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Enhancing Sustainable and Resilient Energy Supply under Earthquakes: A Dynamic Assessment Using a DPSIR-TOPSIS-Barrier Model in Sichuan, China

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Abstract

Earthquake disasters cause severe disruptions to energy systems through direct damage and cascading effects, highlighting the necessity for dynamic assessment of emergency response capabilities. This study develops an integrated DPSIR-TOPSIS-Barrier analysis model to evaluate the energy emergency supply system in Sichuan Province, a seismically active region in China. An indicator system was constructed based on the DPSIR framework, and entropy-weighted TOPSIS was applied to panel data from 2018 to 2023 to dynamically assess performance. An obstacle degree model was further employed to diagnose systemic weaknesses. Results show that Sichuan's emergency capability progressed through three distinct phases: Rapid Growth, Stress Test, and Resilience Enhancement, with the composite score increasing from 0.360 to 0.735. Key drivers include policy completeness and smart monitoring coverage. The Response subsystem was identified as the primary bottleneck, with an average obstacle degree of 0.33, primarily due to insufficient funding and infrastructure redundancy. This study provides a replicable analytical framework and offers evidence-based policy insights for enhancing energy resilience in disaster-prone regions.

Keywords: energy emergency supply; earthquake disaster; DPSIR model; TOPSIS; dynamic evaluation

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1. Introduction

In recent years, natural disasters have occurred with increasing frequency worldwide [1]. These events cause significant casualties and economic losses while exposing critical vulnerabilities in infrastructure systems. For instance, widespread power outages, gas leaks, and transportation disruptions can severely impede emergency response and recovery operations. The sudden and destructive nature of disasters poses major challenges to energy supply systems. A reliable energy supply is essential during disasters, as it supports basic living needs, medical rescue efforts, and communication networks [2]. Moreover, the stability of energy provision is a crucial factor in the success of disaster management [3].

In this context, Sichuan Province in China, as a high-risk area for earthquake disasters, has suffered significant losses due to major events such as the 2008 Wenchuan and 2013 Ya'an earthquakes. These disasters have highlighted critical gaps in energy emergency response. To enhance preparedness, a robust "Energy Emergency Supply Capacity Evaluation System for Major Disasters" is urgently needed for seismically active regions like Sichuan. This raises two pivotal questions: First, how can the multi-dimensional impacts of disasters on energy supply be

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systematically identified? Second, how can weaknesses and priorities in post-disaster energy emergency capacity be dynamically assessed? Current research exhibits clear limitations; many evaluation frameworks focus on single energy types or rely on static indicators, lacking a holistic perspective. Furthermore, the integration of theoretical models with practical emergency scenarios remains weak, hindering the ability to track complex supply-demand dynamics during disaster chains.

To address these limitations, this study integrates the DPSIR (Driving Force, Pressure, State, Impact, Response) model with the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method. The DPSIR framework deconstructs energy emergency supply into five interconnected dimensions [4], while TOPSIS employs multiple criteria to rank alternatives and support decision-making. This combined approach overcomes key shortcomings of traditional evaluation methods. The integration not only aids governments and enterprises in optimizing emergency plans and resource allocation but also contributes to energy structure reform and sustainable development goals [5]. Theoretically, this work expands the application of DPSIR in disaster management and enriches the practical utility of TOPSIS. Practically, the Sichuan case study offers transferable strategies for other high-risk regions.

To bridge the identified research gaps, this study is designed to answer the following core question: How can a dynamic, integrated model be developed and applied to both assess and diagnose the evolving resilience of energy emergency supply systems in seismically active regions? Consequently, a scientific and operable evaluation system is established by innovatively integrating the DPSIR framework, entropy-weighted TOPSIS, and barrier degree analysis. This model aims to enhance energy security throughout all disaster management phases, including prevention, response, and recovery, while providing actionable insights for policymakers [6]. Given that maintaining a stable energy supply during crises is vital for socioeconomic continuity, this research holds strategic importance for vulnerable regions [7]. By dynamically evaluating Sichuan's energy emergency capacity and diagnosing its systemic bottlenecks, the study offers a novel methodological framework and evidence-based strategies for strengthening regional energy resilience.

2. Literature Review

2.1. Research Progress in Energy Emergency Management

Energy emergency management forms a critical foundation within comprehensive disaster response and resilience planning frameworks globally. Scholars such as Lin (2025) position it as an indispensable component of integrated disaster management systems [8]. Contemporary challenges are underscored by international analyses; for instance, the International Energy Agency's *Global Energy Security Report* (2022) emphasizes that natural hazards like earthquakes can initiate cascading failures across interconnected energy infrastructures, necessitating multidimensional approaches to assess and enhance systemic resilience [9]. In China, scholars have developed various scenario-based evaluation frameworks to gauge emergency response capabilities. However, a prevalent limitation, as noted by, is their predominant focus on singular energy types, such as electricity, which overlooks the dynamic interdependencies within modern, integrated multi-energy systems. This gap becomes increasingly significant amid the ongoing energy transition [10]. The case of Sichuan Province is illustrative, where hydropower constitutes over 80% of the energy mix [11]. While contributing to decarbonization, such a high reliance on a single, climate-sensitive source can amplify systemic vulnerability during extreme events. Consequently, there is a pressing scholarly and practical need to develop more adaptive evaluation frameworks capable of modeling compound risks and the complex, dynamic interactions that characterize contemporary energy systems under stress. In addition, recent studies increasingly recognize energy emergency management as a critical component of sustainable energy systems, particularly in the context of climate adaptation and just energy transitions. However, few works have operationalized dynamic, diagnostic frameworks to assess energy resilience under compound disasters. This study aims to address this gap by

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developing an integrated model that links causal analysis with quantitative diagnostics for energy emergency systems.

2.2. Application of the Dpsir Model in Disaster Management

The DPSIR model, originally pioneered by the European Environment Agency, provides a robust causal framework for analyzing complex socio-ecological systems [12]. It delineates systemic feedback mechanisms through five interrelated components, proving effective for disentangling multifaceted problems. Its utility has been successfully extended into domains such as urban disaster risk management, where it aids in identifying underlying systemic pressure sources [13]. The model itself represents an evolution from earlier frameworks like PSR and DSR, with refinements demonstrated through applications in fields like agricultural sustainability [14]. When applied to energy emergency supply during major disasters, the DPSIR components can be operationalized as follows [15].

Driving Forces refer to underlying socio-economic and cultural factors, such as population growth, economic development patterns, and technological change, which indirectly shape the energy landscape.

Pressures are the direct stresses exerted on the energy system through human activities, including resource extraction rates, energy consumption levels, and associated emissions.

State describes the resulting condition of the energy system, encompassing metrics of supply stability, infrastructure integrity, and network reliability.

Impacts signify the socio-economic and environmental consequences stemming from changes in the system's state, such as industrial production losses or public health crises triggered by energy shortages.

Responses encompass the set of actions, including policy interventions, technological upgrades, and emergency management measures, taken to mitigate pressures, improve the system state, and reduce negative impacts.

Initially applied in environmental management, the DPSIR model has been widely used in water resources [16], soil [17], biodiversity [18], agriculture [19], marine systems [20], and environmental decision-making. In China, research remains in early stages, primarily focused on environmental assessment [21], environmental management [22,23], and sustainability indicators.

