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Abstract

This study develops a hybrid analytical framework that bridges data-driven *K2* structural learning with expert-informed Bayesian Networks to decrypt the intricate interdependencies among policy instruments, resource endowments, and socio-economic variables across China's hydropower, wind, and solar power. The results demonstrate a fundamental paradigm shift from resource-bound growth to institutional-steered expansion, notably in the solar sector where the Renewable Portfolio Standard (RPS) has superseded natural radiation as the primary determinant for capacity scaling. Forward sensitivity analysis and backward diagnostic attribution reveal that achieving high-growth milestones requires a synergistic convergence of tech-cost reductions and mandatory consumption quotas, whereas the absence of RPS leads to a catastrophic 64% degradation in systemic causal connectivity. These findings underscore the necessity of transitioning from price-side stimuli to structural consumption-side mandates to ensure a resilient and certain energy transition under stringent carbon constraints.

Keywords: renewable energy transition; bayesian networks; causal discovery; renewable portfolio standard; counterfactual simulation

1. Introduction

The accelerating global climate crisis has catalyzed a paradigm shift toward decarbonized energy systems, with China positioning itself at the vanguard through the Dual Carbon targets, striving for carbon peak by 2030 and carbon neutrality by 2060 [1,2]. As the largest producer and consumer of energy in the world, China's transition toward renewable energy is not merely a technical adjustment but a systemic structural reconfiguration. However, the trajectory of renewable energy generation is dictated by an intricate nexus of volatile policy instruments, heterogeneous resource endowments, and shifting socio-economic dynamics [3,4]. After the comprehensive upgrade of the electricity marketization process, understanding the non-linear causal relationships among policies, markets and resources in the electricity market is of vital importance for ensuring a stable and predictable energy transition [5]. The randomness of these driving factors poses significant challenges to traditional deterministic predictions and policy evaluations.

The multifaceted nature of renewable energy development has prompted an extensive body of scholarship dedicated to identifying its core determinants. Within the dimension of socioeconomic and demographic forcing, economic growth is traditionally posited as a fundamental catalyst [6–8]. Studies have consistently demonstrated a long-term bidirectional causality between GDP per capita and energy consumption, suggesting that financial development provides the necessary capital

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liquidity for green infrastructure [9,10]. Given the higher marginal costs and intermittency of renewable energy, institutional support is indispensable [11–13]. Current research differentiates between price-based instruments (e.g., Feed-in Tariffs, FIT) and quantity-based mandates (e.g., Renewable Portfolio Standards, RPS). While price controls have historically shown immediate efficacy, their marginal utility appears to be diminishing as the industry moves toward grid parity, necessitating a shift toward structural regulatory frameworks [14,15]. Methodologically, traditional linear regression often struggle to capture the nonlinear, stochastic interdependencies and multi-dimensional feedback loops present in modern energy systems; instead, Bayesian networks have emerged as a powerful alternative, designed to handle knowledge uncertainty and complex causal reasoning problems [16]. In the energy field, Bayesian networks have been successfully applied to meteorological forecasting, load prediction, and localized risk assessment [17–20]; however, existing applications remain predominantly static, often treating policy interventions as isolated exogenous shocks rather than dynamic, interconnected variables within a systemic web [21–23].

In addition, the Scenario analysis provides the strategic foresight necessary to navigate the uncertainties of energy governance. Moreover, the scenario modeling has evolved from simple "what-if" projections to complex integrated assessment models [24,25]. Scholars have successfully used scenario-based LEAP and Grey Models to predict energy demand and emission trajectories under varied economic growth rates (optimistic, baseline, and pessimistic) [26–28]. Despite these advancements, existing scenario analyses frequently rely on historical extrapolations and forward-looking projections. Part of researches lack the diagnostic depth to perform inverse reasoning. They also cannot trace back to calculate the specific policy-market configurations required to achieve predefined growth milestones or leapfrog growth targets [29,30].

To bridge the identified research gaps, this study develops a sophisticated hybrid analytical pipeline that integrates data-driven causal discovery with multi-scenario probabilistic reasoning. The methodology is structured into four interactive phases. First, we constructed a comprehensive indicator system comprising 24 variables that capture the multifaceted nature of China's renewable energy system, spanning socioeconomic drivers, natural resource endowments, and multi-dimensional policy instruments. Utilizing a longitudinal dataset (2014 to 2024), we employed the *K2* structural learning algorithm optimized by the Bayesian Dirichlet scoring function to derive the initial Directed Acyclic Graph (DAG). This algorithmic approach allows for the identification of latent causal dependencies that transcend simple statistical correlations. Second, to ensure the logical rigor and practical validity of the learned topology, we implemented a knowledge-informed calibration phase. The preliminary DAG was refined through structured consultations with 35 energy economics experts. The reliability and validity of this expert consensus were rigorously verified using Cronbach's alpha and the Kaiser-Meyer-Olkin test, effectively bridging the gap between machine-learned patterns and real-world energy-economic principles. Third, the study quantifies the hierarchical importance of these drivers using Mutual Information (MI) for sensitivity analysis, identifying the pivotal nodes that dictate system variance. We further utilized node-tree algorithms for backward diagnostic attribution, allowing us to calculate backward the ideal systemic configurations required to achieve specific development milestones for hydro, wind, and solar increments. Finally, we conducted counterfactual simulations based on the *do*-operator to evaluate the systemic resilience of the RE sector under seven distinct scenario designs. This dual-directional inference framework enables the provision of a high-resolution causal roadmap for the strategic scaling, offering a robust scientific foundation for navigating the complexities of the Dual Carbon transition.

The core innovations and contributions of this research are summarized as follows. First, this study proposes a hybrid causal discovery model by combining K2 heuristic structure learning with expert-guided psychometric validation. We have constructed a network topology with high internal consistency through this integration. This integration effectively bridges the ontological gap between statistical correlations and the actual causal relationship in the energy economy. Second, we introduce a dual-directional probabilistic inference mechanism that significantly extends the analytical depth of energy transition modeling. Our framework utilizes node-tree algorithms to perform backward diagnostic attribution, which allows for the calculation backward of specific posterior probability shifts required to reach leapfrog growth milestones, thereby identifying the unique causal signatures that distinguish the development pathways of hydropower, wind power, and solar power. Third, our analysis provides a new information-theoretic evidence for the Resource-Policy decoupling phenomenon within China's renewable energy system. By quantifying the divergence between natural abundance and institutional engineering, we demonstrate that the explanatory power of the RPS has superseded resource endowment as the primary determinant for solar expansion. Finally, we quantify the non-linear synergies and systemic resilience of the renewable energy system through counterfactual stress testing. Our results demonstrate that a synergistic pathway (Tech + Policy + Market) triggers a non-linear leap in growth certainty (rising to 89%), while the removal of the RPS mechanism leads to a catastrophic 64% collapse in systemic causal connectivity.

The remainder of this paper is structured as follows. Section 2 details the methodology, encompassing the construction of the indicator system, the hybrid structural learning protocol combining the *K2* algorithm with expert-informed calibration, and the mathematical foundations of probabilistic inference. Section 3 presents the empirical results and discussions, including the sensitivity analysis of key driving factors, the backward diagnostic attribution of renewable energy increments, and the multi-pathway counterfactual simulations under carbon neutrality constraints. Finally, Section 4 concludes the study, summarizes the core findings regarding the decoupling of policy and resource drivers, and provides strategic policy recommendations for China's energy transition.

2. Methodology

2.1. Research Framework and System Boundary

To systematically decrypt the intricate driving mechanisms and evolutionary trajectories of renewable energy generation within the context of China's Dual Carbon targets, this study develops an integrated analytical framework that bridges causal discovery with multi-scenario probabilistic reasoning. The inherent complexity of the energy transition, characterized by non-linear interdependencies among policy instruments, resource endowments, and socio-economic variables, necessitates a departure from traditional frequentist linear regression paradigms. Consequently, we employ the Bayesian Network based architectural design, which excels in capturing latent causal structures and managing epistemic uncertainties within a complex system. This framework follows a logical progression which begins with identifying the causal topology from high-dimensional empirical data, transitions to quantifying conditional dependencies between heterogeneous drivers, and concludes by projecting the carbon reduction potential under various counterfactual policy interventions.

