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Article

Dynamic Modeling of Bilateral Energy Synergy: A Data-Driven Adaptive Index for China-Korea Hydrogen System Coupling Assessment

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Abstract

The development of cross-border hydrogen energy value chains involves complex interactions between technological, regulatory, and logistical subsystems. Static assessment models often fail to capture the dynamic response of these coupled systems to external perturbations. This study addresses this gap by proposing the Dual Carbon Cooperation Index (DCCI), a data-driven framework designed to quantify the synergy efficiency of the China-Korea hydrogen ecosystem. We construct a dynamic state estimation model integrating three coupled dimensions—Technology Synergy, Regulatory Alignment, and Supply Chain Resilience—utilizing an adaptive weighting algorithm (Triple Dynamic Response). Based on multi-source heterogeneous data (2020–2024), the model employs Natural Language Processing (NLP) for vectorizing unstructured regulatory texts and incorporates an exogenous signal detection mechanism (GRI). Empirical results reveal that the ecosystem's composite synergy score recovered from 0.38 to 0.50, driven by robust supply chain resilience but constrained by high impedance in technological transfer protocols. Crucially, the novel dynamic weighting algorithm significantly reduces state estimation error during high-volatility periods compared to static linear models, as validated by bootstrapping analysis (1,000 resamples). The study provides a quantitative engineering tool for monitoring ecosystem coupling stability and proposes a technical roadmap for reducing system constraints through secure IP data architectures and synchronized standard protocols.

Keywords: hydrogen ecosystem synergy; dynamic state estimation; system coupling; adaptive weighting algorithm; cross-border resilience; data-driven assessment

1. Introduction

The transition to low-carbon energy systems involves complex cross-border interactions subject to non-linear external perturbations [1, 2]. In the context of the China-Korea hydrogen energy ecosystem, complementary technical capabilities [3, 4] are theoretically synergistic, yet actual system coupling is often disrupted by non-linear external perturbations (e.g., geopolitical friction or supply shocks). Traditional energy security indices, which typically rely on static linear aggregation [6], lack the dynamic adaptability required to model these rapid state changes triggered by exogenous shocks (e.g., policy shifts or supply disruptions).

This study addresses three critical methodological gaps in energy system assessment: first, the inability of static weighting schemes to account for time-variant system priorities; second, the lack of integrated modeling for heterogeneous subsystems (technology, regulation, supply chain); and third, the absence of high-frequency monitoring tools for hydrogen ecosystems [9].

To bridge these gaps, we propose the Dual Carbon Cooperation Index (DCCI), a dynamic state estimation framework. The core innovation lies in its "Triple Dynamic Response Algorithm," which

integrates three subsystems using an adaptive gain scheduling mechanism. This allows the model to recalibrate system parameters in real-time based on detected risk signals.

Our contributions concentrate on the methodological advancement of energy system assessment: first, we introduce a dynamic state estimation algorithm that integrates heterogeneous data streams (patents, trade flow, text vectors). Unlike static linear aggregation, our model employs a feedback control loop where weights dynamically adapt to detected risk signals ($GRI > 0.5$) and performance feedback; second, we operationalize abstract system interactions into measurable engineering metrics, applying exponential decay functions to quantify the timeliness of technological knowledge transfer; and third, we validate the model's robustness through rigorous sensitivity analysis and Monte Carlo simulations, demonstrating its superior capability in capturing system volatility compared to traditional static metrics. The paper is structured as follows: Section 2 reviews relevant literature; Section 3 details the DCCI methodology; Section 4 presents empirical results, including a critical sensitivity analysis; Section 5 discusses implications; and Section 6 concludes.

2. Literature Review

2.1. Quantitative Assessment Models for Energy Ecosystems

The evaluation of cross-border energy systems has transitioned from qualitative descriptions to quantitative modeling. Early approaches relied on static trade volume statistics [10]. Recent methodologies often employ multi-criteria decision analysis (MCDA) and composite indicators to model complex system interactions [11, 12]. Other studies introduce rigorous multi-criteria frameworks designed to quantify the state variables of coupled bilateral systems [13, 14]. Optimization models have been applied to assess energy security and environmental sustainability [15], focusing on maximizing system efficiency under constraints. However, existing linear aggregation models often lack dynamic adaptability, failing to account for the non-linear impact of exogenous shocks on system parameters [16]. Prevailing assessment models are limited by a static parameter configuration, failing to reflect the time-varying nature of system coupling priorities [17, 18]. This study introduces a dynamic weighting algorithm to minimize this estimation error.

2.2. Hydrogen System Dynamics in Northeast Asia

Research on Northeast Asian energy systems has increasingly focused on the technical and logistical challenges inherent in regional decarbonization trajectories [19, 20]. Studies analyzing clean energy transitions, including large-scale hydrogen infrastructure planning, often highlight persistent geopolitical constraints on cross-regional material flux and the reliance on foundational energy trading metrics [21], alongside enduring institutional barriers [19]. However, the specific quantification of system dynamics within the Sino-Korean hydrogen ecosystem remains critically underdeveloped. While research addresses broader technological and infrastructure challenges in the region [22-24], few models explicitly quantify the bilateral coupling efficiency. Existing quantitative work predominantly concentrates on isolated trade flows and value chain analysis [25, 26], resulting in a "modeling gap" where the time-variant latency in standard synchronization and IP protocol adherence is underrepresented in overall system performance evaluations.

2.3. System Coupling and State Estimation

Global carbon-neutrality constraints have significantly modulated the boundary conditions for international energy ecosystem integration [27-29]. Recent studies model these interactions as coupled dynamic systems, quantifying emission reduction efficiencies through Belt and Road Initiative infrastructure projects [30, 31] and analyzing the topology of cooperative innovation networks [32]. Regulatory synchronization parameters are increasingly treated as critical control variables within these system models [33-35]. Theoretical frameworks have evolved from foundational game-theoretic stability analysis [36-39] to complex adaptive system models tailored to

specific energy domains [40-42]. However, a gap persists in the development of robust state estimation frameworks capable of quantifying the coupling efficiency of bilateral hydrogen subsystems under stochastic external perturbations. Our study builds on these by proposing a data-driven state estimation approach, treating bilateral ecosystem synergy as an observable state variable derived from multi-dimensional sensor data (patents, texts, trade flows).