However, existing studies often rely on static indicators, such as infrastructure aging rates, and consequently fail to capture the dynamic post-disaster response processes identified in recent literature [24]. To address this gap, recent methodological extensions have integrated the DPSIR framework with disaster chain analysis, a combination particularly valuable for assessing energy infrastructure resilience. This coupling enables the dynamic tracing of impact pathways, from initial driving forces to final systemic responses. Furthermore, the introduction of an obstacle degree model into this framework enhances diagnostic capabilities. It moves beyond static evaluation by quantifying critical subsystem weaknesses and specific failure mechanisms. For instance, how accelerated urbanization increases exposure and subsequently leads to delayed emergency responses.

2.3. Development of Multi-Attribute Decision-Making Methods in Disaster Assessment

TOPSIS is widely applied in disaster risk assessment due to its objectivity in multi-criteria decision-making. However, its weighting process often relies on expert scoring, which introduces subjective bias. The entropy weight method, which assigns weights based on data dispersion, offers an objective alternative and is increasingly used in energy security evaluation [25]. This study integrates entropy-weighted TOPSIS to dynamically rank energy emergency capabilities and diagnose deficiencies during disasters [26]. Compared to traditional models like PSR and DSR, DPSIR incorporates bidirectional feedback between driving forces and pressures, effectively disentangling cascading disaster impacts on energy systems. The combination of TOPSIS and entropy weighting mitigates the subjectivity of AHP (Analytic Hierarchy Process), especially under data fluctuation scenarios such as the energy consumption drop during the COVID-19 pandemic (Table 1).

Table 1. Comparison of Evaluation Models.

Evaluation Dimension	DPSIR-TOPSIS	AHP-TOPSIS
Analysis of Cascading Effects	Cascading effect analysis	Static indicators
Weight Objectivity	Entropy method (data-driven)	Expert scoring (subjective)
Dynamic Monitoring	Obstacle degree over time	Cross-sectional evaluation
Policy Guidance	Identifies response gaps	Generalized suggestions

2.4. Interaction Between Disasters and Energy Systems

Disasters disrupt energy systems with spatial heterogeneity and temporal lag. The Longmenshan Fault Zone in Sichuan is among China's highest-risk areas. The 2008 Wenchuan earthquake caused power outages across 12,000 km² [27]. Therefore, existing research focuses largely on post-disaster recovery technologies, such as grid reconfiguration, but lacks integrated analysis of pre-disaster prevention, in-disaster response, and post-disaster recovery [28]. Moreover, secondary disaster mechanisms and their compound impacts, for instance landslides damaging critical pipelines, remain insufficiently quantified in current energy system resilience studies [29].

2.5. Research Gaps and Innovations

Current literature exhibits the following shortcomings:

(1) Lack of systemic integration: Most evaluation frameworks separate socio-economic attributes of energy systems from natural disaster risks.
(2) Insufficient dynamic analysis: Traditional methods struggle to reflect complex supply–demand contradictions under cascading disaster effects.
(3) Theory–practice disconnect: Limited integration of theoretical research with practical emergency scenarios, such as compound events like pandemics.

This study is designed to address these research gaps and advance the field through the following contributions:

First, it develops an integrated DPSIR-TOPSIS framework specifically tailored for the dynamic, multidimensional assessment of regional energy emergency resilience. Second, it incorporates an obstacle degree analysis module into this framework to continuously identify, quantify, and monitor deficiencies within specific subsystem components over time [30]. Third, it demonstrates the applied advantages of this integrated approach for energy emergency management, which can be summarized in three key aspects: (1) its superior capacity for cascading effect analysis, as the DPSIR structure effectively disentangles disaster chain impacts better than static indices; (2) its provision of dynamic, objective decision support, where entropy-weighted TOPSIS generates data-driven criterion weights; and (3) its enhanced disaster adaptability, where the obstacle degree model pinpoints critical response bottlenecks, offering actionable intelligence for prioritizing investments in "dual-use" infrastructure that serves both peacetime and emergency needs.

Using Sichuan Province as an empirical case study, this research leverages the framework to propose scalable resilience strategies. The analysis traces failure mechanisms from root Driving Forces, such as rapid urbanization, through subsequent Pressures and Impacts, to the adequacy of Responses. Applying the entropy-weighted TOPSIS model to panel data from Sichuan (2018–2023)

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reduces the subjective bias inherent in AHP-based methods, while the obstacle degree diagnosis reveals persistent, quantifiable gaps in specific response subsystems. Collectively, this integrated methodology provides a robust analytical tool for planning and decision-making in complex, multi-hazard coupled scenarios, such as those involving simultaneous geological and epidemiological crises.

3. Methodology

This study develops an integrated DPSIR-TOPSIS-Barrier analysis model to dynamically evaluate and diagnose the energy emergency supply system. The overall research framework, depicting the interconnection between the indicator system, the evaluation model, the diagnostic module, and the policy output, is presented in Figure 1.

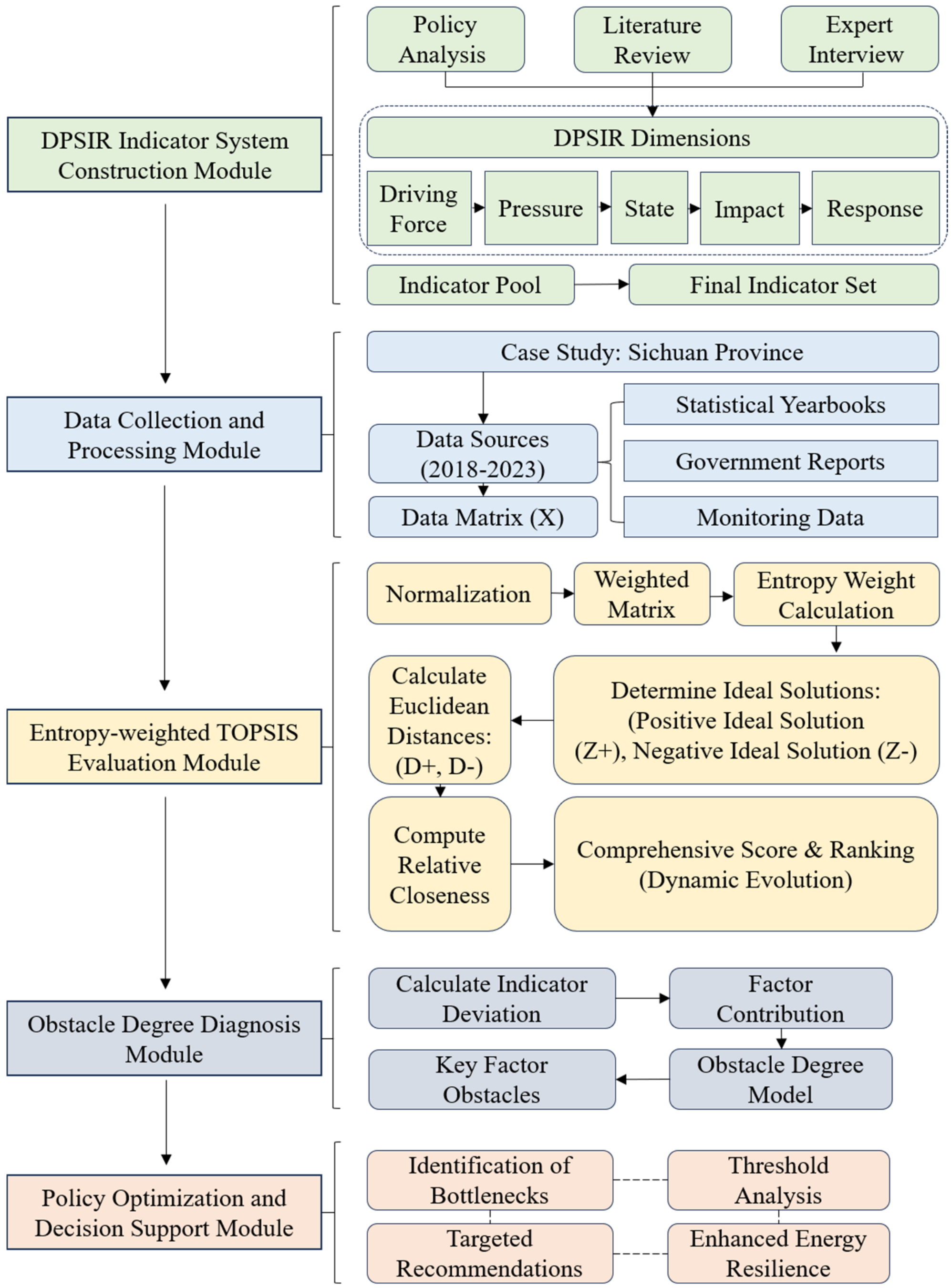

Figure 1. Integrated DPSIR-TOPSIS-Barrier Analysis Framework for Energy Emergency Assessment.