In our disaggregated analysis of hydropower (HG), wind (WG), and solar (SG) power, we move beyond the monolithic treatment of renewable energy to acknowledge the distinct techno-economic trajectories and geographical constraints of each source. Economic affluence, proxied by per capita GDP and urbanization rates, reflects both the capital intensity required for infrastructure deployment and the structural shifts in energy demand density. These socioeconomic foundations are inextricably linked to technological maturity, and FIT modulate the market's transition from subsidy-dependent growth to competitive parity.

The spatial and temporal boundaries of this research are strategically defined to encompass the critical transition period of China's energy landscape. The analysis utilizes a provincial-level panel dataset covering 30 Chinese provinces (excluding Hong Kong, Macao, Taiwan, and Tibet) from 2014 to 2024. This decade represents a pivotal shift from subsidy-driven scaling to market-oriented integration in China's renewable sector. Within this system boundary, the generation volumes of hydropower, wind, and solar energy are treated as endogenous target variables, while nine distinct

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dimensions, are defined as exogenous or mediating drivers. By delineating these boundaries, the model ensures that regional heterogeneity in resource availability and economic development stages is rigorously incorporated into the causal inference process, thereby providing a robust foundation for identifying optimal decarbonization pathways.

2.2. Data Sources and Pre-Processing

The empirical foundation of this study is a multidimensional panel dataset encompassing 30 Chinese provinces over the period 2014-2024. Data were primarily synthesized from the China Statistical Yearbook, the China Energy Statistical Yearbook, and the National Bureau of Statistics. To ensure the reliability of the causal inference, the raw indicators (including techno-economic metrics, resource endowments, and policy instruments) have been conducted a rigorous two-stage pre-processing procedure, including the multi-source harmonization and the non-linear discretization.

Initially, to eliminate the dimensional discrepancies and magnitude effects inherent in heterogeneous indicators, we employed the Max-Min normalization method. This procedure scales all continuous variables into a dimensionless range of [0,1], thereby preserving the underlying distribution of the data while enhancing the convergence stability of the structural learning algorithms. The normalization is formulated as Eq. (1).

$$X_{it}^{'} = \frac{X_{it} - \min(X_i)}{\max(X_i) - \min(X_i)} \tag{1}$$

where $X_{it}^{'}$ represents the normalized value of indicator *i* in year *t*, while $\max(X_i)$ and $\min(X_i)$ denote the temporal extremes within the study boundary.

Subsequently, given that Bayesian Networks operate on discrete probability distributions to capture non-linear causalities, we implemented a discretization strategy based on the *K*-means clustering algorithm. Unlike traditional equal-interval binning, *K*-means discretization minimizes the intra-cluster variance, ensuring that the discretized states (e.g., Low, Medium, High) reflect the intrinsic structural breakpoints of China's energy development stages. For each continuous variable $X^{'}$, the discretization process seeks to partition *n* observations into *k* clusters $S = \{S_1, S_2, \ldots, S_k\}$ by minimizing the following objective function, as shown in Eq. (2).

$$\min \sum_{j=1}^{k} \sum_{X^{'} \in S_j} \| X^{'} - \mu_j \|^2 \tag{2}$$

where μ_j is the centroid of cluster S_j. This data-driven partitioning approach mitigates the subjectivity of manual threshold setting and enhances the model's sensitivity to regional heterogeneity, such as the distinct transition from subsidy-dependent to grid-parity-ready phases in wind and solar power sectors.

2.3. Causal Discovery via Bayesian Networks

To elucidate the autonomous causal mechanisms underlying renewable energy trajectories, we employ the Bayesian Network framework, which defines a joint probability distribution over a set of random variables $V = \{V_1, V_2, \ldots, V_n\}$ through the DAG. The construction of the Bayesian Network involves a two-stage computational optimization: structural learning for causal topology identification and parameter learning for quantifying conditional dependencies.

We utilize the *K2* algorithm, a score-based heuristic search, to derive the optimal causal structure from the pre-processed provincial datasets. The *K2* algorithm systematically searches for the parent set π_i for each node V_i by maximizing the Bayesian score, which represents the posterior probability of the structure given the observed data *D*. The objective function, based on the Cooper-Herskovits criterion, is expressed as Eq. (3).

$$P(G,D)=P(G)\prod_{i=1}^{n}\prod_{j=1}^{q_i}\frac{(r_i-1)!}{(N_{ij}+r_i-1)!}\prod_{k=1}^{r_i}N_{ijk}! \quad (3)$$

where n is the number of variables, r_i denotes the number of states for variable V_i, q_i represents the number of possible configurations of the parent set π_i, and N_{ijk} is the frequency of the k-th state of variable V_i occurring under the j-th configuration of its parents. By imposing a predetermined node ordering (from macro-socioeconomic drivers to specific policy instruments and finally to energy outputs), the algorithm effectively mitigates the search space complexity and prevents the formation of cyclic dependencies, ensuring a robust representation of the energy system's causal hierarchy.

Once the causal DAG is established, the strength of the relationships is quantified through Maximum Likelihood Estimation (MLE) to populate the Conditional Probability Tables (CPTs). For each node, the conditional probability $P(V_i \mid \pi_i)$ is computed to characterize the stochastic response of renewable energy generation to various policy and economic stimuli. The joint probability distribution of the entire system is then factorized as the Eq. (4).

$$P(V_1,V_2,\ldots,V_n)=\prod_{i=1}^{n}P(V_i \mid \pi_i) \quad (4)$$

This probabilistic expression method supports bidirectional reasoning, including forward prediction (estimating the possibility of renewable energy growth based on specific policy scenarios) and backward diagnosis (determining the most likely configuration of driving factors that led to the high capacity energy state). This dual capability is crucial for addressing the black-box nature of traditional econometric models and provides a transparent analytical tool for carbon neutrality policy design.

2.4. Model Validation and Performance Evaluation

To ensure the robustness and predictive reliability of the learned Bayesian Network, we implement a rigorous validation protocol consisting of *K*-fold cross-validation and probabilistic sensitivity analysis. This dual-validation approach ensures that the model not only captures the historical causalities within the training data but also maintains generalizability across heterogeneous regional contexts.

The predictive performance of the Bayesian Network is evaluated using the Log-Likelihood and the Classification Accuracy metrics. Through a 10-fold cross-validation process, the dataset is partitioned into ten mutually exclusive subsets, where the model is iteratively trained on nine subsets and validated on the remaining one. The Log-Likelihood score, which measures how well the probability distribution estimated by the Bayesian Network represents the actual observed data *D*, is defined as the Eq. (5).

$$LL(B \mid D)=\sum_{i=1}^{n}\sum_{j=1}^{q_i}\sum_{k=1}^{r_i}N_{ijk}\log\left(\frac{N_{ijk}}{N_{ij}}\right) \quad (5)$$

A higher LL value indicates a superior fit between the network structure and the empirical data. Additionally, we employ the Spherical Payoff (SP) to evaluate the probability forecasting accuracy, which ranges from 0 to 1, where 1 signifies a perfect prediction.

To identify the core drivers of renewable energy transition and quantify the strength of causal influence, we perform a sensitivity analysis based on Mutual Information (MI). This entropy-based metric measures the reduction in uncertainty of the target variable Y given the knowledge of a driver X. The MI between X and Y is expressed as the Eq. (6).

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$$I(X;Y)=\sum_{x\in X}\sum_{y\in Y}P(x,y)\log(\frac{P(x,y)}{P(x)P(y)}) \quad (6)$$

where $P(x,y)$ is the joint probability distribution, and $P(x)$ and $P(y)$ are the marginal distributions. A higher $P(x)$ value implies that variable *X* possesses higher explanatory power over the variance of *Y*. By ranking the MI values across all 24 nodes, we distinguish between pivotal drivers (high sensitivity) and auxiliary factors (low sensitivity), providing a data-driven basis for prioritizing policy interventions in the subsequent scenario analysis.

