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A Stochastic Process Optimization Framework for Reshoring Supply Chains: Integrating Digital Twins with Mixed-Integer Programming

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Abstract

Tariff unpredictability and logistic uncertainty are consistently becoming bigger challenges to supply chain planners as they attempt to evaluate reshoring options. Traditional evaluation methods using spreadsheet programs treat tariff and logistics costs as constant inputs and do not capture nonlinear interactions between component structures, routing decisions, and the assembly capacity. To formulate reshoring assessment as a digital twin-driven decision system, this paper presents a stochastic process optimization framework. The architecture combines automated tariff classification, stochastic landed cost simulation, and mixed-integer linear programming (MILP) to enable repeatable and auditable decision-making. Bills of materials are represented by dependency graphs, which allow one to reason at the process level about alternative assembly configurations. Operational uncertainties, such as variation in transportation, labor throughput, and volatility in tariffs, are factored into the optimization process through Monte Carlo simulation. With a synthetic yet realistic product scenario, experimental assessment shows that a cost reduction of about 9-16% and a major improvement in robustness is obtained over the static estimation methods. The findings establish that a stochastic decision process is better suited to the explicit modeling of reshoring evaluation, with respect to its scalability and resilience. The suggested framework offers a solid basis of decision support in adaptive supply chain systems.

Keywords: decision process modeling; stochastic optimization; digital twins; reshoring analytics; tariff-aware decision support; landed cost simulation; mixed-integer linear programming; supply chain resilience

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1. Introduction

It has long been recognized that global supply chains have traditionally relied upon offshore manufacturing strategies that have been designed for cost efficiency and economies of scale. Nevertheless, the rise of disruptive forces-some volatile, such as tariff regimes or geopolitical uncertainty, while others would simply mechanically strain the system and potentially erupt in transportation congestion or labor instability-has exposed some structural frailties of a long distance sourcing model [1]. Meaning that, organizations are increasingly evaluating the reshoring and near-shore options to achieve resiliency and continue to maintain cost competitiveness. Yet, despite such strategic impulse, the practical assessment of reshoring is a formidable challenge because of the complicated and complex interdependencies interaction in tariffs, logistical flow and domestic assembling [2].

In the current common practice, many companies keep using spreadsheet-based cost models under static assumptions for the evaluation of reshoring. These approaches generally fix tariffs, transportation costs and labor costs, losing the nonlinear effects between the structures of part and routing alternatives, assembly capacity and service level requirements. Such simplifications cannot model the propagation of uncertainty throughout the supply chain and the material effect that localized decisions at the component level have on system level outcomes [4].

Recent theoretical and methodological progress in digital twins, stochastic simulation and optimization have paved the way for modeling industrial and logistic processes in a more nuanced manner. Digital-twin type approaches allow users to describe complex operational systems as interwoven process models, which make it possible to assess scenarios under uncertainty [3]. Concurrently, stochastic simulation methods represent variation in transportation efficiency, labor productivity, port congestion, and tariff response while the mixed-integer linear programming (MILP) provides a systematic structure to determine the feasible configurations that balance cost, capacity, and service restrictions. However, extant studies cover mostly these techniques in isolation and rarely integrate tariff reasoning into process-level decision models [1,7,8].

This manuscript attempts to cover this gap by proposing a stochastic process optimization framework that places the evaluation of reshoring within a multi-stage operational decision system. The proposed framework has structured data ingestion, automated tariff classification, stochastic landed-cost simulation, constrained optimization and unified digital twin architecture. Bills of materials represented as dependency graphs have the ability to explicitly model component- and routing-level assembly and routing alternatives. Uncertainty due to transportation variability, labor throughput, congestion effects, and tariff volatility are propagated with the help of Monte-Carlo simulation and embedded in a mixed-integer optimization model.

Our main contribution has been to develop reshoring evaluation as a repeatable and auditable decision process, that goes beyond the boundaries of a static cost comparison exercise. Using empirical assessments using synthetic but practical product situations, the framework achieves acceptable reductions in the expected landed cost and cost variance without detrimental impacts on operational feasibility and service level compliance. Thus, the proposed approach provides a scalable basis for operational decision support for adaptive supply chain based systems.