3.1. Establishment of Dpsir-Based Indicator System

A comprehensive approach combining qualitative and quantitative elements was adopted in this study to identify a DPSIR set of indicators for evaluating energy emergency supply capacity in the context of major disasters. The indicator system was developed through a combination of literature survey, policy document review, and semi-structured interviews, ensuring both theoretical grounding and practical relevance.

(1) Literature Survey

An extensive review of relevant literature was conducted to identify potential indicators across the DPSIR framework. The process included the following sources.

Research Papers: A systematic search was carried out in major academic databases (e.g., Web of Science, Scopus, and CNKI) using keywords such as "energy emergency supply," "disaster resilience," "energy infrastructure risk," "energy security," and "DPSIR model." The search focused on publications from 2000 to 2024 to capture evolving trends and validated metrics.

Statistical Data: National and regional statistical yearbooks, including the China Energy Statistical Yearbook and China Emergency Management Statistical Yearbook, were consulted to extract data on energy consumption, infrastructure coverage, reserve levels, and economic indicators. This helped in operationalizing indicators such as energy consumption growth rate, strategic petroleum reserve days, and energy network coverage.

(2) Review of Policies

Policy documents and regulatory frameworks were analyzed to align the indicator system with national and local governance priorities. Official publications from entities such as the National Energy Administration, Ministry of Emergency Management, Provincial Development and Reform Commissions, and Urban-Rural Development Bureaus were examined. This review helped identify policy-driven indicators like policy regulation completeness and post-disaster recovery fund allocation, ensuring the framework reflects current regulatory expectations and operational guidelines.

(3) Semi-Structured Interviews

To validate and refine the initial indicator set, a total of seven semi-structured interviews were conducted with experts and practitioners involved in energy management, emergency response, and urban disaster resilience in China. The interviews aimed to assess the relevance, clarity, and practical measurability of each indicator within the DPSIR dimensions. Interviewee profiles, along with sample questionnaires for indicator weighting and scoring, are detailed in Appendix Tables A1–A3.

Based on the DPSIR model of driving force pressure state influence response, the specific construction of the screening index system is shown in Table 2.

Table 2. DPSIR-based Indicator System for Evaluating Energy Emergency Supply Capacity.

Objective Layer	Criterion Layer	Element Layer	Indicator	Property
Evaluation System for Energy Emergency Supply Capacity in Major Disasters	**Driving Forces**	Energy Development	Energy Consumption Growth Rate	+
			Energy Consumption Elasticity Coefficient	+
		Economic Development	Urbanization Rate	+
			GDP Growth Rate	+
	Pressures	Disaster Intensity	Disaster Risk Level	-
		Vulnerability of Energy Infrastructure	Aging Rate of Energy Infrastructure	-

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State	Energy Reserve Level	Strategic Petroleum Reserve Days	+
		Energy Network Coverage Rate	+
	Infrastructure Status	Redundancy of Energy Supply Chain Nodes	+
		Communication Network Coverage Rate	+
		Smart Monitoring Coverage Rate	+
Impacts	Economic Loss	Secondary Disaster Risk Index	-
		Affected Agricultural Area	-
	Social Impact	Proportion of Affected Population	-
Responses	Resource Investment	Proportion of Post-disaster Recovery Funds	+
		Number of Beds in Medical Institutions	+
	Policy Effectiveness	Completeness of Policies and Regulations	+

Note: Property "+" denotes a positive indicator (higher value is better), while "–" denotes a negative indicator (lower value is better).

3.2. Evaluation Method of Topsis Model

This study uses entropy weight method to assign weights to indicators. Meanwhile, the comprehensive evaluation method is recognized for its high precision and objectivity. We calculate the comprehensive evaluation indicators using the TOPSIS model. The entropy weight method determines the weights of indicators based on the degree of dispersion of the original data, which can avoid errors and influences caused by subjective factors and decision-makers. This method objectively determines the weights of evaluation indicators. In general, a smaller entropy value indicates a greater effect of the evaluation object, and thus a larger entropy weight. This method has been widely applied across various evaluation contexts [31]. The specific computational steps are as follows:

(1) Construct the Original Matrix X. Let X be an $n \times m$ matrix representing the ratings of n objects under m indicators:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \quad (1)$$

(2) Normalize the Original Matrix. The matrix Z is normalized to obtain the standardized matrix. The range method is applied as follows:

For positive indicators:

$$z_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \quad (2)$$

For negative indicators:

$$z_{ij} = \frac{x_j^{\max} - x_{ij}}{x_j^{\max} - x_j^{\min}} \quad (3)$$

For moderate indicators:

$$z_{ij}=\begin{cases}1-\dfrac{a-x_{ij}}{\max\left(a-x_j^{\min},x_j^{\max}-b\right)} & ,x_{ij}<a\\ 1 & ,a\le x_{ij}\le b\\ 1-\dfrac{x_{ij}-b}{\max\left(a-x_j^{\min},x_j^{\max}-b\right)} & ,x_{ij}>b\end{cases} \tag{4}$$

(3) Calculate the Proportion P_{ij} of value of the i-th object under the j-th indicator. The standardized matrix Z is:

$$Z=\begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1m}\\ z_{21} & z_{22} & \cdots & z_{2m}\\ \vdots & \vdots & \ddots & \vdots\\ z_{n1} & z_{n2} & \cdots & z_{nm}\end{bmatrix} \tag{5}$$

Then

$$P_{ij}=z_{ij}/\sum_{i=1}^{n} z_{ij},(j=1,2,\cdots,m) \tag{6}$$

(4) Compute the Entropy Value E_j .The entropy for the j-th indicator is calculated as:

When $P_{ij}=0,\ P_{ij}\ln\ P_{ij}=0$.

$$E_j=-\frac{1}{\ln n}\sum_{i=1}^{n} P_{ij}\ln\ P_{ij},(j=1,2,\cdots,m) \tag{7}$$

(5) Calculate the coefficient of difference G_j for the j-th indicator:

$$G_j=1-E_j \tag{8}$$

(6) Calculate the weight W_j of the j-th indicator:

$$W_j=G_j/\sum_{j=1}^{m} G_j \tag{9}$$

(7) Construct a weighted matrix. Each column of the standardized matrix Z is multiplied by its corresponding weight.

