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A Cloud Model-Based Optimal Combined Weighting Framework for the Comprehensive Reliability Evaluation of Power Systems with High Penetration of Renewable Energies

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Abstract: Reliability has long been a critical attribute of power systems that cannot be ignored. Numerous blackout events have highlighted the increasing risk of outages in power systems due to the prominence of high-proportion power electronics and renewable energy utilization. Traditional reliability assessment methods, which typically take dozens of hours to assess the adequacy of steady-state conditions, cannot reflect the real-time reliability performance of the system. Moreover, the weakness identification methods can only quantify the impact of component outages while ignoring other important operational factors. To address these issues, this paper constructs a three-hierarchy reliability evaluation index system (REIS) for power systems, consisting of the comprehensive reliability evaluation index (CREI) as the top hierarchy, four primary indices in the middle, and lots of subjective and objective indices on the bottom. To quantify the performance of different calculation methods for these indices, a combined weighting framework is proposed. Finally, the REIS level is evaluated according to the Wasserstein distances between the CREI cloud model and standard cloud models. In the case study, the proposed method is verified through its application to the power grids of two cities in a province in southern China, demonstrating its practicality and effectiveness.

Keywords: combined weighting framework; cloud model; new-type power systems; comprehensive reliability evaluation; reliability evaluation index system



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1. Introduction

With the intensification of global climate issues, low-carbon development has become a consensus among most countries. In 2021, China proposed the development of power systems with high penetration of renewable energies [1] in response to the national strategies of “carbon peak” and “carbon neutrality” [2].

Compared with traditional power systems, power systems with high penetration of renewable energies feature a high proportion of power electronics and high penetration of renewable energy. These characteristics have made operational reliability issues more prominent. In recent years, several large-scale blackout events associated with these features have occurred, such as the 2016 South Australia blackout [3] and the 2021 Texas blackout in the United States [4], which severely disrupted the normal functioning of society. Therefore,

it is necessary to assess reliability to quantify the operational risks in power systems. Power system reliability refers to the ability of power systems to continuously supply power to users according to specified requirements and quantities [5]. To date, researchers have conducted modeling and analysis from various perspectives.

For different objects in power systems, studies have established reliability models for specific components as well as system-level reliability models. For example, reliability models of circuit breakers [6], transformers [7], transmission lines [8], and generators [9,10] are proposed according to some model-driven and data-driven methods. Additionally, for power system reliability, models for generation systems [11,12], transmission systems [13], and distribution systems [14] are also developed through analyses of series-parallel systems and optimization methods.

From the perspective of reliability assessment methods, reliability assessment involves three main steps: system state generation, system state analysis, and reliability index calculation. Depending on the principle of system state generation, these methods can be classified into Monte Carlo simulation (MCS) and state enumeration (SE) [5]. MCS uses sampling to obtain system states. When the sample size is large enough, the reliability evaluation results can approach the actual values. SE exhaustively lists all system states. But for large systems, it is not realistic to obtain all states in engineering. In system state analysis, the minimum load shedding for all given system states is calculated by the optimal power flow model [5].

Due to the complex model for system reliability, it takes dozens of hours to assess the reliability of a provincial power system in China, which cannot provide timely and useful information for operation. Therefore, numerous methods are proposed to improve computation efficiency. For MCS, the cross-entropy method [15,16], important sampling [17] and Latin hypercube sampling [18] are proposed to enhance the sampling efficiency. These variance reduction techniques bias the sampling process toward critical regions of the probability space to accelerate convergence while maintaining estimation accuracy. In SE, the root event screening method [19] and the impact increment method [20] are developed to represent higher-order system states with lower-order ones, thereby reducing the number of enumerated states. They avoid the computational burden of a large number of high-order states, thereby reducing the computational burden. Additionally, during the analysis of system states, models based on multi-parameter linear programming [21], load-feasibility regions [22], and polynomial chaos expansion [5] have been proposed. These models simplify the analysis process and establish mapping relationships between input variables and the minimum load shedding for each system state, thereby reducing the computational complexity of reliability assessment.

The above research has resulted in indices that quantify the reliability of power systems, but there are also some shortcomings. Firstly, although numerous methods have been developed to improve assessment efficiency, calculating operational reliability remains a complex and time-consuming process. Secondly, current reliability indices, like loss-of-load probability (LOLP) and expected energy not supplied (EENS), ignore many practical situations of the power grid, such as transient processes [23] and system flexibility [8], which may lead to the oversight of some potential risks. Lastly, existing studies on weakness identification generally fail to quantify the influence of factors except for component outages on reliability [24,25]. However, new energy and load uncertainties, system flexibility, and operational decisions can also affect the level of reliability [8].

Therefore, it is necessary to use a comprehensive evaluation method to conduct a thorough and integrated analysis of power system reliability in order to gain an overall understanding of the reliability of power systems. However, there are only a few studies on power system reliability evaluation in the existing literature. Refs. [26,27] utilize grey

fuzzy theory and entropy weighting methods to evaluate the reliability of generators and renewable power plants, respectively. Ref. [28] employs a combined evaluation model to assess the reliability of distribution systems. However, this model considers only historical statistics and voltage stability, leading to an incomplete set of indices. Moreover, in existing methods that incorporate both subjective and objective indices for comprehensive evaluation, the weighting calculation methods for the indices vary, leading to a lack of a unified standard for calculating the optimal weights.

Therefore, this paper constructs a more comprehensive reliability evaluation index system (REIS) based on statistical data from the power grid company, and uses the hyper-entropy parameter of the cloud model to select the optimal combination of subjective and objective weights. A comprehensive evaluation cloud is established based on real data and expert ratings. Finally, the system reliability level is determined using the Wasserstein distance. The contributions of this paper are as follows:

1. **Reliability evaluation index system:** This paper constructs a three-hierarchy REIS. The top hierarchy is the comprehensive reliability evaluation index (CREI), representing the overall reliability of power systems. The middle hierarchy involves four primary indices: stability, generation capacity, flexibility, and system reliability statistical. The bottom hierarchy consists of many subjective and objective indices that provide detailed evaluations to support the primary indices. Based on real-time collected information, the level of reliability can be monitored in real time.
2. **Weight calculation of subjective and objective indices:** This paper first uses various weighting methods for both subjective and objective indices to calculate the index weights under various combinations. Then, the hyperentropy parameters of these weight cloud models are calculated to quantify the rationality of the combinations. Finally, the optimal combined weighting method is selected as the weights with the minimum super entropy. According to the weight and real-time level of each index, it is possible to more comprehensively identify the weakness in the power grid.
3. **Reliability evaluation methodology:** A comprehensive evaluation cloud is constructed based on real data or expert ratings. Then, standard clouds for five levels—best, good, middle, poor, and worse—are calculated. The distance between these clouds is defined using the Wasserstein distance. Then, the standard cloud corresponding to the minimum distance is considered as the final reliability level.

