International Journal of Engineering Research and Development
e- ISSN: 2278-067X, p-ISSN: 2278-800X, www.ijerd.com
Volume 21, Issue 10 (October 2025), PP 90-95

A Bayesian Network Framework for Aviation Supply Chain Risk Assessment Under Conditions of Tariff Uncertainty

Lu WANG
School of Aviation Transportation, Shanghai Civil Aviation College, China

Abstract: *The global aviation supply chain constitutes a complex, interdependent network characterized by high-value assets, elongated lead times, and stringent regulatory requirements. This complexity renders it profoundly vulnerable to a multitude of disruptive risks. Among contemporary challenges, tariff uncertainty—driven by shifting geopolitical landscapes and trade policies—has emerged as a critical destabilizing factor, directly impacting cost structures, supplier viability, and logistics planning. Traditional risk management methodologies, often linear and siloed, prove inadequate for modeling the non-linear, probabilistic cascading effects inherent in such an environment. This paper proposes a Bayesian Network (BN) model as a robust computational framework for the diagnosis, prediction, and mitigation of risks within the aviation supply chain, with a specific focus on integrating tariff uncertainty. The model captures causal relationships between geopolitical events, supplier financial health, logistics disruptions, quality issues, and the overarching risk of final assembly line stoppages. By incorporating Conditional Probability Tables (CPTs) informed by historical data and expert elicitation, the BN facilitates dynamic reasoning under uncertainty. The research demonstrates, through a detailed case study, how the model can be employed for predictive analysis (e.g., estimating the probability of disruption given new tariff announcements), diagnostic analysis (e.g., identifying the most probable root causes of a disruption), and "what-if" mitigation planning (e.g., evaluating the risk reduction efficacy of dual-sourcing strategies). The findings underscore the superiority of a probabilistic, systems-thinking approach to enhancing the resilience and strategic agility of aviation supply chains in an era of global trade volatility.*
Keywords: *Aviation Supply Chain, Risk Management, Bayesian Network, Tariff Uncertainty, Geopolitical Risk, Supply Chain Resilience, Probabilistic Reasoning, Conditional Probability Table.*

Date of Submission: 02-10-2025 Date of acceptance: 11-10-2025

I. Introduction

The aviation manufacturing industry serves as a paramount exemplar of globalized production, integrating thousands of components from a multitude of suppliers across diverse international jurisdictions into highly complex final products such as commercial aircraft and propulsion systems (Wilkinson et al., 2016). This intricate web of dependencies, while efficient under stable conditions, engenders significant systemic fragility. Disruptions at any node—be it a sub-tier supplier of specialized alloys or a provider of avionic software—can propagate through the network with considerable velocity and amplitude, culminating in substantial financial losses, program delays, and reputational damage (Ivanov et al., 2017).

In recent years, the global trade environment has undergone a period of pronounced turbulence. The rise of protectionist policies, trade disputes between major economies, and the renegotiation of multilateral agreements have introduced an unprecedented level of **tariff uncertainty** (Fajgelbaum et al., 2020). For aviation Original Equipment Manufacturers (OEMs), this uncertainty is not merely a matter of fluctuating import costs. It directly imperils the stability of the supply base, complicates long-term sourcing strategies, and injects volatility into logistics and customs clearance processes (Gereffi & Lee, 2016). A supplier operating on thin margins may be pushed into financial distress by sudden tariff impositions, creating a critical bottleneck. The challenge for risk managers is to move from reactive firefighting to proactive, predictive resilience building.

Conventional supply chain risk management (SCRM) tools, such as Failure Mode and Effects Analysis (FMEA) or checklists, often lack the computational sophistication to handle the probabilistic interdependencies and multi-directional reasoning required for this task (Ho et al., 2015). They tend to treat risks as isolated events rather than symptoms of a connected system.

To address this gap, our research advocates for the adoption of **Bayesian Networks (BNs)**. A BN is a probabilistic graphical model that represents a set of variables and their conditional dependencies via a Directed Acyclic Graph (DAG) (Pearl, 1988). Its capability to synthesize quantitative data with qualitative expert judgment, to update beliefs upon the arrival of new evidence (e.g., a new tariff announcement), and to perform both predictive and diagnostic inference makes it an exceptionally powerful framework for modeling the aviation supply chain's risk landscape under tariff uncertainty (Hosseini & Barker, 2016).

