# *Operational Friction in Multimodal Logistics Networks and Supply Chain Resilience: Implications for Onshoring and Offshoring Decisions*

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**Abstract:** Disruption-driven transit-time uncertainty and volatile logistics costs are intensifying interest in shoring decisions and the resilience of multimodal logistics networks. This study introduces an Operational Friction Index (OFI) to quantify execution frictions on transport service-arcs (e.g., congestion, transfer complexity, and documentation delays) and examines how these frictions shape robust routing and shoring outcomes. We formulate a robust single-commodity multimodal freight routing problem under budgeted transit-time uncertainty and incorporate OFI into the objective via a penalty term, yielding a single augmented evaluation criterion. To solve large-scale instances, we develop an adaptive large neighborhood search (ALNS) algorithm with OFI-aware scoring in selected destroy/repair operators and a record-to-record acceptance rule based on the augmented objective. Computational experiments benchmark ALNS against CPLEX and a Max–Min Ant System baseline across instance sizes, reporting optimality gaps and runtimes. The results show that ALNS achieves near-optimal solutions on tractable instances and scales effectively when exact optimization becomes time-consuming, while OFI helps explain performance differences across operational settings and industry profiles. The proposed framework supports the evaluation of shoring configurations and multimodal network designs under transit-time uncertainty

***Keywords:*** Supply chain resilience; Logistics service networks; Multimodal logistics networks; Transit time uncertainty; Robust optimization; Adaptive large neighborhood search (ALNS); Operational Friction Index (OFI)

## ➢ Introduction

Over the past several decades, large manufacturing firms have shifted from onshoring to offshoring (or near-shoring) to reduce supply chain costs for global markets (Kumar and Tang, 2022). This shift often involves relocating domestic production to low-wage regions to lower production costs (Choi et al., 2021; Cheng et al., 2024). These contrasting strategies create distinct logistics network typologies: onshoring typically relies on shorter, domestic networks, whereas offshoring depends on longer global networks with greater exposure to transit-time variability and disruption risk. In recent years, heightened exposure to global disruptions and crises (e.g., COVID-19 and geopolitical conflicts), together with rising logistics costs linked to tariffs and energy, has led academics and practitioners to reassess offshoring and to consider shifting production closer to end markets—i.e., reshoring—particularly for critical products (Cheng et al., 2024). During the COVID-19 pandemic, spot container shipping prices from China to U.S. West Coast ports surged to over 1000% of 2019 levels (Council of Economic Advisers,

2023). Consistently, the NAM Q4 2023 Outlook Survey reported that 86.2% of manufacturers have taken steps to de-risk their supply chains over the past two years, reflecting increased emphasis on resilience and efficiency through actions such as nearshoring and expanding U.S. operations (National Association of Manufacturers, 2023). While prior research has examined reshoring impacts such as market valuation (Choi et al., 2021) and outsourcing-related decision making (Sawik, 2023), the role of logistics network robustness and resilience in shaping onshoring/offshoring choices under transit-time uncertainty remains insufficiently investigated. Logistics service networks are central to supply chain resilience (SCR). SCR is commonly defined as the ability to endure, adapt to, and recover from disruptions while meeting demand and sustaining target performance in vulnerable contexts (Hosseini et al., 2019). Practically, this implies that strategic supply chain design decisions—including shoring strategies—cannot be evaluated without explicitly accounting for the resilience performance of the logistics service network that enables product flows, especially when disruptions manifest as uncertain transit times. Resilience requirements also vary substantially across industries because products differ in value, perishability, and societal criticality (e.g., fresh produce versus vaccines) (Poo et al., 2024; Mohammadi et al., 2022). Highly critical products such as vaccines or essential medicines typically require strict lead times and high reliability and therefore depend more on faster and flexible transportation services than daily consumer goods. Yet firms may still lack clear guidance on which resilience measures best fit their operational needs and what benefits those measures deliver (Maharjan and Kato, 2022). To help explain why comparable disruption levels can yield markedly different operational outcomes across firms and contexts, this study introduces the Operational Friction Index (OFI) as a simple diagnostic indicator of execution frictions along multimodal logistics services. OFI summarizes day-to-day impediments—such as coordination frictions across modes and hubs, documentation and procedural burdens, congestion, and handling constraints at transfers—that can compound delays and reduce service reliability. When OFI is higher, a given level of transit-time uncertainty is more likely to translate into larger effective delays, higher penalty and deterioration exposure, and greater pressure to redesign routing choices and associated shoring configurations. When OFI is lower, networks can absorb uncertainty more smoothly through better coordination and operational flexibility, reducing the sensitivity of performance to disruption-driven time variability.

Against this background, this work examines how SCR considerations influence shoring strategies across industries, focusing on global multimodal logistics service networks under transit-time uncertainty and using OFI to characterize execution conditions that intensify or mitigate disruption impacts. Specifically, we investigate the following research questions (RQ): RQ1 – How will logistics service uncertainty impact strategic global supply chain design, and how does this impact change under different levels of OFI?

RQ2 – How may the two major supply chain typologies—onshoring and offshoring—leverage the multi-modal transportation service network, and how does OFI influence their ability to exploit modal flexibility?

RQ3 – How does the resilience performance of the logistics service network differentiate among diverse industries and supply chain typologies under uncertainty, and how is this differentiation shaped by OFI alongside product value, deterioration rate, and criticality?

To address these questions, we pay particular attention to key industry properties—product value, deterioration rate, and criticality—and examine how they influence total logistics cost, service performance, and resilience outcomes under varying levels of operational friction.

This study makes three main contributions. First, from a supply chain management

perspective, we model the global single-commodity multimodal freight routing problem under transit-time uncertainty, moving beyond a purely cost-driven view of logistics by emphasizing its role in enabling resilient product flows during disruptions. Second, from a methodological perspective, we develop a robust optimization framework using a budget-of-uncertainty formulation and propose a tailored adaptive large neighborhood search (ALNS) algorithm to solve large-scale, near-real logistics networks that are computationally intractable for exact solvers. Third, to generate actionable managerial insights, we conduct extensive numerical experiments across shoring strategies, industry characteristics, and operational contexts, demonstrating that the relative resilience performance of onshoring and offshoring networks depends not only on disruption severity and product attributes, but also on OFI as a diagnostic indicator that helps explain why similar disruption levels can lead to different operational outcomes.