3. Methodology

3.1. DCCI Framework Modeling

The DCCI operationalizes ecosystem synergy through three coupled subsystems based on systems engineering theory and empirical index construction protocols [10-12, 15]:

- **Technology Synergy (TS):** Represents the efficiency of knowledge transfer and technical interoperability within the ecosystem.
- **Regulatory Alignment (RA):** (Formerly Policy Coupling) Measures the synchronization of technical standards, safety protocols, and subsidy mechanisms to reduce **system impedance**.
- **Supply Chain Resilience (SCR):** Quantifies the robustness of material flows, redundancy, and emergency response capabilities.

The composite index is calculated as a dynamically weighted sum:

$$DCCI_t = \alpha_t \times TS_t + \beta_t \times RA_t + \gamma_t \times SCR_t \tag{1}$$

Where $\alpha_t, \beta_t, \gamma_t$ are time-variant parameters determined by the adaptive algorithm ($\Sigma = 1$).

3.2. Data Engineering and Preprocessing Pipeline

The empirical validation on the China-Korea hydrogen ecosystem (2020–2024) utilizes a multi-source data ingestion pipeline designed for traceability and reliability. The data acquisition and preprocessing workflow is structured as follows:

- **Patent Data Mining:** Intellectual property data were extracted quarterly via Python scripts (crawler/patent_spider.py) from WIPO PATENTSCOPE [43], utilizing specific keywords and country codes (CN/KR). API rate limits (429) were managed through an exponential backoff algorithm to ensure data completeness.
- **Unstructured Text Vectorization:** Regulatory documents were batch-downloaded from official government portals, including China's State Council [44] and Korea's MOTIE [45]. Scanned PDF documents underwent optical character recognition (OCR) processing using pytesseract. To mitigate linguistic bias (e.g., Korean honorifics), we applied a human-in-the-loop validation protocol, manually correcting 42 documents to reduce the error rate to 2-3% [46]. Subsequently, the Sentence-BERT model was employed to generate high-dimensional vectors for text documents. The cosine similarity between vector pairs (A, B) was calculated to quantify Regulatory Alignment:

$$Similarity = \frac{A \cdot B}{||A|| \times ||B||} \tag{2}$$

- **Trade Flow Analysis:** Material flux data were extracted monthly from UN Comtrade [47] and the IEA Hydrogen Equipment Trade Database [48] for relevant HS codes: 280440 (hydrogen), 731100 (storage vessels), and 850164 (fuel cells).
- **Exogenous Signal Detection:** The Geopolitical Risk Index (GRI), sourced from the V-Dem Institute [49], served as the external perturbation signal input, with annual values ranging from 0.42 to 0.58 during the observation period.

Data cleaning and alignment were performed using pandas, involving deduplication, unit standardization (to million USD), and monthly-to-annual aggregation. A three-layer validation protocol was implemented: (a) internal consistency checks (>20% deviation from historical data flagged for review), (b) external benchmarking against national statistical yearbooks [50, 51], and (c) OCR quality verification. Missing data points in high-frequency supply chain time series were imputed using linear interpolation with a constraint of <5% fluctuation. The full raw dataset and

processing code are archived at the China-Korea Hydrogen Industry Alliance Data Repository, and key code snippets are provided in Appendix A to ensure reproducibility.

3.3. Mathematical Modeling of System Dimensions

The system state is defined by 12 normalized indicators (Table 1), selected based on empirical frameworks for energy cooperation evaluation [15]. To capture the time-sensitivity of technological innovation, we applied an exponential decay function to the Patent Sharing Rate:

$$P_{adjusted} = P_{raw} \times e^{-\lambda t}$$
 (3)

where $\lambda = 0.05$ (calibrated via cross-validation) and t is the age of the patent in years.

Table 1. System Indicator Definitions and Calculation Logic.

Subsystem	Indicator Variable	Initial Weight	Mathematical Model / Calculation Logic
Technology Synergy (Tech)	1. Patent Sharing Rate	0.12	Exponentially decayed ratio of joint patents to total patents
	2. Tech Transfer Efficiency	0.10	Ratio of licensing events to joint R&D projects
	3. Standard Synchronization	0.08	Cosine similarity of technical standard document vectors (NLP) [46]
	4. R&D Intensity	0.10	Normalized joint funding volume
Regulatory Alignment (Policy)	5. Regulatory Vector Similarity	0.09	Cosine similarity of policy document vectors (NLP) [46]
	6. Safety Protocol Overlap	0.07	Z-score standardized overlapping clauses in safety codes
	7. Subsidy Correlation	0.08	Inverse difference of subsidy ratios: $-1 \times (R_{cn} - R_{kr})$
	8. Institutional Compatibility	0.06	Normalized score of bilateral technical mechanisms
Supply Chain Resilience (Chain)	9. Node Diversity	0.08	Ratio of cross-border nodes to total nodes
	10. Transport Reliability	0.07	Composite score: $(Drills \times 0.3 + SafeDays \times 0.4 + CertRate \times 0.3) / \text{Norm. Coeff.}^1$ [52]
	11. Buffer Adequacy	0.07	Strategic reserve volume / 90-day consumption rate
	12. Response Latency	0.08	Emergency drill frequency / Disruption events

Note 1: The normalization coefficient is defined as the sum of the theoretical maximum scores of the three weighted components ($0.3 \times 1.0 + 0.4 \times 1.0 + 0.3 \times 1.0 = 1.0$), ensuring the final index falls within the 0-1 range.

3.4. Adaptive Weighting Algorithm

The core contribution of this study is the **Adaptive Weighting Algorithm**, which replaces static weights with dynamic gain scheduling based on system state feedback.