The rest of this paper is organized as follows: Section 2 analyzes the causes of typical major blackout incidents in recent years. Section 3 constructs a multi-level REIS and introduces the meaning of each index. Section 4 proposes the combined weighting framework based on data generation and then constructs a cloud model to evaluate reliability. Section 5 presents a case study analysis, and Section 6 provides the conclusions.

2. Analysis of Typical Major Blackout Incidents

This section summarizes the blackout processes of some typical major blackout incidents around the world in recent years and analyzes the main causes of these incidents. The details are as follows:

1. In late July 2012, India faced an unprecedented surge in power demand due to extreme heat conditions [29]. On 30 and 31 July, a series of cascading failures occurred in the power grids in the northern and eastern regions, the largest blackout in history by affected population, impacting over 670 million people. The incident exposed issues and some reasons for them. The Indian grid infrastructure was aging, often operating near its full capacity. Additionally, some states were over-drawing electricity to meet their demands, putting undue stress on the grid. The lack of adequate dispatching

capabilities and emergency response measures further exacerbated the situation, preventing timely isolation and resolution of faults.

2. On 28 September 2016, South Australia experienced a major blackout initiated by storm-induced transmission line failures [3]. These failures led to multiple voltage disturbances, which subsequently caused wind farms to disconnect from the grid as they reached their low-voltage ride-through limits. Ultimately, the system experienced a frequency collapse, resulting in a blackout lasting approximately 50 h with a load loss of 1895 MW. The high penetration of renewable energy, which resulted in low system inertia, made it difficult for the grid to stabilize after disturbances. Furthermore, insufficient reserve capacity and ineffective load-shedding strategies compounded the issue, highlighting the need for improved stability and flexibility in managing high-renewable grids.
3. On 9 August 2019, the UK experienced a significant blackout that began with a lightning strike causing a fault on transmission line [30]. Subsequent disturbances caused the disconnection of distributed generators and the failure of two conventional generators. After shedding 931 MW of load, the system frequency stabilized. This event underscored the challenges posed by integrating high penetration of renewable energy (about 30% wind power at the time of the incident). Issues included poor system stability, insufficient operational flexibility, and inadequate contingency planning for handling multiple simultaneous faults.
4. In February 2021, Texas was hit by an unusually severe cold wave that froze wind turbines, covered solar panels with snow, and iced natural gas equipment, severely disrupting both renewable and conventional power generation [4]. These conditions made it extremely difficult to maintain power supply. The Electric Reliability Council of Texas was forced to implement rolling blackouts, reaching a maximum load shedding of 20,000 MW, with outages lasting up to 70.5 h. This blackout exposed Texas' inadequate preparation of power plants and other critical infrastructure for extreme low temperatures. It also highlighted the vulnerabilities associated with Texas's independent grid structure, limiting its ability to receive support from neighboring grids during emergencies.
5. On 3 March 2022, Taiwan in China experienced an incident triggered by a short-circuit fault by an operational error at a large power plant [31]. This fault led to the tripping of both the power plant and transmission lines, finally affecting about 5.5 million households and impacting two-thirds of Taiwan's regions. The incident brought to light issues with equipment reliability at the power plant and inadequate emergency response plans by the grid operator. It highlighted the importance of rigorous maintenance checks and having robust contingency plans in place for rapid recovery from faults.
6. During the summer of 2022 in Sichuan, China [32], prolonged high temperatures reduced hydropower generation capacity, which is a crucial component of Sichuan's power supply. Meanwhile, demand for air-conditioning loads continued to rise, leading to severe power-rationing measures implemented by the Sichuan power grid. This incident underscored the risks associated with heavy reliance on a single energy source and the lack of sufficient reserve power supplies during extreme weather conditions. It also emphasized the need for diversified energy sources and improved planning for peak load management.
7. On 15 August 2023, in northeastern Brazil [33], a blackout began with a 500 kV transmission line in northeastern Brazil tripping due to a fault in reclosing protection equipment. Following this initial fault, power flow transfers led to failures in tie-lines between regions, eventually causing grid segmentation into three parts: northern,

northeastern, and southeastern–central grids, resulting in a 31% loss of load. This outage exposed the inadequate conventional power support to balance the variability introduced by high levels of renewable energy. Moreover, deficiencies in the reliability and coordination of grid protection systems exacerbated the impact of the incident.

8. According to Ref. [34], South Africa has faced long-term blackouts since 2007, with particularly severe impacts in 2023, where power was unavailable to 78% of the population. The prolonged blackouts can be attributed to several factors: an outdated and unreliable energy infrastructure heavily reliant on aging coal-fired plants, which make up over 80% of the country’s electricity supply, and difficulties in integrating new renewable energy sources into the existing grid due to technical challenges and regulatory barriers. Additionally, poor maintenance practices and extended repair times for existing facilities contribute significantly to the frequency and duration of outages.

In summary, as Table 1 shows, meteorological conditions, insufficient stability, generation capacity, and flexibility are some common causes of these power outages. Meteorological reasons objectively exist as the trigger for these blackout incidents. Insufficient stability, generation capacity, and flexibility are inherent reasons in the power grid itself. Therefore, the authors of this paper believe that reliability is related to these three reasons.

Table 1. The main causes of typical blackout incidents.

Time	Location	Meteorological Conditions	Stability	Generation Capacity	Flexibility
2012	India	✓	✓		✓
2016	South Australia	✓	✓	✓	✓
2019	UK	✓	✓	✓	✓
2021	Texas, USA	✓	✓	✓	
2022	Taiwan, China		✓	✓	✓
2022	Sichuan, China	✓		✓	✓
2023	Brazil		✓	✓	✓
2007–Now	South Africa		✓	✓	✓

3. Reliability Evaluation Index System

As the above analysis illustrates, this paper argues that power system reliability is related to the system’s stability, generation capacity, and flexibility. In addition, as a reference for the reliability evaluation, statistical data on system blackouts and component failures during the statistic period are also incorporated into the REIS. Therefore, this paper establishes the REIS shown in Table 2, where Q1 and Q2 refer to “quantitative” and “qualitative,” respectively. This section provides details about their definitions and calculations.

Table 2. The reliability evaluation index system of power systems.

