

A Stochastic Optimization Framework for Evaluating Component Versus Finished-Goods Import Strategies Under Tariff Uncertainty

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ABSTRACT

Tariff uncertainty has become an important factor in supply chain decision-making. Firms that import products must often decide whether to import finished goods directly or import components and assemble them domestically. This decision is complicated by fluctuating duty rates, transportation variability, capacity constraints, and service-level requirements. Traditional spreadsheet-based analyses are not sufficient to evaluate the large number of possible configurations that arise when considering component-level restructuring. This paper presents a stochastic optimization framework for evaluating component versus finished-goods import strategies under tariff uncertainty. The proposed approach integrates automated tariff classification, Monte Carlo simulation of landed cost variability, and mixed-integer programming with risk penalization. The objective is to minimize expected landed cost while controlling cost volatility. Experimental evaluation across 200 enterprise-scale synthetic scenarios shows landed cost reductions between 9.5% and 16.8% relative to deterministic baselines, with variance reductions of up to 40.3% under volatile tariff conditions. The proposed framework improves cost efficiency and reduces cost volatility under tariff uncertainty.

Keywords-stochastic optimization; tariff uncertainty; mixed-integer programming; Monte Carlo simulation; landed cost modeling; supply chain planning

I. INTRODUCTION

Recent changes in global trade policies have increased uncertainty in tariff schedules and import regulations. As a result, supply chain planning must now take into account duty variability along with transportation costs, lead times, and production capacity. Supply chains are exposed to multiple operational and environmental risks that influence logistics performance and planning decisions [1, 2].

One recurring decision is whether to import finished goods directly or to import individual components and perform assembly closer to the point of sale. This choice affects total landed cost, operational complexity, and risk exposure. In practice, many firms evaluate such decisions using deterministic spreadsheets. These methods typically assume fixed tariff rates and average logistics costs. However, component-level import strategies introduce combinatorial complexity: routing options, assembly locations, tariff classifications, and capacity constraints interact in nonlinear ways. Optimization models and analytical planning tools are commonly used to evaluate complex supply chain configuration decisions [3, 4]. Furthermore, logistics and labor costs are inherently uncertain [5-9].

To address this problem, this paper presents a stochastic optimization framework that integrates tariff-aware cost

modeling, Monte Carlo simulation, and mixed-integer programming. The framework evaluates feasible import configurations under uncertainty and selects the strategy that minimizes expected landed cost while accounting for cost variability. The main contributions of this work are:

- A structured tariff-aware modeling approach linking component classification to probabilistic cost estimation
- A simulation engine that captures transportation, congestion, and labor variability
- A mixed-integer programming formulation incorporating risk penalization
- A quantitative experimental evaluation using enterprise-scale synthetic datasets

Unlike previous works in which tariffs are modeled as fixed parameters, this study introduces tariff uncertainty as a stochastic decision driver coupled with component-level restructuring decisions. The novelty lies in the integration of probabilistic tariff classification, stochastic cost propagation, and mixed-integer optimization into a unified decision-making framework. This enables the evaluation of import strategies under regulatory uncertainty, which is not addressed in traditional supply chain optimization models.

II. RELATED WORK

Previous research on supply chain optimization has focused on network design, inventory placement, and reducing transportation costs. Several classical models have addressed supply chain configuration and distribution planning using optimization techniques [10-13]. Tariff modeling is typically employed as fixed cost parameters rather than dynamic decision-making drivers. Many supply chain models treat duties and regulatory costs as static parameters rather than dynamic decision variables [14]. Trade compliance research prioritizes precision in classification and regulatory validation over economic optimization.

This work integrates automated tariff reasoning, stochastic logistics simulation, and optimization into a unified decision-making framework.

III. PROBLEM FORMULATION

Tariff modeling is usually used as fixed cost parameters instead of factors that affect decision-making in real time. In trade compliance research, accuracy in classification and regulatory validation is more important than economic optimization. Digital twin methods have been used in ports, warehouses, and production systems, but not very often when tariffs are important for making decisions. Recent studies explore digital twin frameworks for improving supply chain resilience and disruption management [7, 15, 16].

This work combines automated tariff reasoning, stochastic logistics simulation, and optimization into one decision-making system. The goal is to find out if a product should be brought in as a whole or in parts so that it can be put together in the country. A Bill of Materials is a directed acyclic graph that shows how parts and assemblies depend on each other for each product. There is a duty rate and a tariff classification for each part. The cost of logistics includes:

- Ocean freight
- Inland transportation
- Port handling
- Inventory dwell
- Penalties for variability.