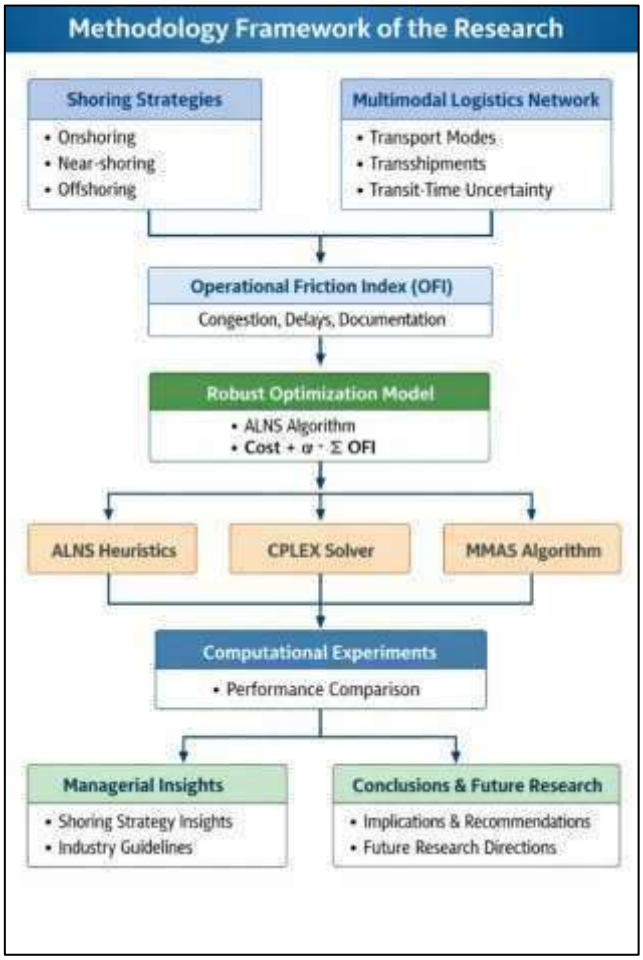



***Figure 1. Integrated Modeling and Solution Framework.***

The framework combines shoring strategies and a multimodal logistics network, defines the Operational Friction Index (OFI) as an operational measure of congestion, transshipments, and documentation delays, integrates OFI into the robust optimization evaluation, and compares solution approaches (ALNS, CPLEX, and MMAS) through computational experiments to produce managerial insights and identify future research directions.

***Table 1: Characteristics of the Selected Industries and Anticipated Effects of Operational Friction on Transport Performance***

| *Industry* | *Product Value* | *Deterioration Rate* | *Criticality* | *Impact of OFI* |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| Pharmaceuticals | High | High | Very High | Very High; disruptions in transport cause delays and loss of product efficacy |
| Fresh Produce | Medium | Very High | High | High; delays and inefficient routes result in product spoilage |
| Fast-Moving Consumer Goods (FMCG) | Medium | Medium | Medium | Medium; transport inefficiencies can lead to higher costs but minimal losses |
| Automotive | High | Low | High | Low to Medium; operational friction has minimal impact on product quality |
| Electronics | High | Low | Very High | Medium to High; delays lead to higher costs but product integrity is preserved |

## ➢ Managerial implications

Table 1 can be translated into simple if-then guidance on when onshoring/near-shoring versus offshoring is likely to be preferred in our computational scenarios.

For pharmaceuticals and electronics (high value and very high criticality), if disruptions are strong and/or operational friction is high (high OFI), then shorter and more controllable networks (onshoring or near-shoring) combined with low-OFI route designs (fewer transfers, less congested hubs, and streamlined documentation) substantially reduce late-delivery penalties and deterioration exposure. If OFI is low and disruption intensity is moderate, offshoring can remain competitive, but performance becomes sensitive to transfers and port/terminal congestion.

For fresh produce (very high deterioration), if OFI is high, then routes with fewer transshipments and shorter total travel time dominate (typically favoring onshoring/near-shoring or direct services) because even small delays cause large spoilage costs. For FMCG and automotive, if disruptions are moderate and OFI is low-to-medium, then offshoring can remain cost-effective because deterioration losses are limited; however, if disruptions become severe and OFI increases, then shifting to near-shoring or redesigning to low-OFI multimodal options becomes preferable to avoid compounding delay penalties.

Despite the significance of this research problem, existing studies rarely analyze shoring strategies from the logistics perspective under uncertainty. This study addresses this gap by presenting evidence from both qualitative and quantitative analyses, highlighting the importance of logistics network resilience for strategic shoring decisions and providing practical tools and managerial insights for real-world decision-making (Fig. 1). The contributions of this paper are highlighted as follows. First, from a practical supply chain management perspective, address the global single-commodity multi-modal freight routing problem (SCMFRP) under transit time uncertainty, moving beyond the common oversimplification of logistics as merely a cost variable by emphasizing its role as the linchpin of resilient product flow during disruptions. Second, from a methodological perspective, develop a robust optimization model with budget-

of-uncertainty for the SCMFRP and propose a tailored adaptive large neighborhood search (ALNS) algorithm for large-scale near-real cases, enabling practical diagnosis and enhancement of resilience in multimodal logistics networks. Third, to generate actionable managerial insights, conduct realistic numerical experiments showing that onshoring and offshoring networks exhibit distinct resilience performance patterns and that their relative superiority shifts with disruption severity and product attributes—while the newly introduced OFI explains why operational contexts can further tilt these trade-offs even when disruption conditions appear similar.

The remainder of this paper is organized as follows. Section 2 provides a brief review of related works. Section 3 describes the SCMFRP under uncertainty and the MILP model. Section 4 focuses on ALNS algorithm design and computational experiments to validate its performance. Section 5 states the case design for numerical experiments to validate the effectiveness of the proposed approach. Section 6 presents observations and insights from sensitivity analysis. Section 7 concludes the work and provides an outlook on future research.