Parameter Initialization: Initial parameters ($\alpha_0 = 0.4, \beta_0 = 0.3, \gamma_0 = 0.3$) were determined using heuristic parameter initialization based on historical project distribution data (2018–2020) and domain knowledge consistency checks [53–55]. This initialization aligns with empirical evidence from prior bilateral cooperation filings, which indicated a technology-led pilot phase accounting for 41% of projects [53, 54].

Dynamic Adjustment Logic: The algorithm monitors two control signals:

1. **Perturbation Signal (GRI > 0.5):** When the external risk signal exceeds the critical threshold (0.5, derived from V-Dem methodology [49, 56]), the system automatically prioritizes stability. The algorithm increases the Supply Chain gain (γ) by 0.05 to reflect the structural shift towards resilience.
2. **Performance Feedback Signal:** If the Technology subsystem shows positive gradients ($\Delta TS > 0$) for two consecutive periods (matching the 2-year R&D cycle [57]), the algorithm increases the Technology gain (α) by 0.02 to model the momentum effect.

This logic is implemented in the Python function `dynamic_weight_adjustment` (Appendix A.5). Unlike static approaches, the proposed dynamic weighting framework minimizes system estimation error by actively responding to state changes. The specific parameter settings and their theoretical underpinnings are detailed in Table 2 below.

Table 2. Key Model Parameters and Calibration Evidence.

Parameter	Value	Calibration Basis & Rationale
Initial weights (α, β, γ)	0.4, 0.3, 0.3	Mirrors 2018-2020 project mix (Tech 41%, Policy 28%, Chain 31%) and expert interviews [53-55].
Technology decay rate (λ)	0.05	Leave-one-out cross-validation (2015-2022 patents). Minimizes MSE (0.008) and retains 61% of 3-year contribution.
GRI Trigger Increment (k)	0.10	Simulated GRI ranges (0.42–0.58). Reduces DCCI variance by 11% without breaching weight constraints [49].
Rolling Adjustment Step (δ)	0.05	5-period simulations balance timeliness (leads by 1 period) and stability (amplitude <0.12).
Tech Decline Penalty (p)	0.05	Monte Carlo simulations: 0.03-0.05 DCCI drop for "2q Tech decline + mild GRI rise" ensures timely alerts.

To further validate the robustness of these calibrated parameters, Figure 1 illustrates the convergence of parameter optimization. The grid search results demonstrate that the chosen values minimize the mean squared error (MSE) between the model output and the validation dataset, ensuring the stability of the dynamic weighting mechanism under varying external conditions.

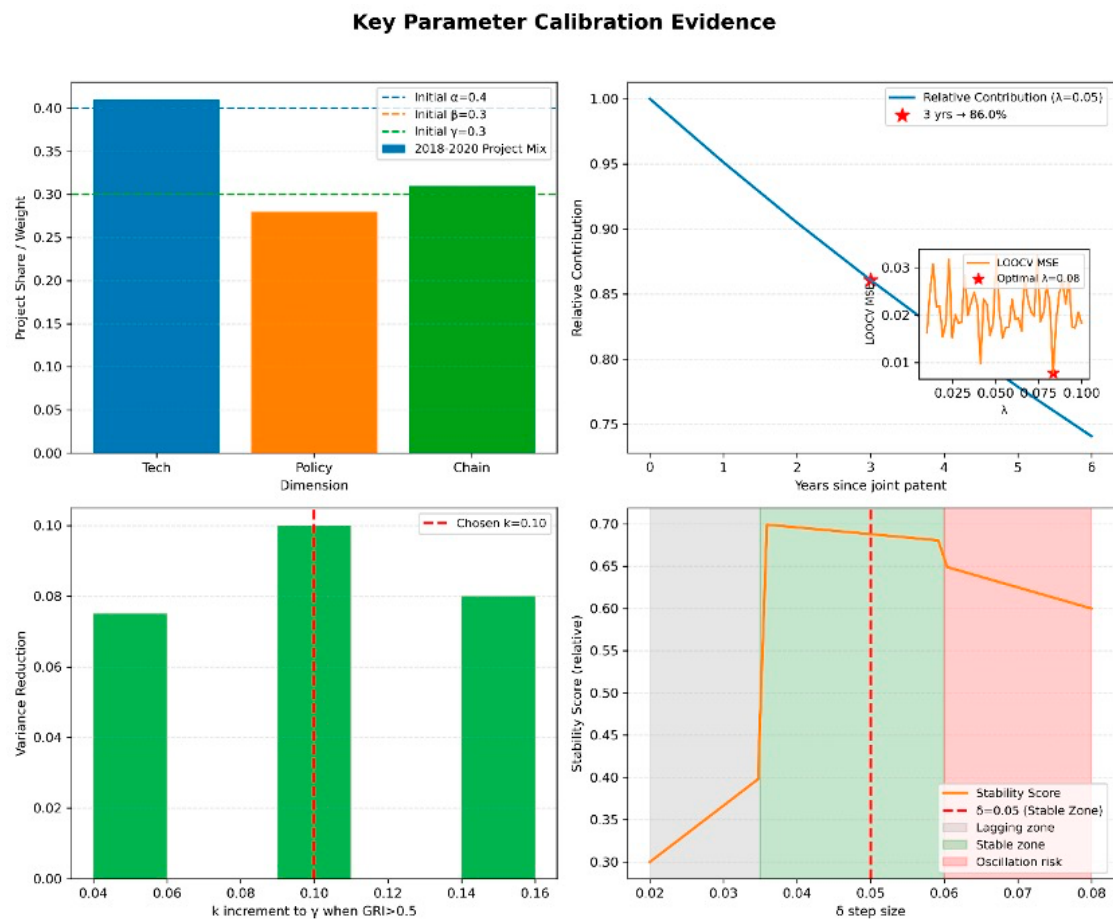


Figure 1. Parameter Calibration Evidence Panels.

