

# Cascading Bayesian Choke-Node Forecasting for Multi-Era Paradigm Shifts

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### Abstract

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Strategic planners and technology-road-mapping teams must allocate scarce resources across long-horizon scientific and technological transitions. Existing foresight methods treat each milestone as an independent probabilistic estimate, ignoring the cascading dependency structure that links successive eras. This paper introduces **Cascading Bayesian Choke-Node Forecasting (CBCNF)**, a framework that models a sequence of eras as a Markov chain whose transition probabilities are conditioned on the state (optimistic, baseline, pessimistic) of the preceding era. Analytic sensitivity analysis identifies conditional probability pairs that exert maximal leverage on the total expected value (EV) of the forecast. A three-era toy example yields marginal era distributions, a total EV of **3.0396**, and a choke node (baseline  $\rightarrow$  optimistic in the first era) with sensitivity **1.14**. By exposing high-leverage transitions, CBCNF enables targeted stress-testing and more disciplined resource allocation, offering a principled alternative to independent-era baselines.

### 1. Introduction

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Technology-focused organizations—corporate R&D divisions, government research agencies, and venture-capital firms—must decide which emerging paradigms to fund, which prototypes to scale, and which regulatory pathways to pursue. Misallocation costs billions of dollars and can stall societal benefits such as clean energy, advanced computing, or resilient infrastructure. Current foresight pipelines typically produce independent probabilistic forecasts for each milestone (e.g., “solid-state batteries will achieve  $300 \text{ Wh kg}^{-1}$  by 2030”) and then aggregate them naïvely. This ignores the fact that the outcome of one era conditions the feasible outcomes of the next, leading to over-optimistic portfolios and fragile investment strategies.

If a forecasting framework could **explicitly model inter-era dependencies** and **highlight the transitions that dominate the overall expected value**, decision makers could focus validation effort on those *choke nodes*, thereby reducing uncertainty where it matters most. The present work addresses this gap.

#### Contributions.

- **C1.** Formal definition of a multi-era Markov-chain forecasting model with Bayesian priors (Section 3).
- **C2.** Derivation of the total expected value as a function of conditional transition probabilities (Section 3).
- **C3.** Analytic sensitivity formula that ranks each conditional probability by its impact on total EV (Section 3).
- **C4.** Complete numerical illustration: marginal distributions, total EV = 3.0396, and identification of the choke node (baseline  $\rightarrow$  optimistic) with sensitivity 1.14 (Section 4).
- **C5.** Discussion of limitations, falsification criteria, and a concrete next-step experiment applying CBCNF to historical road-maps (Section 6).
- **C6.** Practical pathway for adoption, including TRL assessment, required data, and risk considerations (Section 7).

## 2. Background and Related Work

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Probabilistic forecasting of complex time series has motivated a range of Bayesian and machine-learning approaches. Gaussian-process latent variable models quantify uncertainty in intermittent demand and propagate it to predictive distributions, demonstrating the value of Bayesian treatment for sparse observations[1]. Quantile-regression methods for load forecasting show that **quantile loss** (pinball score) is a widely accepted metric for evaluating probabilistic forecasts[2]. Deep state-space models provide a recurrent architecture for multi-step forecasting with uncertainty estimates[5]. Hierarchical forecasting with deep Poisson mixtures extends these ideas to multi-level aggregation, employing **continuous ranked probability score (CRPS)** and quantile loss as evaluation criteria[4]. Scalable Gaussian process regression enables large-scale forecasting while preserving Bayesian uncertainty quantification[6]. Bayesian neural networks further illustrate flexible posterior inference for time-series data[3]. Finally, Bayesian model selection for regular vine copulas shows that **reversible-jump MCMC** can efficiently explore large model spaces and select high-leverage dependency structures[8]. Copula-based dependency modeling for energy systems demonstrates the practical impact of structured probabilistic models[7]. Together, these works establish a methodological foundation for Bayesian, probabilistic, and hierarchical forecasting, which we extend to the multi-era cascade setting.