2.5. Scenario Simulation and Counterfactual Design

To explore the optimal pathways for China's renewable energy transition under the Dual Carbon constraints, we develop a scenario simulation framework based on probabilistic belief updating and counterfactual reasoning. This approach allows us to quantify how systematic shifts in policy intensity or economic conditions propagate through the causal network to alter the probability distribution of energy outputs.

The simulation is grounded in the principle of Bayesian inference. By setting a specific configuration of evidence *e* (e.g., a high-intensity Renewable Portfolio Standard or a low-cost technology scenario), we update the prior beliefs of the target variable *Y* to a posterior distribution. The updated probability for *Y* in state *y* is computed via Bayes' Theorem, as shown in Eq. (7).

$$P(y\mid e)=\frac{P(y,e)}{P(e)}=\frac{\sum_{V\setminus\{Y,E\}}\prod_{i=1}^{n}P(v_i\mid\pi_i)}{\sum_{V\setminus E}\prod_{i=1}^{n}P(v_i\mid\pi_i)} \quad (7)$$

where *e* represents the set of evidence nodes, and the summation is performed over all variables in the network excluding the target and evidence sets. This mechanism captures the systemic synergy between drivers that traditional ceteris paribus analysis often overlooks.

We define seven distinct scenarios by modulating the states of pivotal drivers identified in Section 2.4. The detailed evidence configurations and the logic for setting these states are thoroughly documented in Appendix A. To isolate the net impact of a specific policy, we employ a counterfactual logic by comparing the expected generation *E[Y]* under the actual policy state *X*=*x* versus a hypothetical state $X = x'$. The marginal effect of the policy intervention is quantified as the Eq. (8).

$$\Delta E=\sum_{y\in Y}y\cdot P(y\mid do(X=x'))-\sum_{y\in Y}y\cdot P(y\mid do(X=x)) \quad (8)$$

where the *do*-operator signifies a structural intervention, effectively simulating a pure policy shock. This counterfactual design enables a robust evaluation of "what-if" policy combinations, providing a scientific basis for identifying the most cost-effective strategies for wind, solar, and hydro power integration.

3. Results and Discussion

3.1. The Causal Topology of China's Renewable Energy Development

The network topology was constructed through a constrained search-and-score approach using the *K2* algorithm, optimized by the Bayesian Dirichlet scoring function. To ensure the learned arcs reflect true physical and economic causality rather than mere statistical correlation, we imposed a strictly defined node ordering based on chronological and logical dependencies, starting from exogenous demographic factors and concluding with endogenous generation increments. For detailed information, please refer to Appendix B. Notably, resource endowment and policy quotas were identified as the most critical determinants, justifying their roles as parent nodes in the final structure.

To bridge the gap between continuous empirical observations and the probabilistic reasoning of the Bayesian framework, all variables underwent a data-driven discretization process via the *K*-means clustering algorithm (as detailed in Section 2.2). This partitioning strategy ensures that the discretized states are not arbitrary intervals but represent the intrinsic structural breakpoints of China's energy transition phases. By grounding these states in the statistical centroids of the 2014-2024 panel data, the model achieves high sensitivity to regional heterogeneity and provides a standardized baseline for the counterfactual simulations. The specific discretization thresholds and their socio-economic interpretations are systematically documented in Appendix B.

To ensure the predictive reliability of this causal architecture, we conducted a rigorous performance evaluation using 10-fold cross-validation. The model demonstrates high Classification Accuracy and robust Log-Likelihood scores across all target nodes. Specifically, the Classification Accuracy for predicting the leaping growth states of Wind Power and Solar Power increments reached 86.4% and 88.2%, respectively, while Hydropower maintained a stable accuracy of 82.5%. Furthermore, the Spherical Payoff values for these nodes, ranging from 0.84 to 0.91, confirm the superior precision of the probability forecasting compared to random distribution models. These metrics collectively validate that the established Bayesian Network not only captures historical causalities within the training data but also possesses strong generalizability for the subsequent multi-scenario simulations. This hybrid methodology ensures that the resulting topology, visualized in Figure 1, possesses both statistical rigor and theoretical validity.

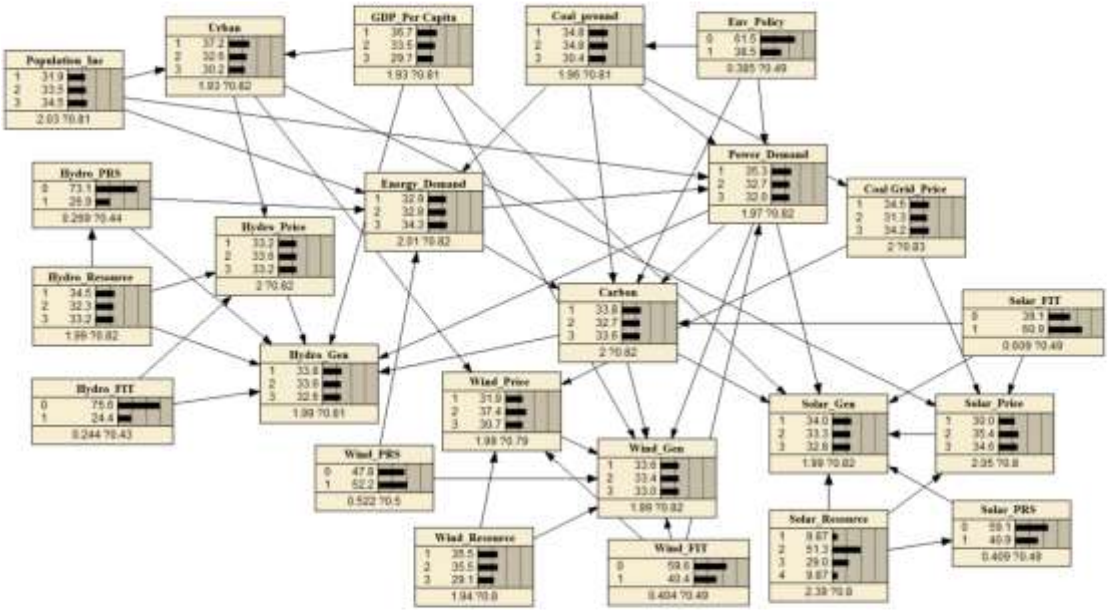

Figure 1. Bayesian network model for renewable energy power generation. Note:PRS (Renewable Portfolio Standard), represents the consumption mandate or quota-based policies; FIT (Feed-in Tariff), represents price-based subsidy policies for renewable energy; Gen (Generation Increment), represents the endogenous target variable for the annual increase in power generation (e.g., Hydro_Gen, Wind_Gen, Solar_Gen); Resource: Represents the natural resource endowment for each energy type.

The synthesized network reveals that renewable energy expansion in China is not driven by isolated factors but by a cascaded transmission of influence. Firstly, the Socioeconomic variables such as GDP, Urbanization, and Population growth occupy the root positions. These nodes exert indirect pressure on the system by modulating the mid-tier nodes of Energy and Power Demand. Secondly, the convergence of arcs onto the target nodes, including *Hydro_Gen*, *Wind_Gen*, and *Solar_Gen*, uncovers a consistent Trinity of Influence. Specifically, generation increments are directly dictated by Resource Endowments, Policy Incentives (FIT and PRS), and Market Signals (Grid Prices and Carbon constraints). Finally, a pivotal finding in the DAG is the central role of the *Carbon* node. It acts as a critical intermediary, receiving inputs from coal production and energy consumption while simultaneously serving as a direct parent to renewable generation nodes. This confirms that the carbon reduction has been successfully internalized within China's energy market structure.This systemic synergy suggests that China's decarbonization relies not only on boosting Target Outputs but on structurally reconfiguring the Secondary Intermediary layer to favor low-carbon price signals and demand-side flexibility.