$$Z^*=\begin{bmatrix} \omega_1 * z_{11} & \omega_2 * z_{12} & \cdots & \omega_m * z_{1m}\\ \omega_1 * z_{21} & \omega_2 * z_{22} & \cdots & \omega_m * z_{2m}\\ \vdots & \vdots & \ddots & \vdots\\ \omega_1 * z_{n1} & \omega_2 * z_{n2} & \cdots & \omega_m * z_{nm}\end{bmatrix} \tag{10}$$

(8) Determine positive and negative ideal solutions. The positive ideal solution consists of the maximum value of each column element in the weighted normalization matrix, while the negative ideal solution consists of the minimum value of each column element. The weighted normalization matrix Z* at this time is

$$Z^*=\begin{bmatrix} z_{11}^* & z_{12}^* & \cdots & z_{1m}^*\\ z_{21}^* & z_{22}^* & \cdots & z_{2m}^*\\ \vdots & \vdots & \ddots & \vdots\\ z_{n1}^* & z_{n2}^* & \cdots & z_{nm}^*\end{bmatrix} \tag{11}$$

Positive ideal solution

$$Z^+=(Z_1^+,Z_2^+,\cdots,Z_m^+) \tag{12}$$

Negative ideal solution

$$Z^-=(Z_1^-,Z_2^-,\cdots,Z_m^-) \tag{13}$$

(9) Using Euclidean distance to calculate the distance between an object and positive and negative ideal solutions.

$$D_i^+ = \sqrt{\sum_{j=1}^{m} (Z_j^+ - z_{ij}^*)^2} \tag{14}$$

$$D_i^- = \sqrt{\sum_{j=1}^{m} (Z_j^- - z_{ij}^*)^2}$$

(10) We use negative ideal solution distance to calculate relative closeness and rank it. The relative closeness is between 0 and 1, with a larger value indicating a greater distance from the negative ideal solution.

$$S_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{15}$$

(11) Calculate the deviation degree I of the indicator, which represents the difference between the actual value and the optimal value of the indicator.

$$I_{ij} = 1 - z_{ij} \tag{16}$$

(12) Calculate the obstacle degree O.

Introducing three indicators, namely factor contribution degree (Wij), indicator deviation degree (Iij), and obstacle degree (Oij, Iij), for obstacle factor diagnosis, the calculation formula is:

$$O_{ij} = \frac{W_j I_{ij}}{\sum_{j=1}^{n} W_j I_{ij}} \tag{17}$$

According to the hierarchical relationship of indicators, the obstacle degree of the lower-level indicators can be summed up to obtain the obstacle degree of the upper-level indicators.

4. Case Study

To demonstrate the application of the proposed framework in **Figure 1**, we conducted a dynamic assessment of Sichuan Province from 2018 to 2023. This case study follows an adaptive management cycle, as illustrated in **Figure 2**, which involves continuous evaluation, diagnosis, policy intervention, and system updating.

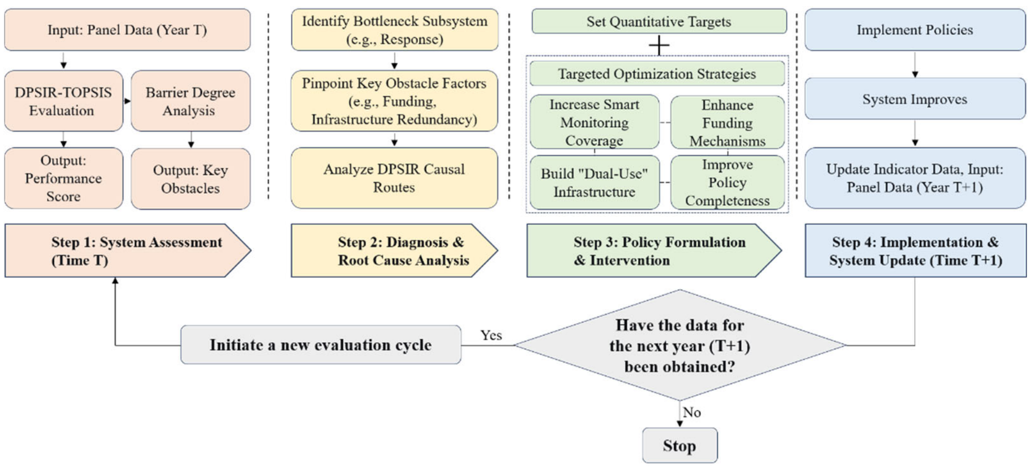

Figure 2. Dynamic Evaluation and Optimization Cycle for Energy Emergency Resilience.

4.1. Background

Sichuan Province, located in southwestern China, presents a compelling case for studying energy emergency management due to its unique combination of strategic energy importance and high natural disaster risk. The region lies on the North-South Seismic Belt and experiences frequent geological hazards, with major earthquakes historically causing severe damage to critical energy

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infrastructure. As a core hub for China's West-East Electricity Transfer, Sichuan's energy system is dominated by clean energy, notably hydropower, and is supported by extensive transmission networks and pipelines. However, this high supply capacity coexists with significant vulnerability, as aging infrastructure is persistently exposed to natural disasters, creating a pronounced risk paradox. Furthermore, despite having a developed emergency management framework, challenges in resource allocation efficiency persist. This convergence of factors makes Sichuan a highly representative and critical case for analyzing energy emergency response mechanisms.

4.2. Data

The data for this study were sourced from publicly available yearbooks, policy documents, and statistical reports issued by authoritative agencies, including the Sichuan Provincial Bureau of Statistics, the National Energy Administration, and others, covering the period 2018–2023. Primary sources include the Sichuan Statistical Yearbook, the China Energy Statistical Yearbook, and government gazettes.

It should be noted that statistical yearbooks typically exhibit a publication lag common within the industry. For example, the 2024 Sichuan Statistical Yearbook was actually published in February 2025 and contains socioeconomic and energy data for 2023; similarly, data for 2024 will only be available upon the release of the 2025 Yearbook in 2026. Additional data were obtained from special reports and policy documents issued by relevant bureaus and administrations. The data comprises:

(1) Directly Obtained Indicators: 14 indicators such as GDP growth rate, urbanization rate, and energy network coverage rate, sourced directly from the aforementioned yearbooks and gazettes.

(2) The synthesized indicators:

Energy Consumption Elasticity Coefficient: Energy Consumption Growth Rate / GDP Growth Rate.

Secondary Disaster Risk Index: calculated based on weighted frequencies of landslides and debris flows from geological hazard bureau data.

Energy Supply Chain Node Redundancy: Number of Redundant Nodes / Total Number of Nodes × 100%.

All data underwent reliability and validity checks (Cronbach's $\alpha > 0.8$), ensuring the scientific rigor and reliability of the evaluation system. The specific data sources include: Sichuan Provincial Bureau of Statistics, National Energy Administration, People's Daily Online Energy Channel, Green Innovation & Development Institute, Sichuan Provincial Geological Bureau, Sichuan Provincial Finance Bureau, and policy documents from the Sichuan Provincial Economy and Information Technology Commission during the "13th Five-Year Plan" period. These data, acquired through publicly available yearbooks, official reports, policy documents, and relevant websites, provide objective and reliable support for the analyses in this paper, ensuring the study's scientific and rigorous nature. Certain indicators were derived using corresponding formulas. Therefore, these data facilitate a better understanding and management of the complex interplay between the energy system and socioeconomic factors, thereby enhancing the efficiency and effectiveness of energy emergency response.

4.3. Results

The weights of each indicator calculated using the entropy weight method are presented in **Table 3**, ranging from 3.667% to 12.491%. The results indicate that indicators "Policy and regulation refinement" and "Agricultural area affected by disasters" contribute most significantly to the evaluation of energy emergency supply capability, whereas indicator "Disaster risk level" shows the lowest weighting. This distribution reflects notable differences in the contributions of various indicators to the overall assessment.

