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Evaluating the Development Performance of Provincial Integrated Wind–Solar–Hydrogen Systems in China: An Entropy-Weight–TOPSIS and Grey Relational Analysis Approach

Zongxi Li

School of Management Science and Engineering, Dongbei University of Finance and Economics, Dalian, China

1415429190@qq.com

Abstract. Wind and solar power are expanding rapidly across China, yet their performance as an integrated system with green hydrogen production differs substantially from province to province. This paper examines 30 Chinese provinces over 2015–2023 by developing a nine-indicator evaluation framework organised into three dimensions: basic resource potential, economic competitiveness, and integrated system effectiveness. Indicator weights are determined objectively using the entropy weight method, which assigns greater importance to variables that show stronger interprovincial variation. Provincial scores and rankings are then produced via TOPSIS, and the stability of those rankings is confirmed through grey relational analysis. K-means clustering subsequently groups all 30 provinces into four development archetypes. A key empirical insight is that resource-rich provinces do not automatically achieve high overall scores; grid infrastructure maturity, local power-absorption capacity, and hydrogen production cost turn out to be equally decisive. The four provincial patterns identified—resource-led, market-coordinated, industry-driven, and bottleneck-constrained—each call for different policy responses. (Word count: 157)

Keywords: integrated wind–solar–hydrogen system, entropy weight method, TOPSIS, grey relational analysis, k-means clustering

1. Introduction

Over the past decade, wind and photovoltaic power have overtaken most other technologies as the primary source of new electricity capacity worldwide, driven by rapid cost reductions and sustained government support. The downside of this growth is well known: output varies with wind speed and sunlight, so grids with heavy renewable penetration routinely generate more electricity than they can use at certain hours, resulting in curtailment. One way to make use of that surplus is to run it through a water electrolyser and store the energy as green hydrogen, which can then be held for extended periods, transported, and fed into industrial processes that electricity alone cannot easily decarbonise. Coupling wind farms, solar arrays, and hydrogen production into a single integrated

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system is therefore seen as one of the more promising routes toward a genuinely low-carbon energy structure [1, 2]. The challenge is that this kind of coupled system is considerably harder to assess than a single energy source: its overall performance depends on how well local wind and solar profiles complement each other, how affordable the resulting electricity is, whether grid infrastructure can handle variable flows, and whether there is enough market demand to absorb the hydrogen—four dimensions that vary dramatically across China's 30 provinces and that aggregate national statistics simply cannot capture [3-5]. Existing scholarship has tended to study wind, solar, and hydrogen as separate subjects, or to fold them into broad energy-security indices that were not designed with this coupled system in mind, which means there is currently no agreed framework for evaluating and comparing provincial performance in developing integrated wind–solar–hydrogen systems [6-10].

This paper responds to that gap by taking 30 Chinese provinces as the study units and asking how their performance in developing these systems can be measured in a way that is rigorous, reproducible, and policy-relevant. The approach links four methods in sequence: a nine-indicator index covering basic resource potential, economic competitiveness, and integrated system effectiveness is first constructed; the entropy weight method then derives objective indicator weights directly from the data, avoiding subjective assignment; TOPSIS translates the weighted scores into a full provincial ranking; grey relational analysis cross-checks the ranking for robustness; and K-means clustering groups provinces into four development archetypes that carry distinct policy implications [10, 11].