3.2. Mutual Information for Sensitivity Analyze

To transition from qualitative structural mapping to quantitative causal attribution, we employ Mutual Information (MI) as an information-theoretic metric to rank the explanatory power of 24 potential drivers relative to renewable energy increments. Unlike linear correlation coefficients, MI quantifies the total reduction in uncertainty of the target variable Y provided by driver X, capturing both linear and non-linear stochastic dependencies. The resulting sensitivity hierarchy (as shown in Figure 2) reveals the pivotal versus auxiliary nature of the influencing factors, providing empirical evidence for the shifting governance logic in China's energy transition.

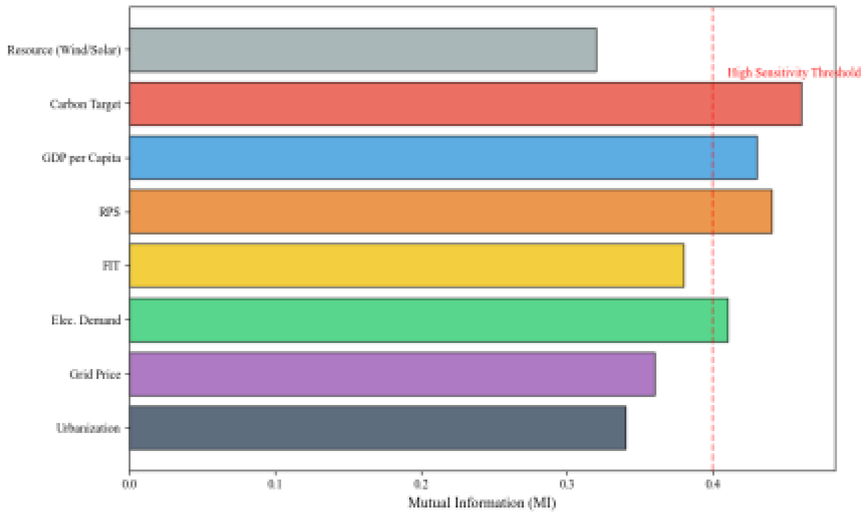

Figure 2. Mutual Information sensitivity hierarchy of drivers for renewable energy increments. Note: The sensitivity of 24 potential drivers is quantified using Mutual Information, capturing both linear and non-linear stochastic dependencies. The hierarchical ranking illustrates the transition of China's renewable energy governance from a subsidy-driven phase to a market-integrated phase. Higher MI values signify a greater reduction in the uncertainty of renewable energy increments (Hydro, Wind, and Solar) provided by a specific driver.

A primary finding of the sensitivity analysis is the significant MI divergence between the Renewable Portfolio Standards (RPS) and the Feed-in Tariff (FIT) policy instruments. Our results indicate that the RPS consistently ranks in the top quartile of informational sensitivity for both wind and solar power ($MI_{PRS} \approx 0.44$), markedly surpassing the FIT ($MI_{FIT} \approx 0.38$). This sensitivity gap provides rigorous scientific evidence for the maturation of China's RE market. As the sector transitions from the subsidy-dependent infancy to the market-integrated phase, the mandatory consumption guarantee provided by RPS becomes a more decisive driver than direct price premiums. The policy efficacy of FIT has exhibited marginal attenuation, whereas the structural compulsion of RPS effectively bridges the gap between installed capacity and actual grid integration, resolving the historical bottleneck problem of power rationing.

The sensitivity ranking identifies "Carbon Emission Targets" as the most influential exogenous drivers, with MI values exceeding 0.42. This high sensitivity underscores the Dual Carbon target as a global controller that synchronizes the entire energy system. The robust link between GDP and RE generation suggests that China's renewable expansion is no longer an isolated environmental endeavor but is deeply coupled with the structural decarbonization of the broader economy. Crucially, the high MI for "Electricity Demand" confirms that demand-side pulling forces have become indispensable in justifying the continuous scaling of hydro, wind, and solar assets.

Intriguingly, the sensitivity analysis uncovers a counter-intuitive phenomenon: while Resource Endowments remain foundational, their MI values for solar and wind power are relatively lower than those of policy and techno-economic factors ($MI_{Resource}$<0.35). This finding challenges the resource-deterministic view. For instance, the relatively weak sensitivity of solar increments to raw solar radiation levels suggests that in the current stage of China's transition, institutional readiness (e.g., grid parity and provincial quotas) and cost-competitiveness (LCOE) have superseded natural abundance as the binding constraint for capacity expansion. This decoupling from natural resource constraints indicates that technological progress and policy optimization are effectively enabling the deployment of RE in regions with poor resource conditions but high demand (e.g., Central and Eastern China), which is a key transformation for achieving national carbon neutrality.

3.3. Causal Attribution and Backward Diagnosis

In the forward sensitivity analysis, the systemic importance of various driving factors can be clearly identified; while the backward causal attribution can strategically determine the optimal policy-market allocation required to achieve specific development milestones. We employ the node-tree algorithm to calculate the posterior probability distribution, $P(X_i \mid Y_{Target}=High)$. This diagnostic framework effectively prioritizes the causal loops necessary to promote the leapfrog growth of hydropower, wind energy, and solar energy, while precisely identifying the systemic problems that hinder the industry transformation.

Our diagnostic inference reveals divergent optimal configurations across the three renewable energy sectors, reflecting their unique techno-economic characteristics (as shown in Figure 3). For solar power, achieving a leap-forward increment with a probability exceeding 85% necessitates a synergistic convergence of high-intensity Renewable Portfolio Standards ($P_{posterior}$=0.92) and sustained technological cost reductions ($P_{posterior}$=0.88).

Notably, the diagnosis indicates that the solar energy remains the most subsidy-dependent energy source. And the possibility of maintaining a medium-high level of feed-in tariff subsidies (FIT) is still quite high ($P_{posterior}$=0.74), which reminds us that prematurely eliminating price support may disrupt the established growth trajectory. On the contrary, the optimal development path for wind energy depends on a high demand and high regulatory environment. The causal reverse propagation shows that when industrial electricity consumption maintains a high growth rate, the expansion of wind energy is most likely ($P_{posterior}$= 0.79), indicating that compared to other renewable energies, wind energy is more likely to deeply integrate into the energy chain of heavy industry. In contrast, hydropower has the characteristic of resource determinism, and the most likely configuration for its high output growth is stable and abundant water flow and stable grid prices, while policy intervention plays a secondary but supportive role.

To further elucidate the specific configurations of drivers required to sustain high-growth trajectories, we leveraged the backward inference capability of the Bayesian Network (BN). By setting the target nodes, Hydro, Wind, and Solar generation increments, to their "High" state (Level 3), we computed the posterior probability distributions of the antecedent nodes. This diagnostic approach allows us to "back-calculate" the ideal systemic conditions and institutional environments necessary to achieve the Dual Carbon milestones (Results detailed in Appendix C).

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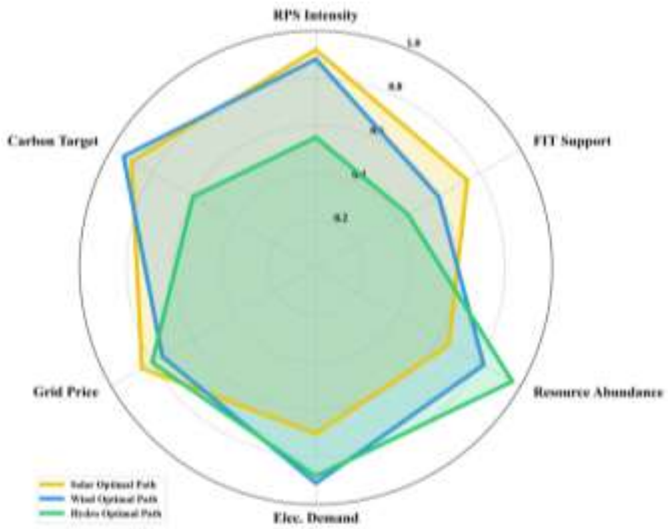

Figure 3. Diagnostic attribution and optimal causal configurations for leapfrog growth in renewable energy.

