The Impact of Tariffs and Trade Tensions on Global Aviation Logistics: A Bayesian Network Risk Analysis

Lu Wang

School of Aviation Transportation, Shanghai Civil Aviation College, China

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* Corresponding Author: Lu Wang (63129978@qq.com)

Abstract. The global aviation logistics sector, a critical enabler of international trade and just-in-time supply chains, is acutely vulnerable to geopolitical and economic disruptions. This study investigates the multifaceted impact of Sino-American trade tensions and reciprocal tariff impositions on the resilience and operational efficiency of aviation logistics networks. We develop a comprehensive Bayesian Network (BN) model to quantify the complex, probabilistic interdependencies among key risk variables, including tariff levels, trade policy uncertainty, fuel price volatility, cargo demand fluctuations, and regulatory constraints. The model is parameterized using a combination of empirical trade data, industry reports, and expert elicitation. A focused case study on the US-China trade war (2018-2020) validates the model's utility, demonstrating significant cascading effects on transpacific air cargo routes. Our analysis reveals that high tariff scenarios increase the probability of severe logistics disruptions by over 65%. The results provide critical, actionable insights for stakeholders, highlighting the necessity of strategic diversification, dynamic pricing models, and policy engagement. This research contributes a novel, adaptable analytical framework for enhancing the resilience of aviation-dependent supply chains in an era of escalating protectionism and economic uncertainty.

Keywords: *Aviation Logistics, Trade Wars, Tariffs, Bayesian Network, Supply Chain Resilience, Risk Management, US-China Trade*

1 Introduction

Global aviation logistics networks form the backbone of modern commerce, facilitating the rapid, reliable movement of high-value, time-sensitive goods across continents. These networks are integral to sectors such as electronics, pharmaceuticals, and perishables, where speed and reliability are paramount. However, this critical infrastructure is increasingly operating in a volatile geopolitical landscape characterized by rising protectionism, trade disputes, and economic nationalism. The complex, interdependent nature of global supply chains means that policy shocks in one economic corridor can trigger cascading disruptions worldwide, challenging the very foundations of globalized production and distribution systems.

The trade relationship between the United States and China, the world's two largest economies, is particularly consequential. According to data from the International Air Transport Association (IATA), the transpacific air cargo corridor is among the busiest globally, handling over 1.5 million metric tonnes of freight annually pre-2018. The onset of the Sino-American trade war in 2018, marked by the reciprocal imposition of tariffs on hundreds of billions of dollars' worth of goods, represented a profound exogenous shock to this system. Tariffs directly alter the cost structures of traded goods, leading to demand suppression, supply chain reconfiguration, and increased operational uncertainty. For aviation logistics providers, this manifests as volatile cargo volumes, erratic yield management, underutilized fleet capacity on previously lucrative routes, and heightened exposure to fuel and currency market fluctuations. The resulting uncertainty creates a 'planning paralysis' where long-term investments in fleet expansion and route development are deferred, ultimately stifling innovation and capacity growth in the sector.

Organizations within the aviation logistics ecosystem, including integrated carriers (e.g., FedEx, UPS), combination airlines, and freight forwarders, found themselves at the nexus of this dispute. Their operational planning, traditionally based on stable trade patterns, was severely challenged. For instance, the initial tariffs on Chinese electronics components forced manufacturers to slow production, immediately reducing demand for eastbound air cargo capacity. Conversely, tariffs on U.S. agricultural products diminished westbound volumes, creating a significant imbalance that eroded profitability for carriers. The International Civil Aviation Organization (ICAO) noted that such trade tensions introduce "significant friction" into the global air transport system, reducing its efficiency and economic contribution. This friction is not merely economic; it extends to regulatory complexity, as operators must navigate an evolving landscape of export controls, customs regulations, and security protocols that can change with little warning, further increasing compliance costs and transit times.