## ➢ Literature review

Overall, few studies jointly consider (i) shoring strategy choices (onshoring vs. offshoring), (ii) multimodal logistics service networks with transshipments, and (iii) robust routing under transit-time uncertainty. In this work, OFI is introduced as a simple diagnostic indicator to explain when similar disruption levels lead to different operational outcomes due to execution frictions.

### *A. Supply Chain Resilience under Operational Friction (OFI)*

Supply chain resilience (SCR) has been studied for decades, and network design under uncertainty remains one of its most intensively investigated themes. The COVID-19 period further reinforced this focus, particularly in vaccine distribution where demand surges and logistics conditions were highly volatile; for example, Mohammadi et al. (2022) developed a bi-objective model balancing service level and costs. Similar uncertainty-driven resilience concerns arise in other time-sensitive sectors, such as blood supply chains after disruptions (Fariman et al., 2024) and food supply chains that combine production-to-supply ratios with transportation connectivity (Poo et al., 2024). These studies collectively highlight that resilience outcomes are industry-dependent, yet the literature has rarely examined SCR through the dual lens of shoring strategy (onshoring vs. offshoring) and multi-modal logistics service networks.

To strengthen this perspective, introduce the Operational Friction Index (OFI) as a diagnostic indicator in the resilience discussion. OFI captures the "day-to-day drag" that accumulates within logistics operations—such as coordination inefficiencies, handling and transshipment frictions, administrative delays, and congestion-like effects—factors that can amplify or dampen how disruptions translate into realized service unreliability. Conceptually, OFI helps diagnose the effect of logistics service uncertainty on SCR outcomes: when operational friction is high, the same disruption intensity is more likely to propagate into larger effective delays, poorer service reliability, and sharper cost–service tradeoffs; when OFI is low, networks can absorb uncertainty more effectively through smoother transfers and better execution. On the diagnosis and assessment side, scholars have proposed diverse transportation-network resilience indicators. Yin et al. (2023) evaluated road network resilience using topological and functional measures (e.g., links and speed), while Bai et al. (2023) integrated topology and traffic flow in a liner shipping context. In decision-support approaches, Sawik and Sawik (2024) proposed a risk-averse tool minimizing CVaR-related total costs while accounting for service level impacts under propagated disruptions. Goodarzi et al. (2024) examined resilience and sustainability for intermodal networks via stochastic programming and demonstrated consolidation benefits for cost reduction. Building on this stream, the present work emphasizes logistics cost and service-level indicators as core resilience

lenses—while OFI provides an additional explanation of why similarly structured networks may display different resilience behavior under the same disruption environment.

Finally, freight transportation research provides a critical foundation for SCR because global supply chains inherently rely on multi-modal movement. While some studies consider single-mode settings (Bai et al., 2023), multi-modal transportation is widely promoted for resource utilization, sustainability, and cost efficiency (Archetti et al., 2022; SteadieSeifi et al., 2014). At the same time, multi-modal systems introduce added complexity—mode selection, transshipment coordination, distinct cost structures, and combinatorial routing alternatives—making resilience assessment more challenging. Recent work reflects these challenges: Chen et al. (2024) used a genetic algorithm for multi-modal route choice under uncertain demand; Song et al. (2023) addressed service mode and routing under road restrictions using a Max-Min Ant-Colony Optimization method; Guo et al. (2024) studied multi-period multi-modal routing and storage decisions under uncertainty and proposed an ALNS-based heuristic with a budget-of-uncertainty. Relatedly, Qi et al. (2022) modeled deterministic capacitated service selection and routing. Differing from these operational emphases, this study adopts a strategic resilience view centered on service levels and cost efficiency under transit time uncertainty, while OFI sharpens the resilience argument by highlighting how operational execution frictions can condition the resilience benefits (or penalties) of different multi-modal designs and shoring configurations.

### *B. Robust optimization*

Uncertainty in logistics planning is commonly addressed via scenario-based stochastic programming or robust optimization (RO). Stochastic programming typically requires distributional information (or reliable scenarios) for uncertain parameters, while RO can work with only a support set (i.e., an interval or uncertainty set) and seeks solutions that remain feasible (and perform well) under worst-case realizations within that set. This is particularly suitable for rare, high-impact disruptions where historical data are scarce or not representative. A key concern in RO is over-conservatism. To balance robustness and performance, many studies adopt structured uncertainty sets; among them, the budgeted uncertainty set (Bertsimas–Sim) is widely used because it: limits how many coefficients can simultaneously hit worst-case values (a realistic assumption for network disruptions), and retains good computational tractability (robust counterparts of linear models stay linear).

In a multimodal service network, disruptions rarely delay all service-arcs at their maximum deviations at the same time. The budget parameter Γ directly controls this realism–conservatism trade-off by bounding the total deviation "mass" across selected arcs.

## ➢ Problem statement and design

### *C. Problem statement*

Consider a shipper (e.g., a manufacturer) that must deliver a set of ready orders from an origin (factory/warehouse) to client cities through a multimodal logistics service network. The network is composed of: city nodes (origins, destinations, and transshipment hubs), and service-arcs representing available transport services between city pairs under a given mode/service. Each order has a due date, and early/late arrivals may incur penalties reflecting service-level loss. Some products also deteriorate/depreciate over time, creating additional time-dependent costs. Hence, the shipper must decide (i) which services to use along a route, (ii) where to transship between services/modes, and (iii) the outbound (dispatch) time of each order to trade off cost and service quality.

This study accept demands and client locations are known, orders are not split, and disruptions are modeled through transit time uncertainty on service-arcs. Specifically,

disruptions are assumed to increase transit times relative to their nominal values (delay-focused worst-case planning). The problem is thus a single-commodity multi-modal freight routing problem (SCMFRP) under transit time uncertainty. The objective is to minimize total distribution cost, including: transportation, transshipment, deterioration/depreciation, and early/late delivery penalties.