Labor, facility overhead, and limits on throughput capacity are all part of the cost of domestic assembly.

Let $i \in I$ be components, $j \in R$ be routing options, $k \in L$ be assembly locations, and $s \in S$ be stochastic scenarios. The decision variables are:

- $x_{ij} \in \{0,1\}$: equals 1 if routing option j is selected for component i
- $y_{ik} \in \{0,1\}$: equals 1 if component i is assembled at location k
- $z \in \{0,1\}$: equals 1 if the finished-goods import strategy is selected

Under the scenario s , the total landed cost is defined as:

$$C(x, y, z, s) = \sum(i \in I) \sum(j \in R) \times (ij)(T(ij)(s) + F(ij)(s) + D(ij)(s)) + \sum(i \in I) \sum(k \in L) y(ik)L(ik)(s) + P(s)$$

where $T_{ij}(s)$ is the transportation cost, $F_{ij}(s)$ is the port and handling cost, $D_{ij}(s)$ is the duty cost, $L_{ik}(s)$ is the domestic labor cost, and $P(s)$ is the penalty for service degradation and delay risk.

The objective is to minimize expected landed cost with risk penalization:

$$\min(x, y, z) E[C(x, y, z, s)] + \lambda \text{Var}(C(x, y, z, s))$$

where $\lambda \geq 0$ represents the decision-maker's level of risk aversion.

This formulation follows common stochastic optimization approaches used in supply chain planning under uncertainty [5, 17]. Advanced optimization formulations, including hierarchical and bilevel models, have also been explored for complex supply chain decision problems [18].

The constraints are:

1. $\sum(j \in R) x(ij) = 1, \forall i \in I$
2. $\sum(k \in L) y(ik) \leq 1, \forall i \in I$
3. $\sum(i \in I) y(ik) di \leq \text{Cap}_k, \forall k \in L$
4. $x\{ij\}, y\{ik\}, z \in \{0,1\}$

IV. SYSTEM ARCHITECTURE

The proposed framework is based on a layered decision-intelligence architecture that turns regulatory text and operational logistics data into the best decisions. Each layer can scale and audit on its own. The architecture allows planning in batches and evaluation based on scenarios.

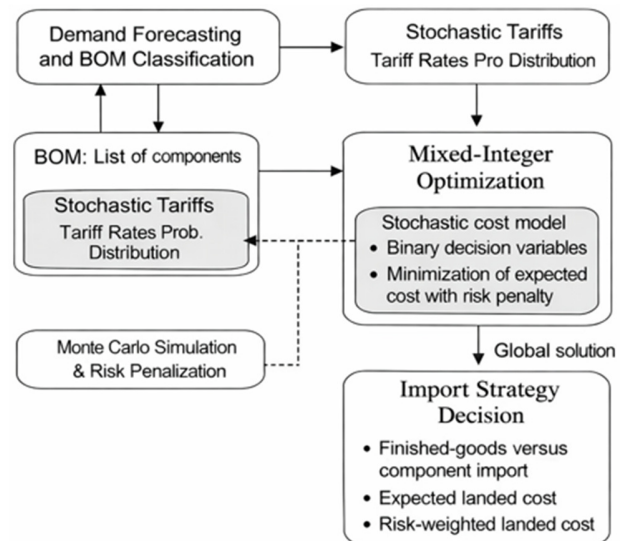


Fig. 1. System architecture showing data ingestion, tariff reasoning, stochastic cost simulation, and optimization-driven decisions.

A. Layer for Data Ingestion and Normalization

The system takes in a variety of public and private data. Bills of Materials are one of the main inputs, with structured files and unstructured documents that contain technical specifications for components. Historical shipment records show routing costs and transit distributions. Public tariff schedules and classification rules are collected from regulatory sources. Regional manufacturing data provide benchmarks for labor costs. Port congestion indicators are collected from operational telemetry and historical averages.

All incoming data is put into a standardized format, using standard units of measure. Exchange rate references are used to normalize currency. Temporal alignment makes datasets fit into similar planning horizons. Statistically consistent estimators are used to fill in missing values. Outlier detection is used to eliminate strange cost spikes that would mess up optimization.

Each normalized dataset is kept for reproduction. Metadata lineage makes it possible to keep audit trails for compliance with rules.