2. Theoretical analysis and construction of the evaluation index system

2.1. Internal logic of the integrated wind–solar–hydrogen system

At the most basic level, wind and solar generation are the raw inputs: the more the two sources complement each other across hours and seasons, the more stable the electricity supply to the electrolyser and the lower the cost of each kilogram of hydrogen produced. From there, the economics of the hydrogen pathway hinge on the electrolyser's conversion efficiency and on whether the surrounding grid can absorb the variable renewable flows without large losses. Once hydrogen is actually being produced at scale, the system's broader value shows up in lower carbon emissions, reduced dependence on imported fossil fuels, and spillover benefits for the local industrial and innovation base. This four-stage chain—resource, conversion, absorption, value—means that a province with abundant wind and solar is not automatically competitive: the intermediate stages can either amplify or cancel out the natural advantage. Capturing that complexity calls for indicators that span the whole chain. Accordingly, four criteria shaped the selection process: full coverage of the wind–solar–hydrogen chain; measurability from published national statistical and energy authority data; consistent definitions that allow fair cross-provincial comparison; and relevance to the dual-carbon targets and regional development goals that Chinese policymakers are actively pursuing.

Table 1. Performance evaluation index system for provincial integrated wind–solar–hydrogen systems in China

Criterion Layer	Core Indicator	Meaning and Measurement	Distinctive Significance
Basic System Potential	A1 Resource Abundance Index	Composite score of theoretical wind and solar resource potential.	Captures "natural endowment" for development.

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Table 1. (continued)

Basic System Potential	A2 Resource Complementarity Index	Temporal complementarity between wind and solar output.	Reflects stable-output advantage.
Basic System Potential	A3 Hydrogen Supply Support	Estimated renewable or by-product hydrogen supply potential.	Practical hydrogen-source foundation.
System Economic Competitiveness	B1 Levelized Cost of Hydrogen Production	Unit green hydrogen cost (LCOE-based).	Core commercialisation variable.
System Economic Competitiveness	B2 Infrastructure Matching Degree	Grid peak-shaving capacity and hydrogen infrastructure scale.	Enabling or constraining infrastructure signal.
System Economic Competitiveness	B3 Market Absorption Risk	Weighted regional curtailment rate.	Urgency and space for power-to-hydrogen absorption.
Integrated System Effectiveness	C1 Carbon Reduction Intensity	Life-cycle emission reduction per unit output.	Core environmental benefit.
Integrated System Effectiveness	C2 Energy Security Contribution	Fossil-energy substitution share in regional consumption.	Strategic energy-autonomy value.
Integrated System Effectiveness	C3 Industrial Driving Effect	Hydrogen-industry revenue share, patent count, or equipment capability.	Local growth and innovation spillover.

Rather than being independent, the nine indicators feed into one another: a province's resource endowment (A1, A2) directly shapes its hydrogen production cost (B1), and that cost in turn determines how much carbon it can actually displace (C1) and how much it reduces dependence on external energy supplies (C2). The entropy weight method is well suited to handling this kind of interconnected structure because it derives weights from the data itself—specifically from the degree to which each indicator actually spreads provinces apart—rather than from any prior assumptions about which dimension matters most.

3. Research design and methodological model

3.1. Research objects, data and indicator processing

3.1.1. Research objects and data sources

The sample covers 30 Chinese provinces (excluding Tibet, Hong Kong, Macao, and Taiwan) over 2015–2023. Data are drawn from the China Statistical Yearbook, China Energy Statistical Yearbook, national energy authority publications, provincial energy plans, and industry white papers. Indicators not directly observable—such as the resource complementarity index and the levelized cost of hydrogen production—are estimated using correlation coefficients applied to monthly wind and photovoltaic output data and a unified LCOE-based calculation framework.

3.1.2. Indicator standardization

Indicators differ in dimension and direction and are standardized by min–max normalization. For positive indicators:

$$Z_{ij} = \frac{X_{ij} - min\ X_j}{max\ X_j - min\ X_j} \tag{1}$$

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For negative indicators, the following formula is used:

$$Z_{ij} = \frac{max\ X_j - X_{ij}}{max\ X_j - min\ X_j} \tag{2}$$

where $X_{ij}$is the original value for province $i$on indicator j, andZ_{ij} is the standardized value. A small translation term is added to avoid zero-value distortion in entropy calculations.