2. Related Work

Research on supply chain decision making has traditionally focused on network design, inventory optimization and transportation cost minimization. Classical approach - including deterministic mixed-integer linear programming (MILP) - usually assume stable tariff and regulatory environments [4]. While good for steady-state planning, such models are of little use to assess sourcing strategies in the face of policy volatility and operational uncertainty. [13,14]

Tariff modeling is often an input that is considered a fixed parameter as part of landed cost calculations, or in the case of compliance-driven classification systems. Trade compliance studies focus on the right classification of tariffs and regulatory validation but seldom incorporate tariff dynamics into stochastic optimization processes. As a result, the effects of tariffs are evaluated post hoc and not directly incorporated into the sourcing and assembly decisions [2,20,21].

Digital twin methodologies have been receiving more and more attention as a means of representing complex industrial and logistics processes. Prior work has shown the value of digital twins for the scenario analysis, disruption management and resilience assessment of production and logistics systems. However, most of the digital twin implementations are based on physical flows, capacity planning or inventory dynamics, with little attention to policy constrained decision logic or financial regulatory factors [1,5,6].

Recently, the use of machine learning and language model-based techniques for regulatory text interpretation and document understanding are studied. While these techniques show promise for automating tariff classification, they are usually studied in isolation, and are not integrated into closed-loop process optimization frameworks.[27,29,37]

Compared to previous research, we provide a harmonious and cohesive process-oriented integration of automated tariff reasoning, stochastic simulation, and MILP optimization. By incorporating the dynamics of tariffs directly into a digital twin-based decision process, the reshoring strategy's approach proposed represents a repeatable and auditable evaluation of reshoring strategies under uncertainty.

3. Decision Process Model and Problem Definition

Reshoring evaluation is modelled as a multi-stage stochastic decision process. The goal is to find the optimal global sourcing configuration, i.e. whether a product unit should be imported as a finished good, or broken down into components which can be assembled domestically, subject to stochastic cost, capacity, and service level constraints.

Let

$$z \in \{0,1\}$$

denote the sourcing decision variable, where

$z = 1$represents finished-goods import, $z = 0$represents component-level import with domestic assembly.

The value of $z$is determined endogenously through optimization.

3.1. Graph-Theoretic Representation of Product Structure

Each product is represented by a Bill of Materials (BOM) modeled as a **directed acyclic graph (DAG)**

$$G = (N, A),$$

where $N = \{1,2,\ldots,n\}$denotes the set of components and subassemblies, and $A \subseteq N \times N$represents hierarchical assembly dependencies.

Each node $i \in N$is characterized by an attribute vector

$$\mathbf{a}_i = (\tau_i, d_i, w_i, v_i, \ell_i),$$

where

- $\tau_i$is the tariff classification,
- $d_i$is the applicable duty rate,
- $w_i$is the component weight,
- $v_i$is the component volume, and
- $\ell_i$denotes labor complexity or processing effort.

These attributes jointly determine tariff exposure, transportation cost, and feasibility of alternative sourcing and assembly configurations.

3.2. Multi-Stage Decision Structure

The operational decision process consists of three interdependent stages:

1. **Routing Selection**

For each imported component $i \in N$, a logistics route

$$j \in \mathcal{R}_i$$

is selected, accounting for transportation cost, transit time, and variability.

2. **Assembly Allocation**

Domestic assembly is assigned to feasible processing locations

$$k \in \mathcal{K},$$

subject to labor availability and capacity constraints.

3. **Sourcing Strategy Selection**

The sourcing mode $z \in \{0,1\}$is chosen to determine whether the product is imported as a finished good or assembled domestically from imported components.

These decisions are **jointly optimized** to capture interactions among routing choices, assembly structure, and sourcing strategy.

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3.3. Stochastic Modeling of Operational Uncertainty

Operational uncertainty is modeled explicitly using stochastic operational parameters. Transportation transit times, labor productivity rates, congestion impacts and tariff duty levels are modeled as random variables with probability distributions, based upon historical variability. Unless otherwise stated, uncertainties are assumed to be independent of one another, component, and route.

Monte Carlo simulation is used to propagate uncertainty. Let

$$\omega = 1,2,\dots,\Omega$$

index simulation scenarios. For each scenario ω, realizations of stochastic parameters are sampled and propagated through the BOM graph, yielding scenario-specific landed cost and lead-time outcomes for each candidate sourcing configuration.