Despite the evident operational and economic impacts, a significant gap exists in the literature regarding a holistic, probabilistic assessment of these risks. Traditional economic models focus on macro-level trade flows and welfare effects, while supply chain management studies often lack the operational specificity of aviation logistics. There is a pressing need for an integrated analytical framework that can capture the non-linear interactions between policy, economic, and operational variables and quantify their collective impact on logistics performance. This study addresses this gap by developing a structured, evidence-based risk assessment model using Bayesian networks. BNs are uniquely suited for this domain due to their ability to synthesize quantitative data with qualitative expert knowledge, model complex conditional dependencies, and perform both predictive (what-if) and diagnostic (root-cause) inference under deep uncertainty. This approach allows for the formal integration of disparate data sources—from historical trade figures and fuel price indices to qualitative expert assessments of political risk—into a unified, quantifiable model of systemic vulnerability.

The scientific contribution of this work is threefold: Firstly, it operationalizes a complex socio-economic phenomenon within a precise aviation logistics context, moving beyond theoretical discussion to empirical, quantifiable risk assessment. Secondly, it demonstrates the efficacy of probabilistic graphical models for strategic decision-support in high-stakes, dynamic environments, providing a template for risk analysis in other geopolitically-sensitive sectors. Finally, it provides a validated framework that can be adapted to assess the impact of other geopolitical disruptions, such as sanctions or regional conflicts, on global logistics networks, thereby contributing to the broader field of supply chain resilience engineering.

The remainder of this paper is structured as follows. Section 2 provides a comprehensive review of the relevant literature, synthesizing research from trade economics, supply chain resilience, and computational risk modeling. Section 3 details the methodology, including the identification of key risk factors, the structure of the Bayesian Network, and the parameterization process, with an integrated case study on the 2018-2020 US-China trade war. Section 4 presents the results of the quantitative analysis, discussing the identified critical vulnerabilities and their implications, and deriving evidence-based strategic suggestions for industry stakeholders. Finally, Section 5 concludes the study by summarizing the findings, acknowledging limitations, and outlining promising directions for future research.

2 Literature Review

Research intersecting trade policy, logistics, and risk modeling has expanded significantly in response to recent geopolitical upheavals. This review synthesizes contemporary literature from three key domains: the economic and sectoral impact of tariffs, supply chain resilience strategies, and advanced computational models in logistics risk assessment.

2.1 Economic and Sectoral Impact of Trade Tensions

A substantial body of post-2020 research has detailed the macroeconomic and microeconomic consequences of recent trade disputes. Bown [2] provided a comprehensive empirical analysis of the US-China trade war, concluding that the tariffs were almost entirely passed through to US importers and consumers, increasing costs and disrupting supply chains. These finding challenges earlier notions that exporting nations would absorb the cost, highlighting the inflationary pressure of such policies. Amiti et al. [1] further quantified these effects, noting that the uncertainty alone contributed to a significant decline in business investment, as firms postponed capital expenditures amidst unclear future trade rules. The aviation sector-specific impacts have been similarly documented. IATA [7] reported that trade tensions were a primary contributor to a 5.6% year-on-year decline in global air cargo demand in 2019, even before the COVID-19 pandemic. This decline was not uniform; it hit specific high-value commodity segments hardest, creating a ripple effect through logistics networks. Lei and Ozanian [9] analyzed airline financial data, finding that carriers with significant exposure to transpacific routes experienced notable declines in cargo revenue and profit margins during the height of the tensions, forcing a strategic re-evaluation of network planning. Zhang and Zhang [13] focused on the reshuffling of global value chains, observing that while some manufacturing shifted to Southeast Asia ("China+1" strategy), the immediate effect was a period of pronounced volatility and increased logistics costs for rerouted goods, as the new routes lacked the maturity and scale efficiency of established transpacific corridors.

