Proc. of the European Safety and Reliability Conference (ESREL 2026)
Edited by José C. Matos, Paulo B. Lourenço, Michael Beer, Daniel Oliveira, Edoardo Patelli, Hélder S. Sousa, Rui A. Silva and Monica Santamaria

doi: 10.3850/ESREL2026061419_esrel26-p27645-cd

A Dynamic Safety Assessment Method for Cascading Effects in Complex Systems Based on Uncertainty Quantification

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The safety of complex systems, such as in aerospace, is severely threatened by cascading effects, the evolution of which is fraught with dynamics and uncertainty. Traditional safety assessment methods are often static or deterministic, struggling to characterize the time-varying nature of failure propagation and the combined impact of epistemic and aleatory uncertainties. To address this, this paper proposes a novel method for the dynamic safety assessment of cascading effects, capable of quantifying multi-source uncertainty. This paper proposes a dynamic assessment framework for Cascading Effects Analysis (CEA) that integrates Dynamic Bayesian Network (DBN) and Dempster-Shafer Theory (DST). First, a system functional dependency model is constructed to identify critical components and potential failure propagation paths. Second, DBN is employed to model the temporal evolution of the cascading effect. Innovatively, DST is introduced into the DBN's parameter learning and inference stages. Belief functions are used instead of traditional probability distributions to represent epistemic uncertainty arising from expert knowledge, small datasets, and model inaccuracies. Dempster's rule of combination is applied to handle conflicting or incomplete evidence from various sources, enabling a more robust estimation of component failure probabilities. Finally, a dynamic inference algorithm updates the belief about the system's safety state, achieving a dynamic safety assessment of cascading effects. The proposed method is validated through an application to an flight control system, simulating the propagation of cascading effects following an initial soft sensor fault. The results demonstrate that, compared to traditional probabilistic methods like standard DBN, our approach better distinguishes between "uncertainty" and "ignorance." When fault information is ambiguous or conflicting, it provides more conservative and informative assessment intervals, avoiding overconfident estimations of failure probabilities. The method identifies high-risk propagation paths earlier, providing robust theoretical and technical support for dynamic risk management and fault diagnosis in high-safety requirement systems like those in aerospace.

Keywords: Cascading Effects, Complex Systems, Dynamic Safety Assessment, Uncertainty Quantification, Dynamic Bayesian Network, Dempster-Shafer Theory.

1. Introduction

Modern aerospace systems (such as flight control systems and avionics systems) are typical complex technical systems with high integration and safety-critical requirements. These systems are composed of a vast number of physical components, software modules, and sensor networks coupled through complex functional dependencies. Although high-reliability measures such as redundancy and backup are adopted in system design, minor faults in a single component (especially concealed soft sensor faults) or external perturbations can still propagate and amplify within the system through the functional coupling network. This triggers a chain reaction known as "Cascading Effects"(Wu et al., 2020; Dong et al., 2024; Chen et al., 2025; Cumelles et al., 2021). Such effects can lead to the degradation or even loss of flight control functions, potentially resulting in catastrophic aviation accidents(Bauranov and Rakas, 2024; Ayra et al., 2019). With the continuous increase in the electrification and intelligence of aircraft, the complexity of internal system interactions has grown exponentially. Consequently, accurately assessing and predicting the evolutionary paths and risks of cascading effects has become a critical challenge for ensuring aviation safety and passing airworthiness certification(Wang et al., 2019).

However, dynamic safety assessment targeting cascading effects in complex aerospace systems faces two core challenges:

First, the Dynamics of Fault Evolution. Aircraft operations possess distinct temporal characteristics, and the fault propagation process often evolves dynamically with changes in flight phases and the passage of time. Traditional aviation safety assessment methods, such as Fault Tree Analysis (FTA) and Event Tree Analysis (ETA), are mostly based on static models. They assume that the system structure and fault logic remain unchanged during the assessment period, making it difficult to capture the time-dependency of fault propagation and the time-varying characteristics of system states. Although dynamic methods like Markov chains are used for reliability analysis, they are prone to the "state space explosion" problem when dealing with large-scale aviation networks containing numerous nodes. While Dynamic Bayesian Network (DBN) provide a powerful framework for temporal probabilistic reasoning, applying them to complex aviation cascading fault analysis still requires resolving the balance between network construction and inference efficiency(Chen and Qian, 2024; Lee and Choi, 2020; Li et al., 2017; Park et al., 2024).