	Primary Indices		Second Indices	Attribute	c ₁	c ₂
Comprehensive Reliability Evaluation Index (CREI)	Stability C ₁	Coverage capability of the three lines of defense C ₁₁		Q2	--	--
		Busbar short-circuit safety margin C ₁₂		Q2	--	--
		Static voltage stability reserve coefficient C ₁₃		Q1	5%	8%
		Static power angle stability reserve coefficient C ₁₄		Q1	10%	15%
		System equivalent inertia C ₁₅		Q1	4	8
	Generation capability C ₂	Short-term renewable energy forecasting accuracy C ₂₁		Q1	0%	100%
		Renewable energy penetration C ₂₂		Q1	30%	60%
		Coal stockpile warning days C ₂₃		Q1	7	14
		Inflow level in major river basins C ₂₄		Q2	--	--
	Flexibility C ₃	Flexibility regulation resource capacity C ₃₁		Q1	10%	30%
		Thermal unit equivalent ramp C ₃₂		Q1	0%	10%
		Hydropower unit equivalent ramp C ₃₃		Q1	50%	100%
		Demand response participation level C ₃₄		Q2	--	--
		Load management execution capability C ₃₅		Q2	--	--
	Reliability statistics C ₄	Forced outage rate of transmission equipment C ₄₁		Q1	1%	0.1%
		Correct action rate of protection and stability control devices C ₄₂		Q1	99.9%	99.99%
		Customer average interruption duration C ₄₃		Q1	0.1%	0.01%
		Average customer load not supplied C ₄₄		Q1	5%	1%

3.1. System Stability

Power system stability refers to the ability of power systems to return to normal operating conditions after experiencing a disturbance.

1. Coverage Capability of the Three Lines of Defense C_{11}

The three lines of defense are measures designed to maintain the stable operation of power systems and prevent large-scale blackouts, including preventive control, emergency control, and recovery control [35]. The coverage capability refers to the ability of these measures to effectively respond to different outages and abnormal situations.

2. Busbar Short-Circuit Safety Margin C_{12}

The busbar short-circuit safety margin refers to the margin by which power systems can maintain stable operation in the event of a short-circuit fault. It reflects the tolerance ability and safety level when subjected to busbar short-circuit faults.

3. Static Voltage Stability Reserve Coefficient C_{13}

The static voltage stability reserve coefficient refers to the system's ability to maintain or restore the voltage within the allowable range after a disturbance during the statistical period. It can be calculated by the following formula:

$$C_{13} = \frac{1}{N_0} \sum_{j=1}^{N_0} \min_i \left(\frac{P_{\max V,i} - P_{ij}}{P_{ij}} \right) \quad (1)$$

where N_0 is the sample number during the statistical period, $P_{\max V,i}$ is the static voltage stability power limit of the section i , and P_{ij} is the actual power of the section i in the j -th sample.

4. Static Power Angle Stability Reserve Coefficient C_{14}

The static power angle stability reserve coefficient refers to the system's ability to maintain or restore the power angle within the allowable range after a disturbance during the statistical period. It can be calculated by the following formula:

$$C_{14} = \frac{1}{N_0} \sum_{j=1}^{N_0} \min_i \left(\frac{P_{\max \delta,i} - P_{ij}}{P_{ij}} \right) \quad (2)$$

where $P_{\max \delta,i}$ is the static power angle stability power limit of the section i .

5. System Equivalent Inertia C_{15}

The system equivalent inertia refers to a constant of the rotational inertia during the statistical period. It can be calculated by the following formula:

$$C_{15} = \frac{1}{N_0} \sum_{j=1}^{N_0} \left(\sum_{i=1}^{M_j} H_{g,i} S_{g,i} / \sum_{i=1}^{M_j} S_{g,i} \right) \quad (3)$$

where M_j is the number of committed units in the j -th sample on the generation side, and $H_{g,i}$ and $S_{g,i}$ are the inertia constant and rated capacity of unit i , respectively.

3.2. Generation Capacity

The generation capacity of power systems refers to the maximum amount of electrical power that all available units can produce under normal operating conditions.

1. Short-Term Renewable Energy Forecasting Accuracy C_{21}

Short-term renewable energy forecasting accuracy refers to the accuracy of the forecasting renewable energy generation compared to real one during the statistical period. It is an important index for evaluating the forecasting technology of renewable energy and the scheduling ability of power systems. It can be calculated by the following formula:

$$C_{21} = \frac{1}{N_0} \sum_{j=1}^{N_0} \left| \frac{P_{\text{RES},fj} - P_{\text{RES},rj}}{P_{\text{RES},rj}} \right| \quad (4)$$

where $P_{\text{RES},fj}$ and $P_{\text{RES},rj}$ represent the forecasting and real renewable energy generation in the j -th sample, respectively.

2. Renewable Energy Penetration C_{22}

Renewable energy penetration refers to the proportion of renewable energy generation in the total generation of power systems during the statistical period. It is an important index to measure the proportion and significance of renewable energy in power systems. It can be calculated by the following formula:

$$C_{22} = \frac{1}{N_0} \sum_{j=1}^{N_0} \frac{P_{\text{RES},rj}}{P_{g,j}} \quad (5)$$

where $P_{g,j}$ represents the generation of all the units in the j -th sample.

3. Coal Stockpile Warning Days C_{23}

Coal stockpile warning days refers to the number of days the current coal inventory can sustain normal power generation. It can be calculated by the following formula:

$$C_{23} = \frac{S_{\text{coal}}}{P_{\text{day}} / \eta_{\text{TH}} Q_{\text{coal}}} \quad (6)$$

where S_{coal} represents the current coal stockpile of a power plant, obtained from inventory data; Q_{coal} is the calorific value of the coal; and P_{day} and η_{TH} are the daily generation and efficiency.

4. Inflow Level in Major River Basins C_{24}

The inflow level in major river basins refers to the water volume, flow variations, and water-quality conditions of rivers within major basins during a certain period. It reflects the abundance and development potential of water resources in basins.

3.3. Flexibility

The flexibility of power systems is the ability to quickly and efficiently adapt generation, energy storage, and demand response resources to accommodate load variation and recover from unexpected disturbances.

1. Flexibility Regulation Resource Capacity C_{31}

Flexibility regulation resource capacity refers to the capacity of resources in power systems that can be used to adjust the supply–demand balance and address emergencies, including dispatchable units, energy storage equipment, demand response resources, etc. It can be calculated by the following formula:

$$C_{31} = \frac{1}{N_0} \sum_{j=1}^{N_0} \alpha_{ij} \sum_{i=1}^{m_j} C_i \eta_i \quad (7)$$

where C_i and η_i represent the rated capacity and energy conversion efficiency of the i -th type of flexibility resource, respectively, and α_{ij} and m_j represent the availability factor of the i -th flexibility resource and the number of flexibility resources in the j -th sample.

2. Thermal Unit Equivalent Ramp C_{32}

The thermal unit equivalent ramp refers to the ratio of the maximum power adjustment of a thermal unit in a given time to its rated capacity during the statistical period. It reflects the flexibility and response speed of thermal units. It can be calculated by the following formula:

$$C_{32} = \frac{1}{N_0} \sum_{j=1}^{N_0} \left(\sum_{i=1}^{M_j} R_{g,i} S_{g,i} / \sum_{i=1}^{M_j} S_{g,i} \right) \quad (8)$$

where $R_{g,i}$ represents the ramp of the i -th unit.

