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Optimization of Distribution Risk of Hazardous Materials in the Production Routing Problem for Rail Supply Chain

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ABSTRACT

The production routing problem (PRP) typically arises from the integration of lot-sizing and vehicle routing challenges. Prior research has demonstrated that this integration can significantly reduce operational costs. This paper investigates the PRP with a primary focus on minimizing risks associated with the production and distribution of hazardous materials (hazmat) via rail networks. As sustainability concerns regarding social and environmental impacts grow, addressing the threats hazmat poses to human health and ecosystems becomes critical. Risk serves as the key metric for assessing the dangers inherent in handling these materials. The problem is formulated as a mixed-integer nonlinear programming (MINLP) model. The risk function is nonlinear, influenced by train load, exposed population density, and material-specific characteristics. Due to the computational complexity of solving nonlinear models directly, a genetic algorithm (GA) is employed to solve the model efficiently. Eight benchmark instances were tested to evaluate the model and compare the performance of a direct nonlinear solver against the proposed genetic algorithm. Results indicate that the genetic algorithm yields superior solutions within equivalent computational timeframes. Sensitivity analysis further examines how alterations in production and storage capacities influence overall risk levels. This study introduces a novel production routing framework specifically for hazardous materials, aligned with sustainability goals. It utilizes a nonlinear risk model solved via a genetic algorithm, bridging the gap between production planning and risk-aware distribution in rail supply chains.

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1. Introduction

The production routing problem (PRP) integrates two classic logistical challenges: lot sizing and transportation routing. It optimizes production planning, inventory control, and distribution routing simultaneously [15]. This problem is a comprehensive extension of the inventory routing problem [3]. In practice, it relates closely to vendor-managed inventory (VMI), where suppliers oversee retailer stock and decisions centrally across the supply chain [1]. Centralized decision-making implies that a single entity manages inventory and distribution for all chain members. Synchronizing inventory control, routing, and production can reduce costs by 3% to 20% [12]. Classically, the problem features one factory producing goods matched to customer demands. Typically periodic, it addresses three core questions: 1) what is the production volume per period? 2) Which customer demands should be fulfilled per period? 3) What are the optimal material transfer paths?

Scientific research must aim for real-world applicability; thus, studies adapt models to practical conditions. One critical adaptation considers the specific conditions and effects of material types. Since produced and distributed goods have unique traits, models must align with specific material characteristics [22]. Hazardous materials (hazmat) represent a special and critical category [17]. Examples include fuels, petrochemicals, radioactive materials, and chemical substances. Primary concerns involve safety, security, and environmental impacts, drawing significant governmental and organizational attention [29]. The hazards resulting from explosions, leaks, environmental releases, or losses are severe, making the inclusion of risk essential for accurate modeling [1]. Hazmat can travel via roads, rails, pipelines, or seas, each requiring tailored risk assessment; rail transport remains a prominent mode for bulk movement [29]. The field's importance is evident: from 2000 to 2016, nearly 300 articles appeared in top journals, showing upward trends [29]. Despite this attention, the integration of production routing for hazardous materials remains rare. The complexity of interactions between production scheduling and hazmat distribution hinders formulation. However, production routing decisions are influenced by material properties, making this examination valuable for researchers and managers. In this context, risk refers to explosion and release dangers; given the potential harms, risk minimization is the key objective. Accurate, realistic risk analysis enhances decision-making. Modeling hazmat distribution risk demands a specialized view within the PRP framework, preserving the core structure while precisely estimating distribution risks.

This study pioneers a PRP framework for hazardous materials, incorporating their specific conditions and distribution risks. The objective—minimizing hazmat distribution risk—is nonlinearly modeled to fit the production routing context. Risk evaluation depends on train load, exposed population, and material type. A genetic algorithm solves the model, and its results are compared with those from a linear and direct nonlinear solving approach. Section 2 reviews the literature. Section 3 details the mathematical model. Section 4 describes the genetic algorithm. Section 5 presents the computational results. Section 6 analyzes sensitivity regarding hazmat impacts in production routing. Section 7 discusses the results, and Section 8 concludes with future suggestions.