***Table 2. List of notations***

| *Category* | *Notation* | *Definition* |
|---|---|---|
| Sets & indices | $\mathcal{N}$ | set of city nodes, $i, j \in \mathcal{N}$ |
| | $\mathcal{C}$ | set of transport services, $c \in \mathcal{C}$ |
| | $\mathcal{A}$ | set of service-arcs, $(c,i,j) \in \mathcal{A}$ |
| | $\mathcal{O}$ | set of orders, $o \in \mathcal{O}$ |
| | $s$ | departure/origin node, $s \in \mathcal{N}$ |
| | $d_o$ | destination (client city) for order $o$, $d_o \in \mathcal{N}$ |
| Parameters | $e_o$ | demand quantity of order $o$ |
| | $l_o$ | due date of order $o$ |
| | $k_{i,j}$ | distance (km) between city nodes $i$ and $j$ |
| | $t^o_{(c,i,j)}$ | transit time of arc $(c,i,j)$ for order $o$ |
| | $t_{(c,i,j)}$ | nominal transit time of $(c,i,j)$ |
| | $\hat{t}_{(c,i,j)}$ | max deviation range of transit time on $(c,i,j)$ |
| | $r(c,i,j)$ | 1 if $(i,j)$ is on the route of service $c$; else 0 |
| | $\xi_c$ | transportation cost per km·tonne by service $c$ |
| | $\lambda_{c,c'}$ | transshipment cost per tonne from service $c$ to $c'$ |
| | $\theta$ | deterioration cost per tonne per day |
| | $\rho$ | early delivery cost per tonne per day |
| | $\tau$ | late delivery cost per tonne per day |
| | $\Gamma$ | budget of transit-time uncertainty |
| Decision variables | $x^o_{(c,i,j)} \in \{0,1\}$ | 1 if order $o$ uses service-arc $(c,i,j)$ |
| | $y_o \geq 0$ | outbound/dispatch time of order $o$ |
| | $u^o_{(c,i,j)} \in [0,1]$ | deviation degree of transit time on $(c,i,j)$ for order $o$ |
| | $z^o_{i,c,c'} \in \{0,1\}$ | 1 if order $o$ transships at node $i$ from $c$ to $c'$ |
| | $k_o, w_o \geq 0$ | early/late time-span auxiliaries |
| | $\alpha_o, \beta^o_{(c,i,j)}$ | dual variables (linearization) |
| | $\psi^o_{(c,i,j)}$ | auxiliary variable (linearization) |

### *D. Mathematical formulation*

Uncertainty set (budgeted uncertainty) For each order $o$, the uncertain transit time of service-arc
$(c, i, j)$ is modeled as $t^{o}_{(c,i,j)} = t^{-}_{(c,i,j)} + u^{o}_{(c,i,j)}\, t^{\wedge}_{(c,i,j)}, \quad (c,i,j) \in \mathcal{A},\ o \in \mathcal{O},$

where the deviation variables satisfy the budgeted uncertainty set

$$\sum_{(c,i,j)\in\mathcal{A}} u^{o}_{(c,i,j)} \le \Gamma, \qquad 0 \le u^{o}_{(c,i,j)} \le 1.$$

This captures "not all arcs are maximally delayed at once," while allowing the decision-maker to tune robustness via $\Gamma$. Robust MINLP model
The robust SCMFRP minimizes total distribution cost:
minimize $\tilde{F} = F + \omega \cdot \Sigma_{k\in K} \Sigma_{a\in A}$ OFI_a x_{ka}.
Here, F is the baseline robust total cost defined by transportation, transshipment, earliness/lateness, and deterioration components, and OFI_a is the arc-level friction score in [0,1]. The weight $\omega \ge 0$ controls the importance of operational friction ($\omega = 0$ recovers the baseline robust model).
with the following components: Transportation cost

$$\Phi_1 = \sum_{o\in\mathcal{O}} \sum_{(c,i,j)\in\mathcal{A}} \xi_c\, k_{i,j}\, e_o\, x^{o}_{(c,i,j)}.$$

Transshipment cost

$$\Phi_2 = \sum_{o\in\mathcal{O}} \sum_{i\in\mathcal{N}} \sum_{\substack{c,c'\in\mathcal{C} \\ c\neq c'}} \lambda_{c,c'}\, e_o\, z^{o}_{i,c,c'}.$$

Earliness/lateness penalty cost

$$\Phi_3 = \sum_{o\in\mathcal{O}} (\rho\, e_o\, k_o + \tau\, e_o\, w_o).$$

Deterioration cost under worst-case transit time

$$\Phi_4 = \theta \sum \max_{o\in\mathcal{O}} e_o\, (y_o + \sum_{t\in\mathcal{T}} \sum_{(c,i,j)\in\mathcal{A}} t^{o}_{(c,i,j)}\, x^{o}_{(c,i,j)}).$$

Equations (3)– (7) follow the cost structure in the robust model definition.
Constraints
Flow conservation at intermediate nodes

$$\sum_{c\in\mathcal{C}} \sum_{i\in\mathcal{N}} x^{o}_{(c,i,j)} = \sum_{c\in\mathcal{C}} \sum_{i\in\mathcal{N}} x^{o}_{(c,j,i)}, \quad \forall o \in \mathcal{O},\ \forall j \in \mathcal{N}\backslash\{s, d_o\}.$$

Exactly one departure from origin and one arrival at destination
$\sum_{c\in\mathcal{C}} \sum_{i\in\mathcal{N}} x^{o}_{(c,s,i)} = 1, \quad \forall o \in \mathcal{O}, \sum_{c\in\mathcal{C}} \sum_{i\in\mathcal{N}} x^{o}_{(c,i,d_o)} = 1, \quad \forall o \in \mathcal{O}.$
Arc feasibility (select only arcs that belong to a service route)

$$x^{o}_{(c,i,j)} \le r(c,i,j), \quad \forall o \in \mathcal{O},\ (c,i,j) \in \mathcal{A}.$$

Transshipment activation

$$z^{o}_{i,c,c'} \ge \sum_{j\in\mathcal{N}} x^{o}_{(c,j,i)} + \sum_{j\in\mathcal{N}} x^{o}_{(c',i,j)} - 1, \quad \forall o,\ i,\ c \neq c'.$$

Earliness/lateness time-span constraints (relative to due date)
$y_o + \max_{t^o} \sum_{(c,i,j)\in\mathcal{A}} x^{o}_{(c,i,j)} - w_o \le l_o + 1,\ \forall o \in \mathcal{O},\ y_o + \max \sum_{(c,i,j)\in\mathcal{A}} t^{o} x^{o} + k_o \le$

$t\in\mathcal{T}$ $(c,i,j)$ $(c,i,j)$ $t\in\mathcal{T}$ $(c,i,j)$ $(c,i,j)$
$l_o$, $\forall o \in \mathcal{O}$.