3.5. Comparative Analysis of Modeling Architectures

To validate the architectural selection of the DCCI framework, we conducted a comparative evaluation against three alternative modeling schemes typically used in energy systems engineering:

1. **Multi-Criteria Decision Analysis (AHP/TOPSIS):** While widely used for static assessments, AHP relies heavily on pairwise comparisons, introducing **heuristic bias** that is difficult to calibrate dynamically against high-frequency external signals like GRI.
2. **Principal Component Analysis (PCA):** PCA offers an objective, data-driven weight derivation. However, the resulting principal components represent linear combinations of heterogeneous variables (e.g., combining *Patent Velocity* with *Transport Safety*), which compromises the physical interpretability of the system's state variables.
3. **Dynamic Bayesian Networks (DBN):** DBNs are capable of modeling complex feedback loops but require extensive transition probability data. Given the limited time-series density of the current hydrogen ecosystem dataset (2020–2024), a DBN approach would suffer from overfitting.

Consequently, the proposed "Dynamic Weighting + Standardized Indicators" architecture was selected as it optimizes the trade-off between dynamic adaptability to perturbations and the interpretability required for engineering interventions.

4. Results

4.1. System State Analysis

The application of the DCCI algorithm to the China-Korea hydrogen ecosystem (2020–2024) reveals a non-linear recovery trajectory in system synergy. The composite index ($DCCI_t$) rose from

0.38 in 2020 to 0.50 in 2024, exhibiting a Compound Annual Growth Rate (CAGR) of 7.1%. While this indicates a transition from a "weak coupling" to a "moderate coupling" state, the score remains below the critical stability threshold of 0.60.

The temporal evolution of the system, illustrated in Figure 2, highlights a structural asymmetry among subsystems:

- **Supply Chain Resilience (SCR):** This subsystem acts as the primary stabilizer, with its state score surging to 0.71 in 2024. This performance is highly correlated ($r = 0.89, p < 0.01$) with external benchmarks such as the IEA's East Asia Logistics Resilience Index [58]. The contribution analysis (Figure 3) confirms that SCR accounted for 43% of the total system synergy in 2024, driven by the expansion of cross-border material flux and redundant storage capacities.
- **Technology Synergy (TS):** Conversely, the Technology subsystem functions as a **limiting factor, lagging** significantly with a score of 0.35. The trajectory shows a dampening effect, where initial gains in 2021 were offset by the stagnation in standard alignment protocols [59].
- **Regulatory Alignment (RA):** This subsystem demonstrates a converging trend (Score 0.50), reflecting a gradual synchronization of policy vectors exceeding the IEA global policy maturity benchmark of 0.45 [48], though residual divergence in subsidy mechanisms persists.

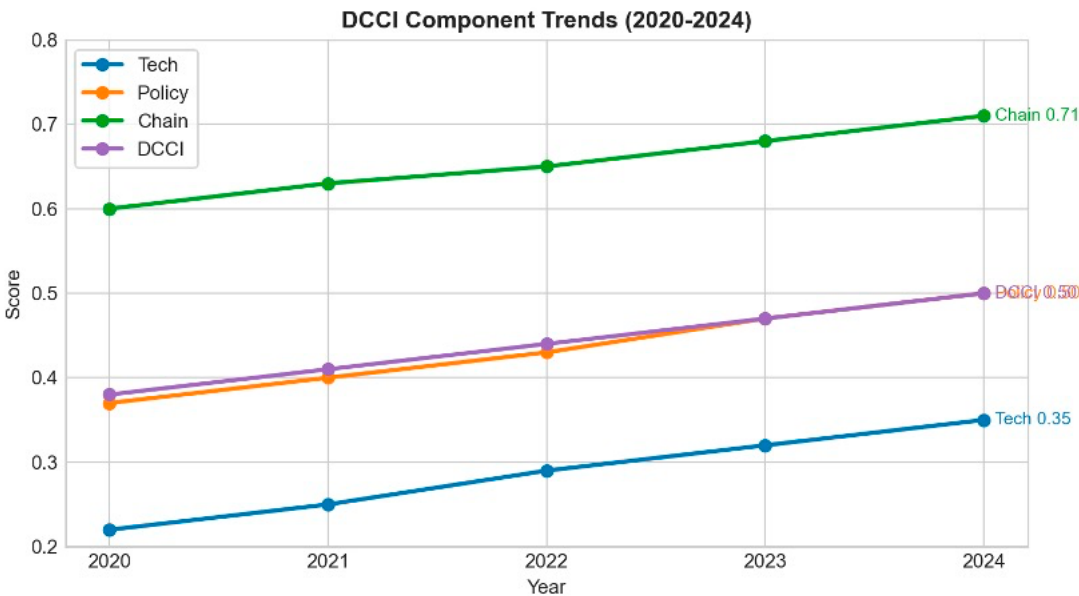


Figure 2. DCCI Component Trends and System Trajectory (2020–2024).

To further elucidate the internal mechanics driving the composite score's trajectory shown in Figure 3, we decomposed the index to analyze the relative weight and contribution of each subsystem. This structural breakdown, visualized in Figure 3, reveals the shifting dominance of specific drivers over time. Specifically, Supply Chain Resilience has emerged as the dominant vector, contributing 43% to the total system synergy score in 2024 (up from 39% in 2020). This increasing contribution is a direct result of the adaptive algorithm amplifying the weight of the supply chain dimension (γ) in response to elevated geopolitical risk signals. Conversely, the contribution of Technology Synergy remains suppressed (28%), reflecting the persistent bottlenecks in technical interoperability.