3. Hydropower Unit Equivalent Ramp C_{33}

The hydropower unit equivalent ramp is defined and calculated similarly to the thermal unit equivalent ramp.

4. Demand Response Participation Level C_{34}

The demand response participation level is used to measure the ability of participants to effectively execute demand response actions on time according to the schedule plan throughout the entire demand response period.

5. Load Management Execution Capability C_{35}

The load management execution capability refers to the ability of system operators to monitor, control, and adjust the load during the implementation of a load management plan.

3.4. System Reliability Statistics

In addition to the above subjective and objective indices, the impact of blackouts during the statistical period is also an important aspect of reliability evaluation. System reliability statistics refers to the statistical analysis of the reliability parameters of various equipment and the load losses in outages.

1. Forced Outage Rate of Transmission Equipment C_{41}

The forced outage rate of transmission equipment refers to the proportion of time that the equipment is unavailable due to failure, abnormalities, or maintenance, relative to the total duration of the statistical period. This index reflects the reliability of transmission equipment. It can be calculated by the following formula:

$$C_{41} = \frac{1}{M_L} \sum_{j=1}^{M_L} \frac{T_{\text{outage},j}}{T} \quad (9)$$

where M_L represents the amount of equipment, T is the total duration of the statistical period, and $T_{\text{outage},j}$ is the outage time of equipment j .

2. Correct Action Rate of Protection and Stability Control Devices C_{42}

The correct action rate of protection and stability control devices refers to the proportion of time these devices operate correctly during the statistical period. It can be calculated using the following formula:

$$C_{42} = \frac{1}{M_D} \sum_{j=1}^{M_D} \frac{F_{D,j}}{F_j} \quad (10)$$

where M_D represents the number of devices, $F_{D,j}$ is the number of correct actions taken by the device j during the statistical period, and F_j is the total number of faults.

3. Customer Average Interruption Duration C_{43}

The customer average interruption duration refers to the proportion of the average time, during the statistical period, that all customers experience power interruptions due to system faults or planned maintenance outages. It can be calculated using the following formula:

$$C_{43} = \frac{1}{N_0 T} \sum_{j=1}^{N_0} T_{\text{outage},j} \quad (11)$$

where $T_{\text{outage},j}$ represents the outage duration of the customer during the statistical period in the j -th sample.

4. Average Customer Load Not Supplied C_{44}

The average customer load not supplied refers to the proportion of the load that systems fail to supply due to system faults or planned maintenance outages during the statistical period. It can be calculated using the following formula:

$$C_{44} = \frac{1}{N_0 P_{T,\max}} \sum_{j=1}^{N_0} P_{\text{outage},j} \quad (12)$$

where $P_{\text{outage},j}$ and $P_{T,\max}$ represent the load that systems fail to supply during the statistical period and the maximum load, respectively.

Based on these subjective and objective data, the evaluation results for these indices can be obtained to construct the comprehensive evaluation cloud model in Section 4. The evaluation results range from 0 to 100, with 100 as the highest and 0 as the lowest. The subjective indices are evaluated by expert ranking, while the objective indices are evaluated using a linear interpolation method, as shown in the following equation:

$$A_{j,d} = \begin{cases} 0, & C_{j,d} \leq c_1 \\ 100 \frac{C_{j,d} - c_1}{c_2 - c_1}, & c_1 < C_{j,d} \leq c_2 \\ 100, & c_2 < C_{j,d} \end{cases} \quad (13)$$

where $C_{j,d}$ and $A_{j,d}$ represent the calculated result and the scoring result for the d -th sample of the secondary index j , respectively. The values of c_1 and c_2 for each index are shown in Table 2.

Note that in the reliability statistical indicators, the C_{41} , C_{43} , and C_{44} index evaluation levels are higher, with smaller values. Therefore, the evaluation model for them needs to be adjusted. When $C_{j,d}$ is less than c_1 , $A_{j,d} = 100$; conversely, when $C_{j,d}$ is greater than c_2 , $A_{j,d} = 0$, and when $C_{j,d}$ is between c_1 and c_2 , the linear interpolation model is still used.

4. Cloud Model-Based Comprehensive Reliability Evaluation Model

4.1. Data Generation Based on CGAN

In practice power grids, hardware issues or communication failures can cause sampling devices such as supervisory control and data acquisition and phasor measurement units to produce incomplete data. This leads to inconsistencies in the data scales of various indices in Section 3. Therefore, it is necessary to generate a large amount of usable data based on the original dataset to support the comprehensive reliability evaluation method.

This paper uses the conditional generative adversarial network (CGAN) [36] to generate and expand sample data, addressing the issue of insufficient and missing samples

obtained by sampling devices in the historical database. CGAN can generate data that align with actual patterns, providing support for subsequent analysis.

In this paper, the CGAN inputs include random noise and conditional information composed of real historical data and theoretically calculated values. The generator produces samples based on these inputs, while the discriminator, which employs a convolutional neural network, evaluates the authenticity of the generated data and whether they satisfy the conditions. To address the issues of gradient vanishing and mode collapse, the loss function uses Wasserstein distance. Through adversarial training between the generator and discriminator, the output results closely resemble real data.

4.2. Combined Weighting Framework Based on Optimal Hyperentropy of Cloud Model

This section calculates the weights of each index based on the large amount of secondary index data. In determining these weights, both the subjective opinions of experts and the objective factors derived from the data affect the accuracy. Therefore, this section adopts a combined weighting method to balance both subjective and objective factors, thereby deriving relatively fair weights.

However, due to the various ways subjective and objective weighting methods are integrated, the weight results vary. Currently, the selection of combination schemes primarily relies on subjective choice, lacking an objective and fair evaluation criterion. Therefore, it is necessary to propose a method for objectively assessing the rationality of these combination schemes. In this paper, the cloud model is used to evaluate the rationality of different combined weighting schemes. Finally, a combined weighting framework for the comprehensive reliability evaluation model is constructed.

The cloud model [37] is an uncertainty transformation model that converts fuzzy concepts into specific numerical values. A cloud model is composed of several cloud drops with three numerical characteristics: the expectation value (Ex), entropy (En), and hyperentropy (He). Ex is the central position of the fuzzy concept, representing the most likely value for the concept. En describes the uncertainty of the concept, i.e., the distribution range of cloud drops around the expectation value. With a larger En , the uncertainty of the concept is greater, and the distribution of the cloud drops is wider. He further describes the distribution of entropy, reflecting the degree of fuzziness of the concept, i.e., the density of the cloud drops.

This paper uses the hyperentropy value to describe the rationality of the index weight cloud. The more concentrated the cloud drops are, the smaller the randomness of the membership degree of the rationality of the index weights, indicating that the combined weight is more reasonable. Therefore, the combination scheme with the smallest hyperentropy value is selected as the optimal combination. The combined weighting framework based on the minimum hyperentropy of the cloud model is shown in Figure 1.

