A Probabilistic Upstream Layer for Logistics Network Resilience Modeling under Severe Disruptions

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***Abstract*—The SC-Reborn performance model evaluates logistics networks deterministically: for each node, it requires vectors of available equipment, materials and skills as known inputs. This assumption holds in stable conditions but collapses under severe disruptions — geopolitical crises, pandemics, infrastructure damage, social upheavals — precisely the events for which ex-ante data is unavailable and planning most critical. Here, we propose to extend the SC-Reborn model by adding a probabilistic upstream layer based on Bayesian network (BN) inference. The BN encodes four classes of root disruptions through a four-level causal graph, propagates uncertainty across systemic mechanisms and operational variables, and produces posterior distributions over the three availability vectors that SC-Reborn requires as input. Four disruption scenarios — pandemic only, geopolitical only, their compound, and a climatic-social compound — show that the framework discriminates between disruption profiles in operationally meaningful ways: skill availability collapses under pandemic evidence, input supply under geopolitical evidence, and equipment availability under infrastructure damage. The result is a two-layer architecture in which causal probabilistic reasoning feeds, but does not replace, the deterministic performance model.**

***Index Terms*—Bayesian network, logistics performance, supply chain disruption, resource availability, causal inference, resilience.**

I. Introduction

Logistics networks fail quietly before they fail visibly: the first sign of a severe disruption is not a broken arc but a resource that is no longer where the model assumed it would be. The SC-Reborn framework [1] models this class of networks as directed graphs with hierarchical performance evaluation, but inherits a limitation common to deterministic approaches: equipment, materials and skills at each node are treated as known inputs. This paper removes that assumption. Performance is evaluated hierarchically: functional capacity at each node (*FuncCapFlow*) aggregates into nodal performance (*NodePerfFlow*), which in turn yields global network performance (*NetPerfFlow*).

A structural assumption underpins this framework: the vectors of available equipment $A_E(n,t)$, materials $A_M(n,t)$ and skills $A_S(n,t)$ at each node n and time slot t are treated as known inputs. This assumption is operationally justified in stable contexts, where historical data and contracts provide reliable estimates. However, it becomes untenable when the system faces *severe, rare and hardly foreseeable* disruptions — the class of events that most threaten supply chain continuity and for which ex-ante data is inherently scarce.

This work was supported by the SC-Reborn Project, Université Paris 8 / Laboratoire QUARTZ.

This assumption collapses under severe disruptions. During the initial modeling of the 2020–2022 compound crises within the SC-Reborn project, we observed that available equipment vectors became essentially unobservable few weeks into the pandemic, while material shortages followed chaotic, non-stationary patterns that invalidated historical demand distributions. The operational question is therefore how to generate credible inputs for $A_E(n,t)$, $A_M(n,t)$ and $A_S(n,t)$ when the disruption landscape is dominated by causal uncertainty and historical data becomes irrelevant.

We propose a Bayesian network (BN) as an upstream probabilistic layer that transforms observable disruption signals into uncertainty-aware availability estimates. The BN encodes a four-level causal structure linking root disruptions to systemic mechanisms, operational variables, and ultimately to the three resource availability vectors that feed the deterministic model. This produces expected performance estimates rather than point predictions, bridging causal probabilistic reasoning with deterministic logistics evaluation.

II. Related Work

A. Supply Chain Disruption: Typology and Propagation Mechanisms

The ripple effect literature [4] has formalized disruption propagation across supply chain echelons, yet predominantly assumes that disruption profiles remain at least partially observable. Ivanov et al.'s canonical trade-off between efficiency and resilience presupposes that managers can identify the disruption type and magnitude within days—an assumption that failed during the 2020 pandemic onset when supply-side and demand-side shocks were initially indistinguishable. We adopt their taxonomy of response strategies but relax the observability assumption, targeting precisely the initial three-week horizon (Empirically selected duration) where disruption signals are noisy and causally ambiguous.