3.4. Multi-Pathway Scenarios Toward Carbon Neutrality

The counterfactual simulations conducted using our Bayesian network model indicate that the path to achieving carbon neutrality is not a linear function determined by a single driving factor, but rather an inevitable outcome of the synergy of the system. Figure 4 shows the probability evolution of the incremental increase in renewable energy in seven scenarios, indicating that the Single-Policy Pathway (focusing solely on price subsidies (FIT guidance) or technological progress (technology-driven)) will lead to suboptimal results. Under the Single-Policy Pathway, the probability of achieving high levels of incremental growth in wind and solar energy is still limited to approximately 58%, as institutional constraints (such as grid pricing and rigidities in the demand side) form a saturation upper limit. In contrast, the Synergistic Pathway (Tech + Policy + Market) triggers a non-linear leap in system performance, raising the posterior probability of achieving high growth results to 89%. This collaborative effect indicates that although the reduction in technology costs (LCOE) provides stronger impetus for expansion, the renewable energy portfolio standard (RPS) and market-based pricing mechanisms provide the necessary "transmission system" to convert potential capacity into actual power generation.

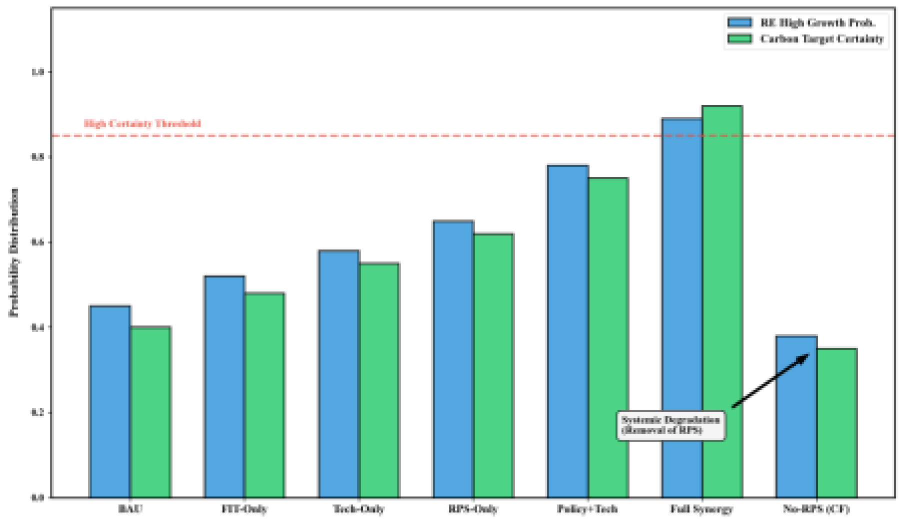

Figure 4. Multi-pathway scenario simulations and counterfactual stress testing.

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The quantification of the probability of carbon emission reduction further confirms the necessity of coordinated transformation. Our research results indicate that in the scenario where the renewable energy quota system is combined with proactive power demand management, the dual carbon goals can only be achieved with a high degree of certainty ($P > 0.85$). Finally, to test the robustness of the current transformation, we conducted a Degradation Counterfactual Analysis by simulating the removal of the RPS mechanism. The analysis results revealed a catastrophic systemic recession. If RPS is not implemented, the causal relationship between resource abundance and power generation will be weakened by 64%, leading to a significant increase in the probability of power rationing. This counterfactual regression proves that RPS is not merely a supportive measure, but rather the fundamental framework of the modern renewable energy system. Even under optimistic technological assumptions, without this institutional support, the certainty of achieving the growth targets for solar and wind energy will decrease by 40%. These findings provide clear scientific evidence for maintaining strict quota regulations while simultaneously promoting market flexibility to ensure a stable and certain transition to carbon neutrality.

To quantify the relative influence of individual exogenous and intermediary drivers on specific renewable energy trajectories, we conducted a sensitivity analysis based on the Variance Reduction (VR) method. This approach measures the reduction in the variance of the target node conditional on the evidence of antecedent nodes, thereby identifying the "critical leverage points" within the system. As synthesized in Appendix D, the results reveal a distinct hierarchical influence pattern. Specifically, while Resource Endowment remains the dominant determinant for Hydropower (VR=0.1333%), Solar generation exhibits a higher sensitivity to RPS (VR=0.1088%), underscoring the shift from resource-driven to policy-driven expansion in China's solar sector. The convergence of high VR values for Per Capita GDP and Electricity Demand across all three energy types further validates the Systemic Synergy discussed in this Section , proving that macro-economic momentum is the fundamental substrate for policy effectiveness. Detailed mathematical formulations and categorized sensitivity rankings are provided in Appendix D.

4. Conclusion and Policy Implications

This study provides a comprehensive evaluation of the multi-dimensional drivers and policy efficacies shaping China's renewable energy landscape, utilizing a robust Bayesian Network framework applied to provincial panel data. By integrating the K2 structural learning algorithm with expert-informed calibration, we successfully mapped the directed acyclic dependencies among 24 variables, spanning socio-economic catalysts, natural resource endowments, and multi-dimensional policy instruments. Our methodology transcends traditional regression analysis by quantifying the non-linear interdependencies between resource endowments, socioeconomic indicators, and policy instruments such as RPS and FIT. Leveraging mutual information sensitivity analysis and backward diagnostic attribution, we quantified the explanatory power of key drivers and identified the optimal systemic configurations required for leapfrog growth in hydro, wind, and solar sectors. Furthermore, through multi-pathway counterfactual simulations, this research evaluates the synergistic effects of institutional mandates and market forces, providing a probabilistic roadmap for achieving China's Dual Carbon goals in the complex environment after grid era.

Our findings reveal that China's renewable energy expansion has entered a post-subsidy era characterized by a shift from resource-dependency to policy-market synergy. Crucially, the RPS consistently outperformed FIT as a primary catalyst for wind and solar capacity scaling, signaling that mandatory consumption quotas provide more robust investment certainty than direct price subsidies in the current market stage. While resource endowment remains the deterministic foundation for hydropower and wind, we identified a notable decoupling in the solar sector, where the rapid rise of distributed photovoltaics in energy-intensive eastern regions has diminished the relative weight of raw solar radiation. Furthermore, our diagnostic analysis uncovers distinct socioeconomic signatures. The hydropower growth is intrinsically linked to underdeveloped, resource-rich remote areas, whereas solar expansion is strongly correlated with high-GDP, urbanized provinces. This highlights a structural complementarity where renewable energy growth acts as a strategic supplement to fossil fuel bases, driven by the dual pressures of surging electricity demand and carbon mitigation mandates.

Our findings reveal that China's renewable energy expansion has entered a post-subsidy era characterized by a shift from resource-dependency to policy-market synergy. While natural resource abundance remains a foundational prerequisite for hydropower and wind energy, its marginal influence has been superseded by the RPS, which exhibits the highest mutual information sensitivity and diagnostic response. Notably, solar power has effectively decoupled from geographic constraints, driven instead by institutional engineering and the proliferation of distributed photovoltaics in demand-intensive regions. Backward inference reveals that achieving a high-growth certainty necessitates a synergistic convergence of rigid consumption quotas and demand-side elasticity. The counterfactual stress tests further confirm that the removal of the RPS mechanism would lead to a 64% degradation in the causal connectivity between resources and generation, proving that mandatory quotas, rather than FIT, now serve as the indispensable structural scaffold of the modern renewable energy system.