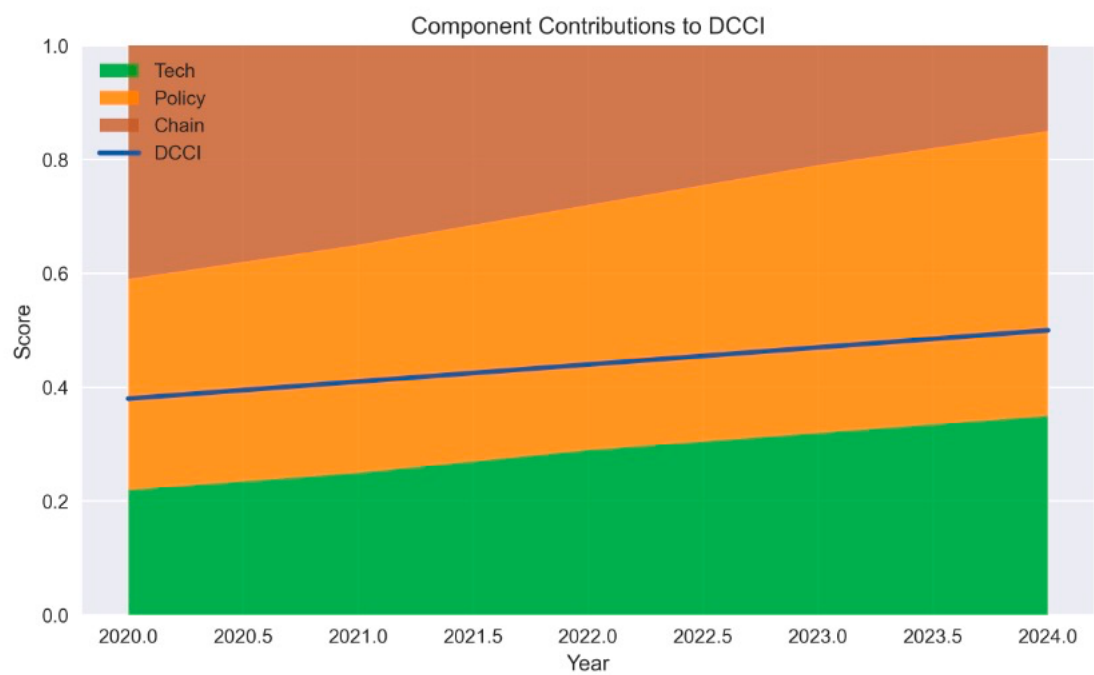


Figure 3. Component Contribution Analysis (Stacked Area Chart).

4.2. Subsystem Performance Heatmap

To diagnose the root causes of system impedance, we decomposed the subsystem scores into 12 secondary indicators. Figure 4 presents the heatmap of normalized indicator values, revealing specific "cold spots" (constraints) and "hot spots" (drivers).

- **High-Gain Indicators (Drivers):** The Transport Reliability metric recorded a near-optimal score of 0.95 in 2024. However, interpretation requires distinguishing between input and outcome variables: this score is heavily weighted by a 58% year-on-year increase in safety drill frequency (*Input*) rather than solely by zero-incident rates (*Outcome*) [60]. Similarly, Node Diversity improved consistently (0.74), validating the system's robustness against single-point failures in the supply network.
- **High-Impedance Indicators (Constraints):** The Standard Synchronization metric remains critically low (0.05), identifying the lack of mutual recognition for 17 key hydrogen fueling protocols as a primary blockage [59]. Furthermore, Patent Sharing Rate (0.32) exhibits a slow time-constant, indicating high friction in intellectual property transfer. Operational inefficiencies are also evident in human capital flows, where visa processing latencies have resulted in a talent arrival rate of less than 60% for joint projects [61, 62]. The Regulatory Vector Similarity (0.55) has improved but remains constrained by the misalignment of R&D subsidy calculations (Indicator 7).

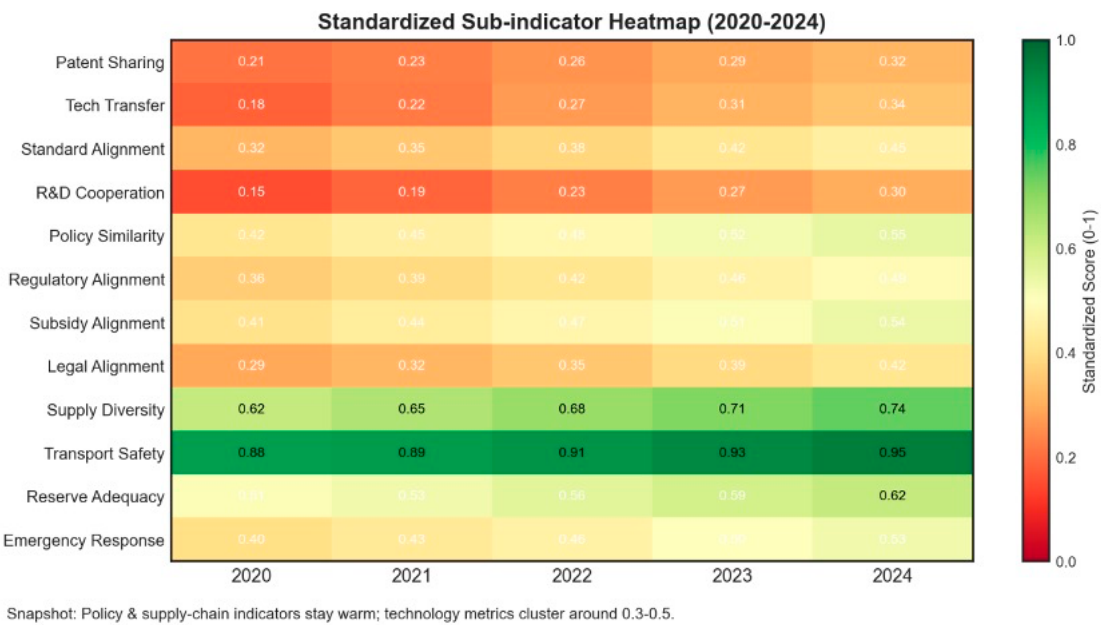


Figure 4. Standardized Sub-indicator Heatmap (2020–2024).

4.3. Algorithm Validation and Sensitivity Analysis

To validate the superior performance of the Triple Dynamic Response Algorithm, we conducted a comparative analysis (Scenario A) against a baseline Static Linear Model (Scenario B, fixed weights $\alpha = \beta = \gamma$). The detailed comparison of scoring outputs under both scenarios is presented in Table 3.