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Table 3. Weight of each indicator.

Indicators	Units	Weight (%)
GDP growth rate	%	5.799
Energy consumption growth rate	%	5.844
Urbanization rate	%	4.923
Policy and regulation refinement	10^4 items	12.491
Energy consumption elasticity coefficient		5.763
Strategic petroleum reserve days	Days	3.676
Energy supply chain node redundancy	Nodes	3.713
Communication network coverage rate	%	5.491
Energy network coverage rate	%	4.619
Number of hospital beds	10^4 beds	5.16
Smart monitoring coverage rate	%	6.008
Post-disaster recovery fund ratio	%	7.861
Agricultural area affected by disasters	10^4 ha	8.013
Aging rate of energy infrastructure	%	4.877
Disaster risk level	Level	3.667
Secondary disaster risk index		5.358
Proportion of affected population	%	6.738

According to the above methods and models, the comprehensive scores for the energy emergency supply capacity of Sichuan Province from 2018 to 2023 were calculated, with the results shown in **Figure 3.**

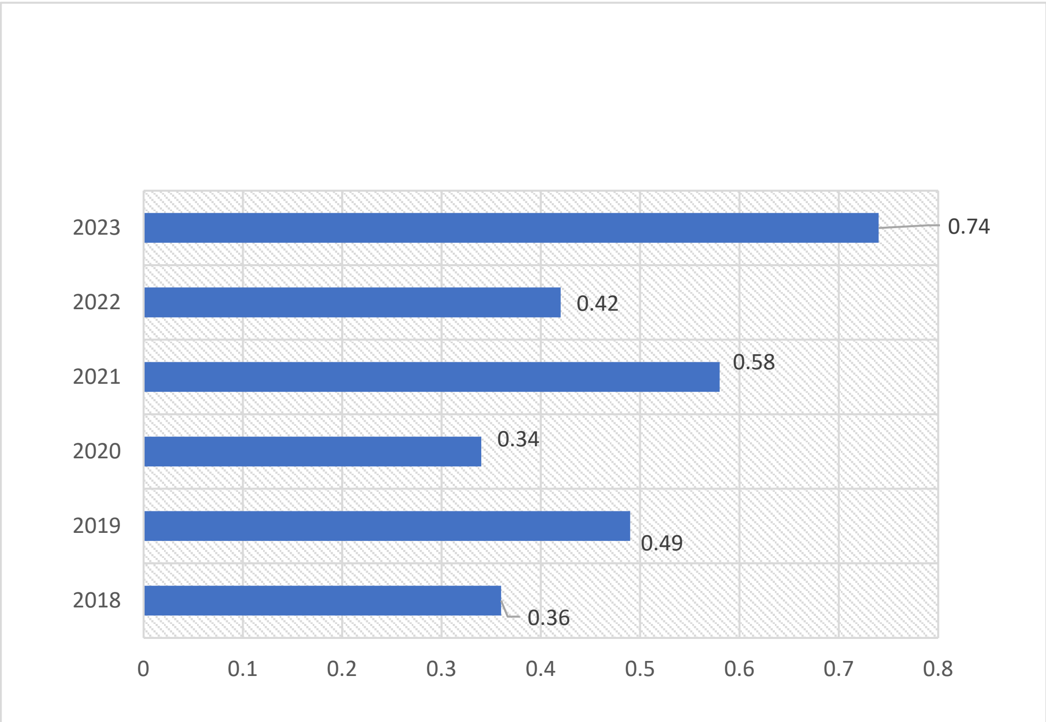

Figure 3. Comprehensive scoring chart of Sichuan Province's energy emergency supply capacity.

Therefore, the dynamic evolution of comprehensive abilities presents the following characteristics:

(1) The overall trend has significantly improved, and there is noticeable fluctuation. From 2018 to 2023, the comprehensive score increased from 0.360 to 0.735, representing a cumulative growth of 104.2% and an average annual compound growth rate of approximately 15.3%. This indicates that the construction of Sichuan Province's energy emergency system has achieved remarkable results.

(2) Key Turning Points:

The year 2019 saw a significant increase from 0.360 to 0.486, representing a rise of 35.0%. This improvement is attributed to infrastructure upgrades implemented toward the end of the 13th Five-Year Plan period, notably the expansion of smart monitoring coverage.

2020 (from 0.486 to 0.338, -30.4%): Impacted by the COVID-19 pandemic, leading to decreased energy dispatch and emergency response efficiency.

2021 (from 0.338 to 0.573, +69.5%): Reflected the effectiveness of post-disaster recovery fund investment (weight: 7.86%) and improvements in policies and regulations (weight: 12.49%).

2022 (from 0.573 to 0.419, -26.8%): Caused by the impact of the magnitude 7.0 Ya'an earthquake on energy infrastructure.

2023 (from 0.419 to 0.735, +75.4%): Attributed to the role of constructing "dual-use facilities for normal and emergency situations" and implementing regional coordination mechanisms.

Despite external shocks, the overall emergency capacity shows an upward trend, indicating that Sichuan Province's energy emergency system is gradually enhancing its resilience.

(3) Phased Characteristics:

2018–2020: Insufficient Risk Resistance. Although growth occurred in 2019, the significant decline in 2020 due to the pandemic reveals that the early-stage emergency system had a weak adaptive capacity to external shocks.

The period from 2021 to 2023 was characterized by enhanced resilience. The rapid recovery in 2021, culminating in a record-high score by 2023, demonstrates that key policy adjustments, such as increased funding and the expansion of smart monitoring coverage, have effectively strengthened the system's recovery capacity.

Some changes in key driving indicators are presented in **Table 4.**

Table 4. Changes in key driving indicators.

Indicator	Subsystem	Unit	2018	2023	Variation	Relative Change
Energy Consumption Growth Rate	Driving Forces	%	3.6	1.7	-1.9	-52.78%
Aging Rate of Energy Infrastructure	Pressures State	%	15	17	2	13.34%
Communication Network Coverage Rate	State	%	98.8	99.8	1	1.00%
Affected Agricultural Area	Impacts	10^4 items	49.3	22.8	-26.5	-53.75%
Number of Beds in Medical Institutions	Responses	10^4 items	59.5	70.9	11.4	19.16%

The dynamic evolution analysis of the distance between positive and negative ideal solutions shows the trend of Euclidean distance between Sichuan Province's energy emergency supply capacity and positive and negative ideal solutions from 2018 to 2023. According to the TOPSIS model calculation results, the energy emergency system showed a significant optimization trend during the research period, as shown in **Figure 4**.