Second, Hybrid Uncertainty. The fault evolution of aerospace systems is influenced by multiple uncertainty factors. On one hand, the physical failure of electronic components possesses inherent randomness, known as aleatory uncertainty. On the other hand, since aviation accidents are rare events, fault data often exhibits "small sample" or even "zero sample" characteristics. Coupled with the ambiguity of soft sensor faults (such as drift and bias) and the limitations of expert cognition, the system contains a significant amount of epistemic uncertainty(Zhang and Mahadevan, 2021; Jia et al., 2021). Traditional probabilistic methods are mature in handling aleatory uncertainty, but when facing epistemic uncertainty, forcing the assignment of precise probability values (such as point estimates) often leads to "overconfident" assessment results, masking the true risk level. Dempster-Shafer Theory (DST) introduces "Belief Functions" and "Plausibility Functions," which can explicitly distinguish between "uncertainty" and "ignorance," providing a more flexible theoretical framework for handling ambiguous and incomplete information in the aviation domain(Lu et al., 2017; Liu et al., 2024; Tang et al., 2023).

Although existing studies have made contributions to dynamic reliability modeling or uncertainty quantification respectively, organically combining the two to construct a unified assessment framework—one that can characterize the dynamic propagation of aviation faults while effectively quantifying hybrid uncertainty—remains an open problem urgently needing solution. In existing literature, few models can conduct an in-depth analysis of the evolutionary mechanism of cascading effects under soft sensor faults for high-safety-level objects like flight control systems.

To address the aforementioned challenges, this paper proposes a dynamic safety assessment method for cascading effects in complex aerospace systems based on Dynamic Bayesian Network (DBN) and Dempster-Shafer Theory (DST), termed DBN-DST-CEA. The core idea of this method is to utilize the temporal reasoning capability of DBN to characterize the dynamic propagation process of faults within the functional dependency network, while deeply integrating Evidence Theory during the parameter learning and inference stages to effectively handle hybrid uncertainty stemming from data scarcity and expert judgment ambiguity.

The main contributions of this paper are threefold: First, we construct a hybrid assessment framework integrating DBN and Dempster-Shafer Theory (DST) by embedding the belief structure into the "Conditional Probability Table" (CPT) to define a "Conditional Belief Table" (CBT). Second, we propose a dynamic assessment workflow covering the process from functional dependency modeling to risk prediction, resolving limitations in characterizing time-varying risks. Third, the method is validated on an aviation flight control system, demonstrating robust assessment capabilities under information ambiguity and identifying high-risk paths earlier than traditional methods.

The remainder of this paper is organized as follows: Section 2 details the proposed DBN-DST-CEA model. Section 3 validates the method using an aviation flight control system. Section 4 concludes the paper.

2. Proposed Model and Method

2.1. *Framework Overview*

The DBN-DST-CEA framework (Figure 1) consists of four layers. The "Physical/Functional Network Layer" abstracts the system topology and dependencies. The "Model Mapping and Construction Layer" converts this topology into DBN nodes and edges. The "Evidence-based Parameter Learning Layer" introduces Dempster-Shafer Theory to parameterize the DBN, using CBTs to replace traditional CPTs. Finally, the "Dynamic Reasoning and Assessment Layer" performs real-time monitoring and risk prediction using dynamic inference based on evidence combination.

2.2. *Mathematical Formulation*

To describe the cascading effect evolution process containing hybrid uncertainty, we formalize the proposed DBN-DST-CEA framework as Eq. (1):

$$\boldsymbol{M} = \langle \boldsymbol{G}, \boldsymbol{S}, \boldsymbol{T}, Pa, \Theta, \boldsymbol{m}_0, \boldsymbol{m}_{\rightarrow}, \oplus \rangle \quad (1)$$

Here, $\boldsymbol{G}$ is the Functional Dependency Graph; $\boldsymbol{S}$ is the set of state variables; $\boldsymbol{T}$ is the discretized time sequence; Pa is the parent node mapping function determining network structure; Θ is the Frame of Discernment (FOD) (e.g., $\{\text{Normal}, \text{Failed}\}$); $\boldsymbol{m}_0$ represents Initial Basic Belief Assignments (BBA); $\boldsymbol{m}_{\rightarrow}$ denotes Conditional Belief Tables (CBTs); and $\oplus$ represents Dempster's Rule of Combination for evidence fusion. This model replaces probability distributions with belief functions to handle epistemic uncertainty.