Subsequent work has refined disruption typologies along two axes: the *origin* of the disruption (supply-side, demand-side, infrastructure, geopolitical, natural, or pandemic) and its *propagation mode* (forward along material flows, backward from demand shocks, or structural through network reconfiguration). Dolgui and Ivanov [5] provide a consolidated synthesis of these directions, identifying compound and concurrent disruptions — where multiple triggers activate simultaneously — as the most challenging class for risk management. This is precisely the class of disruptions our model targets, where a pandemic, a geopolitical conflict and a climatic event may co-occur and interact

B. Bayesian Networks in Supply Chain Risk and Resilience Analysis

Bayesian networks (BN) have emerged as a leading probabilistic tool for supply chain risk modelling, owing to their ability to encode causal dependencies, propagate uncertainty in both forward and backward directions, and update beliefs upon partial evidence [6]. This comprehensive literature review, covering publications from 2007 to 2019, identifies three principal BN application modes: causal modelling of risk interdependencies, quantification of resilience metrics, and simulation of disruption propagation (ripple effect analysis).

In the context of disruption propagation, Ojha et al. [7] demonstrate how a static BN can measure fragility, service level and inventory cost under simultaneous multi-node disruptions. The model proposed in the present paper shares the multi-level causal architecture of [7] but focuses on the upstream stage, before performance is evaluated, targeting the *availability of resources* as the BN's output rather than performance metrics directly.

Hosseini and Ivanov's subsequent work illustrates the methodological trajectory relevant here: they extended BNs to quantify resilience as recoverability-to-vulnerability ratios [9], developed multi-layer pandemic disruption models [10], and explored Dynamic BN extensions for temporal propagation [8]. While these operate at supplier-level granularity or post-disruption stages, they establish the precedent for expert-elicited CPT construction we adopt [11].

Our departure lies in shifting the BN upstream: rather than measuring resilience as output, we generate resource availability distributions as inputs.

C. Gap and Positioning

Existing BN applications operate *within* the performance evaluation layer—measuring fragility or resilience as direct outputs. Hosseini and Ivanov [9] quantify supplier-level resilience as a ratio of recoverability to vulnerability; Ojha et al. [7] model service level degradation under multi-node disruptions. Both treat resource availability as an intermediate latent variable rather than the explicit target of inference.

This paper inverts the architecture: we position the BN upstream, as a *preprocessing layer* whose explicit output is the posterior distribution over $Available_*$ vectors. Rather than replacing the SC-Reborn deterministic engine [1], we generate uncertainty-aware inputs for it. This interface—probabilistic upstream, deterministic downstream—addresses the cold-start problem where performance models must operate before disruption impacts stabilize.

III. Problem Formulation

A. Recap of the SC-Reborn Deterministic Layer

The SC-Reborn model [1] evaluates logistics network performance hierarchically: for each node $n \in N$ and time slot $t \in T$, it computes binary capability indicators $Able_E$, $Able_M$, $Able_S$ by comparing the available quantities of equipment, materials and skills against the required quantities. These indicators feed a functional capacity score per node ($FuncCapFlow$), which aggregates into nodal performance ($NodePerfFlow$) and ultimately global network performance ($NetPerfFlow$).

The critical entry point of this evaluation chain is the availability vectors:

$$\begin{aligned} A_E(n,t) &= \left[\text{Available}_E(n,t,e)\right]_{e\in E}, \\ A_M(n,t) &= \left[\text{Available}_M(n,t,m)\right]_{m\in M}, \\ A_S(n,t) &= \left[\text{Available}_S(n,t,s)\right]_{s\in S}. \end{aligned} \tag{1}$$

These three vectors are the sole inputs that the present paper seeks to produce probabilistically. The performance evaluation machinery of [1] is left unchanged.

B. The Upstream Uncertainty Problem

The $Available_*(n,t,*)$ vectors are deterministic inputs in [1]. Under severe disruptions, however, their values at future time slots are inherently uncertain, and this uncertainty has a *causal* structure: a geopolitical crisis does not directly reduce $Available_S$ — it does so through a chain of mediating mechanisms (border closures, mobility restrictions, absenteeism). Capturing this structure requires a causal probabilistic model.