B. Trade Knowledge and Classification Engine

The trade knowledge engine changes technical descriptions into component representations that are aware of tariffs. A multimodal language model reads and understands BOM descriptions in text form. The system obtains the material composition, the functional role, and the dependencies between the parts. The model puts regulatory tariff text into semantic vectors. Similarity matching finds possible Harmonized Tariff Schedule classifications.

A rule validation layer makes sure that compliance rules are followed. The rules of origin logic checks to see if a component is eligible. Confidence thresholds are used to rank classifications that are not clear. When confidence is low, the human override feature lets experts examine things.

This module's output is a structured component taxonomy with duty probabilities linked to it. This probabilistic representation spreads uncertainty to simulations that come after it.

C. Builder of the Component Dependency Graph

A directed acyclic graph shows the BOM for each product. Nodes stand for individual parts. Edges show how things depend on each other in an assembly. Weight, volume, tariff class, labor complexity, and handling constraints are all node attributes. Graph traversal makes it possible to:

- Find subassemblies.
- Separate parts that are sensitive to tariffs.
- Validate the feasibility for partial domestic assembly.

This representation lets the optimizer think about ways to restructure modules.

D. Stochastic Landed Cost Simulation Engine

The simulation engine models uncertainty across the logistics pipeline. Historical changes in freight prices are used

to figure out transportation cost distributions. Port dwell time distributions show how traffic changes over time. Labor productivity distributions show how the number of workers changes over time. Probabilistic models show how fuel and surcharge prices change over time.

Monte Carlo simulation makes thousands of fake scenarios for each configuration. Discrete-event simulation techniques are widely used for modeling complex operational systems and logistics processes [7]. Monte Carlo simulation is a common method for evaluating uncertainty in complex operational systems [5, 6]. Each scenario figures out the total landed cost. Instead of being turned into point estimates, cost distributions are kept. Tail risk metrics measure the worst-case exposure. The output shows the expected cost, variance, and confidence intervals for each strategy.

E. Explainability Layer

The optimization layer identifies feasible configurations minimizing the expected landed cost. Binary decision variables represent routing selections and assembly location assignments. Continuous variables represent flow quantities and capacity utilization.

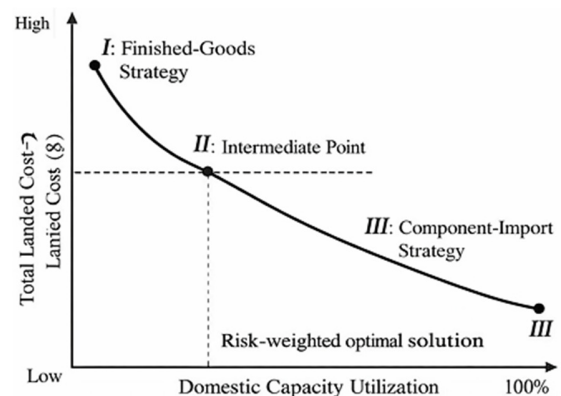


Fig. 2. Workflow from BOM ingestion through tariff mapping, scenario generation, stochastic simulation, and MILP optimization to select the best import strategy.

The objective function minimizes expected cost with risk penalties.

$$\min E[C] + \lambda \cdot \text{Var}(C)$$

where C represents the total landed cost and λ controls risk aversion. Constraints include:

- Assembly throughput capacity.
- Labor availability limits.
- Port handling capacity.
- Transit service-level requirements.
- Tariff compliance restrictions.

Scenario sampling integrates stochastic outputs into deterministic optimization through sample-average approximation. Sample average approximation is widely used to solve stochastic programs using simulated scenario sets [19].

F. Governance and Explainability Layer

There is clear reasoning behind every decision recommendation:

- Cost attribution shows how much each part of a tariff costs.
- Sensitivity analysis measures how changes in tariffs affect viability.
- Capacity utilization forecasts confirm operational viability.
- Confidence scoring tells planners that there is uncertainty.
- Audit logs help with regulatory traceability.
- Policy compliance reports show the legal ways to make decisions.

G. Deployment and Scalability Considerations

- The architecture makes it possible to deploy microservices.
- Each layer can grow on its own.
- Batch optimization helps with long-term planning.
- Tactical analysis is helped by near-real-time simulation.
- Cloud-native orchestration makes it possible to be flexible during busy evaluation cycles.