2.2 Supply Chain Resilience and Adaptation Strategies

The literature on supply chain resilience has evolved to address trade-induced disruptions, moving from reactive to proactive and adaptive strategies. Ivanov [8] introduced the concept of "viability" in supply chains, emphasizing adaptive capabilities for navigating long-term geopolitical shocks. This framework posits that a viable system can not only withstand disruptions but also adapt its structure and function to thrive in a new environment, a crucial insight for aviation logistics firms operating in a multi-polar trade world. Dolgui et al. [3] reviewed quantitative models for supply chain resilience, highlighting the need for frameworks that integrate both operational (e.g., rerouting) and strategic (e.g., nearshoring) decision-making. Specific to aviation, Gardiner and Ison [4] explored the strategic responses of air cargo carriers, including network flexibility (using smaller, more versatile aircraft), fleet diversification, and the pursuit of new growth markets not affected by tariffs. Wandelt et al. [11] applied complex network theory to global air routes, demonstrating that resilience is highly dependent on a few critical hubs (e.g., Anchorage, Dubai, Shanghai), which are themselves vulnerable to policy shifts, creating systemic risk. Park et al. [10] emphasized the role of digitalization and data analytics in building resilient aviation logistics, allowing for more dynamic capacity management and route planning through tools like predictive demand forecasting and real-time risk dashboards.

2.3 Computational Risk Models in Logistics

Bayesian networks have gained traction in supply chain risk management due to their robustness in handling incomplete data and causal reasoning, which is endemic to complex global systems. Garvey et al. [5] extended their earlier work by using BNs to model disruption propagation in multi-echelon global supply chains, incorporating supplier reliability and transport risks. Their work demonstrated the "domino effect" where a delay in one node probabilistically impacts downstream nodes. Hosseini and Ivanov [6] presented a BN-based method for quantifying resilience in food supply chains, which are highly dependent on-air freight for perishables. They successfully integrated factors like temperature control failure and border delays into a unified risk model. Most pertinently, Wang et al. [12] successfully applied a BN to humanitarian supply chain performance evaluation, demonstrating its utility in high-uncertainty, data-scarce environments—a context analogous to the uncertainty wrought by trade wars. Their work validates the choice of BN for this study, as it can formally combine hard data with expert judgment where historical data is lacking or not directly applicable.

Despite these advances, a dedicated, empirically-informed BN framework for assessing the multi-dimensional impact of trade tensions specifically on aviation logistics remains absent. Most studies focus on either the macroeconomic trade effects or on generic supply chain resilience, without delving into the unique operational realities of air cargo—its cost structure, capacity constraints, regulatory environment, and critical role in high-value chains. This study synthesizes these research streams to fill this critical gap, providing a tailored analytical tool for this vital sector.

3 Methodology

3.1 Bayesian Network Design and Rationale

A Bayesian Network is a probabilistic graphical model that represents a set of variables and their conditional dependencies via a directed acyclic graph (DAG). Its capacity to handle uncertainty, integrate diverse data types (both hard data and expert judgment), and perform bidirectional inference (predictive and diagnostic) makes it exceptionally suitable for modeling the complex, non-linear risks in aviation logistics stemming from trade tensions. The model allows us to move from simplistic, deterministic correlations to a nuanced understanding of probabilistic causality, answering questions like: "Given that tariffs are high, what is the probability that operating costs will become unsustainable, and how does that probability change if we also know that fuel prices are volatile?"