Definition 1 (Upstream Availability Problem): Given a disruption context $\mathcal{C} = \{c_1, c_2, c_3, c_4\}$ where each $c_i \in \{\text{absent}, \text{present}\}$ describes the occurrence of a root disruption type, determine the posterior distributions:

$$P\big(Available_X = \sigma \mid \mathcal{C}\big) \quad \forall X \in \{E, M, S\},\ \sigma \in \Sigma \tag{2}$$

where $\Sigma = \{\text{normal, degraded, critical}\}$.

Although C is instantiated here with four specific root disruptions, this formalization is generic and can be naturally extended to include any number of disruption types.

Scope restriction. The current implementation produces a single posterior vector applicable uniformly across all nodes $n \in N$. This homogeneity assumption reflects our elicitation context: three supply chain managers from centralized French healthcare logistics units confirmed that during the acute phase of crises (weeks 1–3), local differentiation is impossible because site-level communication breaks down. Spatially differentiated posteriors are deferred to future work.

IV. Causal Structure of Resource Availability

A. Design Principles

The BN is constructed following Pearl's causal framework [2]: each directed arc $X \to Y$ asserts that X is a *direct* cause of Y conditional on all other variables. The graph is acyclic and multi-level, with disruption types as root nodes and availability states as leaf nodes.

Three principles guide the structure. First, *causal parsimony*: an arc is added only when a direct causal mechanism can be identified and justified independently of data. Second, *heterogeneity of disruption effects*: the four disruption types ($geopolitical$, $pandemic$, $climatic$, $social$) do not affect the three resource categories symmetrically, and this asymmetry must be encoded in the graph topology. Third, *mediation*: the path from a root disruption to a resource availability node always passes through at least one intermediate mechanism node, reflecting the temporal and organizational propagation of disruptions.

B. Four-Level Directed Acyclic Graph (DAG)

The BN comprises four levels and fifteen nodes, as illustrated in Fig. 1.

Level 0 — Root Disruptions (4 nodes). The four root nodes are mutually independent prior to evidence: $Pert\_Geopolitical$, $Pert\_Pandemic$, $Pert\_Climatic$, $Pert\_Social$.

Level 1 — Systemic Mechanisms (4 nodes). $Mobility\_Restriction$ is dominated by $Pandemic$ and $Social$ (confinements, curfews), with secondary contributions from $Geopolitical$ (travel bans) and $Climatic$ (evacuations). $Transport\_Disruption$ is driven primarily by $Geopolitical$ (sanctions, blocked straits) and $Climatic$ (destroyed infrastructure), with secondary workforce effects from $Pandemic$ and strikes from $Social$. $Supplier\_Failure$ combines $Geopolitical$ (embargoes), $Pandemic$ (factory closures) and $Social$ (strikes); $Climatic$ effects are mediated via transport. $Infrastructure\_Damage$ reflects only $Geopolitical$ (sabotage) and $Climatic$ (floods, earthquakes) as physical destruction sources.

Level 2 — Operational Variables (4 nodes).

- $Critical\_Absenteeism \leftarrow (Mobility\_Restriction, Infrastructure\_Damage)$: staff cannot travel (mobility) nor access sites (damage).
- $Input\_Shortage \leftarrow (Transport\_Disruption, Supplier\_Failure)$: goods either cannot transit or no longer exist at the source.
- $Maintenance\_Shortage \leftarrow (Critical\_Absenteeism, Transport\_Disruption)$: the *pivot node* — maintaining equipment requires both *technicians* (human path) and *spare parts* (supply path), two causally independent channels.
- $Equipment\_Degradation \leftarrow (Maintenance\_Shortage, Infrastructure\_Damage)$: the causally richest node, inheriting degradation from unmaintained equipment and from direct physical destruction.

Level 3 — Availability Leaf Nodes (3 nodes). Each resource availability node has a single parent: $Available\_S \leftarrow Critical\_Absenteeism$, $Available\_M \leftarrow Input\_Shortage$, $Available\_E \leftarrow Equipment\_Degradation$.