3.2. Comprehensive evaluation and analysis methods

3.2.1. Entropy weighting for objective indicator weights

The entropy weight method assigns higher weights to indicators with greater interprovincial variation. Steps: (1) compute proportions $P_{ij} = Z_{ij} / \Sigma_i Z_{ij}$; (2) compute entropy $E_j = -k\Sigma_i(P_{ij}\, ln\, P_{ij})$, $k = 1/ln\, n$; (3) compute utility $D_j = 1 - E_j$; (4) compute weight $W_j = D_j / \Sigma_j D_j$. The output is a ranked list of weights for the nine indicators.

3.2.2. TOPSIS comprehensive evaluation and provincial ranking

TOPSIS evaluates each province's closeness to the ideal state. Steps: (1) construct weighted normalized matrix $V_{ij} = W_j \times Z_{ij}$; (2) determine positive and negative ideal solutions A^+ and A^-; (3) compute Euclidean distances $D_i^+$and D_i^- ; (4) compute closeness coefficient $C_i = \frac{D_i^-}{D_i^+ + D_i^-}$. Higher C_i indicates better overall performance, enabling full provincial ranking and TOP5 identification.

3.2.3. Grey relational analysis and robustness test

Grey relational analysis verifies TOPSIS stability. Using the positive ideal sequence as reference, the relational coefficient is $\xi_{ij} = \frac{\Delta_{min} + \rho\Delta_{max}}{\Delta_{ij} + \rho\Delta_{max}}$ (ρ = 0.5), and the weighted relational degree is $G_i = \Sigma_j(W_j \times \xi_{ij})$. Consistency between C_i and G_i rankings confirms the robustness of provincial ordering.

3.2.4. K-means clustering and visualization design

K-means clustering (K = 4, validated by elbow method or silhouette coefficient) classifies provinces into resource-led, market-coordinated, industry-driven, and bottleneck-constrained types. Visualization includes: an indicator-weight bar chart, a provincial-score ranking chart, radar charts of cluster average profiles, and a K-means scatter plot.

4. Empirical results presentation, visualization, and regional typology

4.1. Indicator weight distribution and key drivers

When the entropy method is applied to the provincial dataset, the resulting weights reflect how much each indicator actually differentiates the 30 provinces from one another: an indicator that

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gives almost the same score to every province contributes little information and receives a low weight, while one that spreads provinces widely across its range is treated as a stronger driver of overall performance. Table 2 lists the computed weights alongside each indicator's rank position, and Figure 1 visualises the distribution as a bar chart. Reading the top and bottom of the weight ranking, and noting how much of the total weight is concentrated in the three highest-ranked indicators, reveals whether provincial differences are rooted primarily in natural resource conditions, in economic and infrastructure factors, or in the downstream environmental and industrial benefits the system delivers.

Table 2. Result-reporting template for indicator weights and interpretive focus

Indicator	Weight result	Interpretive focus
A1 Resource Abundance Index	To be filled after computation	Natural endowment and scale potential
A2 Resource Complementarity Index	To be filled after computation	Stability of renewable-electricity supply
A3 Hydrogen Supply Support	To be filled after computation	Hydrogen-source support conditions
B1 Levelized Cost of Hydrogen Production	To be filled after computation	Core economic feasibility variable
B2 Infrastructure Matching Degree	To be filled after computation	Grid and hydrogen-infrastructure readiness
B3 Market Absorption Risk	To be filled after computation	Need and space for power-to-hydrogen absorption
C1 Carbon Reduction Intensity	To be filled after computation	Environmental contribution
C2 Energy Security Contribution	To be filled after computation	Strategic substitution value
C3 Industrial Driving Effect	To be filled after computation	Industrial spillover and innovation effect