## 3. Methods

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### 3.1 Multi-Era Markov-Chain Formulation

Consider  $E$  eras indexed by  $e = 1, \dots, E$ . Each era can be in one of  $S$  states  $s \in \{\text{optimistic, baseline, pessimistic}\}$ . Let the prior distribution for era 1 be a row vector

$$\mathbf{p}^{(1)} = [p_{\text{opt}}^{(1)}, p_{\text{base}}^{(1)}, p_{\text{pess}}^{(1)}], \quad \sum_s p_s^{(1)} = 1.$$

Conditional transition matrices

$$\mathbf{T}^{(e)} \in \mathbb{R}^{S \times S}, \quad T_{ij}^{(e)} = P(\text{state } j \text{ in era } e + 1 \mid \text{state } i \text{ in era } e),$$

are stochastic ( $\sum_j T_{ij}^{(e)} = 1$  for each  $i$ ). The marginal distribution for era  $e + 1$  follows by matrix multiplication:

$$\mathbf{p}^{(e+1)} = \mathbf{p}^{(e)} \mathbf{T}^{(e)}. \quad (1)$$

### 3.2 State-Value Mapping and Total Expected Value

Assign a numeric value  $v_s$  to each state, reflecting its contribution to the overall paradigm-shift payoff (e.g.,  $v_{\text{opt}} = 1.2, v_{\text{base}} = 1.0, v_{\text{pess}} = 0.8$ ). The expected value for era  $e$  is

$$\text{EV}^{(e)} = \mathbf{p}^{(e)} \cdot \mathbf{v}^\top, \quad \mathbf{v} = [v_{\text{opt}}, v_{\text{base}}, v_{\text{pess}}]. \quad (2)$$

The **total expected value** across all eras is the sum

$$\text{EV}_{\text{tot}} = \sum_{e=1}^E \text{EV}^{(e)}. \quad (3)$$

### 3.3 Choke-Node Identification via Sensitivity

Each conditional probability  $T_{ij}^{(e)}$  affects  $\text{EV}_{\text{tot}}$  through the chain of marginal distributions. The **sensitivity** of total EV to a specific entry is the partial derivative

$$S_{ij}^{(e)} = \frac{\partial \text{EV}_{\text{tot}}}{\partial T_{ij}^{(e)}}. \quad (4)$$

Using the chain rule, the derivative propagates forward:

$$\frac{\partial \mathbf{p}^{(e+1)}}{\partial T_{ij}^{(e)}} = \mathbf{e}_i p_i^{(e)},$$

where  $\mathbf{e}_i$  is a one-hot row vector with a 1 in column  $i$ . Subsequent eras inherit this perturbation via repeated multiplication by later transition matrices. Summing the contributions to (2) across all eras yields (4). The **choke node** is the entry with maximal  $S_{ij}^{(e)}$ .

## 4. Analysis

We illustrate CBCNF with a three-era toy example. All numbers below are **assumptions** introduced for exposition; they are not drawn from external data.

### 4.1 Assumed Prior and Transition Matrices

$$\mathbf{p}^{(1)} = [0.3, 0.5, 0.2]. \quad (5)$$

Transition from era 1 to 2:

$$\mathbf{T}^{(1)} = \begin{bmatrix} 0.6 & 0.3 & 0.1 \\ 0.2 & 0.5 & 0.3 \\ 0.1 & 0.4 & 0.5 \end{bmatrix}. \quad (6)$$

Transition from era 2 to 3:

$$\mathbf{T}^{(2)} = \begin{bmatrix} 0.5 & 0.4 & 0.1 \\ 0.3 & 0.5 & 0.2 \\ 0.2 & 0.3 & 0.5 \end{bmatrix}. \quad (7)$$

State values:

$$\mathbf{v} = [1.2, 1.0, 0.8]. \quad (8)$$

### 4.2 Marginal Distributions

Using (1):

$$\begin{aligned} p_{\text{opt}}^{(2)} &= 0.3 \times 0.6 + 0.5 \times 0.2 + 0.2 \times 0.1 = 0.30, \\ p_{\text{base}}^{(2)} &= 0.3 \times 0.3 + 0.5 \times 0.5 + 0.2 \times 0.4 = 0.42, \\ p_{\text{pess}}^{(2)} &= 0.3 \times 0.1 + 0.5 \times 0.3 + 0.2 \times 0.5 = 0.28. \end{aligned} \quad (9)$$

Thus  $\mathbf{p}^{(2)} = [0.30, 0.42, 0.28]$ .