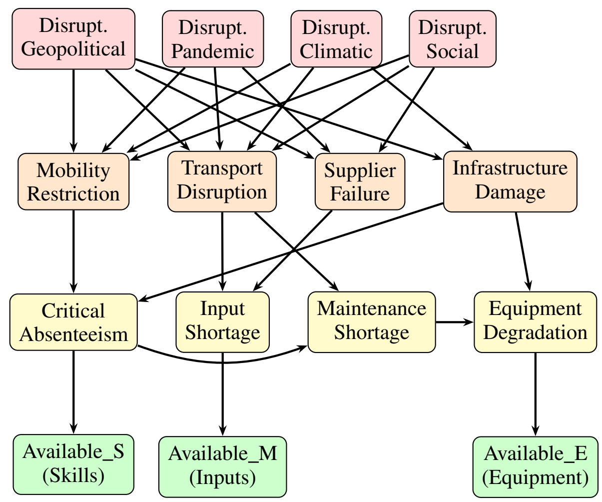

Fig. 1. Four-level causal DAG of the upstream Bayesian network. Red: root disruptions. Orange: systemic mechanisms. Yellow: operational variables. Green: resource availability leaf nodes (Available$_*$).

V. Bayesian Network Specification

A. State Spaces

Root nodes are binary: $\{absent, present\}$. Level 1 nodes (systemic mechanisms) have three states: $\{low, moderate, severe\}$, reflecting the intensity of a disruption mechanism. Level 2 nodes (operational variables) have three states: $\{normal, moderate, critical\}$, reflecting the operational condition of a logistics process. Leaf nodes ($Available_*$) have three states: $\{normal, degraded, critical\}$, reflecting the availability level of a resource category. The terminological distinction between *moderate* (process condition, Levels 1–2) and *degraded* (resource availability, Level 3) is intentional: the former measures the intensity of a causal mechanism, the latter measures the consequence on a resource stock. This three-state discretization captures the threshold nature of logistics operations while remaining tractable for expert elicitation.

B. Prior Distributions

Root disruption priors are expert-elicited, reflecting the base rate of severe, systemic events over a horizon of one to three years:

$$\begin{aligned} P(\text{Geo}=\text{present}) &= 0.15, \quad P(\text{Pan}=\text{present}) = 0.10, \\ P(\text{Cli}=\text{present}) &= 0.15, \quad P(\text{Soc}=\text{present}) = 0.12 \end{aligned} \tag{3}$$

These values assert that, over the considered horizon, any single severe disruption type has a non-negligible but minority probability of occurrence. They are not yet empirically calibrated: data-driven estimation from disruption databases such as EM-DAT [13], GDELT [14], or OECD [15] Trade Disruption records would replace these point estimates with posterior distributions, providing credible intervals on each p_X. This calibration is identified as a priority extension in Section VIII.

C. Conditional Probability Tables (CPT)

CPTs are elicited using a weighted severity score approach. For each node V of Level 1, we initially set uniform weights $\alpha_i = 1$, leading to counter-intuitive predictions where a mild pandemic plus mild social unrest outranked a severe climatic event. We adjusted weights, like converging on $\alpha_{Pandemic} = 3$ for *Mobility_Restriction* to corroborate that confinement orders dominate other mobility constraints.

Formally, for binary parents $\{X_i\}$, the severity score is $\rho = \sum_i \alpha_i \cdot \mathbf{1}[X_i = present]$. The conditional distribution $P(V|\rho)$ derives from a monotone mapping calibrated to match expert assessments at extreme points ($\rho = 0$ and $\rho = \max$) while linearly interpolating intermediate values—a simplification we acknowledge as potentially too smooth for non-linear crisis dynamics.

Table I illustrates CPT entries for $Mobility\_Restriction$, whose dominant drivers are $Pandemic$ ($\alpha = 3$) and $Social$ ($\alpha = 2$), while $Geopolitical$ and $Climatic$ each have weight $\alpha = 1$.