2.3. *Construction and Parameterization of DBN*

2.3.1. *Structure Learning*

The network structure of the DBN determines the path of state inference, and its construction aims to accurately reflect the spatiotemporal causal logic of fault propagation in cascading effects. For any node V_i in the network, The state S_i^{t+1} is driven by *Temporal Autocorrelation* (inertia from previous state S_i^t) and *Spatial Dependency* (influence from parent nodes $Pa(V_i)$). Based on these, the parent node set is defined as Eq. (2):

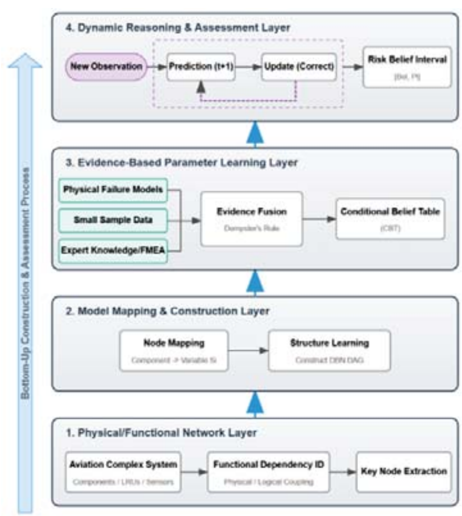

Fig. 1. Overall Implementation Framework of DBN-DST-CEA.

$$Pa(S_i^{t+1}) = \left\{S_i^t\right\} \cup \left\{S_j^t \,\middle|\, V_j \in \mathrm{Adj}(V_i) \text{ in } \boldsymbol{G}\right\} \tag{2}$$

where $\mathrm{Adj}(V_i)$ represents the set of adjacent nodes pointing to V_i in the system functional dependency graph G. This structure ensures that the model can simultaneously capture the temporal dynamics of fault evolution and network topological dependencies.

2.3.2. *Evidence-based Parameter Learning*

To address data scarcity, we replace CPTs with Conditional Belief Tables (CBTs) constructed by fusing three evidence sources:

- Physical Model Evidence (m_{phy}): Based on the "Functional Safety Margin" η_i (Eq. (3)), we use Sigmoid functions to map physical stress to BBA (Eqs. (4)-(6)).

$$\eta_i = \frac{C_i - L_i(Pa_k)}{C_i} \tag{3}$$

$$m_{\text{phy}}(\{\text{Failed}\}) = f_{\text{fail}}(\eta_i) = \frac{1}{1+e^{a\cdot\eta_i}}, \quad (\text{when } \eta_i < 0) \tag{4}$$

$$m_{\text{phy}}(\{\text{Normal}\}) = f_{\text{norm}}(\eta_i) = 1 - \frac{1}{1+e^{b\cdot\eta_i}} \quad (\text{when } \eta_i < 0) \tag{5}$$

$$m_{\text{phy}}(\Theta_i) = 1 - m_{\text{phy}}(\{\text{Failed}\}) - m_{\text{phy}}(\{\text{Normal}\}) \tag{6}$$

- Historical Data Evidence (m_{data}): We introduce a smoothing factor K to handle small samples (Eqs. (7)-(9)).

$$m_{\text{data}}(\text{Failed}) = \frac{\alpha}{n+K} \tag{7}$$

$$m_{\text{data}}(\text{Normal}) = \frac{\beta}{n+K} \tag{8}$$

$$m_{\text{data}}(\Theta_i) = \frac{K + (n-\alpha-\beta)}{n+K} \tag{9}$$

- Expert Knowledge (m_{exp}): Experts provide fuzzy belief assessments (Eqs. (10)-(12)) when data is unavailable.

$$m_{\text{exp}}(\{\text{Failed}\}) = 0.1 \tag{10}$$

$$m_{\text{exp}}(\{\text{Normal}\}) = 0.6 \tag{11}$$

$$m_{\text{exp}}(\Theta_i) = 0.3 \tag{12}$$

Finally, these sources are fused using Dempster's rule (Eq. (13)) to generate the CBT (Eq. (14)). For any two independent BBAs m_1 and m_2, their combination rule is defined as:

$$m_{1\oplus 2}(A) = \frac{\sum_{B\cap C=A} m_1(B)\, m_2(C)}{1-K_{\text{cf}}} \quad (\forall A \subseteq \Theta_i,\ A \neq \emptyset) \tag{13}$$

where $K_{\text{cf}} = \sum_{B\cap C=\emptyset} m_1(B)\, m_2(C)$ is the Conflict Coefficient, used to measure the degree of inconsistency between evidence.