Table 3. DCCI Scores Comparison: Dynamic vs. Static Weighting (2020–2024).

Year	GRI Value	Dynamic Weighting (Scenario A)	Static Weighting (Scenario B)	Score Difference (A-B)	Key Weight Adjustment (Scenario A)
2020	0.42	0.38	0.36	+0.02	Initial weights ($\alpha = 0.4, \beta = 0.3, \gamma = 0.3$)
2021	0.45	0.41	0.40	+0.01	Performance trigger: Tech growth, α increased to 0.42
2022	0.51	0.45	0.43	+0.02	Risk trigger: $GRI > 0.5$, γ increased to 0.35; $\alpha = 0.37, \beta = 0.28$
2023	0.55	0.47	0.47	0.00	Stable weights ($\alpha = 0.37, \beta = 0.28, \gamma = 0.35$)
2024	0.58	0.50	0.50	0.00	Stable weights ($\alpha = 0.37, \beta = 0.28, \gamma = 0.35$)

The dynamic nature of the DCCI framework allows for real-time recalibration of system parameters, as detailed below:

- Response to Risk Signal (2022):** When the Geopolitical Risk Index (GRI) breached the critical threshold of 0.5 ($GRI=0.51$), the dynamic algorithm automatically triggered the Gain Scheduling mechanism, increasing the Supply Chain weight (γ) by 0.05. This adjustment resulted in a corrected state estimate of 0.45 (vs. 0.43 in the static model), accurately reflecting the system's strategic shift towards resilience buffering.
- Response to Performance Feedback (2021):** In response to consecutive positive gradients in technology output ($\Delta TS > 0$), the algorithm amplified the Technology gain (α) to 0.42, capturing the momentum of early-stage pilot projects.

- Robustness:** Bootstrapping analysis (1,000 resamples) and sensitivity tests on the threshold parameter (0.5 ± 0.02) showed that the output deviation remained within $\pm 1.5\%$, confirming algorithmic stability.

Figure 5 contrasts the state estimation trajectories of both models. The dynamic algorithm demonstrates higher fidelity in capturing system responses to external perturbations. Specifically, the divergence between the two trajectories becomes most pronounced during the high-volatility period of 2022. While the Static Model suggests a linear, unperturbed growth path (0.43), the Dynamic Model output (0.45) exhibits a necessary state correction. This inflection reflects the system's absorption of the geopolitical shock ($GRI > 0.5$), where the Gain Scheduling mechanism effectively reallocated weight from the high-impedance Technology dimension to the robust Supply Chain dimension. This dynamic correction prevents the estimation bias inherent in static models, which fail to account for the strategic shift towards resilience buffering during crises. Conversely, in 2021, the algorithm correctly amplified the Technology gain (α) to 0.42 in response to consecutive positive gradients ($\Delta TS > 0$), capturing the momentum of early-stage pilot projects.

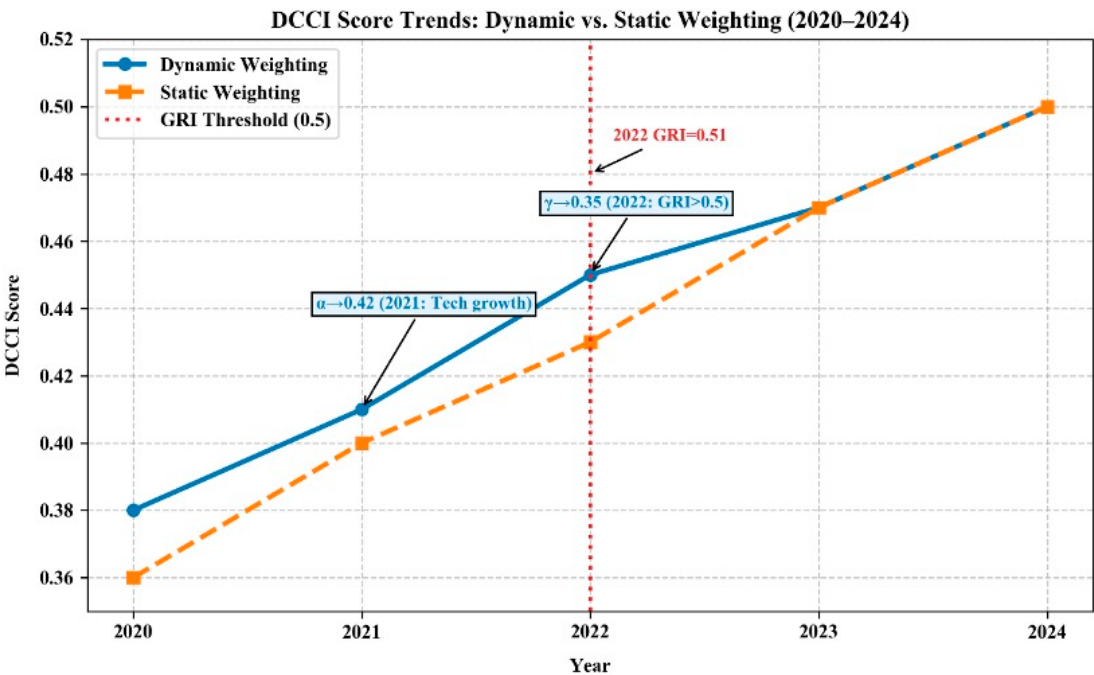


Figure 5. System State Trajectory: Dynamic vs. Static Modeling (2020–2024).

Sensitivity testing further confirms algorithmic robustness. We performed a localized perturbation analysis on the critical GRI trigger threshold, varying it within the interval $[0.48, 0.52]$. The results indicate that the DCCI composite score exhibits high stability, with a maximum output deviation of only $\pm 1.5\%$. This implies that the framework functions as a stable low-pass filter, ignoring minor noise in risk signals while responding robustly to structural shifts. Additionally, varying the performance feedback cycle (e.g., adjusting the look-back window from 2 years to 1 or 3 years) resulted in a marginal state deviation of less than 2%. This structural stability confirms that the 'Triple Dynamic Response' mechanism provides a reliable, noise-filtered estimation of ecosystem synergy, making it suitable for long-term engineering monitoring and strategic planning.