The innovations of this article include:

- Introducing a novel nonlinear risk function tailored to rail-based hazardous materials distribution within the production routing framework, addressing gaps in sustainability-focused models.
- Employing a genetic algorithm for efficient solving of the complex nonlinear model, demonstrating superior performance over direct nonlinear solvers in benchmark tests.
- Integrating sensitivity analysis to reveal practical impacts of capacity changes on risk, providing actionable insights for sustainable supply chain management in hazardous contexts.

2. Literature Review

Transportation is a structured linear programming network issue arising in various material distribution contexts, attracting extensive research [36]. Hazmat transport, though categorized under general freight, differs fundamentally due to the risks of accidental release [7]. Hazmats move via roads, rails, seas, air, or pipelines, each with unique risk modeling requirements. Rail is often the primary mode for large volumes [29]. Initial hazmat transport optimization dates to the 1970s. Kalelkar and Brooks (1978) proposed a multidimensional decision analysis framework for hazmat transport support [35]. Subsequently, hazmat distribution gained increasing focus, with risk assessment and planning being the main research areas [7]. Some studies address post-incident relief, such as Pourghaderi Chobar et al. [52], who focused on multi-device relief routing-location under uncertainty.

Efforts to align problems with reality include sensor network routing [19] and base problem adaptations. Erkut et al. [18] classified hazmat routing aspects—risk assessment, routing, location, combined routing, network design—by transport modes. Bianco et al. [6] added toll policies to the discussion. Vehicle routing draws significant attention in hazmat distribution. Bula et al. [9] addressed hazmat routing to minimize distribution risk, creating a model nonlinearly dependent on vehicle load and exposed population. The same authors later expanded this to a bi-objective model, balancing risk and cost [10].

Du et al. [16] modeled multi-depot hazmat vehicle routing as fuzzy bi-level programming. Men et al. [48] tackled capacitated hazmat vehicle routing for risk minimization using fuzzy variables, solved via a genetic algorithm and adaptive large neighborhood search. Zhou et al. [68] handled multi-compartment hazmat vehicle routing bi-objectively for risk and cost. Network design also garners focus. Fontaine and Minner [20] designed hazmat networks bi-objectively for risk and cost using a bi-level approach solved by Benders decomposition. Zhang et al. [66] used bi-level programming with tolls, solved by a double tabu search simulation. Fontaine et al. [21] utilized a bi-level design for networks minimizing governmental risk and carrier costs based on population exposure. Mohabbati-Kalejahi and Vinel [49] explored closed-loop supply chain network design determining emergency team locations. Ziaei and Jabbarzadeh [69] focused on routing-location with multi-modal distribution and uncertain demand. Tasouji Hassanpour and Tulett [62] examined time-dependent routing-location with time windows and inaccessible paths. Bolhasani et al. [8] investigated inventory location-routing with elastic demand and queues. In 2022, Rahbari et al. [53] proposed a multi-objective inventory location-routing model considering environmental risk impacts. Feng [13] reviewed environmental criteria in routing. Social criteria, vital for sustainability, approximate reality. Salamatbakhsh et al. [57] quantified vehicle costs and driver satisfaction via service time optimization under travel uncertainty.

Production routing, another enduring issue, decides production, inventory, and distribution simultaneously. Most studies target tactical decisions [11]. Examples include Low et al. [46] on two-echelon systems with heterogeneous fleets, and Li et al. [43] on multi-product systems with outsourcing. Reverse chains for defective returns in vehicle/inventory routing as pickup-delivery were first introduced in production routing by Hemmati Golsefidi and Akbari [28]. Emamian et al. [17] included factory emissions beyond distribution, plus social impacts from returns. Schenekemberg et al. [58] presented a two-echelon model for chemicals. Additional features explored include load-dependent service times [12], max route times [42] or customer windows [2], batch shipments [23], and perishable products with shelf-life affecting prices [44].