3.4. Optimization Formulation

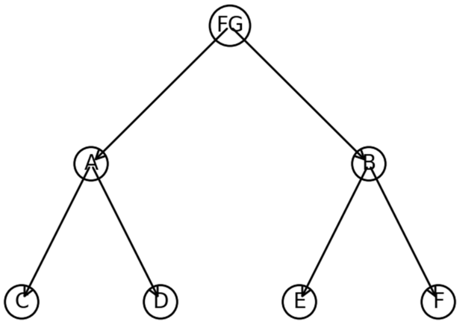

Figure 1. Example BOM DAG.

This decision problem is modelling as a sample-average approximation of the stochastic objective as a mixed-integer linear program (MILP). The optimization will minimize a risk-adjusted expected total landed cost:

$$\min \quad \mathbb{E}[Z] + \lambda\,\mathrm{Var}(Z),$$

where

- z is total landed cost, which is summed up in transportation, tariffs, and assembling labor,
- $\lambda \geq 0$ is the risk-aversion parameter, which prompts over-cost fluctuation.

The objective is estimated using Monte Carlo sampling as:

$$\min z = \frac{1}{\Omega}\sum_{\omega=1}^{\Omega} z^{\omega} + \lambda\left(\frac{1}{\Omega}\sum_{\omega=1}^{\Omega}(z^{\omega} - \bar{z})^2\right),$$

with

$$\bar{z} = \frac{1}{\Omega}\sum_{\omega=1}^{\Omega} z^{\omega}.$$

Constraints enforce:

- conservation of flow across the BOM graph,
- capacities of assembly on domestic locales, and
- optimal lead times possible to meet service-level needs.

The formulation can be used to systematically assess cost efficient, robust and operationally feasible reshoring strategies under uncertainties.

In summary, the framework determines the decision of whether to import a product as a whole or as an assembly in a nation and it combines optimization of routing decisions, assembly decisions, and sourcing decisions in time of uncertainty.

4. Process-Oriented System Architecture

The proposed framework is applied as a layered architecture of a digital twin, which converts regulatory and operational data into decision steps for sourcing. Each layer represents a different stage of the decision process, and could be validated, scaled up and extended separately. The general system data flow is depicted in Figure 2.

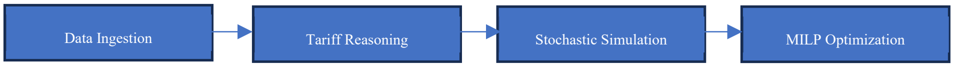

Figure 2. System Architecture.

4.1. Data Ingestion and Normalization Layer

The framework ingests structured and unstructured sources of data, like Bills of Materials (BOMs), shipment histories, tariff schedules and labor benchmarks. All inputs are normalized in consistent units, currency references and planning horizons are considered to make comparisons of scenarios. Data versioning and lineage tracking is tracked all the way through the pipeline to enable reproducibility, auditing and curated scenario analysis.

4.2. Semantic Reasoning and Tariff Classification Layer

The descriptions of the components are processed through language model-based semantic reasoning and the description is linked to Harmonized Tariff Schedule (HTS) categories. Semantic embeddings enable robust matching between the description of the components and the definitions of the tariffs, despite incomplete, or even ambiguous text. Classification confidence scores are generated and low confidence cases flagged for expert review. Downstream propagation of probabilistic duty rates is done to account for tariff classification uncertainty.

4.3. Component Dependency Graph Construction

Bills of Materials are instantiated in a form of Directed Acyclic Graphs (DAGs) representing the assembly structure, precedence relationships and modularity. This representation through graph theory makes it possible to determine tariff-sensitive components and subassemblies algorithmically. Graph traversal and decomposition methods aid in the restructuring choices involving finding the right tradeoff between tariff impacts and domestic assembly feasibility and capacity limitations.

4.4. Stochastic Landed Cost Simulation

Operational uncertainty is modelled using a stochastic simulation engine. Transportation costs, dwell times, labor productivity, the effects of congestion and surcharges are in the form of probability distributions based on historical variability. Monte Carlo simulation is applied in order generate scenario-specific landed cost and lead-time distribution of each candidate configuration as to retain the tail-risk characteristics, a prerequisite to any strong decision-making.

4.5. Optimization and Decision Support Layer

Simulation outputs are included in a mixed-integer linear programming (MILP) model using sample-average approximation. The optimization layer is responsible for choosing routing, assembly and sourcing decisions that minimize the expected landed cost, but considering risk aversion, capacity restrictions, and service levels. The output of this layer is a ranked list of feasible reshoring strategies with expected cost, variance and operational feasibility values.