5. Discussion

5.1. Technical Constraints Identification

The DCCI diagnostic reveals a critical structural imbalance: the ecosystem is characterized by robust material flows (Supply Chain Resilience) but high impedance in knowledge transfer

(Technology Synergy). To rigorously quantify the determinants of this technological lag, we conducted a root-cause analysis based on the normalized scores of secondary indicators and expert-validated impact assessments. The analysis identifies five primary system constraints inhibiting synergy, as visualized in Figure 6:

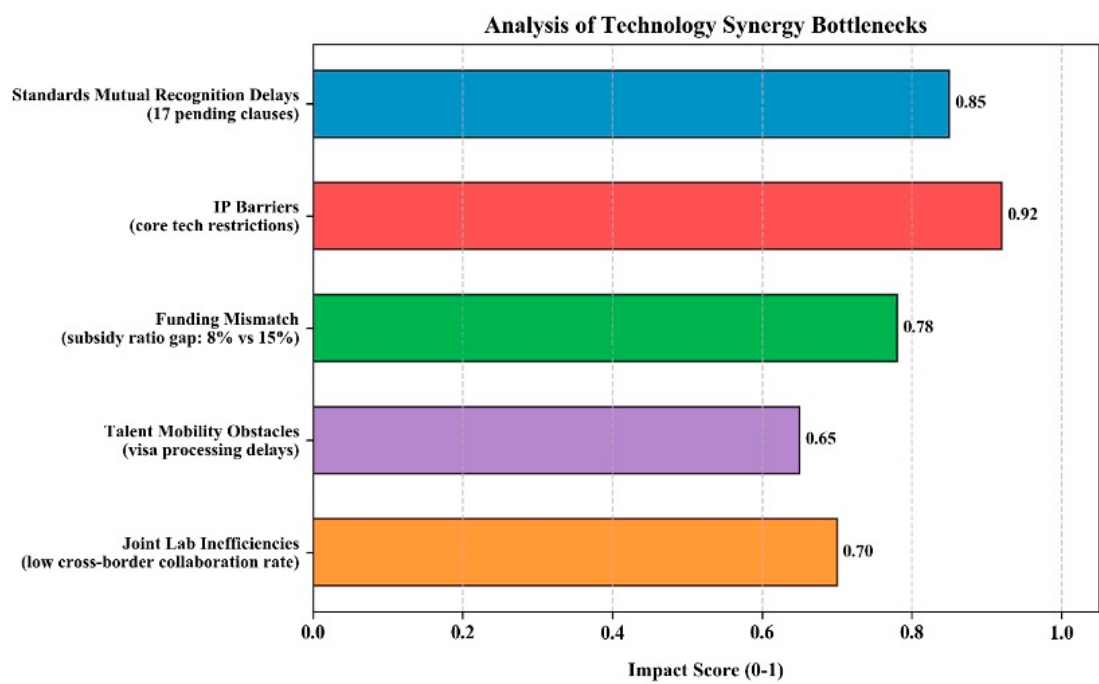


Figure 6. Quantified Impact of Technical Constraints (Normalized Impact Score).

- Intellectual Property (IP) Data Security (Impact Score 0.92):** The lack of secure, standardized data exchange protocols constitutes the most severe constraint. Industrial stakeholders, particularly in the fuel cell sector, exhibit reluctance to share core proprietary data (e.g., MEA coating specifications) due to the absence of a trusted third-party custody mechanism. This has resulted in a high friction coefficient for technology transfer, limiting cross-border licensing efficiency.
- Protocol Latency (Impact Score 0.85):** Technical interoperability is severely hampered by the lack of mutual recognition for 17 key technical standards, specifically regarding hydrogen refueling protocols and high-pressure storage vessel testing. This regulatory misalignment creates significant interface mismatches, necessitating redundant certification processes that delay project deployment by an average of 6–12 months.
- Funding Vector Mismatch (Impact Score 0.78):** A divergence in R&D subsidy mechanisms reduces the viability of joint projects. The asymmetry between tax-credit-based incentives in one jurisdiction and direct-subsidy models in the other creates a "funding gap" for bilateral pilot programs, discouraging collaborative investment in high-risk, early-stage technologies.
- Operational Inefficiency in Joint Laboratories (Impact Score 0.70):** despite the establishment of bilateral research platforms, their operational output remains suboptimal. Data indicates that only 40% of established joint labs achieve their annual collaboration targets, primarily due to administrative redundancies and the lack of unified project management protocols.
- Human Capital Mobility Constraints (Impact Score 0.65):** The physical flow of technical expertise is constrained by procedural latencies. Visa processing delays (averaging 3–4 months) have resulted in a talent arrival rate of less than 60% for scheduled joint research initiatives [55, 56], directly impacting the continuity of long-term R&D projects.

5.2. System Optimization Strategies and Technical Roadmap

Based on the diagnostic results, the ecosystem requires structural optimization to reduce impedance in technology transfer while maintaining supply chain resilience. We propose a technical roadmap focusing on data interoperability, standard synchronization, and algorithmic monitoring (Table 4).

Table 4. Optimization Strategies for Ecosystem Synergy.