The proposed method is divided into the following steps:

1. Establish the index weight library.

Several different subjective and objective weight methods are applied to calculate the weights. Then, the index weight library is established by Equations (14) and (15).

$$\omega_i^S = (\omega_{1i}^S, \omega_{2i}^S, \dots, \omega_{mi}^S), i = 1, 2, M \quad (14)$$

$$\omega_j^O = (\omega_{1j}^O, \omega_{2j}^O, \dots, \omega_{nj}^O), j = 1, 2, N \quad (15)$$

where ω_i^S and ω_j^O represent the weights calculated by the i -th subjective method and the j -th objective method, respectively; m and n are the number of subjective and objective indices; and M and N are the number of subjective and objective weighting methods, respectively.

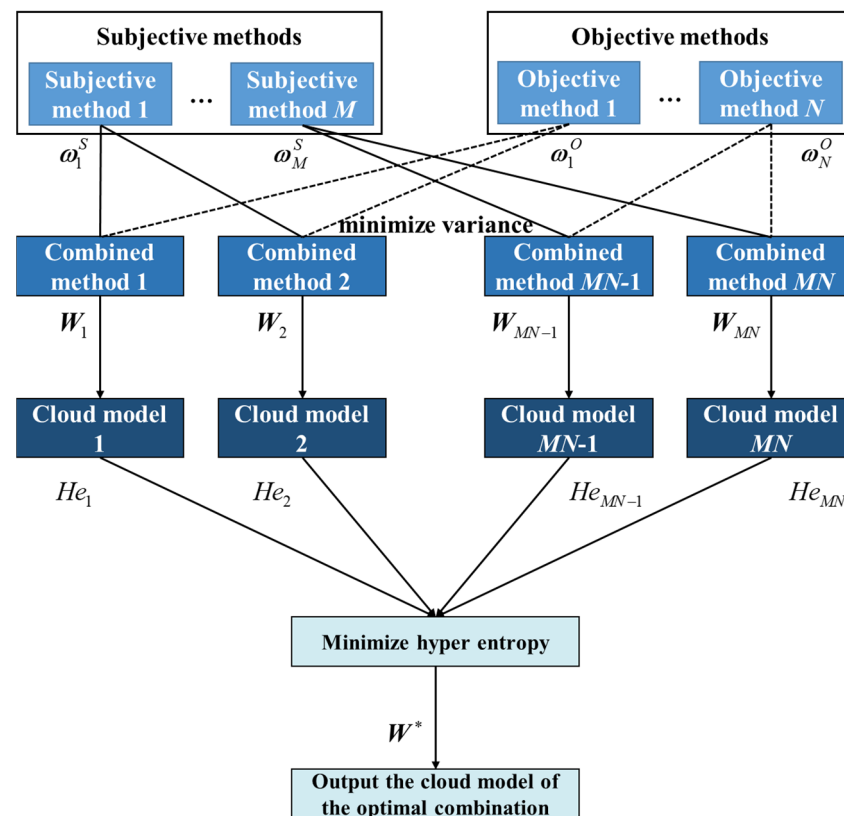


Figure 1. Combined weighting framework based on minimum hyperentropy of cloud models.

2. Establish the index combination library and combined weight cloud.

To eliminate the bias of a single weighting method, this paper combines different subjective and objective weights in pairs to obtain MN combination schemes. Each combination's weight is calculated based on the variance minimization approach.

First, the weights ω_i^S and ω_j^O are combined through a weighted linear combination to obtain the composite weight:

$$W_k = \xi_1 \omega_i^S + \xi_2 \omega_j^O, \quad k = 1, 2, \dots, MN \quad (16)$$

where ξ_1 and ξ_2 are the coefficients for subjective and objective weights, respectively, which satisfy $\xi_1 + \xi_2 = 1$.

To obtain the optimal coefficients, the variance minimization is introduced to minimize the deviation of the linear combination of W_k from the set of weights $W_{ij} = (\omega_i^S, \omega_j^O)$:

$$\Delta = \min |W_k - W_{ij}|^2 \quad (17)$$

The optimal values of ξ_1 and ξ_2 can be derived by gradient calculation:

$$\begin{bmatrix} \omega_i^S (\omega_i^S)^T & \omega_i^S (\omega_j^O)^T \\ \omega_j^O (\omega_i^S)^T & \omega_j^O (\omega_j^O)^T \end{bmatrix} \begin{bmatrix} \xi_1 \\ \xi_2 \end{bmatrix} = \begin{bmatrix} \omega_i^S (\omega_i^S)^T \\ \omega_j^O (\omega_j^O)^T \end{bmatrix} \quad (18)$$

The final combined weight $W_k, k = 1, 2, \dots, MN$ of the subjective weight ω_i^S and the objective weight ω_j^O can be derived from Equation (16).

The weight cloud parameter (Ex_k, En_k, He_k) of the combined weight W_k is calculated as shown in Equations (19)–(21).

$$Ex_k = \frac{1}{M+N} \sum_{s=1}^{M+N} W_{k,s} \quad (19)$$

$$En_k = \sqrt{\frac{\pi}{2}} \frac{1}{M+N} \sum_{s=1}^{M+N} |W_{k,s} - Ex_k| \quad (20)$$

$$He_k = \sqrt{\left| \frac{1}{M+N-1} \sum_{s=1}^{M+N} (W_{k,s} - Ex_k)^2 - En_k^2 \right|} \quad (21)$$

where $W_{k,s}$ is the s -th element in the combination weight W_k .

3. Select the optimal rational combined weights.

In the cloud model, the smaller the value of hyperentropy, the better the rationality of the index weights. Therefore, the set of weights with the smallest hyperentropy among all combinations is the optimal combination, denoted as $W^* = \{W_j^*\}_{j=1}^{M+N}$.

4.3. Comprehensive Reliability Evaluation Model Based on Shortest Wasserstein Distance

In this paper, the reliability level of power systems is standardized into five levels. The risk intervals are estimated according to a 100-point scale, as shown in Table 3. Here, $C_{\min}$ and $C_{\max}$ denote the lower and upper bounds of these reliability intervals, respectively.

Table 3. Power system comprehensive reliability levels.

Level	Status	$[C_{\min}, C_{\max}]$	Descriptions
I	Worst	$[0, 20)$	The reliability is unacceptable, with extremely high operational risks. A maintenance strategy and an emergency response plan for blackouts should be developed.
II	Poor	$[20, 40)$	The reliability is unacceptable, with high operational risks. Special attention should be given to monitoring equipment performance and developing operational risk prevention plans.
III	Middle	$[40, 60)$	The reliability is unacceptable. A reliability management plan should be developed to improve scheduling and maintenance plans.
IV	Good	$[60, 80)$	The reliability is acceptable, but there are some potential issues that need attention. It is necessary to monitor and manage the equipment in power systems.
V	Best	$[80, 100]$	The reliability level is very high, without any additional measures required. Only regular inspections and monitoring are necessary.