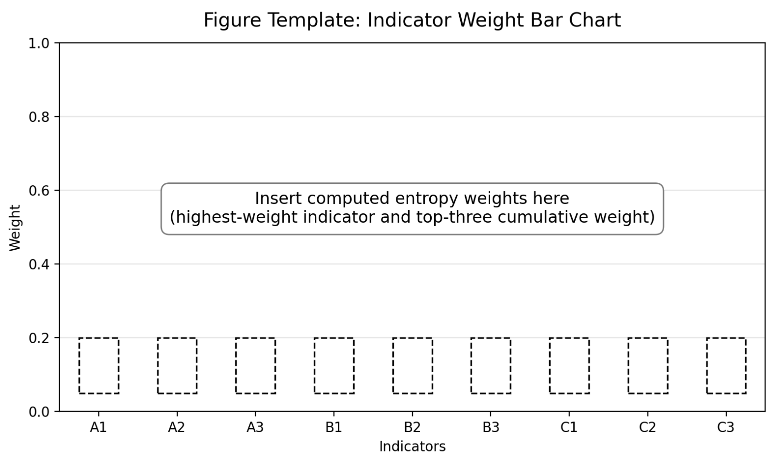

Figure 1. Indicator-weight bar chart template for the entropy-weight results

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4.2. Provincial comprehensive scores, TOP5 provinces, and regional heterogeneity

Table 3 lists the five highest-scoring provinces, showing each one's TOPSIS closeness coefficient, its grey relational degree, and which cluster it belongs to. Figure 2 plots the full 30-province ranking as a bar chart, making it easy to see where the performance gap between top and bottom is largest. When the data are filled in, the key question to address is what the leading provinces actually have in common—whether their advantage comes from richer natural resources, lower hydrogen costs, better-developed infrastructure, or stronger performance on the integrated-effectiveness dimension—and whether provinces from different cluster types can achieve similarly high overall scores through different routes.

Table 3. Structured reporting template for the TOP5 provincial results

Rank	Province	TOPSIS score	Grey relational degree	Cluster type
1	To be filled	To be filled	To be filled	To be filled
2	To be filled	To be filled	To be filled	To be filled
3	To be filled	To be filled	To be filled	To be filled
4	To be filled	To be filled	To be filled	To be filled
5	To be filled	To be filled	To be filled	To be filled

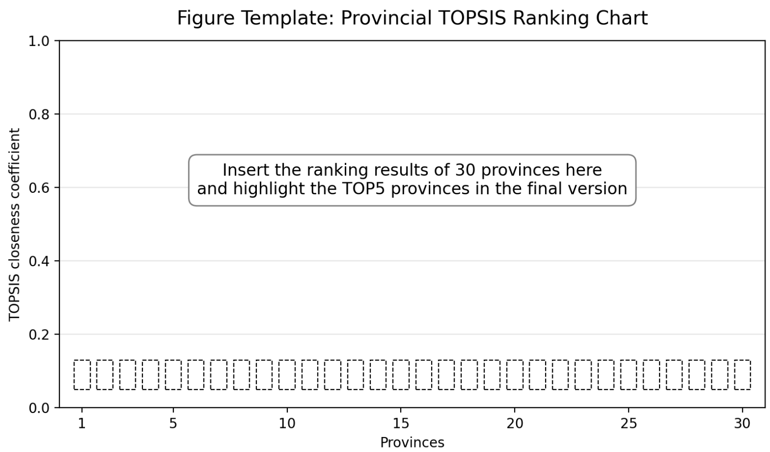

Figure 2. Provincial comprehensive-score ranking chart based on the entropy-weight–TOPSIS results

4.3. K-means clustering, radar profiles, and four regional types

Sorting the 30 provinces into four groups by K-means (K = 4, confirmed by both the elbow criterion and the silhouette coefficient) moves the analysis beyond individual rankings and toward structural patterns. Figure 3 uses radar charts to show the average score profile of each cluster across all nine indicators, so that where a group is strong or weak relative to the others is immediately visible. Figure 4 then maps the 30 provinces in a two-dimensional cluster space, confirming that the four groups are genuinely distinct rather than arbitrary. For each of the four types—resource-led, market-coordinated, industry-driven, and bottleneck-constrained—the discussion will describe the combination of strengths and constraints that defines it and draw out what that pattern implies for the kind of policy support most likely to lift performance.