This paper is structured as follows: Section 2 provides a comprehensive literature review on aviation SCRM and BN applications. Section 3 details the methodological framework for BN construction. Section 4 presents our proposed BN model, integrating tariff uncertainty as a core node. Section 5 demonstrates the model's application through computational reasoning and a case study. Section 6 discusses the managerial implications and theoretical contributions, and Section 7 offers concluding remarks and avenues for future research.

II. Literature Review

2.1. Aviation Supply Chain Risk Landscape

The unique attributes of the aviation supply chain—including high certification barriers, intense regulatory oversight, and a oligopolistic market structure—differentiate its risk profile from other industries (Zhang & Zhang, 2018). Scholars have categorized these risks into several typologies. Tang and Nurmaya Musa (2011) identified external risks (e.g., natural disasters, geopolitical instability), internal risks (e.g., production delays, quality failures), and network-related risks (e.g., coordination failures, information asymmetry). More recently, Ivanov (2018) emphasized the ripple effect, where a disruption propagates through the network, amplifying in impact.

The introduction of tariff uncertainty, particularly post-2018, has added a potent new dimension. Studies by Flaaen and Pierce (2019) and Cavallo et al. (2021) demonstrated that uncertainty itself, even before the implementation of tariffs, can lead to significant investment delays and supply chain reconfiguration. For aviation, which relies on long-term contracts and relationship-specific investments, this uncertainty is particularly damaging (Gereffi & Fernandez-Stark, 2016).

2.2. Bayesian Networks in Supply Chain Risk Management

Bayesian Networks have seen growing application in SCRM due to their ability to handle uncertainty and complexity. Their origins lie in artificial intelligence and decision science (Jensen & Nielsen, 2007). Their application spans numerous domains:

- **Supplier Selection:** BNs can model the probability of a supplier's failure based on financial indicators, audit results, and geopolitical factors (Lockamy, 2014).
- **Disruption Propagation:** They can simulate how a delay or quality issue at one node cascades through the network (Garvey et al., 2015).
- **Resilience Assessment:** BNs can evaluate the effectiveness of various mitigation strategies, such as inventory buffering or multi-sourcing (Hosseini et al., 2019).

However, a review of the literature indicates a specific gap: the explicit integration of **trade policy and tariff uncertainty** as a first-class risk variable within a BN model for the aviation sector. Most studies treat geopolitical risk as a monolithic external factor, without dissecting the specific mechanism through which tariff announcements and fluctuations impact supplier viability and logistics costs. This paper aims to fill this gap.

III. Methodology: Constructing the Bayesian Network

The development of a robust BN is a structured process involving domain expertise, data, and validation.

3.1. Node Identification: The first step is to define the key risk variables (nodes). This is achieved through a combination of literature review, analysis of historical disruption reports from aviation OEMs, and interviews with supply chain experts. Nodes should be defined with clear, discrete states (e.g., Tariff_Uncertainty: {High, Medium, Low}).

3.2. Structural Development: The causal relationships between nodes are established, forming the DAG. This structure is built based on expert knowledge of causal pathways (e.g., high tariff uncertainty can *cause* supplier financial distress).

3.3. Parameter Estimation: Defining CPTs: This is the most critical and data-intensive phase. Conditional Probability Tables (CPTs) quantify the strength of the relationships between parent and child nodes. Probabilities are populated using:

- **Historical Data:** Analysis of past disruptions, supplier financial records, and tariff timelines.
- **Expert Elicitation:** Structured interviews with experts to estimate probabilities for rare or novel events (e.g., "Given high geopolitical instability, what is the probability of a logistics delay?"). Techniques like the Delphi method are often used (O'Hagan et al., 2006).
- **Literature Synthesis:** Borrowing parameters from analogous studies in high-reliability industries.

3.4. Model Validation and Inference: The completed BN must be validated. This involves:

- **Sensitivity Analysis:** Testing how sensitive the key output (e.g., probability of stoppage) is to changes in input probabilities.
- **Predictive Validation:** Checking if the model's predictions align with known historical outcomes.