Standard cloud models are established for these five levels, with the following numerical characteristics:

$$Ex_v = \frac{C_{\min} + C_{\max}}{2} \quad (22)$$

$$En_v = \frac{C_{\max} - C_{\min}}{6} \quad (23)$$

$$He_v = k \quad (24)$$

where the subscript v represents reliability classes I to V and k denotes a given value of hyperentropy.

A cloud model for the optimal combination is established. Using a bottom-up strategy, the cloud model parameters for all the indices can be calculated. Firstly, the parameters for each secondary index are determined based on the subjective and objective data. The optimal parameters ($Ex_{2,j}$, $En_{2,j}$, $He_{2,j}$) are similar to Equations (19)–(21), where the sample elements are replaced by the combination weights W_k of the evaluation results of each index $A_{j,d}$. Based on the cloud model of the secondary indices, the cloud model of the CREI is obtained by following equations:

$$Ex^* = \frac{\sum_{j=1}^{M+N} W_j^* Ex_{2,j}}{\sum_{j=1}^{M+N} W_j^*} \quad (25)$$

$$En^* = \sqrt{\frac{\sum_{j=1}^{M+N} (W_j^* En_{2,j})^2}{\left(\sum_{j=1}^{M+N} W_j^*\right)^2}} \quad (26)$$

$$He^* = \sqrt{\frac{\sum_{j=1}^{M+N} (W_j^* He_{2,j})^2}{\left(\sum_{j=1}^{M+N} W_j^*\right)^2}} \quad (27)$$

where Ex^* , En^* , and He^* are the mean expectation, entropy and hyperentropy of the cloud model, respectively.

Similarly, to calculate the cloud model parameters for each primary index, all secondary index data in Equations (25)–(27) can be replaced with the secondary index data under that primary index.

Finally, the developed cloud model is compared with the standard clouds. The Wasserstein distance between the models is calculated, and the standard cloud with the closest distance to the CREI cloud is selected as the evaluation result. In this paper, the distance between two cloud models is calculated by the following steps:

1. Generate S samples of cloud drops.

Each cloud drop is characterized by the expectation value Ex , entropy En , and hyperentropy He . For the v -th standard cloud, the entropy sample $En_{v,s}$ ($s = 1, 2, \dots, S$) is generated based on $En \sim N(En_v, He_v^2)$. Next, the expectation value sample $Ex_{v,s}$ is generated based on $Ex \sim N(Ex_v, En_{v,s}^2)$. Similarly, the expectation value sample from the CREI cloud is denoted as $Ex_{op,s}$. The membership degree of this sample is calculated as follows:

$$\mu(Ex_{v,s}) = \exp\left(\frac{-(Ex_{v,s} - Ex_v)^2}{2En_{v,s}^2}\right) \quad (28)$$

2. Sort the expectations of cloud drops in ascending order, denoted as Ex_v^A and Ex_{op}^A , with elements denoted as $Ex_{v,s}^A$ and $Ex_{op,s}^A$.
3. Calculate the distances as follows:

$$D_v = \frac{1}{S} \sum_{s=1}^S \|Ex_{v,s}^A - Ex_{op,s}^A\| \quad (29)$$

After calculating the distance D_v ($v = 1, \dots, V$) between the CREI cloud and the five standard clouds, the one with the smallest distance is selected as the result of the CREI.

The flowchart of the comprehensive reliability evaluation method based on the cloud model is shown as Figure 2. Initially, standard cloud models representing the worst, poor, middle, good, and best levels are established to serve as the benchmark for subsequent comparisons. Then, using the Equations (19)–(21), the Ex , En , and He parameters for the cloud models of all the secondary indices are calculated, where the sample elements are replaced by the combination weights W_k of the evaluation results of each index $A_{j,d}$. Next, the three parameters of the cloud model for the CREI are determined. After obtaining the CREI cloud, the distance D_v between the CREI and the five standard clouds are calculated as follows. For each comparison, one standard cloud model is chosen, and S cloud drops are generated to represent its samples. They are then sorted in ascending order of their expected values. The distance is calculated by Equation (29). When all five distances are calculated, choose the smallest distance as the final result. Hence, the evaluation result

of the CREI corresponds to the level indicated by the standard cloud associated with the minimum distance D_v .

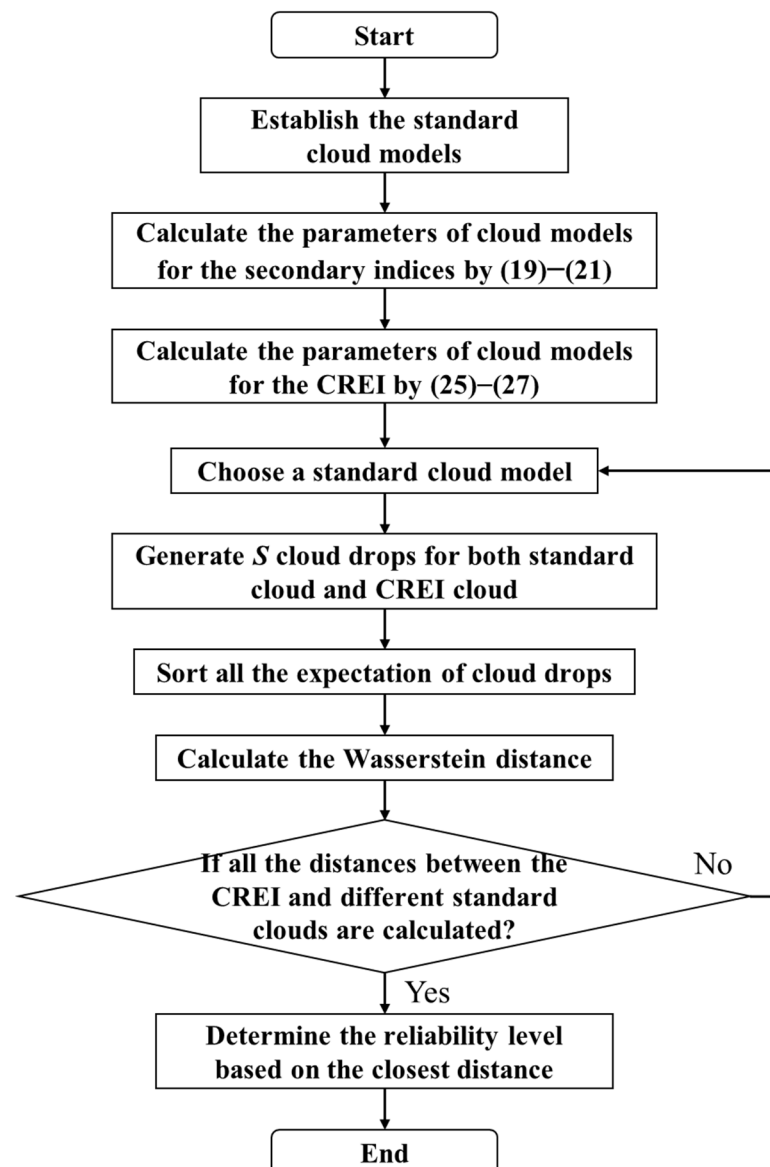


Figure 2. The flowchart of the comprehensive reliability evaluation method based on the cloud model.