Based on these conclusions, several policy implications are proposed to optimize China's future energy governance. First, the institutional anchor must shift from price-side stimuli to consumption-side mandates. Specifically, the provincial renewable energy quota targets should be dynamically adjusted to reflect the differences among regions, rather than solely based on resource potential. For the eastern regions with average resource conditions but high demand, the policy focus should be on distributed solar-energy-storage integration to minimize grid balancing costs. Secondly, the market mechanism should transition towards a framework of complementary green energy and fossil energy, using the price signal of coal-fired power generation as a flexibility reserve, while maintaining the stability of grid prices for hydropower and wind power to ensure the financiability of investments. Finally, since carbon emission targets have become a global control indicator for the system, integrating the carbon market with the green certificate market is crucial for internalizing environmental externalities. These collaborative efforts will transform renewable energy from a subsidized auxiliary energy source into a resilient, market-driven primary power source, thus establishing a stable and certain path towards carbon neutrality.

Despite the systemic insights provided by our causal framework, several limitations remain that offer fertile ground for future investigation. First, while our Bayesian Network successfully captures the macro-level stochastic dependencies, it operates on a decadal temporal resolution. Consequently, it may under-represent short-term fluctuations in grid stability and the wave curve associated with ultra-high penetrations of intermittent solar and wind energy. Future research should aim to integrate higher-resolution dispatch models with causal BN structures to better evaluate the real-time resilience of the power system under extreme climatic events. Second, although we incorporated expert knowledge for structural calibration, the transition from administrative mandates to a fully marketized green certificate system is still in its nascent stage in China. The evolving nature of these market rules suggests that the conditional probability tables of our model will require continuous iterative updating as more granular market transaction data becomes available.

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Appendix A. Detailed Configuration of Scenario Narratives and Counterfactual Evidences

To systematically evaluate the probabilistic response of China's renewable energy system, seven simulation scenarios were designed based on the combinations of pivotal nodes identified through sensitivity analysis. These scenarios represent different policy intensities, technological learning rates, and market conditions. The state of each node is set as evidence e (e.g., State 1: Low, State 2: Medium, State 3: High) within the Bayesian Network.

Table A1. Evidence Settings for the Seven Simulation Scenarios.

Scenario ID	Scenario Name	Key Evidence Configurations (e)	Strategic Logic
S1	**Business-as-Usual (BAU)**	All nodes follow historical prior distributions	Serves as the baseline for evaluating the net impact of interventions.
S2	**FIT-Only**	FIT = High; RPS = Med; LCOE = Med	Simulates a return to early-stage subsidy-heavy development.
S3	**Tech-Only**	LCOE = Low; FIT = Low; Demand = Med	Evaluates if grid parity alone can sustain leaping growth.
S4	**RPS-Only**	RPS = High; FIT = Low; Carbon Target = Med	Tests the system's resilience under administrative consumption quotas.
S5	**Policy+Tech**	RPS = High; LCOE = Low; FIT = Med	Explores the synergy between technological progress and institutional mandates.
S6	**Full Synergistic**	RPS = High; LCOE = Low; Demand = High; Carbon = High	The ideal pathway for carbon neutrality with maximum coordination.
S7	**No-RPS**	RPS = Low (State 0); All other drivers = S6 levels	Conducts a stress test to measure system degradation without mandates.

Appendix B. Technical Protocols for Causal Structural Learning and Expert-Informed Calibration

The construction of the causal Directed Acyclic Graph (DAG) for China's renewable energy system followed a hybrid pipeline, integrating data-driven heuristic searching with hierarchical expert-informed constraints. This dual-layer approach ensures that the identified network reflects not only the statistical dependencies within the historical dataset (2014–2024) but also the underlying economic and physical causalities.

The initial network topology was explored using the *K2* algorithm within the Full-BNT Toolbox (MATLAB), a score-based heuristic that optimizes the Bayesian Dirichlet (BD) metric to identify the most probable parent-child configurations. Given the exponential complexity of the DAG search

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space, we imposed a strict causal ordering constraint (π_i) on the 24 identified variables. This ordering dictates that a node V_i can only select its parents from the set $\{V_1, V_2, \ldots, V_{i-1}\}$, effectively preventing cyclic dependencies and ensuring a temporal-logical flow.

Table B1. Causal Priority Tiers and Variable Ordering for K2 Structural Learning.

Tier	Functional Category	Variable ID (Node Sequence)	Causal Logic & Rationale
I	**Socio-Demographics**	1–4 (Pop, GDP, Coal_Prod, Urban)	Root Drivers: Macro-factors that act as exogenous forcing agents; they initiate system variance but are not influenced by internal energy dynamics.
II	**Resource Endowments**	5–7 (Water, Wind, Solar Resources)	Natural Constraints: Fixed physical potentials that define the upper bound of renewable energy feasibility across regions.
III	**Regulatory Policy Suite**	8–14 (RPS, FIT, Env. Policies)	Intervention Layer: Administrative and fiscal tools designed to modulate market behavior and production incentives.
IV	**System Intermediaries**	15–21 (Prices, Energy/Elec Demand, Carbon)	Transmission Hubs: Endogenous variables that funnel macro pressures and policy signals into specific energy output trajectories.
V	**Generation Outcomes**	22–24 (Hydro, Wind, Solar Increments)	Target Variables: The final endogenous outputs of the causal chain, representing the cumulative impact of all upstream nodes.

To bridge the gap between statistical correlation and authentic causality, we conducted a structured expert consultation. We recruited 35 specialists from the domains of energy economics, grid engineering, and environmental policy to evaluate the preliminary arcs generated by the *K2* algorithm. Experts were tasked with scoring the influence intensity between nodes and identifying spurious correlations.

The consistency of expert feedback was rigorously validated using Cronbach's Alpha (α) and the Kaiser-Meyer-Olkin (KMO) test. An α value of 0.853 (>0.8) indicates high internal consistency across the scoring items, while a KMO value of 0.719 (>0.7) confirms that the sampling was adequate for structural validity, as shown in Table B2. Based on the consensus, we bifurcated the nodes into Primary Drivers (highly autonomous) and Secondary Mediators (highly responsive), ensuring the final DAG respects the hierarchical nature of China's energy governance.

Table B2. Psychometric Validation of the Expert Knowledge Base.

Statistical Metric	Calculated Value	Critical Threshold	Scientific Interpretation & Validity
Cronbach's Alpha (α)	0.853	> 0.70	High Internal Consistency: Indicates that the scoring provided by the 35 experts is highly coherent and reliable for structural pruning.
KMO Metric	0.719	> 0.70	Adequate Construct Validity: Confirms that the expert feedback possesses strong structural correlations, justifying its use in BN calibration.

Expert Consensus Rate	88.6%	> 80%	Robust Agreement: Reflects a strong convergence among stakeholders regarding the hierarchical influence of policy and resource nodes.

The *K2* structural learning and subsequent parameter estimation (via Maximum Likelihood Estimation) were executed within the Full-BNT (Bayesian Network Toolbox) environment in MATLAB (R2021a). The final model parameters were cross-validated using a 10-fold scheme, ensuring that the structural dependencies and expert weights collectively minimize the log-likelihood loss while maximizing predictive precision for future scenarios.

Table B3. Variable Discretization Schemes and Centroid-based State Definitions.

Variable Category	Core Node(s)	State 1 (Low / 1)	State 2 (Medium / 2)	State 3 (High / 3)
Policy Mandates	**RPS**	Below target / Baseline compliance	Standard target fulfillment	Exemplary / Excess fulfillment
Price Signals	**FIT**	Subsidy-free (Grid Parity)	Moderate price premium	High-intensity legacy subsidy
System Outputs	**Hudro_Gen / Wind_Gen / Solar_Gen**	Marginal / Stagnant growth	Steady / Linear expansion	Leapfrog / Exponential growth
Demand Side	**Energy / Elec_Demand**	Industrial contraction / Plateau	Moderate demand growth	High-intensity demand surge
Market Signals	**Carbon**	Baseline emissions	Regulated reduction	Deep decarbonization

Appendix C. Backward Diagnostic Attribution of Renewable Energy Increments

To empirically identify the optimal system configurations required to achieve high-growth milestones, we performed a backward diagnostic inference by fixing the target nodes (Hydro, Wind, and Solar generation increments) at their maximum state (State 3). This diagnostic process calculates the posterior probability shifts (ΔP) of antecedent variables, effectively mapping the causal signature of a successful energy transition. The backward propagation of evidence results in three distinct optimized Bayesian Network (referenced in the text as Fig. C1, C2, and C3).