Domains

$$x^o_{(c,i,j)},\ z^o_{i,c,c'} \in \{0,1\}, \qquad y_o,\ u^o_{(c,i,j)},\ k_o,\ w_o \geq 0.$$

Constraints (8)– (16) match the robust model structure and feasibility requirements. Linearized MILP robust counterpart

The inner maximization in (7), (13), (14) can be dualized to obtain an equivalent

deterministic MILP by introducing dual variables $\alpha_o, \beta^o$ and auxiliary variables $\psi^o$. The resulting

objective replaces $\Phi_4$ with:

$$\Phi_4' = \theta \sum e_o \left[y_o + \Gamma\alpha_o + \sum \left(\bar{t}_{i,j(c,i,j)}\right)x^o\right.$$

and adds linear constraints linking $\alpha, \beta, \psi$ to $x$ and deviations.

### 3.4 ALNS – Adaptive Mechanism

The robust SCMFRP requires selecting routes, services, and transshipment decisions in a large-scale multimodal logistics network, which creates substantial combinatorial complexity. To obtain high-quality solutions within practical runtime limits, we adopt an adaptive large neighborhood search (ALNS) metaheuristic (Ropke and Pisinger, 2006; Mara et al., 2022), which has also shown strong performance in freight routing applications (Zhang et al., 2022a,b; Guo et al., 2024). ALNS iteratively improves an incumbent solution by applying a destroy operator to remove part of the current route/service assignment and then a repair operator to restore feasibility and search for improvements. Operator selection follows an adaptive weighting scheme so that operators that recently led to accepted improvements are selected more often, while all operators retain a nonzero probability to preserve diversification. The overall ALNS framework is summarized in Algorithm 1.

## ➢ Operational Friction Index (OFI)

### *E. Initial path construction and greedy evaluation*

We define the Operational Friction Index (OFI) as a simple, normalized indicator of execution frictions on each service-arc. For an arc $a = (i, j, s)$ used by order $k$ (city $i$ to city $j$ by service $s$), the arc-level friction score $OFI_a$ is a scalar in [0,1], where 0 indicates friction-free execution and 1 indicates severe frictions (e.g., congestion, many transfers, and paperwork delays). Formally, each service-arc $a \in A$ is assigned a nonnegative friction score $OFI_a \in [0,1]$, reflecting congestion, transfer complexity, and documentation delays. For an order $k$, the route-level friction is the aggregation of arc-level frictions along its selected path, given by $\sum_{a\in A} O\ FI_a x_{ka}$, where $x_{ka}$ indicates whether arc $a$ is used by order $k$. This aggregated friction term directly enters the robust objective function through the penalty component $\omega \sum_{k\in K} \sum_{a\in A} O\ FI_a x_{ka}$, ensuring that operational friction influences solution selection within the optimization model.

Operationally, we compute $OFI_a$ as a weighted sum of three normalized components:

$$OFI_a = w_c C_a + w_t T_a + w_d D_a, \quad w_c + w_t + w_d = 1, \quad 0 \le C_a, T_a, D_a \le 1.$$

Here, $C_a$ is a congestion/handling score for arc $a$ ; $T_a$ is a transshipment/coordination score (higher when the route relies on more transfers); and $D_a$ is a documentation/procedural delay score. The weights ($w_c$, $w_t$, $w_d$) reflect managerial priorities; in our experiments we use equal weights as a parsimonious baseline.

For a complete route $R_k$ selected for order $k$ (a sequence of used arcs), the route-level OFI is computed as the average over its used arcs:

$$OFI(R_k) = \frac{1}{|A(R_k)|} \sum_{a \in A(R_k)} OFI_a,$$

where $A(R_k)$ denotes the set of arcs used in route $R_k$.

Note that the route-level indicator $OFI(R_k)$ is fully consistent with the arc-level term $OFI_a$ used in the optimization model, since $OFI(R_k)$ is defined as an aggregation (average) of the arc-level friction scores along the selected route.

In evaluation and search, we incorporate OFI through a simple penalty term added to the robust total cost:

$$\tilde{F} = F + \omega \sum_{k \in K} OFI(R_k), \quad \omega \ge 0,$$

where $F$ is the baseline robust objective value and $\omega$ is a tuning parameter. This preserves a
single objective while making solutions with high operational frictions less attractive; if $\omega = 0$, the model reduces to the baseline robust cost.

Initial feasible paths are generated using a bidirectional breadth-first search between origin and destination nodes. Candidate paths are then evaluated via a greedy service-assignment procedure based on the robust cost components. During this initial construction/evaluation, $OFI(R_k)$ is computed for each candidate route using the above definitions and contributes through the penalty term in $\tilde{F}$.

Once the path construction is complete, the algorithm randomly selects one path from the set of feasible paths generated. Service assignment along the chosen path begins at the initial node, assigning the available service with the lowest potential costs, including transportation service cost, transshipment cost, and deterioration cost associated with the transit time on the service-arc. Notably, the early/late delivery cost is excluded from this calculation during the greedy assignment phase. Given the focus on the worst-case scenario under a budget of uncertainty $\Gamma$: the transit time for each service-arc in the current solution, denoted as $t_{\text{greedy}}$, is estimated by the following equations:

$$t_{\text{greedy}}(c,i,j) = \begin{cases} \bar{t}(c,i,j) + t^{\wedge}(c,i,j)\cdot\frac{\zeta}{\Gamma}, & \text{if } \zeta < \Gamma, \\ \bar{t}(c,i,j) + t^{\wedge}(c,i,j), & \text{if } \zeta \geq \Gamma, \end{cases}$$

where $\zeta$ is the number of service-arcs used in the current solution. Ultimately, a complete path-service solution is constructed at the end of this phase.

Intermediate Decisions

Given a specific path and service selection solution, can identify the worst-case scenario under transit time uncertainty within a budgeted uncertainty set by Proposition 1. The proof of Proposition 1 is provided in Appendix A.