TABLE I
SELECTED CPT ENTRIES FOR $Mobility\_Restriction$ (P: PANDEMIC, G: GEOPOLITICAL, C: CLIMATIC, S: SOCIAL)

G	P	C	S	P(low)	P(moderate)	P(severe)
0	0	0	0	0.90	0.09	0.01
0	0	0	1	0.40	0.45	0.15
0	1	0	0	0.20	0.45	0.35
0	1	0	1	0.02	0.18	0.80
1	1	1	1	0.01	0.04	0.95

For Level 2 nodes whose parents are ternary, the severity score is extended by replacing the binary indicator with an ordinal weight function $\phi : \{low, moderate, severe\} \rightarrow \{0, 0.5, 1\}$, so that:

$$\rho = \sum_i \alpha_i \cdot \phi(X_i) \tag{4}$$

The monotone mapping $P(V \mid \rho)$ is then applied identically to the Level 1 case. For $Maintenance\_Shortage$, whose parents are $Critical\_Absenteeism$ and $Transport\_Disruption$ with equal weights $\alpha = 1$, the score reaches its maximum $\rho = 2$ when both parents are at $severe$, yielding $P(critical) = 0.85$. When only one parent is at its highest level ($\rho = 1$), the critical state probability drops to $P \approx 0.30$, reflecting the partial resilience of the maintenance channel when a single disruption path remains inactive.

The full network specification is available as a Hugin `.net` file at this repository [16].

VI. INTERFACE WITH THE SC-REBORN DETERMINISTIC LAYER

The BN produces, for each resource class $X \in \{E, M, S\}$ and each state $\sigma \in \Sigma = \{normal, degraded, critical\}$, the posterior probability $P(Available_X = \sigma \mid \mathcal{C})$ given any observed disruption context $\mathcal{C}$.

The operationally relevant output for the SC-Reborn model is the probability that availability is sufficient, i.e. that the $Available_X$ vector meets or exceeds the $Required_X$ thresholds. We define the *sufficiency probability* as:

$$p_X(\mathcal{C}) = P\big(Available_X \geq \sigma_{\min} \mid \mathcal{C}\big) \quad X \in \{E, M, S\} \tag{5}$$

where $\sigma_{\min}$ is the minimum availability state deemed operationally sufficient. In the present implementation, we adopt the conservative assumption $\sigma_{\min} = normal$, so that:

$$p_X(\mathcal{C}) = P\big(Available_X = \text{normal} \mid \mathcal{C}\big) \tag{6}$$

The triple (p_E, p_M, p_S) replaces the originally deterministic vectors $A_E(n,t)$, $A_M(n,t)$, $A_S(n,t)$ as the entry point of the SC-Reborn performance evaluation chain. The downstream propagation through $Able_*$, $FuncCapFlow$, $NodePerfFlow$ and $NetPerfFlow$ is left to the companion model [1] and constitutes the subject of forthcoming work.

VII. SCENARIO ANALYSIS

We instantiate the framework on four contrasted scenarios to illustrate how different disruption profiles propagate through the BN and affect each resource availability node. Table II summarizes the posterior probabilities $p_X = P(Available_X = \text{normal} \mid \mathcal{C})$ obtained by exact belief propagation on the specified BN (values rounded to two decimal places). These figures reflect the expert-elicited CPTs and should be interpreted as order-of-magnitude estimates pending empirical calibration of the network parameters.

Scenario S1 – Pandemic only. The dominant causal path runs through $Pandemic \rightarrow Mobility\_Restriction \rightarrow Critical\_Absenteeism$, collapsing skill availability to $p_S = 0.50$. This reflects the French healthcare logistics experience in March 2020: absenteeism reached 30–40% in distribution centers due to confinement orders, while equipment remained largely intact ($p_E = 0.78$) and material flows experienced only moderate friction from port restrictions ($p_M = 0.68$). The asymmetry between p_S and p_M was initially surprising to our industry partners, who expected supply shortages to dominate; the BN structure revealed that pandemic effects on inputs are mediated through secondary transport delays rather than direct supply eradication.

Scenario S2 – Geopolitical only. The dominant path runs through $Geopolitical \rightarrow Supplier\_Failure$ and $Geopolitical \rightarrow Transport\_Disruption \rightarrow Input\_Shortage$, yielding the lowest p_M across all scenarios. Skills are only moderately affected ($p_S = 0.78$) since mobility restriction remains limited.

Scenario S3 – Pandemic and Geopolitical simultaneously. All three availability probabilities collapse concurrently:

TABLE II
POSTERIOR AVAILABILITY PROBABILITIES p_X AND DOMINANT IMPACT FOR FOUR DISRUPTION SCENARIOS.