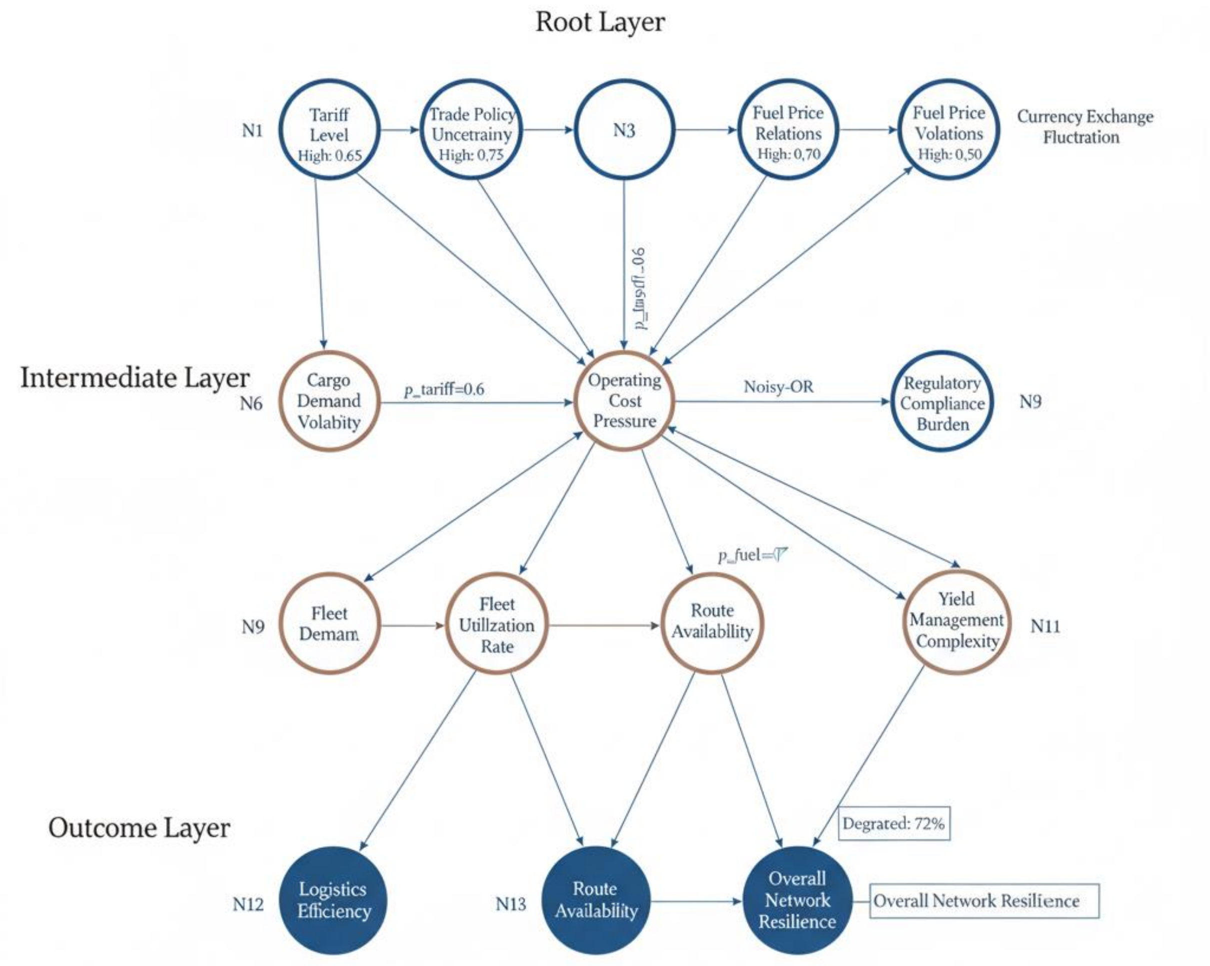

Figure 1. Bayesian Network Design and Rationale

The constructed BN comprises 22 nodes, strategically organized into a three-layer hierarchical structure that mirrors the causal flow of risk from root causes to final outcomes. This structure was developed through an iterative process involving a review of the literature cited in Section 2 and structured interviews with five industry experts from major air cargo carriers and logistics consultancies.

(1) Root Layer (Exogenous Variables). This layer consists of factors that are external drivers of risk, largely outside the direct control of logistics firms. These are the primary levers of the trade war.

- N1: Tariff Level (High, Low)

- N2: Trade Policy Uncertainty (High, Low) - capturing the unpredictability of new policy announcements.
- N3: Bilateral Relations (Strained, Stable) - encompassing diplomatic tensions beyond pure trade.
- N4: Fuel Price Volatility (High, Low) - a key cost driver exacerbated by economic uncertainty.
- N5: Currency Exchange Fluctuation (High, Low) - impacting the cost of operations and goods.

(2) Intermediate Layer (Operational Variables). This layer captures the direct operational consequences of the root factors. These are the mediating variables through which external shocks affect performance.