The Operational Friction Index (OFI) is factored into the evaluation of the worst-case scenario for each order , influencing how the solution adapts to changes in the logistical network. OFI helps diagnose solution quality and resilience performance by adding an explicit friction penalty, especially under disruption and operational inefficiencies.

Suggestion 1: For a given solution $x^*$, the worst-case scenario of transit time uncertainty can be determined as follows:

If the uncertainty budget $\Gamma$ satisfies $\Gamma \leq \zeta^*$, where $\zeta^*$ is the number of service-arcs in the solution

$x^*$, then:

The top $\lfloor\Gamma\rfloor$ service-arcs fully deviate (maximize their $u_o(c,i,j)$ $= 1$). The $\lceil\Gamma\rceil$-th service-arc deviates by $t^{\wedge}(c,i,j)\cdot(\Gamma - \lfloor\Gamma\rfloor)$.

If $\Gamma > \zeta^*$, all $u_o(c,i,j)$ in $\mathcal{A}^*$ are set to $1_o$, as $\sum_{u\ (c,i,j)\in\mathcal{A}^*} u_o\ (c,i,j) \leq \Gamma$ is trivially satisfied. The value of $u_o(c,i,j)$ in $\mathcal{A}\backslash\mathcal{A}^*$ would not impact the value of the objective function since $x_o(c,i,j) = 0$ in $\mathcal{A}\backslash\mathcal{A}^*$.

### *F. Destroy Operators*

To keep OFI integration simple and transparent, only selected operators are OFI-aware. In Worst Node Removal (D4), each candidate node $v$ is scored as

$$score(v) = \Delta F(v) + \omega \cdot \Delta OFI(v),$$

where $\Delta F(v)$ and $\Delta OFI(v)$ denote the changes in robust cost and route-level OFI if $v$ is removed. Nodes with larger scores are removed first.

In Service Removal by History Performance (D6), arcs are ranked by

$$score(a) = \Delta F(a) + \omega \cdot OFI_a,$$

where $OFI_a$ is the arc-level friction score.

In Service Insertion by History Performance (R3), candidate services $s$ for a given arc $a$ are

evaluated as

$$score(s \mid a) = cost_contrib(s \mid a) + \omega \cdot OFI_a(s),$$

and the lowest-score service is selected.

We also tested $\omega = 0$ and $\omega = 0.2$. The overall cost trends remained stable, while larger $\omega$ shifted solutions toward fewer high-friction arcs. For brevity, results are reported for $\omega$ $= 0.1$.

### *G. Repair Operators*

The purpose of the repair operators is to ensure that every arc in the incumbent path is assigned an available service, thereby restoring feasibility after the solution has been disrupted by destroy operations. Designed nine repair operators and carried out computational experiments to choose the most effective and efficient operator combinations for solving large-scale cases. The computational results can be found in Appendix B.1. The Operational Friction Index (OFI) is now integrated into the repair operators to enhance the quality of the solutions by considering operational inefficiencies and disruptions. For example: R3 (Service Insertion by History Performance): for a selected arc a, candidate services s are ranked by score(s|a) = cost_contrib(s|a) + ω·OFI_a(s), where cost_contrib(s|a) is the incremental robust cost of inserting s on a and OFI_a(s) is the arc-level friction score under s. The best (lowest-score) service is inserted.

R6 (History Service Insertion): This operator uses historical performance data to select services based on OFI. Services with lower OFI scores, indicating fewer disruptions and inefficiencies, are prioritized for insertion into the path.

These modifications ensure that the repaired solutions are more resilient and efficient by reducing the OFI, leading to better overall performance in the presence of disruptions.

### *H. ALNS – Adaptive Mechanism*

After each iteration, the operator(s) used receive a reward based on whether the candidate solution improves the best-known objective or is accepted. Operator weights are then updated using a standard reaction-factor rule so that operators with better recent performance are selected more frequently, while others retain a nonzero chance to preserve exploration.

Operator selection in ALNS is controlled adaptively. Each destroy/repair operator is assigned a weight, and operators are sampled with probability proportional to their current weights (roulette selection).

### *I.Acceptance and Termination Criteria*

ALNS uses a record-to-record travel (RTR) acceptance rule based on the single augmented objective

$$\tilde{F}(x) = F(x) + \omega \cdot OFI(x),$$

where $F(x)$ is the robust total cost and $\omega > 0$ is a small weight (set to $\omega = 0.1$ in the experiments). A candidate solution $x'$ is always accepted if $\tilde{F}(x') < \tilde{F}(x_{\text{best}})$. Otherwise, it is accepted if

$$\tilde{F}(x') \leq \tau \cdot \tilde{F}(x),$$

where $x$ is the incumbent solution and $\tau \geq 1$ is a tolerance parameter. Larger $\tau$ allows more non-improving moves, while smaller $\tau$ emphasizes intensification.

If two candidates satisfy the above condition with nearly identical $\tilde{F}$ values (difference below 0.5%), the solution with lower route-level OFI is selected as a tie-breaker.

### *J.Algorithm Validation*

Termination is controlled by three stopping rules: a maximum number of iterations, a maximum number of consecutive iterations without improvement, and an optional wall-clock time limit. All benchmarking results report solution gaps and runtime under these fixed settings for reproducibility.

***Table 3: Experimental Settings***

| *Parameter* | *Description* | *Value* |
|---|---|---|
| Number of Instances | Number of problem instances for testing | 45 |
| Time Limit for CPLEX | Time limit for CPLEX optimization solver | 5 hours per instance |
| $\Gamma$ | Budget for transit time uncertainty (defines the deviation range) | 100% to 1000% |
| $\kappa$ | Reaction factor for the adaptive mechanism in ALNS | 0.3 |
| $\rho$ | Threshold for acceptance criterion | 0.1 - 0.9 |
| $OFI_{\text{threshold}}$ | Threshold for Operational Friction Index: Determines when high OFI conditions trigger adjustments in the algorithm | 0.8 (High OFI) |
| Max Path Number | Maximum number of paths allowed in the solution | 50 |
| Max Iterations | Maximum number of iterations in the ALNS algorithm | 1000 |
| $OFI$ in Sensitivity Testing | Incorporation of OFI to assess its effect on solution quality and computational efficiency | Varying from 0.1 to 0.9 |

To assess the performance of the tailored ALNS algorithm, we use 45 instances with a 100 % deviation from Pang et al. (2024). We compare the results obtained from ALNS with those from the MILP model solved by CPLEX and the MMAS.

