (AEEES), Chengdu, China, 1689–1695.

Liu, T., Jin, W., Xiang, Z., and Chen, H. (2021). "Evaluation index system of power grid corporation's operation benefits based on future low-carbon energy framework," in 6th Asia Conference on Power and Electrical Engineering, Chongqing, China (ACPEE), 1672–1678.

Liu, Z. (2016). *China's carbon emissions report 2016.*

Long, S., Li, Y., Huang, J., Li, Z., and Li, Y. (2022). A review of energy efficiency evaluation technologies in cloud data centers. *Energy Build.* 260, 111848. doi:10.1016/j.enbuild.2022.111848

Oğuz, E., and Şentürk, A. E. (2019). Selection of the most sustainable renewable energy system for Bozcaada Island: wind vs. Photovoltaic *Sustainability* 11 (15), 4098. doi:10.3390/su11154098

Pehl, M., Arvesen, A., Humpenöder, F., Popp, A., Hertwich, E. G., and Luderer, G. (2017). Understanding future emissions from low-carbon power systems by integration of life-cycle assessment and integrated energy modelling. *Nat. Energy* 2, 939–945. doi:10.1038/s41560-017-0032-9

Ruan, J., Liang, G., Zhao, J., Lei, S., He, B., Qiu, J., et al. (2023). Graph deep learning-based retail dynamic pricing for demand response. *IEEE Trans. Smart Grid* 14, 4385–4397. doi:10.1109/tsg.2023.3258605

Shen, L., Dou, X., Long, H., Li, C., Zhou, J., and Chen, K. (2020). A cloud-edge cooperative dispatching method for distribution networks considering photovoltaic generation uncertainty. *J. Mod. Power Syst. Clean Energy* 9 (5), 1111–1120. doi:10.35833/mpce.2019.000582

Wen, M., Tan, Y., Xie, X., Xie, C., Hou, Y., and Liu, J. (2019). "Grid benefit analysis considering the correlation between load characteristics and electricity price," in IEEE 3rd Conference on Energy Internet and Energy System Integration (EI2), Changsha, China, 2807–2810.

Wen, Y., Cai, B., Xue, Y., Wang, S., Chen, Z., Zhu, J., et al. (2018). Assessment of power system low-carbon transition pathways based on China's energy revolution strategy. *Energy Procedia* 152, 1039–1044. doi:10.1016/j.egypro.2018.09.117

Yang, C., He, B., Liao, H., Ruan, J., and Zhao, J. (2022). Price-based low-carbon demand response considering the conduction of carbon emission costs in smart grids. *Front. Energy Res.* 10, 959786. doi:10.3389/fenrg.2022.959786

Zhang, C., Qiu, J., Yang, Y., and Zhao, J. (2021a). Trading-oriented battery energy storage planning for distribution market. *Int. J. Electr. Power & Energy Syst.* 129, 106848. doi:10.1016/j.ijepes.2021.106848

Zhang, Z., Din, T., Zhou, Q., Sun, Y., Qu, M., Zeng, Z., et al. (2021b). A review of technologies and applications on versatile energy storage systems. *Renew. Sustain. Energy Rev.* 148, 111263. doi:10.1016/j.rser.2021.111263

Zhao, H., Zhao, J., Shu, T., and Pan, Z. (2021). Hybrid-model-based deep reinforcement learning for heating, ventilation, and air-conditioning control. *Front. Energy Res.* 8, 610518. doi:10.3389/fenrg.2020.610518

Zhou, T., Chen, Q., Zhu, W., Zhang, L., and Kang, C. (2012). "A comprehensive low-carbon benefits assessment model for power systems," in IEEE International Conference on Power System Technology (POWERCON), Auckland, New Zealand, 1–5.