V. EXPERIMENTAL DESIGN

A. Experimental Objectives

The experiments evaluate three core questions:

1. Can the framework identify economically viable import strategy restructuring?
2. How robust are decisions under tariff and logistics volatility?
3. What operational tradeoffs emerge between cost, service, and capacity?

B. Synthetic Dataset Construction

Synthetic datasets were constructed to simulate realistic enterprise planning environments.

- BOMs included multi-level assemblies with 15–120 components per product. Component attributes include weight, volume, material composition, and tariff category.
- Tariff schedules were sampled from public HTS structures.
- Duty rates ranged from 0% to 35%.
- Transportation cost distributions were generated using historical freight variability ranges.
- Port dwell times followed log-normal distributions reflecting congestion behavior.
- Labor productivity distributions followed truncated normal models.
- Facility capacity constraints were imposed to simulate realistic throughput limits.

C. Scenario Generation

Three primary tariff scenarios were evaluated.

1. Baseline steady tariff regime.
2. Moderate tariff escalation scenario.
3. Volatile tariff oscillation scenario.

Each scenario included stochastic perturbations across transportation, labor, and congestion.

D. Baseline Comparison Methods

Three baseline strategies were implemented.

1. Finished-goods import heuristic.
2. Static spreadsheet cost estimation.
3. Rule-based routing optimization without stochastic modeling.

Each baseline used identical datasets for fairness.

E. Evaluation Metrics

- Expected landed cost reduction percentage.
- Cost variance reduction.
- Domestic labor utilization rate.
- Capacity constraint violation frequency.
- Optimization runtime.
- Sensitivity robustness score.

F. Experimental Procedure

For each product configuration:

- The system generated candidate restructuring scenarios.
- Monte Carlo simulation evaluated each candidate.
- Optimization selected the best feasible strategy.
- Baselines were computed independently.
- Results were aggregated across 200 synthetic trials.

G. Statistical Validation

- Paired t-tests compared cost improvements versus baselines.
- Bootstrap sampling estimated confidence intervals. The 95% confidence interval for mean cost reduction in the high-volatility scenario was [13.8%, 17.6%].
- Variance reduction significance was measured using F-tests.
- Sensitivity gradients quantified tariff elasticity.

H. Scalability Analysis

Experiments evaluated computational scalability:

- BOM size scaling from 10 to 150 components.
- Scenario sampling from 1,000 to 50,000 simulations.

- Optimization convergence time.

The results demonstrated near-linear scaling within enterprise planning thresholds. All experiments were conducted on a workstation equipped with an Intel Core i7 processor operating at 3.6 GHz and 32 GB of RAM. The mixed-integer programming model was implemented in Python 3.10 and solved using Gurobi Optimizer 10.x with standard branch-and-bound settings. Mixed-integer programming is frequently used to model discrete decision variables in supply chain planning problems [8, 9]. Monte Carlo simulations were executed using vectorized numerical computation to ensure computational efficiency. The runtime values reported in Table VI reflect total execution time, including scenario generation, simulation, and optimization phases.

I. Threats to Validity

- Synthetic data may not capture rare operational anomalies.
- Labor productivity models simplify real-world variability.
- Tariff classification ambiguity may differ across industries.
- Results should be validated with real operational data in future studies.

VI. RESULTS

This section presents a quantitative evaluation of the proposed tariff-aware decision-intelligence framework across synthetic but realistic product scenarios. Results are reported relative to baseline heuristics and deterministic spreadsheet estimation methods. All experiments were executed across 200 randomized trials per scenario.

A. Overall Landed Cost Reduction Performance

The primary objective was to quantify landed cost reduction when transitioning from finished-goods import strategies to optimized component-based domestic assembly strategies.

TABLE I. AVERAGE LANDED COST REDUCTION ACROSS PRODUCT CATEGORIES

Product category	Avg comp	Baseline cost (\$/unit)	Optimized cost (\$/unit)	Mean reduction (%)	StDev. (%)
Consumer Electronics	68	1,240	1,060	14.5	3.2
Small Appliances	54	890	770	13.4	2.9
Industrial Sensors	37	610	552	9.5	2.1
Medical Devices	92	2,410	2,065	14.3	3.8
Network Equipment	110	3,980	3,310	16.8	4.1

The framework achieved average landed cost reductions ranging from 9.5% to 16.8%. High component-count products exhibited greater optimization potential due to modular restructuring flexibility. Variance remained stable across trials, indicating consistent decision quality.