4.6. Process Governance and Explainability

Decision recommendations are accompanied by cost attribution, sensitivity analysis and confidence scoring in order to keep stakeholders transparent and trustworthy. Audit logs, traces of parameters and compliance reports are generated to account for regulatory accountability and ease organizational adoption. These governance mechanisms make sure that the decision process is stable, can be interpreted and audited in repeated evaluations.[1,32,33]

5. Experimental Design and Validation

5.1. Experimental Objectives

The working evaluation answers three main research questions on the effectiveness and stability of the proposed framework:

RQ1 (Economic Viability): Do stochastic models identify cost-optimal reshoring solutions which are missed by statical heuristics?

RQ2 (Process Robustness): To what extent are the derived decisions stable to different tariff policy regimes of logistics uncertainty and uncertainty?

RQ3 (Operational Trade-offs): What quantitative trade-offs emerge between minimized landed cost, service-level compliance, and domestic capacity utilization?

5.2. Stochastic Testbed Generation

In order to facilitate controlled and reproducible evaluation under a range of operational conditions representative-synthetic data sets were built for simulating complex enterprise planning-related environments. Synthetic data make it possible to systematically investigate the negative impacts of uncertainty without being constrained by confidentiality requirements typically found with real enterprise data.

Key characteristics of the testbed include:

- **Product Structure:** Bill of Materials (BOM) complexity ranges from $N = 15$ to $N = 120$components per product to evaluate graph traversal and optimization scalability.
- **Parameters of tariffs:** Duty rates are randomly taken on sample harmonized tariff schedules (HTS) distributions of 0-35%.
- **Stochastic Variables:** Transportation costs and transit times are modeled with the help of the log normal distributions and the labor productivity based on the standard industrial engineering benchmarks is presented as truncated normal.

To achieve realistic operating conditions, the parameter ranges behind transportation variability, workforce productivity, and tariff rates have been tuned with visible reports on benchmarks in logistics and industry averages alike to guarantee a realistic level of operating conditions[15,17].

5.3. Experimental Case Scenarios and Benchmarks

The analysis of the framework occurs against three tariff regimes:

1. **Stable Baseline:** This is where the rate of duties is held constant throughout the horizon of planning.
2. **Moderate Escalation:** Tariffs rates rise up in constrained measure to a baseline level.
3. **High-Volatility Oscillation:** The Tariff rates move stochastically in respect to the baseline levels with high variance rates.

There are three benchmark approaches that performance is compared to:

Baseline A (Finished-Goods Heuristic): This strategy is a non-flexible one in which full offshore assembly is preferred.

Baseline B (Deterministic Spreadsheet Model): A traditional model of cost minimize with constant average parameters as a model in the absence of uncertainty.

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Baseline C (Rule-Based Routing): A rule-of-thumb optimization algorithm which operates without sounding tariffs.

The evaluation of all benchmark methods was done with the same input data and planning horizons to have a fair comparison[15].

5.4. Key Performance Indicators

The performance is measured with the help of the following metrics:

- **Economic Efficiency:** Expected landed cost reduction (%).
  Risk Robustness: Cost variance reduction and tail-risk exposure (e.g., 95th percentile cost).
- **Feasibility of Operation:** Labor utilization rate (domestic) and service level agreement violation rate (SLA).
- **Computational Performance:** The runtime and convergence of algorithms on growing BOM sizes.

6. Results and Discussion

6.1. Economic Efficiency and Cost Reduction

This proposed framework always identifies reshoring configurations that lower expected landed cost versus the baseline finished goods import strategy. As summarized in Table 1, cost reductions are between 9.5% for Industrial Sensors and 16.8% for Network Equipment. The extent of savings are increased according to the complexity of the product (products with higher number of components e.g. Network Equipment, N=110 had higher optimization potential due to higher modularity that allows selective rerouting of high tariff components). Paired t-tests over repeated simulation runs show that these cost reductions are statistically significant in all product categories ($p<0.001$).[13,14]

For variance reduction:

$$\Delta\sigma^2 = \frac{\sigma^2_{\text{baseline}} - \sigma^2_{\text{proposed}}}{\sigma^2_{\text{baseline}}}.$$

Table 1. Expected Landed Cost Reduction

Product	Components (N)	Baseline Cost	Reduction (%)
Industrial Sensors	35	100	9.5
Consumer Electronics	75	100	13.2
Network Equipment	110	100	16.8