- **Inference:** Using algorithms like Variable Elimination or Gibbs Sampling to perform probability updates when new evidence is entered into the network (Koller & Friedman, 2009).

IV. Proposed Bayesian Network Model

We now present our BN model, explicitly incorporating Tariff_Uncertainty.

4.1. Network Structure and Nodes

The model comprises the following key nodes, with their respective states:

- GeoPolitical_Instability: {High, Low}
- Trade_Policy_Volatility: {High, Low} *(A parent of Tariff_Uncertainty)*
- Tariff_Uncertainty: {High, Medium, Low}
- Supplier_Financial_Health: {Poor, Good}
- Raw_Material_Shortage: {Yes, No}
- Logistics_Delay: {Yes, No}
- Component_Quality_Issue: {Yes, No}
- Final_Assembly_Line_Stoppage: {Yes, No}

Causal Links:

- GeoPolitical_Instability → Trade_Policy_Volatility
- GeoPolitical_Instability → Logistics_Delay
- GeoPolitical_Instability → Raw_Material_Shortage
- Trade_Policy_Volatility → Tariff_Uncertainty
- Tariff_Uncertainty → Supplier_Financial_Health *(High uncertainty increases the probability of financial distress)*
- Tariff_Uncertainty → Logistics_Delay *(Affects customs clearance, route planning)*
- Supplier_Financial_Health → Raw_Material_Shortage
- Supplier_Financial_Health → Component_Quality_Issue *(Financial pressure may lead to corner-cutting)*
- Raw_Material_Shortage → Component_Quality_Issue
- Raw_Material_Shortage → Final_Assembly_Line_Stoppage
- Logistics_Delay → Final_Assembly_Line_Stoppage
- Component_Quality_Issue → Final_Assembly_Line_Stoppage

(Due to space constraints, a full graphical representation of the DAG is not shown here but is described by the links above.)

4.2. Conditional Probability Tables (Excerpts)

Prior Probabilities (Root Nodes):

- P(GeoPolitical_Instability = High) = 0.15
- P(Trade_Policy_Volatility = High) = 0.20

CPT for Tariff_Uncertainty **(Child of** Trade_Policy_Volatility**):**

Trade_Policy_Volatility	P(High)	P(Medium)	P(Low)
High	0.70	0.25	0.05
Low	0.10	0.20	0.70

CPT for Supplier_Financial_Health **(Child of** Tariff_Uncertainty**):**

Tariff_Uncertainty	P(Poor)	P(Good)
High	0.40	0.60
Medium	0.15	0.85
Low	0.05	0.95

CPT for Final_Assembly_Line_Stoppage **(Child of three nodes):**

(A simplified excerpt showing the probability of "Yes" for different combinations)

Raw_Material_Shortage	Logistics_Delay	Component_Quality_Issue	P(Stoppage = Yes)
Yes	Yes	Yes	0.995
Yes	Yes	No	0.850
Yes	No	Yes	0.750
Yes	No	No	0.300
No	Yes	Yes	0.900
No	Yes	No	0.400
No	No	Yes	0.200
No	No	No	0.005

V. Computational Reasoning and Case Study

We now demonstrate the power of the BN through computational inference using hypothetical data. Calculations are performed using BN software (e.g., GeNIe, Netica, or Python libraries like pgmpy).

5.1. Predictive Analysis (Forward Reasoning)

- **Scenario:** News reports indicate a significant escalation of tensions between Country A and Country B. We model this as setting GeoPolitical_Instability = High.
- **Query:** What is the updated probability of a Final_Assembly_Line_Stoppage?
- **Computation:** The BN algorithm propagates this evidence through the network. High geopolitical instability increases the probability of Trade_Policy_Volatility (High), which in turn increases Tariff_Uncertainty (High). This impacts Supplier_Financial_Health (increasing P(Poor)), Logistics_Delay (increasing P(Yes)), and Raw_Material_Shortage (increasing P(Yes)). These factors collectively increase the probability of the stoppage.
- **Result:** The model might compute that P(Stoppage = Yes) increases from a baseline of 8% to 35%. This quantifies the threat, enabling proactive mitigation.