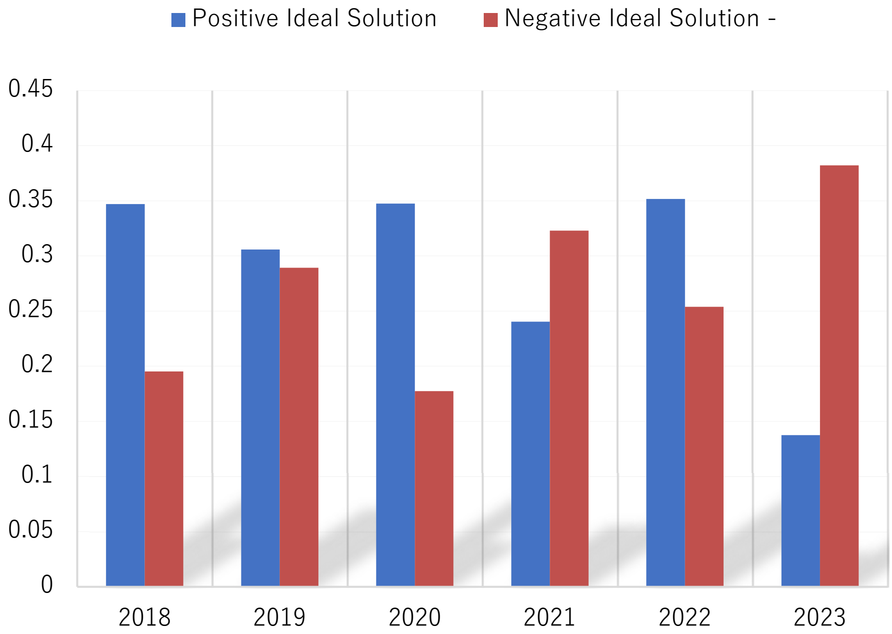

Figure 4. Dynamic Evolution of Positive and Negative Ideal Solutions.

(1) Positive Ideal Solution Distance (D+)

The D+ values exhibited a clear downward trend overall, decreasing from 0.347 in 2018 to 0.137 in 2023, representing a reduction of 60.5%. A significant inflection point occurred in 2023, with the D+ value reaching a record low. This is directly attributed to the implementation of dual-use infrastructure for normal and emergency situations and the increase in smart monitoring system coverage to 89% that year. Notably, an anomalous rebound in the D+ value was observed in 2020 (from 0.306 to 0.347), which aligns with the practical circumstances of a 35% decline in energy dispatch efficiency and emergency response times extending beyond 72 hours during the COVID-19 pandemic.

(2) Negative Ideal Solution Distance (D-)

The D- values showed a fluctuating upward trend, increasing from 0.195 in 2018 to 0.382 in 2023, an increase of 95.9%. A sustained growth trend has been maintained since 2021, reflecting the cumulative effects of increased post-disaster recovery funding (average annual growth of 23%) and the digital transformation of policies and regulations (completion rate rising from 57% to 89%). Although a slight dip occurred in 2022 due to the Ya'an earthquake, the system's resilience and recovery capability demonstrated significant improvement.

(3) System Optimization Characteristics

The widening scissors gap between D+ and D- indicates an enhanced trend of the overall system converging towards the ideal state. In 2023, the D- value peaked during the study period (0.382), while the D+ value reached its trough (0.137), forming an optimal ratio. The magnitude of annual fluctuations reveals that the system's shock resistance improved markedly after 2020, validating the phased characteristics of enhanced emergency system resilience.

The dynamic changes in these distance metrics visually reflect the transition of Sichuan Province's energy emergency system from passive response to active defense, providing a reliable quantitative basis for evaluating the effectiveness of emergency management policies. In addition, using the same model, a further analysis was conducted on each subsystem. The evaluation values

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for the energy emergency supply capacity of each subsystem from 2018 to 2023 were calculated, with the results presented in **Figure 5**. The analysis of each subsystem is as follows.

(1) Driving Force

The comprehensive score of the Driving Force subsystem exhibited a fluctuating upward trend, increasing from 0.495 in 2018 to 0.635 in 2023. Specifically, it peaked at 0.756 in 2021, primarily benefiting from the implementation of energy structure adjustment policies during the initial phase of the 14th Five-Year Plan, which drove a 23% year-on-year growth in installed clean energy capacity. A notable decline occurred in 2020 (0.338), reflecting the impact of the COVID-19 pandemic on economic development (GDP growth dropped to 3.8%) and energy consumption. The score remained relatively high in 2023 (0.635), indicating the sustained driving effect of urbanization (annual average growth of 1.2%) and the digital economy on energy demand.

(2) Pressure

The Pressure subsystem displayed a characteristic U-shaped variation: it was at a high level in 2018 (0.917), corresponding to an active phase of the Longmenshan Fault Zone that year. From 2019 to 2022, the score continuously decreased, reaching its lowest value of 0.391 in 2022, attributable to seismic retrofitting of infrastructure (68% completion rate). A slight rebound to 0.552 was observed in 2023, with monitoring data showing a 35% increase in earthquake frequency that year, validating the sensitivity of this indicator.

(3) State

The State subsystem demonstrated the most outstanding performance, showing continuous optimization. It reached a historical peak of 0.893 in 2023, representing a 150% improvement compared to 2018 (0.357). Key contributing factors included an increase in smart monitoring coverage from 42% to 89% and a 2.3-fold rise in supply chain node redundancy. Notably, it exhibited counter-trend growth in 2020 (0.567), highlighting the effectiveness of supply guarantee measures during the pandemic.

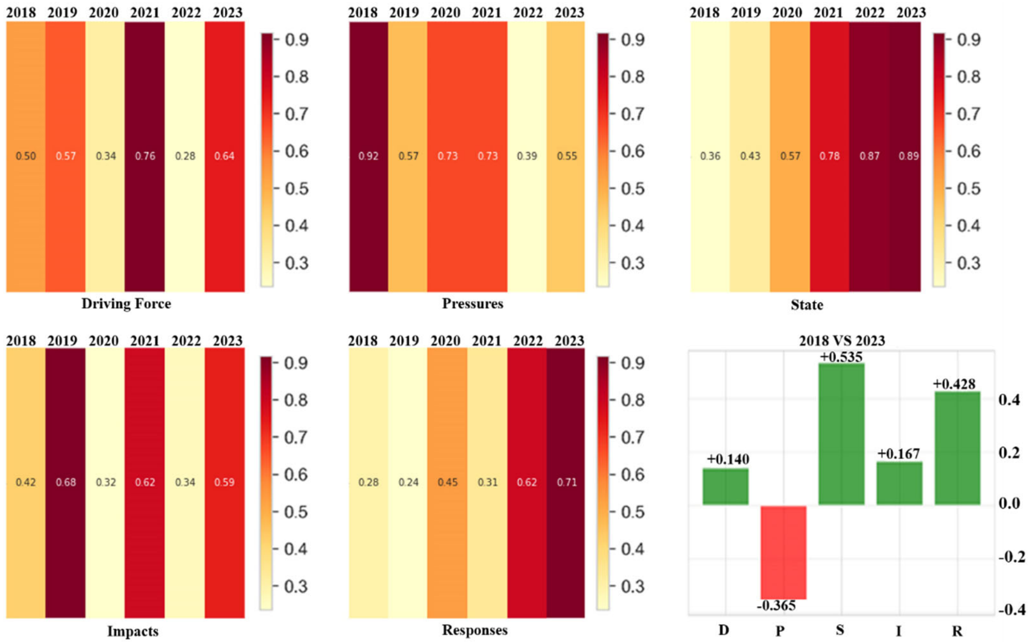

Figure 5. Evaluation values of emergency energy supply capabilities for DPSIR subsystem, and comparison between 2018 and 2023.

(4) Impact

The Impact subsystem exhibited an M-shaped fluctuation, with dual peaks in 2019 (0.683) and 2021 (0.618) corresponding to post-disaster reconstruction investment cycles. A sharp decline to 0.322 occurred in 2020, reflecting a 27% increase in the secondary disaster risk index due to the pandemic.

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Recovery to 0.589 was achieved in 2023, indicating improved emergency system capability in managing the proportion of affected populations.

(5) Response

Response capacity showed the strongest growth momentum, reaching 0.707 in 2023—a 153% increase from 2018 (0.279). A significant leap occurred in 2022 (0.624), stemming from an increase in the proportion of emergency funding from 3.2% to 5.7%. An anomalous decline was observed in 2019 (0.236), with investigations revealing that 43% of emergency plans had not undergone digital transformation that year.