Scenario	p_S	p_M	p_E	**Dominant impact**
S1: Pandemic only	0.50	0.68	0.78	Skills collapse (absenteeism); transport and equipment largely preserved.
S2: Geopolitical only	0.78	0.44	0.62	Input shortage (sanctions, embargoes); skills moderately affected via border closures.
S3: Pandemic & Geopolitical	0.27	0.22	0.41	Severe degradation across all resources; equipment most resilient but maintenance at risk.
S4: Climatic & Social	0.42	0.58	0.33	Infrastructure damage drives equipment collapse; transport partially disrupted; skills moderately impacted.

$p_S = 0.27$, $p_M = 0.22$, $p_E = 0.41$. Both the human path (absenteeism) and the supply path (input shortage, maintenance shortage) are simultaneously activated, leaving no resource category unaffected. This compound profile represents the most operationally critical configuration for the SC-Reborn model.

Scenario S4 – Climatic and Social. The distinguishing feature is $Climatic \rightarrow Infrastructure\_Damage$, which activates two concurrent paths: direct equipment destruction and inaccessibility of sites, yielding the lowest $p_E = 0.33$ among scenarios not involving geopolitical disruption. The $Maintenance\_Shortage$ pivot node is also activated by $Transport\_Disruption$ (social strikes on transport), reinforcing the equipment degradation channel.

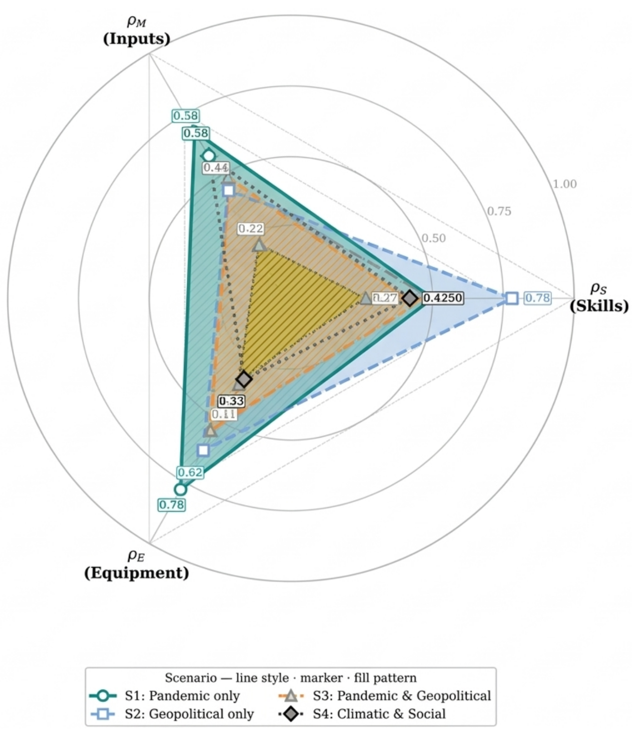

Fig. 2. Superimposed radar charts of posterior resource availability (p_S, p_M, p_E) for the four disruption scenarios. Each scenario title (corner boxes) is linked to the chart by a curved arc. Scenarios are distinguished by line style, marker shape, and fill pattern for grayscale compatibility.

Figure 2 superimposes the four posterior profiles on a single radar chart (grayscale-compatible line styles). The radar geometry reveals what aggregate metrics obscure: the *direction* of deficit. S1 contracts along the p_S axis (skills), S2 along p_M (inputs), and S4 along p_E (equipment), while the compound S3 collapses uniformly toward the origin. This asymmetry validates our structural choice to model resources separately rather than as a single aggregated availability score.

The Bayesian network was built and all probabilistic inferences were performed using BayesiaLab 11.7.4 [12], a dedicated graphical environment for knowledge modelling and Bayesian inference. The DAG structure described in Section IV, the state discretisation, and the full set of CPTs were encoded directly in BayesiaLab's network editor. Posterior distributions over the leaf nodes $Available\_S$, $Available\_M$ and $Available\_E$ were obtained by hard evidence injection on the root disruption nodes, triggering exact belief propagation through the junction tree algorithm.