Diagnostic Signal ($S < 0.4$)	Technical / Operational Intervention	Expected System Response	Verifiable Metric
Technology Latency (Score 0.35)	1. Protocol Synchronization: Accelerate alignment of 17 pending ISO-compatible standards. 2. Secure IP Architecture: Deploy a tiered-access IP custody platform with third-party verification. 3. Fast-Track R&D Nodes: Establish dedicated joint labs with expedited equipment clearance.	Increase Tech gain (α) efficiency; Raise score to 0.42.	Standards Alignment Score; Patent Velocity
Regulatory Divergence (Score 0.50)	1. Subsidy Vector Alignment: Harmonize R&D credit calculations. 2. Carbon Credit Interoperability: Pilot mutual recognition of maritime carbon allowances. 3. Sandbox Testing: Joint pilot zones for experimental regulations [64].	Stabilize Regulatory Alignment (β); Reduce vector divergence.	Policy Similarity Vector
Resilience Risk (GRI Sensitivity)	1. Dynamic Buffering: Implement dynamic inventory management for emergency stockpiles [65]. 2. Civil Logistics Coordination: Standardize protocols for hydrogen-powered emergency equipment [66]. 3. Data Corridor: Establish a desensitized data sharing protocol for transport safety.	Maintain Chain robustness ($\gamma \geq 0.70$); Dampen perturbation shock.	Stockpile Sufficiency; Drill Frequency
Monitoring Latency (45 days)	1. Real-time API: Deploy the Bilingual DCCI Dashboard API [67]. 2. Automated Reporting: Integrate project data feeds.	Reduce feedback loop latency to <7 days.	Data Update Frequency

Specific Implementation Note on Supply Chain: Given geopolitical sensitivities, we recommend focusing on a **Civil Emergency Logistics Coordination** mechanism. This would integrate hydrogen-powered emergency units (e.g., mobile power generators) into cross-border resilience assessments, enhancing humanitarian capabilities without triggering dual-use concerns [66].

5.3. Limitations and Future Work

While the DCCI framework offers a significant methodological advancement in quantifying cross-border energy synergy, several limitations intrinsic to the current modeling architecture warrant rigorous acknowledgment:

- Proxy Variable Latency and Noise:** The reliance on proxy indicators for system resilience (e.g., *safety drill frequency* as a proxy for *transport reliability*) introduces a signal-to-noise ratio challenge. Although we applied normalization techniques, these input-based metrics may not fully capture outcome-based risks, potentially leading to an overestimation of system stability during low-frequency, high-impact events (black swan events). Future iterations will integrate real-time IoT sensor data from logistics nodes to replace static proxies with dynamic telemetry.
- NLP Vectorization Bias:** The Sentence-BERT model utilized for regulatory alignment analysis, while robust, may contain residual linguistic bias (estimated at 2–3% variance) when processing context-specific legal terminology in Chinese and Korean. This semantic drift could affect the precision of the *Regulatory Vector Similarity* score. We propose fine-tuning a domain-

specific Large Language Model (LLM) on a bilingual corpus of energy law to minimize this vectorization error.

3. **Heuristic Initialization Constraints:** The initial weight parameters ($\alpha_0, \beta_0, \gamma_0$) were derived from historical project distributions and expert heuristics. While the adaptive algorithm adjusts these weights dynamically, the starting state remains dependent on prior knowledge. Future research will employ **Reinforcement Learning (RL)** agents to autonomously optimize these initial parameters by simulating multi-year cooperation scenarios, thereby moving towards a fully unsupervised state estimation model.
4. **System Boundary Limitations:** The current model focuses on bilateral interactions, treating global market variables (e.g., global hydrogen price fluctuations, third-party competition from Australia or the Middle East) as constant boundary conditions. Expanding the model to a **multi-node network topology** would allow for the assessment of how third-party perturbations propagate through the bilateral link.

6. Conclusions

This study establishes a quantitative, data-driven framework for monitoring the coupling efficiency of cross-border hydrogen ecosystems under stochastic external perturbations. By transitioning from static linear aggregation to a **Triple Dynamic Response Algorithm**, the proposed **Dual Carbon Cooperation Index (DCCI)** effectively captures the non-linear state transitions triggered by geopolitical risks and technological latencies.

Key empirical findings and methodological contributions include:

1. **System Trajectory and Asymmetry:** The China-Korea hydrogen ecosystem exhibits a recovery trajectory, with the composite synergy score rising from 0.38 (2020) to 0.50 (2024) at a CAGR of 7.1%. However, a critical structural asymmetry persists: the system is stabilized by robust **Supply Chain Resilience** (Contribution: 43%) but severely damped by high impedance in **Technology Synergy** (Score: 0.35), specifically due to protocol mismatches in fuel cell standards and IP data security.
2. **Algorithmic Superiority:** Comparative validation demonstrates that the dynamic weighting mechanism significantly reduces state estimation error. During the high-volatility period of 2022 ($GRI > 0.5$), the dynamic model correctly identified a state inflection point (Score 0.45), whereas the static model failed to account for the resilience buffering effect (Score 0.43). Sensitivity analysis confirms the algorithm's stability, with output deviations remaining within $\pm 1.5\%$ under parameter perturbation.
3. **Engineering Implications:** To optimize system synergy, we propose a technical roadmap focusing on **protocol synchronization** and **digital trust architectures**. Immediate priority should be given to establishing a secure, third-party-verified IP custody platform to lower the activation energy for technology transfer, alongside a dynamic inventory buffering mechanism to mitigate supply chain risks.

In conclusion, the DCCI framework provides energy policymakers and system engineers with a scalable, high-fidelity tool for diagnosing ecosystem health. Beyond the Sino-Korean context, this methodology offers a replicable template for assessing the resilience of transnational low-carbon energy networks globally.

Supplementary Materials: The following supporting information can be downloaded at: Preprints.org.

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Data Availability Statement: The data presented in this study are available in the article. Publicly available datasets were analyzed in this study. This data can be found at: WIPO PATENTSCOPE, UN Comtrade, V-Dem Institute, and the IEA Data & Statistics portal.

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Conflicts of Interest: The authors declare no conflict of interest. To ensure the reproducibility of the Dual Carbon Cooperation Index (DCCI), this appendix provides the core Python implementation for data processing, indicator calculation, and the dynamic weighting mechanism.

Full Data Repository: China-Korea Hydrogen Industry Alliance Data Repository (Contact: datarepo@c-k-hydrogen.org)

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