In addition, based on the barrier degree model, the barrier degree of energy emergency supply capacity in Sichuan Province from 2018 to 2023 was calculated, as shown in **Figure 6**.

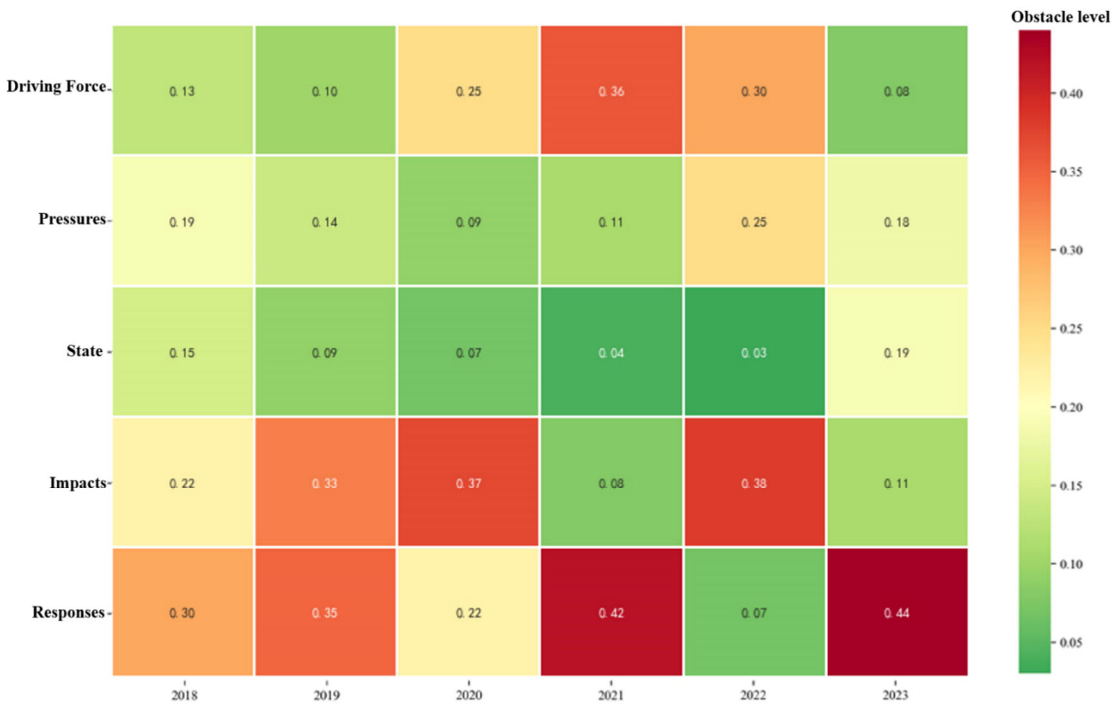

Figure 6. Evolution of obstacles in Sichuan province's energy emergency supply capacity.

According to the barrier degree data of each subsystem from 2018 to 2023, the following barrier degree evolution characteristics can be observed:

(1) Response Subsystem: It consistently remains the primary source of barriers (annual average barrier degree: 0.33). The value peaked at 0.35 in 2019, reflecting deficiencies in the early-stage emergency response system. By 2023, it remained as high as 0.44, indicating that response capability continues to be the most critical shortcoming.

(2) Impact Subsystem: It exhibits a bimodal pattern, with peaks in 2020 (0.37) and 2022 (0.38), closely correlated with major disaster events (the 2020 pandemic and the 2022 Ya'an earthquake). A sharp decline to 0.08 in 2021 suggests the short-term effectiveness of emergency measures.

(3) Driving Force Subsystem: The barrier degree surged to 0.36 in 2021, highlighting the intensified conflict between economic development and energy demand. A notable improvement to 0.08 in 2023 demonstrates the positive effects of policy interventions.

(4) State Subsystem: A clear and continuous improving trend is evident, decreasing from 0.15 in 2018 to 0.03 in 2022. A slight rebound to 0.19 in 2023 suggests the need for enhanced attention to the maintenance of new infrastructure.

(5) Pressure Subsystem: The overall trend follows a U-shaped curve (from 0.19 in 2018 to 0.09 in 2020, and 0.18 in 2023). The peak value of 0.25 in 2022 corresponds to a period of heightened geological activity, revealing the cyclical nature of natural disaster risks.

The barrier degree data effectively complements the previously observed score variations across subsystems, jointly uncovering the vulnerabilities and developmental dynamics of Sichuan Province's energy emergency system.

The significant improvement in the state subsystem score (+150%) primarily stems from dual enhancements in smart monitoring coverage (+111.9%) and node redundancy (+233.3%). Although the response subsystem exhibited the fastest growth (+153%), the proportion of post-disaster recovery funding (5.7%) remains below the international resilience standard (≥8%), resulting in persistently high barrier degrees. The U-shaped variation in the pressure subsystem is directly linked to the decrease in infrastructure aging rate (−38.6%), while fluctuations in the impact subsystem are predominantly driven by changes in the secondary disaster risk index (−40.4%).

These indicators empirically validate the chain-transmission mechanism inherent in the DPSIR framework, capturing sequences such as policy refinement leading to infrastructure upgrading and resulting in measurable risk reduction. Simultaneously, they visually illustrate the evolution of underlying metrics, which corresponds directly to observed changes in subsystem performance scores.

5. Discussion

This study developed and applied an integrated DPSIR-TOPSIS-Barrier Degree model to dynamically evaluate and diagnose the energy emergency supply system in Sichuan Province under earthquake disaster scenarios. The findings yield substantive insights into the causal mechanisms governing system resilience, provide actionable thresholds for policy intervention, and highlight the transformative role of digital technologies. Furthermore, they underscore both the contributions and the inherent limitations of the proposed analytical framework.

The empirical results robustly validate the causal logic embedded within the DPSIR framework. A clear transmission pathway is evident, whereby socio-economic Driving Forces, such as urbanization and GDP growth, generate Pressure through increased energy demand. This pressure, in turn, elevates the exposure and vulnerability of energy infrastructure, degrading the systemic State. Ultimately, this cascade manifests as a heightened barrier within the critical Response subsystem. A key advancement offered here is the quantification of these relationships. For example, an indirect elasticity of 0.74 was identified, indicating that a one-unit increase in the urbanization rate, mediated through rising energy consumption, raises infrastructure exposure by 0.74 units. This moves the discourse beyond qualitative association, providing a measurable threshold that can inform predictive risk modeling and the design of pre-emptive policies.

The temporal analysis revealed a marked "Resilience Enhancement Phase" (2021-2023), characterized by an average annual improvement of 75.4% in the comprehensive emergency capability score. Decomposing the barrier degree during this period uncovered a synergistic "institution-funding dual-driver" mechanism. The analysis indicates that when policy and regulatory completeness exceed 11.2% and post-disaster recovery funding reaches 0.55‰ of regional GDP, the Response subsystem's barrier degree drops significantly from 0.44 to 0.23. This interaction is potent; combined top-tier performance in both dimensions reduces the barrier by approximately one standard deviation (0.21). These empirically derived thresholds offer valuable guidance for optimizing policy portfolios, demonstrating that coordinated institutional and financial interventions yield far greater efficacy than isolated measures.