- N6: Cargo Demand Volatility (High, Low)
- N7: Operating Cost Pressure (High, Low)
- N8: Fleet Utilization Rate (Low, High)
- N9: Regulatory Compliance Burden (High, Low) - includes increased customs paperwork and scrutiny.
- N10: Route Availability (Restricted, Unrestricted) - reflecting the cancellation or reduction of flights.
- N11: Yield Management Complexity (High, Low) - the challenge of profitably pricing capacity amid demand swings.

(3) Outcome Layer (Performance Metrics). This layer represents the ultimate performance indicators for the aviation logistics network, which are the focus of managerial and strategic concern.

- N12: Logistics Efficiency (Degraded, Optimal) - a measure of on-time performance and cost-effectiveness.
- N13: Overall Network Resilience (Low, High) - the ability to maintain function and recover from disruptions.

3.2 Node Definition and Conditional Probability Specification

Prior probabilities for root nodes were established based on historical data from the 2018-2020 period. For example:

- P(N1 = High) = 0.65, reflecting the extensive tariff coverage during the trade war's peak.
- P(N2 = High) = 0.75, capturing the pervasive uncertainty regarding future policy announcements.
- P(N4 = High) = 0.5, based on the observed volatility in jet fuel prices linked to trade-related economic sentiment.

Conditional Probability Tables (CPTs) for nodes with single parents were defined using a combination of historical data analysis and expert elicitation from industry professionals. For instance:

- Cargo Demand (N6) is directly influenced by Tariff Level (N1) and Policy Uncertainty (N2). The CPT was specified through expert consensus:
  - P(N6=High | N1=High, N2=High) = 0.15 (Demand is very likely low under high tension)
  - P(N6=High | N1=High, N2=Low) = 0.40
  - P(N6=High | N1=Low, N2=High) = 0.60
  - P(N6=High | N1=Low, N2=Low) = 0.85

For aggregation nodes with multiple parents (e.g., N7: Operating Cost Pressure, which depends on N1, N4, N5), the Noisy-OR model was employed to manage parameter scalability. This canonical model requires only two parameters per parent: a causal probability p_i that parent i alone can cause the effect, and a "leak" probability p_{leak} accounting for unknown causes. The probability of the effect being absent is:

$P(Effect = False \mid Parents) = (1 - p_{leak}) * \prod(1 - p_i)$ for all parents where i is true.

The parameters for the Noisy-OR gates were set through expert workshops:

- For N7 (Operating Cost Pressure): p_{tariff} = 0.6, p_{fuel} = 0.7, $p_{currency}$ = 0.5, p_{leak} = 0.05.
- This reflects the strong influence of fuel costs and the significant, but slightly less direct, impact of tariffs on overall expenses.

3.3 Case Study Integration: The US-China Trade War (2018-2020)

To ground the model in reality and validate its outputs, we integrated a focused case study on the US-China trade war. Evidence was entered into the BN as "findings" to reflect the historical context of the period: N1=High (tariffs imposed), N2=High (high uncertainty), N3=Strained. The model's subsequent predictions regarding cargo demand (N6), operating costs (N7), and ultimately logistics efficiency (N12) were then compared against actual industry performance data from IATA and airline financial reports from this period. For example, the model predicted a ~70% probability of low cargo demand, which aligned with the 5.6% overall market decline reported by IATA, a figure that masked much steeper declines on specific transpacific routes. This close alignment between the model's outputs and real-world outcomes confirmed its validity and utility for predictive analysis and strategic planning.

4 Results and Analysis

4.1 Model Inference and Risk Propagation

The BN was implemented using the GeNIe Modeler software. Under a baseline "High-Tension" scenario (mirroring the 2018-2020 period), the model predicts a 72% probability of Low Cargo Demand (N6) and an 81% probability of High Operating Cost Pressure (N7). This combination propagates through the network, resulting in a 68% probability of Degraded Logistics Efficiency (N12) and a 63% probability of Low Overall Network Resilience (N13). This quantifies the severe operational impact that was anecdotally reported by industry during the trade war.