Next,

$$\begin{aligned} p_{\text{opt}}^{(3)} &= 0.30 \times 0.5 + 0.42 \times 0.3 + 0.28 \times 0.2 = 0.332, \\ p_{\text{base}}^{(3)} &= 0.30 \times 0.4 + 0.42 \times 0.5 + 0.28 \times 0.3 = 0.414, \\ p_{\text{pess}}^{(3)} &= 0.30 \times 0.1 + 0.42 \times 0.2 + 0.28 \times 0.5 = 0.254. \end{aligned} \tag{10}$$

Hence  $\mathbf{p}^{(3)} = [0.332, 0.414, 0.254]$ .

#### 4.3 Expected Values per Era

Applying (2):

$$\begin{aligned} \text{EV}^{(1)} &= 0.3 \times 1.2 + 0.5 \times 1.0 + 0.2 \times 0.8 = 1.02, \\ \text{EV}^{(2)} &= 0.30 \times 1.2 + 0.42 \times 1.0 + 0.28 \times 0.8 = 1.004, \\ \text{EV}^{(3)} &= 0.332 \times 1.2 + 0.414 \times 1.0 + 0.254 \times 0.8 = 1.0156. \end{aligned} \tag{11}$$

Total expected value:

$$\text{EV}_{\text{tot}} = 1.02 + 1.004 + 1.0156 = \mathbf{3.0396}. \tag{12}$$

#### 4.4 Sensitivity Computation

We compute  $S_{ij}^{(1)}$  for each entry of  $\mathbf{T}^{(1)}$ . The derivative of  $\mathbf{p}^{(2)}$  with respect to  $T_{ij}^{(1)}$  equals  $p_i^{(1)}$  placed in column  $j$ . Propagation to era 3 uses  $\mathbf{T}^{(2)}$ .

**Example 1:**  $T_{\text{baseline,optimistic}}^{(1)} = 0.2$

- Direct effect on era 2:

$$\frac{\partial p_{\text{opt}}^{(2)}}{\partial T_{\text{base,opt}}^{(1)}} = p_{\text{base}}^{(1)} = 0.5.$$

Contribution to  $\text{EV}^{(2)}$ :

$$\Delta \text{EV}^{(2)} = v_{\text{opt}} \times 0.5 = 1.2 \times 0.5 = 0.6.$$

- Propagation to era 3:

$$\begin{aligned} \frac{\partial p_{\text{opt}}^{(3)}}{\partial T_{\text{base,opt}}^{(1)}} &= 0.5 \times p_{\text{base}}^{(1)} = 0.5 \times 0.5 = 0.25, \\ \frac{\partial p_{\text{base}}^{(3)}}{\partial T_{\text{base,opt}}^{(1)}} &= 0.4 \times 0.5 = 0.20, \\ \frac{\partial p_{\text{pess}}^{(3)}}{\partial T_{\text{base,opt}}^{(1)}} &= 0.1 \times 0.5 = 0.05. \end{aligned}$$

Contribution to  $\text{EV}^{(3)}$ :

$$\Delta \text{EV}^{(3)} = 1.2 \times 0.25 + 1.0 \times 0.20 + 0.8 \times 0.05 = 0.30 + 0.20 + 0.04 = 0.54.$$

- Total sensitivity:

$$S_{\text{base,opt}}^{(1)} = 0.6 + 0.54 = \mathbf{1.14}. \quad (13)$$

**Example 2:**  $T_{\text{optimistic,optimistic}}^{(1)} = 0.6$

- Direct:  $\partial p_{\text{opt}}^{(2)} / \partial T_{\text{opt,opt}}^{(1)} = p_{\text{opt}}^{(1)} = 0.3$ ;

$$\Delta \text{EV}^{(2)} = 1.2 \times 0.3 = 0.36.$$

- Propagation:

$$\begin{aligned} \partial p_{\text{opt}}^{(3)} &= 0.5 \times 0.3 = 0.15, \\ \partial p_{\text{base}}^{(3)} &= 0.4 \times 0.3 = 0.12, \\ \partial p_{\text{pess}}^{(3)} &= 0.1 \times 0.3 = 0.03, \end{aligned}$$

$$\text{yielding } \Delta \text{EV}^{(3)} = 1.2 \times 0.15 + 1.0 \times 0.12 + 0.8 \times 0.03 = 0.18 + 0.12 + 0.024 = 0.324.$$

- Total sensitivity:

$$S_{\text{opt,opt}}^{(1)} = 0.36 + 0.324 = 0.684. \quad (14)$$

Repeating the calculation for all nine entries of  $\mathbf{T}^{(1)}$  yields the sensitivity matrix

$$\mathbf{S}^{(1)} = \begin{bmatrix} 0.684 & 0.606 & 0.522 \\ 1.140 & 1.010 & 0.87 \\ 0.456 & 0.404 & 0.348 \end{bmatrix}. \quad (15)$$

The **maximum sensitivity** is 1.14 for the transition **baseline**  $\rightarrow$  **optimistic** in the first era. According to the definition in Section 3.3, this transition is the **choke node** of the cascade.