5. Case Study

In this paper, power grids of two cities in a province in Southern China are used to verify the proposed method. City A, the capital city of the province, features a more diversified power generation structure and advanced grid infrastructure. City B, an industrial hub of the province, hosts well-developed metallurgical and chemical industries. While power generation in City B is dominated by traditional energy sources, the city has begun to develop new energy sources in recent years.

This paper uses both subjective and objective weighting methods to calculate these secondary indices. Without loss of generality, for subjective indices, the fuzzy analytical hierarchy process (FAHP) [38], Delphi method [39], and best–worst method (BWM) [40] are used. For objective weighting, the entropy weight method (EWM) [41], variation coefficient method (VCM) [42], and CRITIC method [43] are adopted. Subjective data are obtained from experts and professors, while objective data are derived from real-world power grid data of the two cities. In the standard cloud models, k is defined as $k = En_v/10$ [44].

According to the framework in Figure 1, Table 4 lists the hyperentropy values for the nine combination schemes. The combination method with the minimum hyperentropy is a combination of the FAHP and VCM methods. This indicates that the combined weighting method using FAHP and VCM is the most reasonable one for the research object of this paper.

Table 4. Hyperentropy values (He) for all combination schemes of subjective and objective weighting methods.

Cities	FAHP + EWM	FAHP + VCM	FAHP + CRITIC	Delphi + EWM	Delphi + VCM
A	0.3643	0.3431	0.5702	0.8623	0.5716
B	0.3092	0.2885	0.3803	0.3793	0.3016
Cities	Delphi + CRITIC	BWM + EWM	BWM + VCM	BWM + CRITIC	
A	0.6173	0.5365	0.4794	0.5631	
B	0.5073	0.4053	0.3943	0.3100	

Based on the combined weighting of FAHP and VCM, this paper calculates the weights of all indices in REIS and establishes their corresponding cloud models. The results for City A are summarized in Table 5. Cloud models for primary indices and the CREI of the two cities are derived. The Wasserstein distances between these indices and the standard clouds are presented in Tables 6 and 7. The evaluation results of the cloud models for the primary indices and the CREI are illustrated in Figures 3 and 4, respectively.

Table 5. Parameters of cloud models and weightings for the REIS in City A.

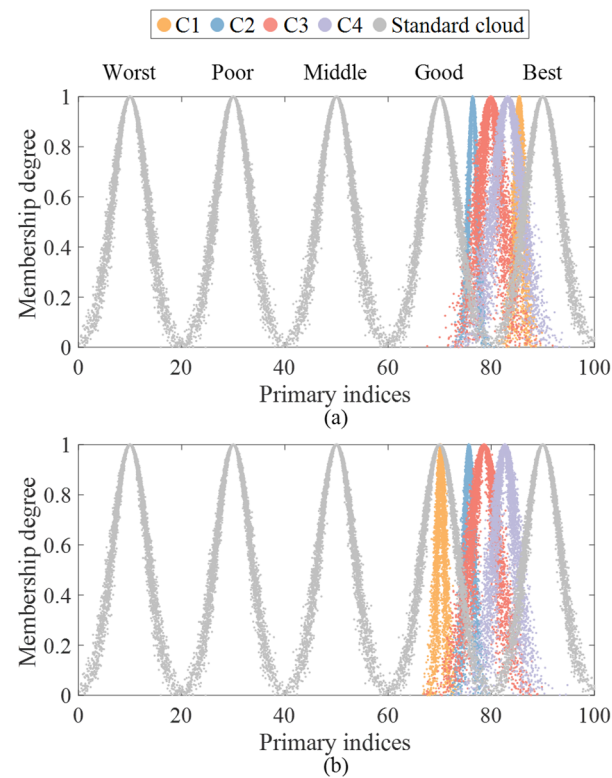
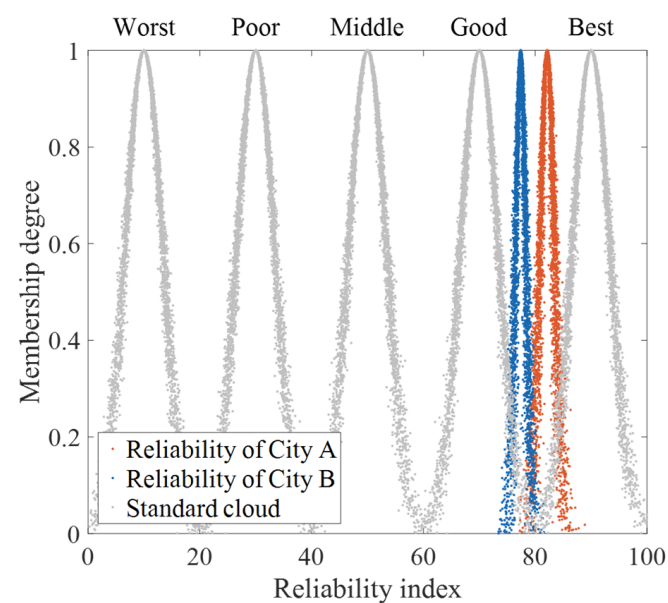
Parameters of the CREI Cloud	Primary Indices	Weights	Parameters of the Primary Indices	Secondary Indices	Weights	Parameters of the Secondary Indices
(82.14, 1.29, 0.34)	C_1	0.2331	(85.44, 0.73, 0.34)	C_{11}	0.0689	(87.25, 1.51, 0.63)
				C_{12}	0.0893	(87.44, 1.60, 0.70)
				C_{13}	0.0232	(70.25, 1.87, 0.46)
				C_{14}	0.0232	(84.30, 2.25, 0.55)
				C_{15}	0.0285	(88.07, 2.12, 0.48)
	C_2	0.1680	(76.42, 0.82, 0.22)	C_{21}	0.0240	(87.66, 1.53, 0.57)
				C_{22}	0.0679	(68.09, 2.00, 0.45)
				C_{23}	0.0408	(72.43, 1.27, 0.28)
				C_{24}	0.0353	(89.43, 0.75, 0.24)
	C_3	0.1347	(79.91, 2.10, 0.79)	C_{31}	0.0303	(80.42, 6.27, 2.41)
				C_{32}	0.0288	(74.54, 2.98, 1.01)
				C_{33}	0.0272	(69.64, 6.40, 2.42)
				C_{34}	0.0250	(88.88, 2.33, 0.90)
				C_{35}	0.0234	(88.21, 2.03, 0.76)
	C_4	0.4642	(83.21, 2.68, 0.66)	C_{41}	0.1453	(94.50, 3.69, 1.52)
				C_{42}	0.0239	(89.07, 2.05, 0.46)
				C_{43}	0.0342	(98.91, 0.69, 0.23)
				C_{44}	0.2608	(74.32, 4.29, 1.49)

Table 6. The Wasserstein distances between the CREI cloud for City A and standard clouds.