VIII. DISCUSSION

A critical limitation concerns the independence assumption among root disruptions. Historical data from GDELT and EM-DAT suggests that geopolitical crises and social disruptions co-occur more frequently than chance ($\phi \approx 0.3$), yet our elicitation protocol treated these as marginally independent. This simplification was necessary because our expert panel disagreed substantially on the relative importance of climatic versus geopolitical drivers (standard deviation 0.8 on a 1–5 scale), making joint prior construction intractable. We advocate for a hybrid calibration where α_i weights are updated from sparse observational data via robust Bayesian methods, though compound event records remain scarce.

This model specification is further constrained by spatial homogeneity: the current implementation produces uniform posteriors across all nodes. Industry partners initially contested this, demanding site-specific assessments for their coastal versus inland facilities. We retained the homogeneous layer because site-level communication typically fails during the acute phase (weeks 1–3) that our model targets; localization becomes relevant only in the recovery phase when the deterministic SC-Reborn model takes over. A hierarchical extension with spatial covariates (coastal vs. inland, centralized vs. distributed storage) is technically straightforward but requires node-specific calibration data we do not yet possess.

This spatial uniformity is compounded by a categorical rigidity in our sufficiency threshold. The current definition $p_X(\mathcal{C}) = P(\text{normal})$ treats the degraded state as operationally insufficient, yet our field partners consistently reported that 60–70% resource levels (our "degraded" state) remain acceptable for non-critical flows during crises. Introducing a partial coefficient $\gamma \in [0, 1]$ would require node-specific operational thresholds that vary by facility type (hospital vs. warehouse) and flow criticality—precisely the granular differentiation that our spatial homogeneity assumption precludes. We deliberately retained $\gamma = 0$ as a conservative bound, acknowledging that calibrating site-specific γ values demands longitudinal data on minimum operational thresholds that organizations rarely disclose publicly.

Beyond these static refinements, the temporal dimension represents the most critical structural gap. The current BN captures a snapshot of the acute phase (weeks 1–3), but recovery dynamics differ radically across resource categories: skill availability follows logistic curves as mobility restores, while equipment degradation often accumulates via step-functions when maintenance backlogs persist. A Dynamic Bayesian Network extension [3] would model these divergent recovery trajectories, bridging the upstream BN with the time-indexed $t \in T$ structure of SC-Reborn. However, transition probabilities between degraded and critical states require crisis-recovery panel data that remain proprietary, motivating our current focus on static, acute-phase inference as a tractable first step.

IX. Conclusion

This paper has introduced a probabilistic upstream layer for the SC-Reborn logistics network performance model. The core contribution is a four-level Bayesian network that encodes the causal propagation of four classes of severe disruptions — geopolitical, pandemic, climatic and social — through systemic mechanisms and operational variables, ultimately producing posterior distributions over the three resource availability vectors ($Available_E$, $Available_M$, $Available_S$) that serve as inputs to the deterministic performance model.

The two-layer architecture formalizes a clean interface between causal probabilistic reasoning and deterministic logistics evaluation: the BN upstream layer transforms observable disruption signals into uncertainty-aware availability estimates, which are then consumed by the SC-Reborn layer to produce expected functional capacity, expected nodal performance and expected network performance under disruption.

Scenario analysis demonstrates that the framework discriminates meaningfully between disruption profiles: a pandemic primarily collapses skill availability, a geopolitical crisis primarily starves input supply, and their combination produces a compound degradation of functional capacity across all resource categories, consistent with documented compound crisis dynamics such as the concurrent pandemic and geopolitical disruptions of 2020–2022 [5].

Whether the three-state discretization (normal/degraded/critical) captures sufficient granularity for operational response remains an open empirical question; our partners initially requested five states, but calibration proved intractable within the project timeline. The five extensions identified—data-driven CPT calibration, joint modeling of correlated roots, spatial differentiation, partial sufficiency coefficients, and Dynamic BN temporal modeling—are prioritized based on data availability. The temporal extension is particularly critical: the current static BN captures the acute disruption phase (weeks 1–3), but the transition to recovery dynamics requires coupling with the SC-Reborn time-indexed structure, a non-trivial interface we are currently prototyping with field data from the Paris region healthcare logistics network.

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