Table 4. Average gap (%) and runtime (s) of CPLEX, MMAS, and ALNS by instance size

| ***Instance size*** | ***Method*** | ***Avg. gap (%)*** | ***Max gap (%)*** | ***Avg. runtime (s)*** |
|---|---|---|---|---|
| *Small* | CPLEX | 0.00 | 0.00 | 1103 |
| | MMAS | 0.01 | 0.39 | 29 |
| | ALNS | 0.02 | 0.70 | 19 |
| *Medium* | CPLEX | 0.00 | 0.00 | 2504 |
| | MMAS | 0.52 | 3.40 | 160 |
| | ALNS | 0.05 | 0.57 | 75 |
| *Large* | CPLEX | 0.00 | 0.00 | 6202 |
| | MMAS | 0.98 | 11.40 | 314 |
| | ALNS | 0.04 | 0.55 | 136 |

Table 4 reports the solution quality and computational efficiency of the three methods—CPLEX (exact MIP solver), MMAS (metaheuristic), and ALNS (metaheuristic)—aggregated by instance size. For each size class, the table shows: (i) the average optimality gap (Avg. gap, %), (ii) the worst observed gap across runs (Max gap, %), and (iii) the average runtime in seconds.

Across all size categories, CPLEX consistently achieves a 0.00% gap, confirming that it finds optimal solutions for the tested instances. However, its computational burden grows rapidly with instance size: the average runtime increases from 1103 s (Small) to 2504 s (Medium), reaching 6202 s (Large). This trend illustrates the expected scalability limitation of exact optimization when problem size increases.

By contrast, the two heuristics are substantially faster. ALNS is the most stable method in terms of solution quality: its average gap remains very low across all sizes (0.02%, 0.05%, and 0.04% for Small, Medium, and Large, respectively), while its maximum gap stays below 0.70% even for the largest instances. In addition, ALNS maintains short runtimes (from 19 s on Small to 136 s on Large), demonstrating strong scalability and robustness.

MMAS also achieves strong performance, but it shows a clearer trade-off between speed and reliability as size increases. While MMAS is fast on Small instances (29 s on average) and nearly optimal on average (0.01% gap), its performance degrades for Medium and Large instances: the average gap rises to 0.52% and 0.98%, and the maximum gap increases sharply to 3.40% (Medium) and 11.40% (Large). This indicates that MMAS can occasionally produce noticeably weaker solutions on harder instances, even though it remains far faster than CPLEX.

Overall, the table highlights a practical message: CPLEX is best for guaranteed optimality but becomes increasingly time-consuming, whereas ALNS offers the best balance of near-optimal quality and computational efficiency, especially as instance size grows. MMAS remains competitive in speed, but its solution quality is less consistent on large-scale cases.

Each instance was tested five times by both ALNS and MMAS. The performance was evaluated comprehensively based on the best, average, and worst results obtained across the five trials. The running time limit for CPLEX is set as 5h. Appendix Table B.3 presents the comparative results among the MILP by CPLEX, ALNS, and MMAS on the above mentioned 45 instances. While CPLEX solves all 45 test instances optimally, runtime grows prohibitively (5 h for 150 service-arc instances). Nevertheless, for real-world scale networks (e.g., with more than 3000 service arcs in the tested network in Section 5), CPLEX fails to return a solution within 10 h. This computational infeasibility

necessitates efficient metaheuristics for practical implementation.
The Tailored ALNS algorithm proves to be the solution, excelling in both solution quality and computational efficiency: Compared to CPLEX: The average gap of the best solutions found by ALNS is marginally higher, by 0.07 %, while the average solving time of the 5 instances solved by ALNS is much smaller, which is 76 seconds, compared to the 3070 seconds of CPLEX. Compared to MMAS: MMAS presents higher average/best/worst solution gaps compared to ALNS. Moreover, ALNS has proven to be more stable and outperforms MMAS, with an average gap of
0.07 % compared to MMAS's 0.94 %, in the worst-case scenario across five runs per instance.
Regarding solving efficiency, ALNS achieves these results in less time, with an average solving time 92 seconds shorter than that of MMAS. Consequently, the proposed ALNS is established as an efficient, stable, and necessary tool for the practical implementation of approach on real-world supply chain networks.

Table 5: Overall benchmarking summary on 45 instances (100% deviation, five runs per heuristic).

| Method | Quality (gap %) | Avg runtime (s) | Notes |
|---|---|---|---|
| CPLEX (MILP) | 0 (optimal on 45 instances) | 3070 | Time limit: 5 h; becomes infeasible for large-scale networks |
| ALNS (proposed) | 0.07 (avg best gap) | 76 | Stable; close-to-optimal o n tractable instances |
| MMAS | 0.94 (worst-case gap across runs) | 168 | Slower and less stable than ALNS in reported tests |

## ➢ Investigational Design and Analysis

We evaluate the proposed ALNS on 45 benchmark instances adapted from Pang et al. (2024) and compare its performance with CPLEX (exact MILP) and MMAS. Each heuristic is run five times per instance, and we report best/average/worst gaps and runtime.

### *K. Experiment Setup*

We specify the instance sizes, service types, uncertainty-budget settings, and solver limits used in the computational study. CPLEX is run with a 5-hour time limit per instance, and ALNS/MMAS are executed under consistent stopping conditions for a fair comparison.