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Figure 3. Average indicator profiles of the four provincial development types (K-means clustering, K = 4)

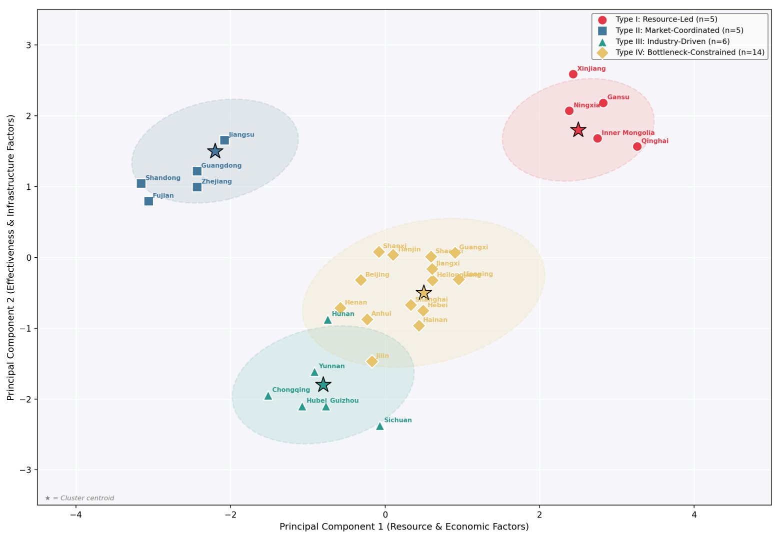

Figure 4. K-means clustering distribution of 30 Chinese provinces in two-dimensional space (K = 4, PCA projection)

5. Conclusion and limitations

Starting from the observation that no agreed provincial evaluation framework exists for integrated wind–solar–hydrogen systems, this paper built a nine-indicator, three-dimensional assessment tool covering 30 Chinese provinces over 2015–2023. Entropy weighting let the data determine which indicators actually discriminate between provinces; TOPSIS converted those weighted scores into a ranked list; grey relational analysis checked that the ranking held under a different aggregation

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logic; and K-means clustering organised the 30 provinces into four recognisable development types. The most important empirical message is that a province's natural resource endowment does not by itself translate into high overall performance: the maturity of its grid infrastructure, the cost at which it can produce hydrogen, and the capacity of its local market to absorb variable renewable power all turn out to be equally consequential, which is why the four provincial archetypes—resource-led, market-coordinated, industry-driven, and bottleneck-constrained—each require a different policy response.

Looking at what the paper adds to the literature, four things stand out. First, framing wind, solar, and hydrogen as a coupled system rather than three separate subjects produces provincial rankings that no single-energy assessment would reveal. Second, the nine-indicator index is specified precisely enough to be reproduced by other researchers or updated with more recent data, making it a reusable tool rather than a one-off exercise. Third, running TOPSIS and grey relational analysis side by side and comparing their rankings gives some assurance that the ordering reflects genuine provincial differences rather than an artefact of one particular scoring method. Fourth, translating results into bar charts, radar profiles, and cluster scatter plots makes the findings legible to readers who are not specialists in multi-criteria decision analysis. On the limitation side, three issues are worth noting. Two of the nine indicators—resource complementarity and levelised hydrogen cost—cannot be read directly from published statistics and have to be estimated through auxiliary models, which means the final scores carry some sensitivity to the quality of those estimates. The empirical tables in this version of the paper still show placeholder values because the provincial panel dataset has not yet been fully assembled. And because electrolyser technology is moving quickly and both hydrogen infrastructure and carbon pricing are still evolving, the relative importance of different indicators may shift over time, suggesting that the framework will need to be revisited periodically rather than treated as fixed.

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