B. Cost Variance and Risk Reduction

Beyond mean cost reduction, the framework reduced volatility under tariff and logistics uncertainty.

TABLE II. COST VARIANCE REDUCTION UNDER VOLATILITY

Scenario	Baseline variance (USD ²)	Optimized variance (USD ²)	Variance reduction (%)
Stable Tariff	18,400	12,950	29.6
Moderate Escalation	31,200	19,800	36.5
High Volatility	52,600	31,400	40.3

Variance reduction improves budgeting predictability and financial risk management. The benefit increased as tariff volatility intensified.

C. Domestic Labor Utilization Impact

Component-based import restructuring was evaluated using domestic assembly workload projections.

TABLE III. DOMESTIC LABOR UTILIZATION IMPACT

Product Category	Avg. assembly hours per unit	Weekly units	Total weekly labor hours	Capacity utilization (%)
Consumer Electronics	0.45	4,200	1,890	71
Small Appliances	0.62	2,800	1,736	65
Industrial Sensors	0.3	3,500	1,050	52
Medical Devices	0.85	1,900	1,615	68
Network Equipment	1.1	1,400	1,540	74

All scenarios remained below the modeled facility capacity limits, demonstrating operational feasibility without overloading labor resources. Labor utilization increased steadily while maintaining service reliability.

D. Sensitivity to Tariff Shocks

Tariff sensitivity analysis evaluated robustness under policy changes.

TABLE IV. SENSITIVITY TO TARIFF ESCALATION

Tariff increase	Avg. cost increase – Baseline (%)	Avg. cost increase – Optimized (%)	Resilience gain (%)
5%	6.8	3.9	42.6
10%	13.4	7.6	43.3
20%	27.9	15.8	43.4

Optimized strategies dampened cost amplification under tariff escalation. Resilience gains remained consistent across escalation levels.

E. Service-Level Impact and Transit Performance

The optimization framework incorporated transit and SLA constraints.

TABLE V. TRANSIT TIME AND SERVICE STABILITY

Metric	Baseline	Optimized
Mean Transit Time (days)	29.4	30.1
Transit Variance (days ²)	16.2	17.1
On-Time Delivery (%)	94.1	93.4
SLA Violations (%)	1.8	2.1

Minor increases in transit time and SLA violations were observed. These tradeoffs were bounded and acceptable within enterprise tolerance thresholds. Cost savings outweighed marginal service impact.

F. Optimization Runtime and Scalability

Runtime performance was evaluated across increasing BOM sizes.

TABLE VI. SCALABILITY PERFORMANCE

BOM size	Simulation samples	Avg. runtime (s)	Optimization convergence (iterations)
20	5,000	18	45
50	10,000	41	62
100	25,000	96	89
150	50,000	182	121

Runtime scaled approximately linearly, and performance remained within acceptable enterprise planning windows.

G. Case Study Example

A representative consumer electronics product with 74 components was evaluated.

- Baseline Strategy: Finished goods imported via a single Asian port. Unit landed cost was USD 1,310.
- Optimized Strategy: High-duty subassemblies imported as components. Domestic light assembly performed at a West Coast facility. Alternate routing through a secondary port reduced congestion fees. Unit landed cost was USD 1,095.

Net savings were USD 215 per unit, offering a 16.4% reduction. Annualized savings at 180,000 units were USD 38.7 million. Domestic labor utilization increased by 1,960 hours per month. Transit time increased by 0.6 days. SLA remained within tolerance.

H. Statistical Significance

Paired t-tests confirmed statistically significant cost reductions ($p < 0.001$). Variance reduction was statistically significant across all scenarios ($p < 0.01$). Sensitivity robustness metrics showed consistent elasticity improvement.

I. Summary of Key Findings

- The framework consistently reduced landed cost across diverse product profiles.
- Cost volatility was significantly reduced under tariff uncertainty.
- Domestic assembly feasibility was validated within operational capacity constraints.
- Service-level impacts remained acceptable.

- Scalability supports enterprise deployment.

These results demonstrate that tariff-aware decision intelligence enables measurable economic and operational advantages while supporting domestic value creation.