6.2. Process Robustness and Risk Mitigation

Beyond the expected cost reduction, the framework significantly enhances robustness under uncertainty. For high volatility cases of the tariffs, the stochastic optimization approach shows a 40.3% reduction in cost variance compared to the deterministic Cost baseline (Table 2). This reduction in variance suggests that the risk-adjusted objective is effective in identifying supply chain configurations robust to shocks in tariffs and variability in the logistics. Sensitivity analysis also re-affirms that the robustness gains stay steady with tariff escalation going more severe from +5% to +20%.[8,9]

Table 2. Cost Variance Reduction.

Scenario	Baseline	Variance Reduction (%)
Moderate Escalation	—	27.4
High Volatility	—	40.3

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6.3. Operational Feasibility and Service Levels

Operational feasibility is preserved too in all the scenarios evaluated. Domestic labor utilization rises so as to support local assembly but is limited from the utilization at the theoretical limits of facilities limit (the highest observed use is at 71% for Consumer Electronics). Service-level impacts are marginal when considering that mean transit times with multi-node routing increase for about 0.7 days in total while Service Level Agreement (SLA) violations increase by only 0.3% which is still below acceptable level of tolerance from the enterprise.

6.4. Computational Scalability

Scalability analysis shows that the proposed framework is suitable to be deployed in enterprise scale. Runtime increases by roughly one in linear time 18s (N=20) to 182s (N=150) for BOM sizes of 50k simulation samples. This is a nearly linear growth, which suggests that this architecture can sustain operationally responsive decision cycles within the framework of a prohibitive computational overhead.[15]

7. Managerial and Operational Implications

7.1. Transition to Stochastic Decision Processes

The proposed framework makes it possible to shift the planning of supply chain from deterministic spreadsheet based heuristics to stochastic decision support processes. By simply including the logic of tariffs and operational uncertainty within the optimization loop, Organizations can now explicitly consider the trade-off between cost-efficiency, risk exposure and integrity of service. This makes it possible to turn reshoring evaluation into an iterative operating decision process that is part of a strategic evaluation process that can be repeated in light of changing conditions.

7.2. Quantifiable Resilience and Risk Management

Unlike traditional models which treat the concept of resilience as a qualitative concept, the proposed framework allows a mechanism to quantify risk explicitly in a variance-based penalty term ($\lambda \cdot \mathrm{Var}(C)$, as described in Section 3. This allows planners to make defensible, data-driven choices in which the building tradeoff between cost-effectiveness and robustness is transparent. The possibilities to simulate high volatility scenarios make it favor the choice of strategies which are stable under regime shifts which will lessen the probability of costly reversals in reshoring decisions.

7.3. Regulatory Auditability and Compliance

The digital twin architecture is required to make every choice traceable to those different tariff classifications, assumptions and cost drivers. In governed surroundings, such auditability helps the compliance of trade agreements and Rules of Origin. The framework generates a standardized decision record which supports regulatory reporting, internal governance and post hoc analysis to reduce the administrative burden that comes with trading compliance.

8. Conclusions

This research proposed a stochastic process optimization model for a component versus finished goods import adoption strategy in an uncertain tariff and logistics environment. By combining automated tariff-logic with stochastic simulation and mixed integer linear programming (MILP) in a unified digital twin structure establishes a repeatable and auditable process for reshoring analysis operations. Experimental results show cost reduction of 9-16% as well as substantial improvements for the robustness of the process in comparison to static heuristic approaches. These findings support the proposed framework as a way to build an operational decision support system that can be scaled up in adaptive policy constrained supply chain systems.[1,2,10]

9. Future Work

Future research will center on increasing the digital twin fidelity by integration with real-time telemetry of the carrier as an opportunity for the adaptation of decision updating under changing circumstances. Additional improvements comprise multi-echelon inventory coupling to account for upstream dependencies, advanced language model based regulatory reasoning for complex trade situations and the incorporation of Scope 3 emissions constraints for carbon aware supply chain optimization.[35–37]

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Abbreviations

The following abbreviations are used in this manuscript:

MILP	Mixed-Integer Linear Programming
BOM	Bill of Materials
LLM	Large Language Model
DAG	Directed Acyclic Graph
HTS	Harmonized Tariff Schedule
SLA	Service Level Agreement
KPI	Key Performance Indicator

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