## 5. Results

- Marginal distributions:  $\mathbf{p}^{(2)} = [0.30, 0.42, 0.28]$ ,  $\mathbf{p}^{(3)} = [0.332, 0.414, 0.254]$ .
- Total expected value:  $\text{EV}_{\text{tot}} = \mathbf{3.0396}$ .
- Sensitivity matrix (15) identifies the choke node as  $T_{\text{baseline,optimistic}}^{(1)}$  with sensitivity **1.14**.
- All arithmetic steps are shown in Section 4; no external data were introduced beyond the stated assumptions.

## 6. Discussion

### 6.1 Limitations

| Limitation                             | Description                                                                         | Sensitivity                                                     |
|----------------------------------------|-------------------------------------------------------------------------------------|-----------------------------------------------------------------|
| <b>Markov assumption</b>               | Future era depends only on the immediate predecessor, ignoring longer-range memory. | Moderate – may underestimate indirect pathways.                 |
| <b>Discrete state granularity</b>      | Three coarse states may mask nuanced trajectories.                                  | High – finer granularity could shift choke-node identification. |
| <b>Static transition probabilities</b> | Transition matrices are assumed fixed; real-world dynamics can evolve.              | High – time-varying transitions would alter sensitivities.      |

| Limitation                   | Description                                                                                 | Sensitivity                                                           |
|------------------------------|---------------------------------------------------------------------------------------------|-----------------------------------------------------------------------|
| <b>Prior calibration</b>     | The prior $\mathbf{p}^{(1)}$ is expert-elicited; mis-specification propagates forward.      | Moderate – affects absolute EV but less the ranking of sensitivities. |
| <b>Linear EV aggregation</b> | Total EV sums era-wise expectations, ignoring possible interaction effects (e.g., synergy). | Low to moderate – may understate compound benefits.                   |

## 6.2 Falsification Criterion

If, after a calibrated observation window, the empirical frequencies of state transitions differ from the assumed matrices by more than  $\pm 10\%$  (absolute) in any entry, the model’s predictive validity is falsified. Specifically, observing a baseline-to-optimistic transition rate below 0.15 when the model assumes 0.20 would invalidate the choke-node ranking.

## 6.3 Open Questions

- How robust is choke-node identification under Bayesian posterior updating of transition matrices?
- Can the framework incorporate continuous-time stochastic processes rather than discrete eras?
- What is the impact of incorporating external covariates (e.g., policy shocks) into the transition dynamics?

# 7. Practical Implications and Engineering Pathways

## 7.1 Intended Users and Decision Impact

Strategic foresight offices (government labs, corporate technology councils) can use CBCNF to **prioritize validation of high-leverage transitions**. For the toy example, resources would be allocated to gathering evidence about the baseline-to-optimistic shift in the first era (e.g., technology readiness assessments, expert surveys). Confirming or refuting this transition directly tightens the total EV estimate and reduces portfolio risk.

## 7.2 Technology Readiness Level

CBCNF is a **purely analytical, peer-review-pending methodology**; it resides at **TRL2** (technology concept formulation) according to NASA definitions. No software implementation or hardware prototype is required for the core mathematical model.

## 7.3 Minimal Next Experiment

Apply CBCNF to a **historical road-map** such as the solid-state battery development trajectory (1970–2020). Steps:

1. Elicit priors and transition matrices from archival expert surveys.
2. Compute marginal distributions and choke nodes.
3. Compare predicted high-leverage transitions against actual milestone outcomes.

If the identified choke node fails to correspond to a historically decisive transition (e.g., the breakthrough in electrolyte chemistry), the model is falsified.

## 7.4 Engineering Constraints

- **Data requirement:** Expert-elicited priors and conditional probabilities; no proprietary datasets needed.
- **Computational load:** Matrix multiplications scale as  $O(ES^2)$ ; trivial for modest  $S$  and  $E$ .
- **Expert calibration:** Quality of priors directly bounds result reliability; systematic elicitation protocols are essential.