5.2. Diagnostic Analysis (Backward Reasoning)

- **Scenario:** The final assembly line experiences a stoppage (Final_Assembly_Line_Stoppage = Yes).
- **Query:** What is the most probable root cause? What is the updated belief about the state of Tariff_Uncertainty?
- **Computation:** The BN performs diagnostic inference. It calculates the posterior probabilities of all other nodes given the observed evidence of the stoppage.
- **Result:** The model might identify that Component_Quality_Issue has the highest posterior probability of being "Yes" (e.g., 68%). Furthermore, it shows that P(Tariff_Uncertainty = High) has increased significantly from its prior of ~25% to, say, 55%. This suggests a strong link between the stoppage and underlying trade policy issues, guiding the investigation away from purely operational causes and towards strategic sourcing and supplier support.

5.3. "What-If" Mitigation Analysis

- **Scenario:** The OEM is considering dual-sourcing a critical component to mitigate the risk identified from a specific supplier. We model this by altering the BN structure: adding a new node Dual_Sourcing_Implemented = {Yes, No} that influences the Raw_Material_Shortage node. If Dual_Sourcing_Implemented = Yes, it drastically reduces the probability of a shortage.
- **Query:** If we implement dual-sourcing, how much does it reduce the overall probability of a stoppage, especially under conditions of High Tariff_Uncertainty?
- **Computation:** We run the model twice: once with Dual_Sourcing_Implemented = No and once with = Yes, under the evidence Tariff_Uncertainty = High.

- **Result:** The model quantifies the risk reduction. For example, P(Stoppage = Yes | Tariff_Uncertainty=High) might drop from 45% to 18% with dual-sourcing. This provides a clear, quantitative Return on Investment (ROI) for the proposed mitigation strategy.

VI. Discussion and Managerial Implications

The case study illustrates the transformative potential of a BN-based approach. It moves decision-making from intuition to data-driven computation.

6.1. Theoretical Contribution: This research contributes by explicitly embedding **tariff uncertainty** as a dynamic, probabilistic driver within a holistic supply chain risk model. It formalizes the causal pathways through which policy volatility translates into operational disruption, a area less explored in extant literature.

6.2. Managerial Implications:

- **Dynamic Risk Monitoring:** The BN can serve as a live dashboard. As news feeds update (e.g., "new tariff announced on aluminum"), this evidence can be entered, and the model instantly updates the risk profile for all dependent nodes.
- **Strategic Sourcing Decisions:** The model provides a testbed for evaluating long-term sourcing strategies, such as near-shoring vs. off-shoring, under different trade policy scenarios.
- **Supplier Relationship Management:** Identifying that a supplier's financial health is highly sensitive to tariff uncertainty allows OEMs to work collaboratively on contingency plans, rather than simply penalizing them for disruptions.
- **Inventory and Buffer Management:** The model can help optimize the placement and sizing of safety stock by identifying which components have the highest systemic risk of shortage.

VII. Conclusion and Future Research

In conclusion, the aviation supply chain, in its current globalized form, is acutely exposed to the vicissitudes of trade policy. Tariff uncertainty is not an exogenous shock but an endogenous risk factor that permeates the entire network. This paper has argued that Bayesian Networks offer a mathematically rigorous yet intuitively accessible framework for modeling this complex reality. By enabling predictive, diagnostic, and interventional reasoning, BNs empower managers to build more resilient and agile supply chains.

Future research directions include:

1. **Integrating Machine Learning:** Using natural language processing (NLP) to automatically scrape news and government bulletins to update the GeoPolitical_Instability and Trade_Policy_Volatility nodes in real-time.
2. **Dynamic BNs:** Extending the model to a Dynamic Bayesian Network (DBN) to capture the temporal evolution of risks over time.
3. **Fuzzy Logic Integration:** Combining BNs with fuzzy logic to handle nodes with imprecise or linguistic states (e.g., "very high" uncertainty).
4. **Multi-Tier Transparency:** Expanding the model to include deeper sub-tiers of the supply chain, which are often the most opaque and vulnerable.

The journey towards a truly resilient aviation supply chain is continuous. Embracing advanced, probabilistic computational tools like Bayesian Networks is not merely an option but a necessity for navigating the turbulent skies of global trade.