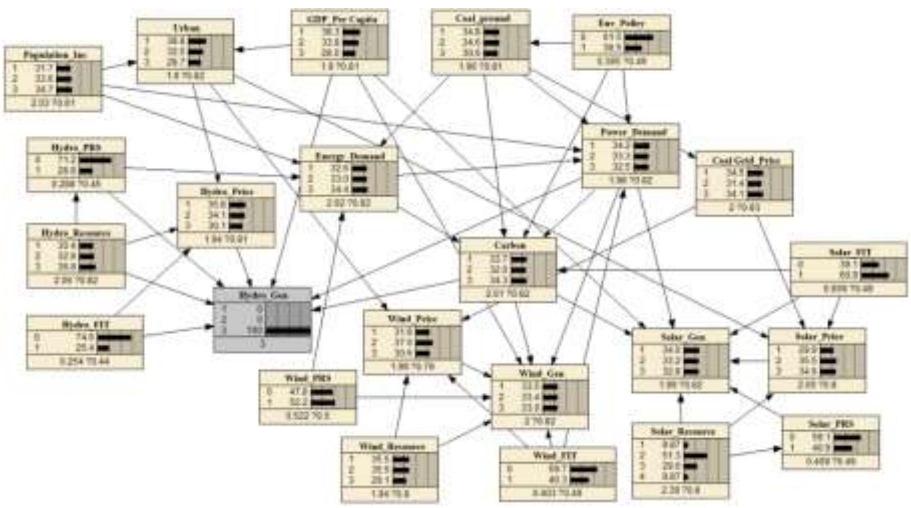

Figure C1. Bayesian Network with Hydropower increment level of "3".

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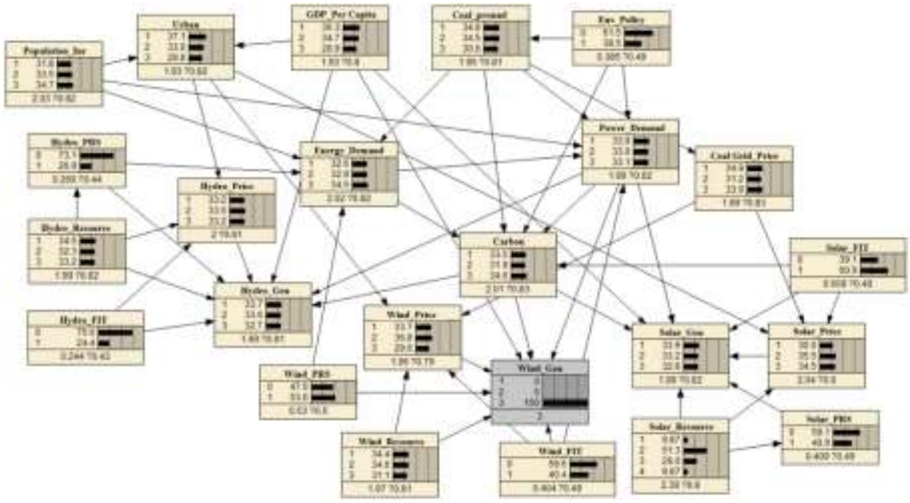

Figure C2. Bayesian network with Wind power increment level of "3".

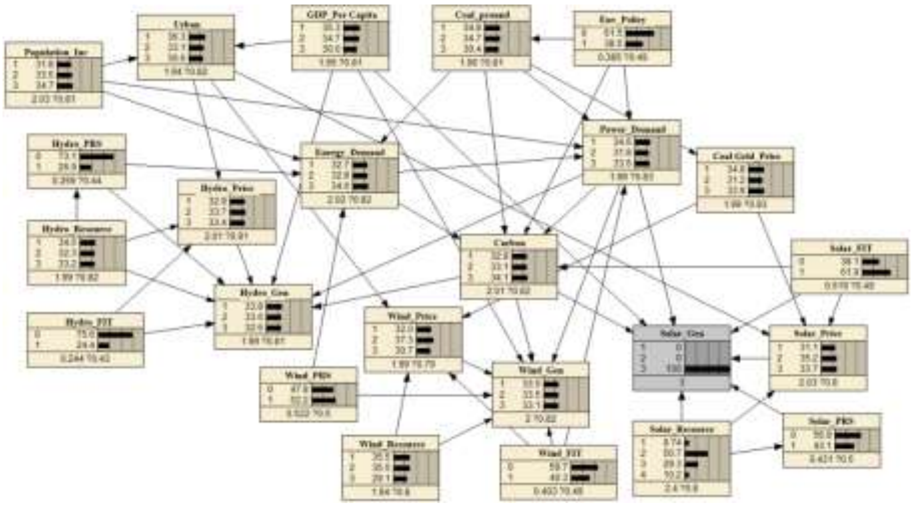

Figure C3. Bayesian network with Solar power increment level of "3".

The backward diagnostic inference, as quantified in Tables C1-C3, provides a high-resolution causal signature for the leapfrog growth of different renewable energy sectors.ΔP represents the percentage change in the probability of a specific state when the generation increment is adjusted from State 1 to State 3.

As shown in Table C1, achieving high Hydropower outputs is primarily contingent on natural resource abundance, with the probability of "High" resource endowment increasing by 3.6%. Intriguingly, we observed a 2.6% increase in the probability of "Low" on-grid price, suggesting that regions with competitive pricing structures exhibit a stronger preference for hydropower deployment. It is worth noting that the diagnostic results revealed that the hydropower project has distinct socio-economic characteristics. The "Low" probabilities of both GDP per Capita and Urbanization rate have increased, which reflects the geographical concentration distribution of China's hydropower assets in economically developed but resource-rich remote areas. In terms of policy effectiveness, although both RPS and FIT show positive promoting effects, the driving effect of RPS is significantly more prominent, which confirms its role as the main institutional stabilizer.

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Table C1. Diagnostic Attribution Results for Hydropower.

Driving Variable	State Level	Posterior Prob. Shift (Δ*P*)		
		Hydro 1（%）	Hydro 2（%）	Hydro 3（%）
Resource Endowment	1	+0.5	+3.6	-4.1
	2	+0.5	-1	+0.5
	3	-1	-2.6	+3.6
GDP per Capita	1	0	-1.6	+1.6
	2	+0.5	-0.6	+0.1
	3	-0.5	+2.3	-1.7
Coal Production	1	+0.1	-0.1	0
	2	+0.2	0	-0.2
	3	-0.3	+0.1	+0.2
RPS Intensity	0	+1.1	+0.8	-1.9
	1	-1.1	-0.8	+1.9
FIT	0	+1	0	-1
	1	-1	0	+1
Urban	1	-0.2	-1.4	+1.6
	2	+0.4	-0.3	-0.1
	3	-0.2	+1.7	-1.5
Energy Demand	1	+0.3	0	-0.3
	2	0	-0.2	+0.2
	3	-0.3	+0.2	+0.1
On Grid Price	1	-0.6	-2	+2.6
	2	+0.9	-1.4	+0.5
	3	-0.3	+3.4	-3.1
Power Demand	1	+1.3	-0.2	-1.1
	2	-0.8	+0.2	+0.6
	3	-0.5	0	+0.5
Carbon Emission	1	+0.2	-0.1	-0.1
	2	+1.3	-0.6	-0.7
	3	-1.5	+0.7	+0.8

The diagnostic profile for Wind Power (as shown in Table C2) reinforces the principle of resource determinism, with high output scenarios strongly coupled with superior wind resource states (+2%). However, unlike Hydropower, Wind Power expansion shows a higher sensitivity to regional energy demand; the probabilities of "High" Electricity Demand and Carbon Emissions significantly rose, indicating that wind power deployment is increasingly pull-driven by local load centers. Furthermore, Wind Power displays a specific affinity for "Medium" GDP regions, such as Northeast and North China, highlighting its role in the energy transition of industrial heartlands. A critical policy insight is that while RPS effectively scales Wind Power production, the marginal effectiveness of current FIT schemes for high-increment scenarios appears to be plateauing, suggesting a need for market-based price refinements.