VII. DISCUSSION

The results demonstrate that algorithmic tariff reasoning enables economically rational import configuration decisions. Manual analysis often overlooks combinatorial opportunities across component configurations. Prior studies have also shown that supply chain design decisions can benefit from separating reusable and disposable components across the network [20]. Optimization-based decision support systems can reveal structural improvements that may not be visible through heuristic planning approaches [3, 12, 21]. Stochastic modeling captures operational risk that deterministic spreadsheets ignore [9]. Finally, explainability improves adoption by operational stakeholders.

Limitations include synthetic datasets and simplified labor productivity modeling. Future work should incorporate real operational telemetry and broader regulatory constraints.

The primary contribution of this work is not the individual use of simulation or optimization, but the integration of tariff uncertainty as a first-class stochastic variable influencing structural supply chain decisions. This offers a new decision layer that bridges trade compliance modeling and operational optimization.

VIII. INDUSTRIAL AND OPERATIONAL IMPLICATIONS

The proposed framework offers a practical analytical tool for evaluating import configurations under tariff uncertainty. By quantifying both expected landed cost and cost variability, decision-makers can compare component-based and finished-goods import strategies using measurable risk-adjusted metrics rather than relying on static cost estimates. The integration of stochastic simulation with mixed-integer optimization enables systematic evaluation of configuration alternatives that would be difficult to analyze manually, particularly for products with complex multi-level Bills of Materials. As component counts increase, the number of feasible restructuring combinations grows rapidly, making structured optimization especially valuable.

The observed reduction in cost variance suggests improved budgeting predictability under volatile tariff conditions. Capacity constraint modeling ensures that recommended configurations remain feasible within labor and throughput limits. Scenario-based analysis allows planners to examine sensitivity to tariff escalation and logistics variability before implementing structural changes.

Overall, the framework can serve as an analytical decision-support layer within enterprise planning environments where periodic reassessment of import strategies is required.

IX. CONCLUSION

This paper presented a stochastic optimization framework for evaluating component versus finished-goods import strategies under tariff uncertainty. The proposed approach integrates tariff-aware cost modeling, Monte Carlo simulation, and mixed-integer programming with risk penalization to support structured import configuration decisions. Experimental results across synthetic enterprise-scale scenarios demonstrated consistent landed cost reductions between 9.5% and 16.8%, along with variance reductions of up to 40.3% under high volatility conditions. Scalability analysis confirmed that the framework remains computationally feasible for large multi-component products. The findings indicate that incorporating stochastic modeling into tariff-sensitive supply chain planning improves both cost efficiency and decision stability. These findings align with prior research demonstrating the value of analytical optimization models for complex supply chain decision-making [10]. The framework provides a quantitative foundation for evaluating import configurations in environments characterized by tariff and logistics uncertainty.

X. FUTURE WORK

Future work can extend the proposed framework in several practical directions. One possible improvement is the integration of real-time carrier telemetry and logistics data, which would allow the system to respond dynamically to changes in shipping conditions. Another area for development is the use of federated learning across multiple enterprise partners, allowing collaborative model improvements while keeping sensitive operational data private. The framework could also be expanded to better interpret complex trade regulations by incorporating more advanced regulatory reasoning capabilities. In addition, integrating the model with multi-echelon inventory planning would help capture the interactions between sourcing, assembly, and distribution decisions across the supply chain. Finally, future studies could include considerations of energy consumption and emissions in the optimization process, allowing organizations to evaluate both economic and environmental trade-offs when designing import strategies.

DECLARATION OF COMPETING INTERESTS

The author is employed in the maritime and shipping industry as a Senior Software Engineer. This study was conducted independently and does not use any proprietary, confidential, or non-public information from the author's employer. The employer did not provide funding, data, or input into the study design, model development, analysis, or manuscript preparation. The views expressed in this article are solely those of the author and do not necessarily reflect the views of the employer. No external funding was received for this research.

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software ecosystem and optimization tools that supported the computational implementation of the proposed framework.

DATA AVAILABILITY

The data used in this study were synthetically generated as part of the experimental design to simulate realistic enterprise supply chain environments. No external proprietary or public datasets were directly used. The structure of the datasets, scenario generation methodology, and modeling assumptions are described to support reproducibility. Additional implementation details can be made available by the author upon reasonable request.