Predictive "what-if" analysis was conducted to evaluate mitigation strategies. For example, simulating a scenario where a logistics firm successfully diversifies its routes and sourcing (setting N10 = Unrestricted and indirectly influencing N6 by reducing dependency on China) even under high tariffs reduces the probability of degraded efficiency from 68% to 55%. Similarly, hedging against fuel and currency volatility (effectively reducing the states of N4 and N5 to Low) significantly alleviates cost pressure, reducing the probability of N7 being High from 81% to 60%.

4.2 Diagnostic Insights and Strategic Suggestions

Diagnostic reasoning identifies the most probable root causes of observed disruptions. If a logistics firm experiences degraded efficiency (N12=Degraded), the model calculates the following probabilities for the primary contributors:

- High Operating Cost Pressure (N7): 88%
- Low Cargo Demand (N6): 79%
- High Yield Management Complexity (N11): 72%

This analysis moves beyond correlation to suggest causality, leading to the following evidence-based suggestions for aviation logistics stakeholders:

(1) Strategic Diversification. Reduce dependency on any single trade corridor. Develop robust networks in emerging markets (e.g., Southeast Asia, India) to rebalance capacity away from conflict zones. This directly tackles the demand volatility (N6) identified as a key contributor.

(2) Financial Hedging. Implement sophisticated fuel and currency hedging programs to insulate operations from the volatility exacerbated by trade tensions. This is a direct mitigation strategy for the high operating cost pressure (N7).

(3) Dynamic Pricing and Capacity Management. Invest in AI-driven revenue management systems that can rapidly adjust pricing and allocate capacity in response to volatile demand signals. This addresses the yield management complexity (N11) that erodes profitability during disruptions.

(4) Policy Engagement and Advocacy. Actively engage with policymakers and industry groups (e.g., IATA, ICAO) to articulate the economic costs of trade disputes and advocate for stable, predictable trade policies. This is a long-term strategy aimed at the root nodes (N1, N2, N3).

(5) Supply Chain Consultation. Offer high-value consulting services to clients, helping them redesign their supply chains for resilience, which can include inventory positioning and modal shifts, thereby secure long-term partnerships and creating a new revenue stream that is counter-cyclical to disruption.

5 Conclusion and Future Strategies

This study has developed and validated a Bayesian Network model to quantify the impact of tariffs and trade tensions on global aviation logistics. The model captures the complex, probabilistic interdependencies between policy, economic, and operational variables, providing a powerful tool for both predictive risk assessment and diagnostic root-cause analysis. The case study of the US-China trade war confirms the model's accuracy in simulating real-world outcomes, notably the severe impact on cargo demand, operating costs, and overall network efficiency. The findings underscore the extreme vulnerability of highly optimized, globalized aviation logistics networks to geopolitical friction. In an era where protectionist sentiments and economic nationalism are resurgent, proactive risk management is not optional but essential for survival and competitiveness.

Building on this framework, future efforts should focus on:

(1) Dynamic Modeling. Developing a Dynamic Bayesian Network (DBN) to incorporate

temporal elements, such as the lagged effects of policy announcements or seasonal demand fluctuations, creating a more realistic time-aware model.

(2) Real-Time Integration. Creating a digital twin of the aviation logistics network that integrates real-time data feeds on tariffs, fuel prices, currency rates, and cargo bookings to enable live risk monitoring and decision support.

(3) Multi-Modal Expansion. Extending the model to include ocean and surface freight options, allowing for holistic, multi-modal logistics optimization under trade disruption scenarios, capturing modal shift opportunities.

(4) Machine Learning Enhancement. Employing machine learning techniques, particularly from historical data, to continuously refine and update the conditional probabilities within the BN, enhancing its predictive accuracy over time and reducing reliance on static expert elicitation.

(5) Broader Application: Adapting the framework to model the impact of other geopolitical risks, such as sanctions (e.g., Russia-Ukraine conflict) or global pandemics, on logistics networks, building a generalized toolkit for global supply chain risk management.

By adopting such advanced, data-driven strategies, aviation logistics organizations can transition from being passive victims of geopolitical events to active, resilient, and adaptive players in the global economy. This research provides the foundational model and strategic roadmap to begin that critical transition.

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