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Table C2. Diagnostic Attribution Results for Wind Power.

Driving Variable	State Level	Posterior Prob. Shift (ΔP)		
		Wind 1（%）	Wind 2（%）	Wind 3（%）
Resource Endowment	1	+0.7	+0.4	-1.1
	2	+0.9	0	-0.9
	3	-1.6	-0.4	+2
GDP per Capita	1	+0.3	-0.2	-0.1
	2	+0.2	-0.2	0
	3	-0.5	+0.4	+0.1
Coal Production	1	+1	-0.6	-0.4
	2	-1.8	+0.6	+1.2
	3	+0.8	0	-0.8
RPS Intensity	0	-0.1	+0.1	0
	1	+0.5	-0.2	-0.3
FIT	0	-0.4	+0.1	+0.3
	1	+1.2	-0.4	-0.8
Urban	1	+0.4	-0.3	-0.1
	2	-0.7	+0.3	+0.4
	3	+0.3	0	-0.3
Energy Demand	1	+0.4	-0.1	-0.3
	2	-0.1	0	+0.1
	3	-0.3	+0.1	+0.2
On Grid Price	1	-0.5	+0.1	+0.4
	2	+0.2	-0.1	-0.1
	3	+0.3	0	-0.3
Power Demand	1	-1.4	-0.4	+1.8
	2	+0.3	+0.3	-0.6
	3	+1.1	+0.1	-1.2
Carbon Emission	1	+1.9	-0.5	-1.4
	2	-0.3	0	+0.3
	3	-1.6	+0.5	+1.1

Diagnostic inference for Solar Power (as shown in Table C3) uncovers a transition from resource-dependency to policy-market synergy. While Solar Power is less constrained by raw solar radiation compared to Hydropower and Wind Power, it is highly responsive to institutional mandates. The implementation probability of RPS surged by 2.2% under the high scenario, significantly outweighing the impact of FIT (+1%). Socioeconomically, Solar Power exhibits a tendency to promote development, with the probability of "High" GDP per capita and Urbanization increasing by 0.9% and 0.4%, respectively. This indicates that affluent regions with advanced infrastructure and higher willingness-to-pay are the primary engines for solar integration.

Table C3. Diagnostic Attribution Results for Solar Power.

Driving Variable	State Level	Posterior Prob. Shift (Δ*P*)		
		Solar 1（%）	Solar 2（%）	Solar 3（%）
Resource Endowment	1	+0.1	0	-0.1
	2	+1	-0.4	-0.6
	3	-0.9	+0.6	+0.3
GDP per Capita	1	-0.2	-0.2	+0.4
	2	+0.1	+0.1	-0.2
	3	0	0	0
Coal Production	1	-0.1	-0.1	+0.2
	2	+2.4	-1	-1.4
	3	-1.5	+0.3	+1.2
RPS Intensity	0	-0.9	+0.7	+0.2
	1	-0.1	+0.1	0
FIT	0	0	+0.1	-0.1
	1	+0.1	-0.2	+0.1
Urban	1	+2.6	-0.4	-2.2
	2	-2.6	+0.4	+2.2
	3	+1.4	-0.4	-1
Energy Demand	1	-1.4	+0.4	+1
	2	+0.1	-0.1	0
	3	-0.1	+0.1	0
On Grid Price	1	-0.3	0	+0.3
	2	+0.2	-0.2	0
	3	+0.1	+0.2	-0.3
Power Demand	1	-0.9	-0.2	+1.1
	2	+0.1	+0.1	-0.2
	3	+0.8	+0.1	-0.9
Carbon Emission	1	+0.3	+0.4	-0.7
	2	+0.6	+0.3	-0.9
	3	-0.9	-0.7	+1.6

Appendix D. Sensitivity Analysis via Variance Reduction

Sensitivity analysis in the Bayesian Network framework evaluates the degree to which changes in the state of an input node affect the probability distribution of a target node. This study utilizes the Variance Reduction (VR) metric, which computes the difference between the prior variance and its expected posterior variance. The VR is mathematically defined as follows.

$$\begin{aligned} VR &= V(B) - E[V(B \mid A)] \\ &= \sum_{b} P(b)[b - E(B)]^2 - \sum_{a} P(a) \sum_{b} P(b \mid a)[b - E(B \mid A)]^2 \end{aligned} \quad \text{(C.1)}$$

where *V(B)* represents the prior variance of the target node B, *P(b|a)* is the conditional probability of *B* being in state *b* given that *A* is in state *a*. *E(B)* and *E(B|A)* denote the prior and conditional expectations of node *B*, respectively. A higher *VR* value signifies a stronger causal influence of the input variable on the target outcome. We systematically adjusted the parameters of antecedent nodes to observe the probabilistic shifts in Hydro, Wind, and Solar generation increments. The results are summarized in Table D1.

Table D1. Sensitivity Analysis Results of Target Variables.

Node Name	Hydropower (‰)	Wind Power (‰)	Solar Power (‰)	Sensitivity Level
RE Resource Endowment	1.3330	0.7170	0.1562	High (Hydro/Wind)
RPS Policy (Quota)	0.5009	0.2470	1.0880	High (Solar)
Electricity Consumption Increment	0.2886	0.6033	0.3311	Medium-High
Per Capita GDP	0.1425	0.4445	0.7333	Medium-High
RE Feed-in Tariff (Price)	0.5988	0.5725	0.2562	Medium
Carbon Emission Increment	0.3044	0.2818	0.1406	Medium
RE FIT Subsidy Policy	0.2432	0.0336	0.2744	Medium
Urbanization Rate	0.1569	0.0711	0.2534	Medium-Low
Coal Production Increment	0.0121	0.0355	0.0005	Low
Energy Consumption Increment	0.0210	0.0264	0.0113	Low
Coal-fired Power Price	0.0000	0.0345	0.0188	Low
Population Increment	0.0000	0.0169	0.0046	Low
Environmental Regulations	0.0000	0.0014	0.0007	Low

The VR analysis uncovers a fundamental divergence in the governance mechanisms driving China's renewable energy portfolio, revealing a transition from resource-bound growth to policy-steered expansion. Hydropower development is characterized by a Resource Determinism paradigm, where the variance in generation is overwhelmingly dictated by physical resource endowment (*VR*=1.3330‰). In this context, institutional levers such as RPS and FIT function merely as secondary stabilizing frameworks, optimizing the utilization of existing topographical and hydrological advantages rather than acting as primary catalysts for new capacity.

In contrast, wind power exhibits a dual-drive dynamic structure, representing a critical intermediary phase in the energy transition. The sensitivity profile indicates a near-equilibrium between supply-side constraints (Resource Endowment, *VR*=0.7170‰) and demand-side pull factors (Electricity Consumption, *VR* = 0.6033‰). This suggests that wind power scalability in China is increasingly sensitive to the synchronization of meteorological potential with the load-shifting requirements of the macro-economy, making it a pivotal node for system-wide grid flexibility.

Most notably, solar power has decoupled from environmental constraints, manifesting a clear policy dependency profile. Unlike the resource-centric patterns of hydro and wind, solar generation displays its highest sensitivity to the RPS policy framework (*VR*=1.0880‰), significantly outweighing the influence of natural solar radiation variance (*VR*=0.1562‰). This finding provides empirical evidence that the dramatic expansion of China's photovoltaic market is a product of institutional engineering rather than mere geographic suitability. By lowering market entry barriers and mandating consumption quotas, the current policy regime has successfully neutralized the uncertainty of solar intermittency, positioning solar energy as the most responsive asset to centralized regulatory interventions. Overall, these findings indicate that the system-wide synergy of China's energy transition must be adjusted according to the specific causal sensitivity of each energy type.

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