For each state combination Pa_k, the above three types of evidence $(m_{\text{phy}}, m_{\text{data}}, m_{\text{exp}})$ are orthogonally fused using Dempster's rule of combination to generate the final CBT parameters:

$$m\left(S_i^{t+1} \,\middle|\, Pa_k\right) \tag{14}$$

2.4. *Evidence-Based Dynamic Inference Process*

2.4.1. *Initialization*

At $t = 0$, node states are initialized based on prior knowledge. For a detected abnormal component V_k, we set $m(S_k^0 = \text{Failed}) = 1$. For unobserved nodes S_j, to reflect ignorance, we assign the Vacuous BBA (Eq. (15)), avoiding unjustified assumptions of normality.

$$m\left(S_j^0 = \Theta_j\right) = 1 \tag{15}$$

2.4.2. *Time Update / Prediction*

Inference at $t+1$ relies on the posterior at t. First, we calculate the Joint BBA of the parent node set using Dempster's rule (Eq. (16)), assuming local conditional independence:

$$m\left(Pa\left(S_i^{t+1}\right)\right) = \bigoplus_{S_j^t \in Pa(S_i^{t+1})} m(S_j^t) \tag{16}$$

Next, using the generalized Total Belief Theorem, we combine the Joint BBA with the CBT to perform Evidential Forward Propagation. The prior BBA $m^{-}(S_i^{t+1})$ for any subset $A \subseteq \Theta_i$ is calculated via Eq. (17):

$$m^{-}\left(S_i^{t+1} = A\right) = \sum_{Pa_k \in \Omega_{Pa}} m\left(Pa(S_i^{t+1}) = Pa_k\right) \cdot m\left(S_i^{t+1} = A \,\middle|\, Pa_k\right) \quad (17)$$

2.4.3. *Measurement Update / Correction*

When new evidence m_{obs} (e.g., sensor data) becomes available, it is fused with the prior belief using Dempster's rule (Eq. (18)) to obtain the posterior BBA:

$$m\left(S_i^{t+1}\right) = m^{-}\left(S_i^{t+1}\right) \oplus m_{\text{obs}}\left(S_i^{t+1}\right) \quad (18)$$

This mechanism robustly handles varying observation qualities: deterministic faults imply $m_{\text{obs}}(\{\text{Failed}\}) = 1$; missing data implies complete ignorance $m_{\text{obs}}(\Theta_i) = 1$ (relying solely on prediction); and ambiguous soft faults are expressed as partial beliefs (e.g., $m_{\text{obs}}(\{\text{Failed}\}) = 0.6$), avoiding false alarms from binary logic.

2.4.4. *Risk Assessment*

By iterating the update and correction steps, the cascading risk is assessed via a Belief Interval $R(t)$ (Eq. (19)):

$$R(t) = [\text{Bel(Risk)}, \text{Pl(Risk)}] \quad (19)$$

Here, Bel represents the confirmed risk (lower bound), and Pl is the theoretical upper bound. The interval width $\text{Pl} - \text{Bel}$ explicitly quantifies epistemic uncertainty, providing a richer basis for decision-making (e.g., distinguishing high uncertainty from low risk) than single probability values.

3. Case Study: Cascading Failure Assessment in Aviation Flight Control Systems

3.1. *System Description and Modeling*

To validate the effectiveness of the proposed DBN-DST dynamic assessment framework, a typical redundant Fly-By-Wire (FBW) system in modern civil aircraft is selected as the research object. Although the architectural design of this system, which belongs to a high Safety Integrity Level (SIL), includes physical redundancy, the tight functional coupling between components means that faults (especially concealed faults) can still propagate through data flows in a cascading manner. The simplified system functional dependency model is shown in Figure 2, mainly containing the following critical components (nodes):

- Inertial Reference Unit (IRU1, IRU2): As sensor nodes, responsible for collecting and outputting the aircraft's attitude, angular rate, and acceleration information.
- Flight Control Computer (FCC1, FCC2): As core processing nodes, running flight control laws, processing sensor data, and calculating control surface deflection commands. They contain internal Fault Detection and Isolation (FDI) logic.
- Actuator Control Electronics (ACE): As command synthesis nodes, receiving FCC commands and driving power amplifiers.
- Aileron Actuator: As the execution end, driving the control surface deflection.