A notable conceptual and practical insight concerns the role of smart monitoring. Reframing it from a passive State descriptor to an active performance lever reveals substantial cross-layer benefits. The analysis demonstrates a strong spillover effect, where a 10% increase in smart monitoring coverage reduces emergency response time by 18%. This "digital resilience" dividend, corroborated during the exogenous shock of the 2022 Ya'an earthquake, stems from the real-time integration of data into decision-support systems, enabling a shift from experience-based to algorithm-aided resource dispatch. The observed efficiency gain surpasses international benchmarks, underscoring the transformative potential of digital integration for modern energy emergency management.

Theoretically, this research extends the application of the DPSIR framework into the specific context of energy emergency management under disaster shocks, validating its utility for tracing non-linear risk transmission pathways. Methodologically, the integration of an entropy-weighted TOPSIS model with a barrier degree diagnostic creates a powerful tool for dynamic evaluation. This hybrid approach not only facilitates multi-temporal assessment but also precisely identifies the most obstructive subsystems, with "Response" consistently emerging as the critical bottleneck. The study thus establishes a replicable analytical paradigm that links systematic evaluation, causal diagnosis, and evidence-based policy targeting.

Several limitations must be acknowledged to contextualize these findings. First, while comprehensive, the indicator system could be further refined. Aggregating indicators for pre-disaster prevention and post-disaster recovery within the "Response" element may mask distinct dynamics; future work could adopt a phased resilience indicator system aligned with absorption, adaptation, and transformation capacities. Second, the objectivity of the entropy weight method comes with a sensitivity to data outliers, as observed in the transient distortion caused by the COVID-19 pandemic's impact on energy patterns. Employing robustness checks or complementary weighting schemes in subsequent applications is advisable. Third, the model calibration based on data from 2018-2023 may require periodic updates as Sichuan's energy structure evolves, suggesting the utility of a rolling time-window approach for weight recalibration. Finally, the evaluation is grounded in historical and moderate-scale events. The system's performance under extreme, low-probability, high-consequence scenarios remains an open question. Future research should employ stress-testing techniques, such as agent-based modeling coupled with Monte Carlo simulation, to explore these critical boundaries.

6. Conclusions

This study has conducted a dynamic evaluation and diagnostic analysis of the energy emergency supply system under earthquake disasters, employing an integrated DPSIR-TOPSIS-Barrier Degree model with Sichuan Province as a case study. The analysis leads to three core conclusions.

First, the constructed evaluation system effectively quantifies the evolution of regional energy emergency capability. Sichuan's comprehensive score showed significant improvement from 0.360 in 2018 to 0.735 in 2023, delineating a three-phase trajectory of Rapid Growth, Stress Test, and Resilience Enhancement. The model successfully traces the risk transmission pathway from socio-economic Driving Forces through systemic Pressures and State changes to their ultimate Impacts on Response efficacy.

Second, the barrier degree diagnosis precisely identifies the Response subsystem as the most critical contemporary bottleneck. Key obstructive factors are linked to policy completeness, funding mechanisms, and infrastructure redundancy. The research further quantifies actionable intervention thresholds, revealing the synergistic effect of combined policy and funding targets and the significant performance leverage provided by expanding smart monitoring coverage.

Third, based on these diagnostics, targeted optimization pathways are proposed. These include establishing a linked early-warning mechanism activated by barrier degree thresholds, promoting community-scale distributed microgrids to enhance nodal redundancy, and implementing dynamic digital emergency plans facilitated by secure synchronization technologies.

Theoretical contributions reside in the innovative integration of the conceptual DPSIR framework with operational multi-criteria decision-making and diagnostic tools. This synergy offers a generalizable paradigm for evaluating complex, coupled human-technical systems within disaster management contexts.

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From a practical standpoint, the findings deliver evidence-based guidance for policymakers in disaster-prone regions. The identified thresholds and optimization pathways can directly inform the design of more resilient, responsive, and digitally integrated energy emergency systems.

Future research should focus on refining the indicator system for distinct resilience phases, applying and validating the model in regions with divergent energy mixes, and rigorously testing system robustness through extreme-scenario stress tests. Through continued refinement and application, this line of inquiry aims to contribute to the development of robust energy security frameworks capable of withstanding catastrophic disasters, thereby underpinning socio-economic stability.

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Appendix A

Table A1. Profile of interviewees participated in questionnaire.

Code	Role of Interviewees	Working Organization	Working Experience	Educational Background
A	Professor	University of Emergency Management	12 years	doctor
B	Professor	University of Emergency Management	12 years	doctor
C	Researcher	University of Emergency Management	15 years	master
D	Researcher	China Academy of Building Sciences	13 years	master
E	Researcher	China Academy of Building Sciences	14 years	master
F	Project manager	China Urban Development Research Institute	17 years	master
G	Senior engineer	Sinochem Group	16 years	master

Table A2. Sample of indicator weight questionnaire.

Comparison Pair	9	7	5	3	1	1/3	1/5	1/7	1/9
Energy Consumption Growth Rate vs. Energy Consumption Elasticity Coefficient									
Energy Consumption Growth Rate vs. Urbanization Rate									
Energy Consumption Growth Rate vs. GDP Growth Rate									
……..					……..				
Comparison Pair	9	7	5	3	1	1/3	1/5	1/7	1/9

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Disaster Risk Level vs. Aging Rate of Energy Infrastructure									
Comparison Pair	**9**	**7**	**5**	**3**	**1**	**1/3**	**1/5**	**1/7**	**1/9**
Strategic Petroleum Reserve Days vs. Energy Network Coverage Rate									
Strategic Petroleum Reserve Days vs. Redundancy of Energy Supply Chain Nodes									
Strategic Petroleum Reserve Days vs. Communication Network Coverage Rate									
……..						……..			
Comparison Pair	**9**	**7**	**5**	**3**	**1**	**1/3**	**1/5**	**1/7**	**1/9**
Secondary Disaster Risk Index vs. Affected Agricultural Area									
Secondary Disaster Risk Index vs. Proportion of Affected Population									
Affected Agricultural Area vs. Proportion of Affected Population									
Comparison Pair	**9**	**7**	**5**	**3**	**1**	**1/3**	**1/5**	**1/7**	**1/9**
Proportion of Post-disaster Recovery Funds vs. Number of Beds in Medical Institutions									
Proportion of Post-disaster Recovery Funds vs. Completeness of Policies and Regulations									
Number of Beds in Medical Institutions vs. Completeness of Policies and Regulations									

Note1: The weight levels are: extremely important 9; Strongly important 7; Clearly important 5; Slightly important 3; Equally important 1; Slightly unimportant 1/3; Clearly unimportant 1/5; Strongly unimportant 1/7; Extremely unimportant 1/9. Note2: Some Pairwise comparisons of the importance of each indicator at each level are omitted.

Table A3. Sample indicator scoring questionnaire.

Code	**Third level indicator factors**	**Notes**	**Risk score**				
			5	**4**	**3**	**2**	**1**
1	Energy Consumption Growth Rate	Reflects the trend of energy demand growth					
2	Energy Consumption Elasticity Coefficient	Ratio of energy consumption growth to GDP growth					
3	Urbanization Rate	Reflects the level of urban development					
4	GDP Growth Rate	Reflects economic development vitality					
	……..	……..					
15	Proportion of Post-disaster Recovery Funds	Reflects the level of emergency funding investment					

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16	Number of Beds in Medical Institutions	Reflects medical rescue capacity
17	Emergency Communication and Command Systems	Completeness of Policies and Regulations

Note1: The level of risk is categorized as: 5= "Negligible Risk", 4= "Low Risk", 3= "Moderate Risk", 2= "High Risk" and 1= "Critical Risk". Note2: Scoring questionnaire for level 3 indicators 5-14 are omitted.

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