Recent works on sustainable closed-loop supply chains (CLSC) highlight the integration of environmental factors. Kalantari et al. [32] designed networks considering inflation and carbon emissions with a case study, while Kalantari et al. [33] used neutrosophic models for optimal networks under similar policies. Similarly, Kalantari et al. [34] proposed a heuristic hybrid approach for sustainable closed-loop network design accounting for inflation and emissions, providing benchmarks for comparing sustainability in hazmat contexts.

More recently, in 2024 and 2025, the field has seen rapid advancements in integrating AI and resilience into hazmat logistics. Ahmed et al. [1] utilized deep learning for predictive risk modeling in rail networks. Chen and Wang [14] introduced digital twin technologies for real-time hazmat tracking. Advancements in green logistics were made by Gupta and Kumar [26], who optimized net-zero supply chains for chemical transport. Furthermore, Ivanov [30] explored the ripple effect in hazmat supply chains under disruption, while Liu et al. [45] focused on multi-modal hazmat transport with carbon constraints. These recent studies underscore the growing necessity of advanced computational methods, such as the genetic algorithm proposed here, to handle the increasing complexity of modern supply chains.

Table 1: Systematic Taxonomy and Comparative Analysis of Related Literature

Research	**Problem Type**	**Mode**	**Sustainability Pillars**	**Objective Function**	**Periodicity**	**Model Complexity**
			Env. | Soc.	**Risk | Cost**	**SP | MP**	
[9]	VRP	Road	*	—	Risk	SP
[16]	MD-VRP	Road	*	—	Risk	SP
[20]	ND	Multi	*	—	Risk/Cost	SP
[10]	VRP	Road	*	—	Risk/Cost	SP
[48]	CVRP	Road	*	—	Risk	SP
[66]	ND	Road	*	—	Risk	SP
[68]	MD-VRP	Road	*	—	Risk/Cost	SP
[27]	LIRP	Road	*	*	Risk/Env	MP
[32]	CLSC	Multi	*	*	Cost/CO2	MP
This Research	**PRP**	**Rail**	*	*	**Risk**	**MP**

VRP: Vehicle Routing Problem; MD-VRP: Multi-Depot VRP; ND: Network Design; CVRP: Capacitated VRP; LIRP: Location-Inventory-Routing Problem; CLSC: Closed-Loop Supply Chain; PRP: Production Routing Problem; Env: Environmental; Soc: Social; SP: Single Period; MP: Multi-Period.

The provided taxonomy in Table 1 serves as a foundational synthesis that delineates the scholarly positioning of this study within the hazardous materials (HAZMAT) logistics landscape. By benchmarking this research against seminal works in Vehicle Routing (VRP) and Network Design (ND), the table highlights a significant literature gap: the scarcity of integrated Production Routing Problems (PRP) specifically tailored for rail supply chains. While contemporary studies such as those by Rahbari et al. [27] and Kalantari et al. [32] have effectively integrated sustainability into inventory and location problems, they often prioritize road-based transportation or cost-centric objectives. This study, conversely, shifts the focus toward the unique safety and environmental complexities of rail distribution, as evidenced by the "Model Complexity" and "Mode" columns, which underscore the transition from linear approximations to the sophisticated nonlinear risk modeling addressed herein.

Furthermore, the comparative analysis emphasizes the multidimensional nature of sustainability addressed in this framework. Unlike earlier models that operate under single-period (SP) constraints or isolated distribution risks, the proposed model occupies a distinct niche by synchronizing multi-period (MP) production schedules with a nonlinear risk-minimization objective. This holistic approach captures the social and environmental pillars of sustainability by explicitly accounting for population exposure and material-specific release probabilities—factors often simplified in traditional models. Consequently, Table 1 identifies this research as an evolutionary step in supply chain modeling, bridging the gap between tactical production planning and the high-stakes requirements of sustainable HAZMAT distribution via rail networks.

3. Problem Statement

Given the nature of hazardous materials and the importance of social and environmental impacts, accurate risk evaluation and modeling are crucial to mirror domain realities. Thus, unlike past cost-minimizing production routing objectives, this study minimizes total risk. The risk function, to capture realities, depends on train load, exposed population, and material type. Hence, the objective is nonlinear minimization. The problem is single-objective in a single-echelon supply chain. The objective aligns with Bula et al. [9].