We model this system as a Dynamic Bayesian Network (DBN). Nodes in the network represent the health states $S_i^t \in \{\text{Normal}, \text{Failed}\}$ of components at different times. Edges represent information flow and functional control logic between components. Specifically, the ACE node is modeled as a multi-parent structure, where its state depends on the combined state of $\{S_{\text{FCC1}}, S_{\text{FCC2}}\}$ and the validity of the voting logic.

3.2. *Scenario Setup and Parameterization*

3.2.1. *Initial Event and Observation*

To simulate a realistic flight environment, the initial time ($t = 0$) is set with the aircraft in the cruise phase.

Assume sensor IRU1 develops an intermittent Soft Fault, manifesting as a small zero-point drift in data output. This drift amount is on the edge of the system fault detection threshold.

The system's monitoring module (Monitor) captures abnormal fluctuations but cannot issue a definitive isolation command. This "plausible but uncertain" observation state generates a Basic Belief Assignment (BBA) containing high epis-

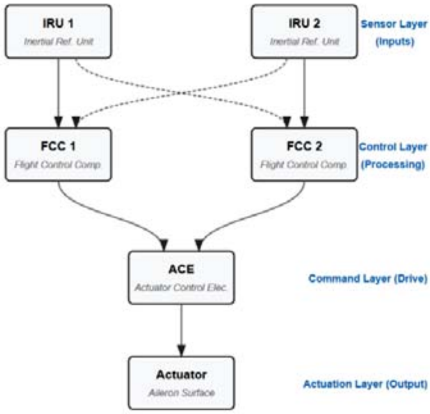

Fig. 2. Simplified System Functional Dependency Model.

temic uncertainty: $m_{\text{obs}}\left(S^0_{\text{IRU1}}\right) = \{\text{Failed} : 0.4, \text{Normal} : 0.3, \Theta : 0.3\}$.

Here, $\Theta = \{\text{Normal}, \text{Failed}\}$, and the mass $m_{\text{obs}}(\Theta) = 0.3$ explicitly quantifies the degree to which the current monitoring means are "unable to determine" the fault state.

At the same time, assume the redundant channel IRU2 and FCC2 are in a healthy working state, i.e., $m\left(S_{\text{IRU2}} = \text{Normal}\right) = 1$.

3.2.2. *Evidence-Based Parameter Construction*

According to the parameter learning method proposed in Section 2.3.2, Conditional Belief Tables (CBT) are constructed for critical nodes in the network.

(i) FCC1 CBT: Expert Knowledge Dominant

FCC1 is responsible for solving data from IRU1. Facing the soft fault input from IRU1, the internal FDI (Fault Detection and Isolation) logic of FCC1 faces a challenge. Due to the lack of historical statistical data for such specific soft faults, we introduce the empirical judgment of senior aviation system engineers.

The expert assessment states: "When there is a critical drift in the input signal, FCC1 has a high probability of passing the erroneous data down, but there is also a possibility of triggering the protection mechanism, and judgment is extremely difficult."

This fuzzy language is converted into BBA: $m\left(S^{t+1}_{\text{FCC1}} \,\middle|\, S_{\text{IRU1}} = \text{Failed}\right) = \{\text{Failed} : 0.60, \text{Normal} : 0.10, \Theta : 0.30\}$.

Here, $\Theta = \{\text{Normal}, \text{Failed}\}$, and the mass $m(\Theta) = 0.30$ explicitly expresses the limitation of the expert's cognition regarding system behavior under this complex condition.

(ii) ACE CBT: Small Sample Data Dominant

ACE (Actuator Control Electronics) is a critical node embodying the system's redundant design. It simultaneously receives commands from FCC1 (potentially failed) and FCC2 (normal) and executes "signal selection and voting" logic.

To obtain reliability parameters for ACE under the "One-Fail-One-Nominal" condition, we cite test data from Hardware-in-the-Loop (HIL) simulation.