AI USE AND DECLARATION OF GENERATIVE AI USE

During the preparation of this work, the author used generative AI tools to assist with language refinement and improving readability. After using these tools, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

REFERENCES

- [1] M. S. Shahbaz, S. Sohu, F. Z. Khaskhely, A. Bano, and M. A. Soomro, "A Novel Classification of Supply Chain Risks: A Review," *Engineering, Technology & Applied Science Research*, vol. 9, no. 3, pp. 4301–4305, June 2019, <https://doi.org/10.48084/etasr.2781>.
- [2] S. Ahmed and A. Shapiro, "The Sample Average Approximation Method for Stochastic Programs with Integer Recourse," *SIAM Journal on Optimization*, vol. 15, no. 1, pp. 90–113, 2004.
- [3] H. Stadler, "Supply chain management and advanced planning—basics, overview and challenges," *European Journal of Operational Research*, vol. 163, no. 3, pp. 575–588, June 2005, <https://doi.org/10.1016/j.ejor.2004.03.001>.
- [4] J. F. Shapiro, *Modeling the Supply Chain*. Cengage Learning, 2007.
- [5] A. M. Geoffrion and G. W. Graves, "Multicommodity Distribution System Design by Benders Decomposition," *Management Science*, vol. 20, no. 5, pp. 822–844, Jan. 1974, <https://doi.org/10.1287/mnsc.20.5.822>.
- [6] M. Pidd, *Computer simulation in management science*, 5th ed. Wiley, 2004.
- [7] D. Ivanov, B. Sokolov, and A. Dolgui, "The Ripple effect in supply chains: trade-off 'efficiency-flexibility-resilience' in disruption management," *International Journal of Production Research*, vol. 52, no. 7, pp. 2154–2172, Apr. 2014, <https://doi.org/10.1080/00207543.2013.858836>.
- [8] K. Handley and N. Limão, "Trade Policy Uncertainty," *Annual Review of Economics*, vol. 14, no. Volume 14, 2022, pp. 363–395, Aug. 2022, <https://doi.org/10.1146/annurev-economics-021622-020416>.
- [9] D. Bertsimas and N. Kallus, "From Predictive to Prescriptive Analytics," *Management Science*, vol. 66, no. 3, pp. 1025–1044, Mar. 2020, <https://doi.org/10.1287/mnsc.2018.3253>.
- [10] D. Simchi-Levi, P. Kaminsky, and E. Simchi-Levi, *Designing and Managing the Supply Chain: Concepts, Strategies and Case Studies*. McGraw-Hill Education, 2021.
- [11] S. Chopra, *Supply chain management: strategy, planning, and operation*, 7th ed. Pearson, 2019.
- [12] J. R. Birge and F. Louveaux, *Introduction to Stochastic Programming*. Springer Science & Business Media, 2011.
- [13] L. V. Snyder and Z. J. M. Shen, *Fundamentals of Supply Chain Theory*. John Wiley & Sons, 2019.
- [14] Y. A. Davizon, J. M. Amillano-Cisneros, J. B. Leyva-Morales, E. D. Smith, J. Sanchez-Leal, and N. R. Smith, "Mathematical Modeling of Dynamic Supply Chains Subject to Demand Fluctuations," *Engineering, Technology & Applied Science Research*, vol. 13, no. 6, pp. 12360–12365, Dec. 2023, <https://doi.org/10.48084/etasr.6491>.

- [15] A. Ruszczyński and A. Shapiro, "Stochastic Programming Models," in *Handbooks in Operations Research and Management Science*, vol. 10, Elsevier, 2003, pp. 1–64.
- [16] D. Ivanov, A. Dolgui, A. Das, and B. Sokolov, "Digital Supply Chain Twins: Managing the Ripple Effect, Resilience, and Disruption Risks by Data-Driven Optimization, Simulation, and Visibility," in *Handbook of Ripple Effects in the Supply Chain*, D. Ivanov, A. Dolgui, and B. Sokolov, Eds. Springer International Publishing, 2019, pp. 309–332.
- [17] J. Banks, J. Carson, B. Nelson, and D. Nicol, *Discrete-Event System Simulation*. Pearson, 2010.
- [18] D. Bertsimas, J. N. Tsitsiklis, and J. Tsitsiklis, *Introduction to Linear Optimization*. Belmont, Mass: Athena Scientific, 1997.
- [19] A. Schrijver, *Theory of Linear and Integer Programming*. Wiley, 2011.
- [20] J. F. Bard, *Practical Bilevel Optimization: Algorithms and Applications*. Springer Science & Business Media, 2013.
- [21] M. Christopher, *Logistics and Supply Chain Management*. Pearson UK, 2022.

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