Primary Index Clouds	Standard Clouds				
	I	II	III	IV	V
C_1	76.41	55.25	35.97	14.57	4.37
C_2	66.96	46.03	25.43	6.49	13.29
C_3	68.81	49.26	29.63	11.33	10.51
C_4	74.58	54.24	29.41	12.67	6.67
CREI	74.58	54.24	31.23	14.69	6.96

Table 7. The Wasserstein distances between the CREI cloud for City B and standard clouds.

Primary Index Clouds	Standard Clouds				
	I	II	III	IV	V
C ₁	60.70	40.29	20.20	2.66	18.64
C ₂	67.06	45.88	26.53	6.46	14.42
C ₃	68.10	51.42	28.07	12.03	11.79
C ₄	72.93	51.38	32.85	11.38	8.03
CREI	66.58	48.42	26.63	7.66	14.15

**Figure 3.** Evaluation results of cloud models for primary indices: (a) City A; (b) City B.**Figure 4.** Evaluation results of the CREI cloud model.

As shown in Table 5, the CREI of City A is most closely related to reliability statistics C_4 . In contrast, the flexibility of power systems contributes the least to reliability, with a weight of only 13.47%. Among all the secondary indices, the static voltage stability reserve coefficient C_{13} and the static power angle stability reserve coefficient C_{14} have the least impact on the CREI. Conversely, the average customer load not supplied C_{44} has a significant impact on the CREI.

In addition, for stability C_1 , the static voltage stability reserve coefficient C_{13} ranks the lowest, while the system equivalent inertia C_{15} achieves the highest rating. Concerning generating capacity C_2 , renewable energy penetration C_{22} has the lowest score, whereas the inflow level in major river basins C_{24} is rated the highest. For flexibility C_3 , the hydropower unit equivalent ramp C_{33} is rated the lowest, but both the demand response participation level C_{34} and the load management execution capability C_{35} are rated the highest. Regarding the system reliability statistics, the average customer load not supplied C_{44} has the lowest rating, while the average customer load not supplied C_{42} is rated the highest.

According to Table 6, the comprehensive evaluation results shows that City A excels in the stability, flexibility, and reliability statistics indices, all rated as “best.” The generation capacity, however, is rated as “good.” Consequently, the CREI for City A is “best.” Despite these high ratings, the results reveal specific weaknesses in City A’s grid, notably in generation capacity, particularly in renewable energy penetration C_{22} and coal stockpile warning days C_{23} . To further enhance the reliability of the grid, it is recommended to prioritize improvements in generation capacity.

In Table 7, City B’s grid is evaluated as “best” for both flexibility and reliability statistics, but only “good” for stability and generating capacity. The CREI for City B is also rated “good.” This suggests that while the grid performs well in some aspects, targeted improvements in stability and generating capacity are necessary to elevate the reliability level of City B’s grid.

By comparing the Wasserstein distances in Tables 6 and 7, it can be concluded that City A outperforms City B in stability, flexibility, and reliability statistics. In contrast, City B has a slight advantage in generating capacity. The largest difference between the two cities is in the stability index and the smallest difference is in the generation capacity. Similar conclusions can be drawn from Figure 3. Moreover, it can be seen from Figure 4 that the reliability of the City A’s grid is stronger than that of City B. Therefore, the provincial grid company’s needs should prioritize improvements in City B to enhance the reliability of the provincial grid.

Moreover, to validate the accuracy of the proposed method, the reliability of the two cities can also be compared through other methods. Three methods are used: technique for order preference by similarity to ideal solution (TOPSIS) [45], VIKOR [46,47], and grey relational analysis (GRA) [48]. The evaluation results are listed in Tables 8–10.

Table 8. TOPSIS evaluation results.

Cities	D+	D−	Relative Closeness	Rank
A	0.0035	0.0533	0.9383	1
B	0.0533	0.0035	0.0617	2

Table 9. VIKOR evaluation results.

Cities	Group Utility	Individual Regret	Compromise Solution	Rank
A	0.1213	0.0408	0	1
B	0.8787	0.2608	1	2

Table 10. GRA evaluation results.

Cities	Correlation Degree	Rank
A	0.9831	1
B	0.7310	2

As the tables show, the reliability level of city A was higher than that of city B in all three methods. It indicates the correctness of the proposed method.

6. Conclusions

This paper establishes a reliability evaluation index system (REIS) and proposes an evaluation method to comprehensively evaluate the reliability of power systems with high penetration of renewable energies. Based on the analyses of some major blackout incidents in recent years, a three-hierarchy REIS is constructed. The top hierarchy is the comprehensive reliability evaluation index (CREI), which serves as an overall measure of system reliability. The middle hierarchy comprises four primary indices: stability, generation capacity, flexibility and system reliability statistics. The bottom hierarchy includes some specific secondary indices for each primary index.

To quantify the overall impact of each index on reliability, this paper proposes a combined weighting framework that selects the optimal combination from a variety of subjective and objective weighting methods according to their hyperentropy in weight cloud models. Five standard clouds, representing the worst, poor, middle, good, and best reliability levels, are constructed to quantify the reliability level of power systems. Based on the evaluation results of the secondary indices, cloud models for primary indices and the CREI are developed. Finally, the reliability level is determined by selecting the standard cloud with the closest Wasserstein distance to the CREI cloud.

The proposed method is particularly suitable for highly informatized power systems with substantial renewable energy integration. Its implementation primarily relies on data from advanced information systems (e.g., supervisory control and data acquisition, and phasor measurement units) and operational strategy records from grid operators, which can ensure adaptability to real-time system dynamics.

This paper illustrates the practicality of the proposed method by two city grids in a province in Southern China. The results indicate that, as an industrial hub of the province, the CREI of City B is on the second level, which is inferior to that of the provincial capital, City A. Therefore, to enhance the overall reliability of the province, the provincial grid company should prioritize improving the system reliability of City B, especially focusing on the stability and generation capacity, to reduce the potential risks.

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Abbreviations

The following abbreviations are used in this manuscript:

REIS	Reliability evaluation index system
CREI	Comprehensive reliability evaluation index
MCS	Monte Carlo simulation
SE	State enumeration
LOLP	Loss-of-load probability
EENS	Expected energy not supplied
FAHP	Fuzzy analytical hierarchy process
BWM	Best–worst method
EWM	Entropy weight method
VCM	Variation coefficient method
TOPSIS	Technique for order preference by similarity to ideal solution
GRA	Grey relational analysis

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