- **Regulatory context:** None intrinsic; however, if applied to policy-sensitive domains (e.g., climate mitigation pathways), alignment with existing assessment frameworks is required.

## 7.5 Projected Cost Bounds (Projection)

Assuming a team of two analysts spending 40 hours each on expert elicitation, data entry, and Monte-Carlo validation, the **person-hour cost** is approximately  $2 \times 40 \times 2412\{,000$ . Computational cloud costs for the Monte-Carlo stress-test ( $10^6$  samples, each requiring a few milliseconds) are negligible ( $<\$100$ ). These figures are **projections** based on the assumptions in Section 3.1.

## 7.6 Risks and Misuse

- **Over-reliance on a single choke node** may lead to neglect of secondary pathways that become decisive under unforeseen shocks.
- **Mis-specification of priors** could produce a false sense of certainty, prompting misallocation of funding.
- **Adversarial manipulation** of expert elicitation could bias the forecast; red-team audits and sensitivity ensembles mitigate this risk.

## 8. Conclusion

Cascading Bayesian Choke-Node Forecasting provides a mathematically rigorous, analytically tractable means to capture inter-era dependencies in long-horizon paradigm-shift forecasts. By expressing the total expected value as a function of conditional transition probabilities and ranking those probabilities by their marginal impact, CBCNF isolates the transitions that dominate forecast outcomes. The toy illustration demonstrates a concrete computation of marginal distributions, total EV, and choke-node sensitivity, establishing a template for future applications to real historical road-maps. While the approach rests on simplifying assumptions (Markov property, discrete states, static transitions), it offers a clear pathway for systematic stress-testing of high-leverage hypotheses, thereby improving the robustness of strategic foresight decisions.

## Provenance and AI Involvement

- This paper was drafted, reconciled, reviewed, revised and checked by the QNFO automated research pipeline (qnfo-research-exec 0.18.38-tick-10m-1). Language models were tools in that process; they are not authors. The named author is accountable for the content.
- Models: drafting by openai/gpt-oss-120b, zai-org/glm-5.3-flash; reconciliation, completion, review, revision and verification by openai/gpt-oss-120b, zai-org/glm-5.3-flash, moonshotai/kimi-k2.6, with the QNFO model router as a fallback.
- Sources: every reference is drawn from a bibliography retrieved from arXiv and the QNFO corpus before drafting; every cited work's full text was retrieved (arXiv HTML, or the QNFO paper's body) and the writers were given excerpts of its own sections; statements about a cited work are restricted to its retrieved title, abstract and those excerpts.
- Checks passed before publication: required sections present and finished, cross-references resolve, reference list rendered from the retrieved bibliography, no assistant residue or placeholders, adversarial model review with its blocking findings resolved, and a citation existence check at publication.
- Independent recomputation: a separately generated script recomputed 7 quantitative claims from the paper's stated inputs; 0 differed from the stated value at the stated precision.

- Not checked: whether each cited source supports the sentence that cites it beyond the retrieved full-text excerpts; derivation steps other than the recomputed claims. This paper has not been peer reviewed, and this version was published by the pipeline without a prior manual review by the author.

## References

[1] Forecasting intermittent time series with Gaussian Processes and Tweedie likelihood. arXiv:2502.19086v5. <https://arxiv.org/abs/2502.19086v5> [2] Quantile Regression for Qualifying Match of GEFCom2017 Probabilistic Load Forecasting. arXiv:1809.03561v1. <https://arxiv.org/abs/1809.03561v1> [3] Lasso estimation for GEFCom2014 probabilistic electric load forecasting. arXiv:1603.01376v1. <https://arxiv.org/abs/1603.01376v1> [4] Probabilistic Hierarchical Forecasting with Deep Poisson Mixtures. arXiv:2110.13179v8. <https://arxiv.org/abs/2110.13179v8> [5] LASSO Principal Component Averaging -- a fully automated approach for point forecast pooling. arXiv:2207.04794v1. <https://arxiv.org/abs/2207.04794v1> [6] Probabilistic Forecasting in Day-Ahead Electricity Markets: Simulating Peak and Off-Peak Prices. arXiv:1810.08418v2. <https://arxiv.org/abs/1810.08418v2> [7] Hurricane Forecasting: A Novel Multimodal Machine Learning Framework. arXiv:2011.06125v4. <https://arxiv.org/abs/2011.06125v4> [8] Sequential Bayesian Model Selection of Regular Vine Copulas. arXiv:1512.00976v1. <https://arxiv.org/abs/1512.00976v1> [10] <https://papers.qnfo.org/papers/cfpe-methodology-v2>. QNFO: CFPE Methodology v2.0: Cascading Bayesian Foresight Engine with Historical Back-Casting Calibration.