In 50 simulation tests ($n = 50$) for this condition:

(a) ACE successfully identified and masked the erroneous command from FCC1 (maintaining normal output) 46 times ($\beta = 46$);
(b) ACE failed to mask the error (leading to failure) 1 time ($\alpha = 1$);
(c) In another 3 tests, signal jitter led to inconclusive results (data missing/invalid).

Considering the limited sample size, using the frequency method directly is prone to bias. Using the K-factor smoothing method proposed in this paper (setting $K = 2$), the CBT for ACE under the parent node state $\{\text{FCC1}_{\text{Fail}}, \text{FCC2}_{\text{Nom}}\}$ is constructed:

$$m_{\text{data}}(\text{Failed}) = \frac{1}{50+2} \approx 0.02,$$
$$m_{\text{data}}(\text{Normal}) = \frac{46}{50+2} \approx 0.88,$$
$$m_{\text{data}}(\Theta) = \frac{2+(50-46-1)}{50+2} \approx 0.10.$$

Finally, the fused CBT entry is: $m\left(S^{t+1}_{\text{ACE}} \,\middle|\, \text{FCC1}_{\text{Fail}}, \text{FCC2}_{\text{Nom}}\right) = \{\text{Failed} : 0.02, \text{Normal} : 0.88, \Theta : 0.10\}$.

Analysis: These parameters indicate that despite redundancy protection (Normal belief 0.88), due to limited test samples and complexity, ACE still possesses 10% epistemic uncertainty. This 10% uncertainty is precisely the "hidden risk" ignored by traditional probabilistic models (which usually simply assume failure probability is $1/50 = 0.02$).

3.3. *Results Analysis and Discussion*

We performed a dynamic inference of the system's safety state over four time steps ($t = 1$ to $t = 4$). The results, benchmarked against a standard DBN, are summarized in Table 1.

At $t = 1$, the IRU1 soft fault propagates. While Standard DBN gives a specific failure probability (0.28), our method yields a belief interval $[0.15, 0.45]$, reflecting the high uncertainty of the sensor data. At $t = 2$, a conflict arises between the faulty FCC1 and healthy FCC2. Standard DBN masks this conflict ($P(\mathrm{ACE_{Fail}}) \approx 0.56\%$), suggesting absolute safety. In contrast, DBN-DST-CEA reveals a "latent risk" with a plausibility of 12% ($[0.005, 0.12]$), warning against high-risk maneuvers. At $t = 3$, explicit failure evidence reduces the uncertainty interval width from 0.115 to 0.03, demonstrating the method's ability to converge dynamically. Finally, at $t = 4$, system reconfiguration restores the safety baseline.

The comparison highlights that DBN-DST-CEA effectively distinguishes between "low risk" and "high uncertainty" (ignorance), avoiding the overconfidence typical of probabilistic methods in small-sample or conflicting scenarios.

4. Conclusion and Future Work

This paper proposes the DBN-DST-CEA framework for dynamic safety assessment in aerospace systems. By replacing CPTs with Conditional Belief Tables and employing evidence fusion, the method addresses the limitations of traditional DBNs in handling hybrid uncertainty and small sample data. Case validation confirms that the method provides more informative belief intervals, effectively identifying latent risks caused by conflicting information that probabilistic methods might overlook.

Future work will focus on: (1) optimizing computational efficiency for large-scale networks; (2) integrating Transfer Learning to automate CBT construction; and (3) developing dynamic decision support strategies based on belief interval boundaries.

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Table 1. Comparison of Risk Assessment Data During Cascading Fault Evolution.

Time Step	Key Event	Standard DBN (Failubre Prob P)	DBN-DST-CEA (Risk Interval)	Decision Implication
$t = 1$	Fault Inception	$P(\text{FCC1}) \approx 0.28$	FCC1: $[0.15, 0.45]$	Warning Phase: Wide interval indicates "undecided" state; necessitates monitoring.
$t = 2$	Redundancy Intervention	$P(\text{ACE}) \approx 0.0056$	ACE: $[0.005, 0.12]$	Critical Divergence: DST warns of 12% latent risk upper bound masked by DBN.
$t = 3$	Observation Update	$P(\text{ACE}) \approx 0.019$	ACE: $[0.02, 0.05]$	Confirmation: Isolation logic narrows uncertainty, increasing confidence.
$t = 4$	Reconfiguration	$P(Actuator) \approx 0$	Actuator: $[0, 0.002]$	Recovery: The system returns to a safe baseline state.

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