***Table 6: summarizes the input settings and parameter ranges used in the computational experiments***

| *Parameter* | *Description* | *Value* |
|---|---|---|
| $\mathcal{N}$ | Set of city nodes | 50, 100, 150 nodes |
| $\mathcal{C}$ | Set of transport services | 5 types of services (air, rail, road, maritime, multimodal) |
| $\mathcal{A}$ | Set of service arcs | Varies by network size |
| $t_{(c,i,j)}$ | Transit time for service-arc $(c, i, j)$ | Random values based on real-world data |
| $\hat{t}_{(c,i,j)}$ | Maximum deviation of transit time | Based on uncertainty budget $\Gamma$ |

| | | |
|---|---|---|
| $\xi_c$ | Transportation cost per km·tonne by service $c$ | \$2 - \$15 per km |
| $\lambda_{c,c'}$ | Transshipment cost per tonne product from service $c$ to $c'$ | \$0.5 - \$5 per tonne |
| $\theta$ | Deterioration cost per tonne per day | \$0.1 per tonne per day |
| $\rho$ | Early delivery cost per tonne per day | \$0.2 per tonne per day |
| $\tau$ | Late delivery cost per tonne per day | \$0.3 per tonne per day |
| $OFI_o$ | Operational Friction Index: Represents operational inefficiencies or disruptions | Calculated dynamically based on path service choice and congestion |

Perform two main sets of experiments:
ALNS vs. CPLEX: Compare the performance of the ALNS algorithm with the MILP model solved by CPLEX. The main focus here is to evaluate how well the ALNS algorithm performs in terms of solution quality and computational efficiency, especially when CPLEX struggles to solve larger instances due to its computational complexity.
CPLEX is set to a time limit of 5 hours for each test case. If CPLEX cannot return a solution within this time frame, it is considered infeasible for real-world networks, where the scale can exceed 150 service arcs.
ALNS vs. MMAS (Max-Min Ant Colony System): As an alternative metaheuristic, compare the ALNS algorithm against the Max-Min Ant Colony System (MMAS), which has been shown to work effectively on similar transportation network design problems (Song et al., 2023). This comparison evaluates which algorithm performs better in terms of both solution quality and time efficiency. Each instance is tested five times with both algorithms to account for the inherent randomness in the algorithms' behavior. The results from the multiple trials are averaged to provide a comprehensive assessment.

### *L. Results and Analysis*

The computational results are summarized in **Table 4** (average and maximum optimality gaps and runtimes by instance size). The discussion below highlights the key performance differences among CPLEX, ALNS, and MMAS in terms of solution quality, computational efficiency, and scalability under the tested uncertainty settings:
ALNS vs. CPLEX:
Solution Quality: The ALNS algorithm produces solutions with a very small gap (average 0.07%) compared to CPLEX. While CPLEX can solve smaller instances optimally, it struggles with larger networks (with more than 150 service arcs), where the ALNS algorithm excels in both solution quality and efficiency.
Computational Efficiency: The ALNS algorithm is significantly faster than CPLEX, with an average solving time of 76 seconds per instance, compared to CPLEX's 3070 seconds for the same test cases. This demonstrates that ALNS is more suitable for large-scale supply chain problems.
Impact of OFI: As the OFI increases (indicating higher operational friction), the solution quality tends to decrease, but ALNS maintains resilience by adapting its search strategy to mitigate the effects of OFI. This shows the ALNS algorithm's ability to adapt to operational challenges and improve resilience.
ALNS vs. MMAS:
Solution Quality: The ALNS algorithm outperforms MMAS in both average and worst-case performance. The OFI-aware adaptation mechanism in ALNS allows it to better handle disruptions, leading to more stable and higher-quality solutions across multiple trials.
Computational Efficiency: The ALNS algorithm is more computationally efficient than MMAS, with an average solving time 92 seconds shorter than MMAS for the same test instances. This indicates that ALNS strikes a better balance between efficiency and solution quality, especially when the OFI is high.

### *M. Sensitivity Analysis*

A sensitivity analysis is conducted to understand how the OFI influences the solution quality and efficiency of the ALNS algorithm.

| Sensitivity Factor | Description | Low Value | High Value |
|---|---|---|---|
| $\Gamma$ | Budget for Transit Time Uncertainty (affects path flexibility) | 100% | 1000% |
| $K$ | Reaction Factor in ALNS | 0.1 | 1.0 |
| $OFI_{impact}$ | Operational Friction Index Impact | 0.1 | 0.9 |
| $\rho$ | Acceptance Criterion Threshold | 0.1 | 0.9 |
| $\omega_n, \omega_m$ | Operator Weighting Factors (Destroy & Repair Operators) | 0.05 | 0.9 |

***Figure 2: Sensitivity analysis parameter ranges for the ALNS algorithm***

test the algorithm under different levels of OFI, simulating both high and low friction conditions in the logistics network.

Low OFI (Efficient Network): When the network operates with low OFI, the ALNS algorithm quickly converges to a near-optimal solution with minimal operational disruptions. The computational efficiency is high, and the solution quality is close to the optimal result.

High OFI (Disrupted Network): When the network experiences high OFI, indicating significant operational inefficiencies or disruptions, the ALNS algorithm takes longer to converge, and the solution quality decreases slightly. However, the algorithm still adapts by selecting operators that reduce OFI and improve resilience, making it highly effective for disrupted network conditions.

### *N. Discussion*

The results demonstrate that the ALNS algorithm is robust to variations in OFI and adapts well to disruptions in the logistics network. The incorporation of OFI into the algorithm allows it to prioritize solutions that reduce operational friction, making it more resilient and efficient in uncertain environments. While CPLEX excels at solving small-scale instances optimally, the ALNS algorithm is better suited for larger, real-world networks where computational efficiency is crucial.

The OFI-aware enhancements in ALNS give it a clear advantage over MMAS in terms of both solution quality and computational efficiency. The ALNS algorithm consistently outperforms MMAS in all tested cases, proving its capability to handle large-scale supply chain problems with operational disruptions.

## ➢ Conclusion

This study proposes a robust optimization model for multimodal freight routing under budgeted transit-time uncertainty and an ALNS-based solution approach that incorporates OFI as a parsimonious indicator of execution frictions. In computational experiments, the heuristic achieves near-optimal solutions on tractable instances with substantially lower runtimes than an exact solver, and it scales to larger network sizes where exact optimization becomes impractical. The analysis suggests that the relative attractiveness of onshoring/near-shoring versus offshoring depends jointly on disruption severity, product characteristics, and operational friction levels. A limitation is that OFI is modeled as a simplified index rather than being calibrated from detailed operational data; improving calibration and validating the indicator in real implementations will be a subject of future research.

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