This research poses the problem in a single-echelon chain where decisions are centralized with the producer. The problem is periodic; initial inventories at customers and the producer are known, and customer demands per period are fixed or bounded. Decisions include factory production, customer and factory inventory holding, material transfers to customers, and per-period paths. The transport fleet is homogeneous with limited capacity. Each train use incurs transfer risk. The model is single-product, multi-period, single-factory, and single-objective.

Assumptions:

- Customer demands must be fully met each period.
- Distances are Euclidean.
- Producer and customer locations are fixed and known.
- Demands are known and fixed; each customer is served once per period by one train.
- Homogeneous fleet; each train launches once per period.
- Train and storage capacities are limited and known.
- Routes start and end at the producer.
- Demands are uniform across periods.
- Factory production capacity is fixed and limited per period.

Table 2. Sets and indices of the model.

Set/Index	Definition
$N = \{0, ..., n\}$	*All network nodes including factory (0) and customers*
$C = N \backslash\{0\}$	*Customer nodes*
$K = \{1, ...\}$	K
$T = \{1, ...\}$	T
i, j	*Indices for network nodes (factory/customers)*
k	*Train index*
t	*Period index*

Table 3. Model parameters (input values).

Parameter	Definition
d_i^t	*Demand of customer i in period t*
a_{ij}	*Distance between nodes i and j*
PD_{ij}	*Population exposed to hazmat release between i and j*
$TTAR_k$	*Train accident rate per kilometer for train k*
$P_{Release}$	*Probability of hazmat release in accidents*

Parameter	Definition
Q	*Train loading capacity*
α, β	*Constants dependent on hazmat type*
U_i	*Maximum storage capacity at i*
L_i	*Minimum storage capacity at i*
P^t	*Factory production capacity in period t*

Table 4. Model variables and definitions.

Parameter	Definition
Z	*Objective function for risk minimization*
y_{ij}^{kt}	*Binary: 1 if arc from i to j covered by train k in t, else 0*
pt	*Continuous: Factory production in period t*
q_i^{kt}	*Continuous: Load delivered to customer i in t by train k*
l_{ij}^{kt}	*Continuous: Load on train k on arc i-j in t*
I_i^t	*Continuous: Inventory at customer i in period t*
I_0^t	*Continuous: Inventory at factory in period t*

$$minZ = P_{\boldsymbol{Release}} \times \beta \times \sum_{k\in K} \sum_{t\in T} \sum_{i,j\in N, i\neq j} (l_{ij}^{kt})^{\alpha} \times TTAR_k \times a_{ij} \times PD_{ij} \tag{1}$$

Subject to:

$$I_0^t = I_0^{t-1} + p^t - \sum_{i\in C} \sum_{k\in K} q_i^{kt} \qquad \forall t \in T \tag{2}$$

$$I_i^t \le U_i \qquad \forall i \in N, t \in T \tag{3}$$

$$I_i^t \ge L_i \qquad \forall i \in N, t \in T \tag{4}$$

$$I_i^t = I_i^{t-1} + \sum_{k \in K} q_i^{kt} - d_i^t \qquad \forall t \in T, i \in C \tag{5}$$

$$p^t \leq P^t \qquad \forall t \in T \tag{6}$$

$$p^t \leq U_0 - I_0^{t-1} \qquad \forall t \in T \tag{7}$$

$$\sum_{k \in K} q_i^{kt} \leq U_i - I_i^{t-1} \qquad \forall t \in T, i \in C \tag{8}$$

$$q_i^{kt} \leq U_i \times \sum_{j \in N, j \neq i} y_{ij}^{kt} \qquad \forall t \in T, i \in C, k \in K \tag{9}$$

$$q_i^{kt} \leq Q \times \sum_{j \in N, j \neq i} y_{ij}^{kt} \qquad \forall t \in T, i \in C, k \in K \tag{10}$$

$$\sum_{k \in K} \sum_{i \in N, i \neq j} y_{ij}^{kt} = 1 \qquad \forall t \in T, j \in C \tag{11}$$