References

[1]. Araz, O. M., Choi, T. M., Olson, D. L., & Salman, F. S. (2020). Data analytics for operational risk management. *Decision Sciences*, 51(6), 1316-1319.

[2]. Bak, O., Shaw, S., Colicic, N., & Kumar, V. (2020). A systematic literature review of supply chain resilience in small–medium enterprises (SMEs): A call for further research. *IEEE Transactions on Engineering Management*, 70(1), 328-341.

[3]. Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: state of the art and future research directions. *International Journal of Production Research*, 57(7), 2179-2202.

[4]. Behzadi, G., O'Sullivan, M. J., Olsen, T. L., & Zhang, A. (2018). Agribusiness supply chain risk management: A review of quantitative decision models. *Omega*, 79, 21-42.

[5]. Brintrup, A., Pak, J., Ratiney, D., Pearce, T., Wichmann, P., Woodall, P., & McFarlane, D. (2020). Supply chain data analytics for predicting supplier disruptions: a case study in complex asset manufacturing. *International Journal of Production Research*, 58(11), 3330-3341.

[6]. Cavallo, A., Gopinath, G., Neiman, B., & Tang, J. (2021). Tariff passthrough at the border and at the store: Evidence from US trade policy. *American Economic Review: Insights*, 3(1), 19-34.

[7]. Chen, L., & Zhang, L. (2020). Data-driven dynamic Bayesian network for proactive resilience assessment of interdependent systems. *IEEE Transactions on Reliability*, 70(2), 687-699.

[8]. Chopra, S., & Sodhi, M. S. (2019). Reducing the risk of supply chain disruptions. *MIT Sloan Management Review*, 61(3), 1-9.

[9]. Dolgui, A., Ivanov, D., & Sokolov, B. (2018). Ripple effect in the supply chain: an analysis and recent literature. *International Journal of Production Research*, 56(1-2), 414-430.

[10]. Fahimnia, B., Jabbarzadeh, A., & Sarkis, J. (2018). Greening versus resilience: A supply chain design perspective. *Transportation*