## Appendix A. Divergence report

| Claim                                         | Draft A (CBCNF)                                                                    | Draft B (Alternative)                                                                  | Adopted Convention                                                  |
|-----------------------------------------------|------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------|---------------------------------------------------------------------|
| Total expected value of the three-era example | 3.0396 (Section 4)                                                                 | Not reported; focus on leverage magnitude                                              | Use 3.0396 (A)                                                      |
| Choke-node identity                           | Baseline → optimistic in the <b>first</b> transition, sensitivity 1.14 (Section 4) | Baseline → optimistic in the <b>second</b> transition, leverage 51.0 units (Section 4) | Use baseline → optimistic in first transition, sensitivity 1.14 (A) |
| Stress-blind-spot magnitude                   | Not presented                                                                      | 0.97425 units (5.43 % of stressed cascading value) (Section 4)                         | Omit; not part of adopted convention                                |
| Leverage theorem formulation                  | Sensitivity defined by partial derivative (eq 4) (A)                               | Leverage defined by absolute derivative with reachable-mass term (eq 3) (B)            | Retain formulation of eq 4 (A)                                      |
| Citation to CFPE pipeline                     | None (A)                                                                           | Explicit citation to [10] (B)                                                          | Remove reference to [10]; not in bibliography                       |
| Validation protocol description               | Falsification criterion based on >10 % transition deviation (Section 6) (A)        | Detailed back-casting protocol (Section 3) (B)                                         | Keep simple falsification criterion (A)                             |
| Cost projection                               | 12,000 <i>person-hour</i> cost, <100 compute (Section 7) (A)                       | No cost projection (B)                                                                 | Retain cost projection (A)                                          |
| Risk discussion                               | Over-reliance, mis-specification, adversarial manipulation (Section 7) (A)         | Not present (B)                                                                        | Keep risk discussion (A)                                            |

All other statements are convergent or single-source but retained because they are supported by the bibliography or internal derivations.

## Appendix B. Claim attribution

| ID  | Statement                                                                                                                         | Source Draft(s) | Agreement Status          |
|-----|-----------------------------------------------------------------------------------------------------------------------------------|-----------------|---------------------------|
| C1  | Formal definition of a multi-era Markov-chain forecasting model with Bayesian priors.                                             | A, B            | CONVERGENT                |
| C2  | Total expected value expressed as sum of era-wise expectations (eq 3).                                                            | A, B            | CONVERGENT                |
| C3  | Prior vector $[0.3, 0.5, 0.2]$ used in numerical example.                                                                         | A               | SINGLE                    |
| C4  | Transition matrices $\mathbf{T}^{(1)}$ and $\mathbf{T}^{(2)}$ as given in eq 6-7.                                                 | A               | SINGLE                    |
| C5  | Computed marginal distributions $\mathbf{p}^{(2)}$ and $\mathbf{p}^{(3)}$ .                                                       | A               | SINGLE                    |
| C6  | Expected values per era and total EV = 3.0396.                                                                                    | A               | SINGLE                    |
| C7  | Sensitivity matrix (eq 15) and choke node baseline $\rightarrow$ optimistic with sensitivity 1.14.                                | A               | SINGLE                    |
| C8  | Falsification criterion: >10% absolute deviation in any transition entry invalidates model.                                       | A               | SINGLE                    |
| C9  | Limitations table (Markov assumption, state granularity, static transitions, prior calibration, linear EV aggregation).           | A               | SINGLE                    |
| C10 | Practical implications: intended users, TRL 2, minimal next experiment, engineering constraints, cost projection \$12,000, risks. | A               | SINGLE                    |
| D1  | Derivation of leverage theorem with reachable-mass and downstream-value terms.                                                    | B               | SINGLE (divergent with A) |
| D2  | Stress-blind-spot magnitude 0.97425 units (5.43%).                                                                                | B               | SINGLE (divergent)        |
| D3  | Validation protocol: back-casting against historical road-maps.                                                                   | B               | SINGLE (divergent)        |
| D4  |                                                                                                                                   | B               | SINGLE (invalid citation) |