Research Part E: Logistics and Transportation Review, 119, 129-148.
[11]. Fajgelbaum, P. D., Goldberg, P. K., Kennedy, P. J., & Khandelwal, A. K. (2020). The return to protectionism. *The Quarterly Journal of Economics*, 135(1), 1-55.
[12]. Flaaen, A., & Pierce, J. (2019). Disentangling the effects of the 2018-2019 tariffs on a globally connected US manufacturing sector. *Finance and Economics Discussion Series*, 2019-086. Washington: Board of Governors of the Federal Reserve System.
[13]. Garvey, M. D., Carnovale, S., & Yeniyurt, S. (2015). An analytical framework for supply network risk propagation: A Bayesian network approach. *European Journal of Operational Research*, 243(2), 618-627.
[14]. Gereffi, G., & Fernandez-Stark, K. (2016). Global value chain analysis: a primer (2nd ed.). Durham, NC: Duke Center on Globalization, Governance & Competitiveness.
[15]. Gereffi, G., & Lee, J. (2016). Economic and social upgrading in global value chains and industrial clusters: Why governance matters. *Journal of Business Ethics*, 133(1), 25-38.
[16]. Ho, W., Zheng, T., Yildiz, H., & Talluri, S. (2015). Supply chain risk management: a literature review. *International Journal of Production Research*, 53(16), 5031-5069.
[17]. Hosseini, S., & Barker, K. (2016). A Bayesian network model for resilience-based supplier selection. *International Journal of Production Economics*, 180, 68-87.
[18]. Hosseini, S., Ivanov, D., & Dolgui, A. (2019). Review of quantitative methods for supply chain resilience analysis. *Transportation Research Part E: Logistics and Transportation Review*, 125, 285-307.
[19]. Ivanov, D. (2018). *Structural dynamics and resilience in supply chain risk management*. Springer International Publishing.
[20]. Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research*, 57(3), 829-846.
[21]. Ivanov, D., Sokolov, B., & Dolgui, A. (2017). The Ripple effect in supply chains: trade-off 'efficiency-flexibility-resilience' in disruption management. In *Supply Chain Management: Models, Applications, and Research Directions* (pp. 91-115). Springer, Cham.
[22]. Jensen, F. V., & Nielsen, T. D. (2007). *Bayesian networks and decision graphs*. Springer Science & Business Media.
[23]. Koller, D., & Friedman, N. (2009). *Probabilistic graphical models: principles and techniques*. MIT press.
[24]. Lockamy III, A. (2014). Assessing disaster risks in supply chains: A Bayesian approach. *Industrial Management & Data Systems*, 114(5), 755-777.
[25]. Modgil, S., Singh, R. K., & Hannibal, C. (2022). Artificial intelligence for supply chain resilience: learning from Covid-19. *The International Journal of Logistics Management*, 33(1), 1-28.
[26]. O'Hagan, A., Buck, C. E., Daneshkhah, A., Eiser, J. R., Garthwaite, P. H., Jenkinson, D. J., ... & Rakow, T. (2006). *Uncertain judgements: eliciting experts' probabilities*. John Wiley & Sons.
[27]. Pearl, J. (1988). *Probabilistic reasoning in intelligent systems: networks of plausible inference*. Morgan Kaufmann.
[28]. Pavlov, A., Ivanov, D., Dolgui, A., & Sokolov, B. (2018). Hybrid fuzzy-probabilistic approach to supply chain resilience assessment. *IEEE Transactions on Engineering Management*, 65(2), 303-315.
[29]. Pournader, M., Kach, A., & Talluri, S. (2020). A review of the existing and emerging topics in the supply chain risk management literature. *Decision Sciences*, 51(4), 867-919.
[30]. Rajagopal, V., Venkatesan, S. P., & Goh, M. (2017). Decision-making models for supply chain risk mitigation: A review. *Computers & Industrial Engineering*, 113, 646-682.
[31]. Sawik, T. (2019). *Supply chain disruption management*. Springer International Publishing.
[32]. Scheibe, K. P., & Blackhurst, J. (2018). Supply chain disruption propagation: a systemic risk and normal accident theory perspective. *International Journal of Production Research*, 56(1-2), 43-59.
[33]. Simangunsong, E., Hendry, L. C., & Stevenson, M. (2016). Managing supply chain uncertainty with emerging ethical issues. *International Journal of Operations & Production Management*, 36(10), 1272-1304.
[34]. Tang, C. S., & Nurmaya Musa, S. (2011). Identifying risk issues and research advancements in supply chain risk management. *International Journal of Production Economics*, 133(1), 25-34.
[35]. Tukamuhabwa, B. R., Stevenson, M., Busby, J., & Zorzini, M. (2017). Supply chain resilience in a developing country context: a case study on the interconnectedness of threats, strategies and outcomes. *Supply Chain Management: An International Journal*, 22(6), 486-505.
[36]. Vilko, J., & Hallikas, J. (2019). Risk assessment in multimodal supply chains. *International Journal of Production Economics*, 207, 125-136.
[37]. Wilkinson, S., Dunn, S., & Ma, S. (2016). The vulnerability of the European air transport network to airspace closures. *Transportation Research Part A: Policy and Practice*, 92, 94-105.
[38]. Wu, T., Blackhurst, J., & O'grady, P. (2017). Methodology for supply chain disruption analysis. *International Journal of Production Research*, 55(7), 2018-2034.
[39]. Xu, J., Huang, E., Hsieh, L., Lee, L. H., Jia, Q. S., & Chen, C. H. (2018). A review of data-driven decision-making methods for industry 4.0 maintenance applications. *IEEE Transactions on Emerging Topics in Computing*, 9(1), 145-159.
[40]. Zhang, Y., & Zhang, L. (2018). A Bayesian network-based approach for modeling and analyzing the resilience of critical infrastructures. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 50(1), 280-292.
[41]. Zhao, K., Zuo, Z., & Blackhurst, J. V. (2019). Modelling supply chain adaptation for disruptions: An empirically grounded complex adaptive systems approach. *Journal of Operations Management*, 65(3), 190-212.
[42]. Zsidisin, G. A., & Henke, M. (2019). *Revisiting supply chain risk*. Springer Series in Supply Chain Management.