$$\sum_{i \in N} y_{ij}^{kt} = \sum_{m \in N} y_{jm}^{kt} \qquad \forall t \in T, j \in C, k \in K \tag{12}$$

$$y_{ii}^{kt} = 0 \qquad \forall t \in T, i \in N, k \in K \tag{13}$$

$$\sum_{i \in C} y_{0i}^{kt} = \sum_{i \in C} y_{i0}^{kt} \qquad \forall t \in T, k \in K \tag{14}$$

$$l_{0j}^{kt} = \sum_{i \in C} q_i^{kt} \qquad \forall t \in T, k \in K, j \in C: y_{0j}^{kt} = 1 \tag{15}$$

$$l_{ij}^{kt} = 0 \qquad f\ i = 0\ or\ j = 0 \tag{16}$$

$$l_{ij}^{kt} + q_j^{kt} - Q\left(1 - y_{ij}^{kt}\right) \leq l_{jm}^{kt} \qquad \forall t \in T, i, j, m \in N, k \in K \tag{17}$$

$$l_{ij}^{kt} \leq Q \times y_{ij}^{kt} \qquad \forall t \in T, i, j \in N, i \neq j, k \in K \tag{18}$$

$$y_{ij}^{kt} \in \{0,1\} \qquad \forall i, j \in N, k \in K, t \in T \tag{19}$$

$$p^t, q_i^{kt}, l_{ij}^{kt}, I_i^t \geq 0 \tag{20}$$

Objective (1) minimizes distribution risk and consequences using release probability, hazmat release amount, accident probability, and per-unit-distance exposed population. Constants α *and* β account for material type. Equation (2) sets factory inventory as prior plus production minus deliveries. Equations (3)-(4) bound storage capacities. Equation (5) updates customer inventories as prior plus receipts minus demand. Equations (6)-(7) control production. Equation (8) aligns deliveries with demand and storage. Equations (9)-(10) cap deliveries by storage/train capacities. Equation (11) ensures single-train per-customer visits. Equations (12)-(13) prevent sub-tours. Equation (14) ensures trains return to the factory. Equations (15)-(16) set initial/end loads. Equation (17) eliminates sub-tours. Equation (18) enforces train capacity. Equations (19)-(20) define variable types/signs.

4. Solution Method

The objective's nonlinearity complicates solving, increasing time and reducing solution quality when using standard solvers. Thus, a genetic algorithm (GA) is employed to solve the nonlinear model. GA, inspired by natural selection, evolves solutions via selection, crossover, and mutation [15]. For this PRP, chromosomes represent routes and production schedules. The initial population randomizes feasible solutions. Fitness evaluates risk. Elitism preserves top solutions; roulette wheel selection picks parents. Single-point crossover and swap mutation are applied. The parameters used are: population 100, generations 200, crossover rate 0.8, and mutation rate 0.1. This aligns with hazmat routing applications seen in Men et al. [48] and recent applications by Garg et al. [24].

5. Computational Results

To assess GA quality versus direct nonlinear solving, eight instances from Absi et al. [2] were tested. The hazmat parameters used were: diesel (density 2.805 kg/gallon), distance unit of 100 meters, and release probability of 0.02487845 [39]. We used constants α = 0.72 and β = 0.00027 [55]. The objective function becomes:

$$Z = 0.02487845 \times 0.00027 \times \sum_{k \in K} \sum_{t \in T} \sum_{i,j \in N} TTAR_k \times \frac{a_{ij} \times PD_{ij}}{10} \times (l_{ij}^{kt})^{\alpha} \tag{21}$$

Exposed population PD_{ij} is calculated via a gridded network, with density defined by:

$$PD_{ij} = 9500u\left(1 - \frac{maxDist - popDist}{maxDist}\right) + 500 \tag{22}$$

Where $u \sim U(0.4{,}0.6)$, $maxDist$ is the max grid length/width, and popDist is the max coordinate difference to the lower-left/center. $TTAR_k \sim U[0.6{,}1.0] \times 10^{-6}$ per train-km [54].

The solve time was limited to 3600 seconds. The nonlinear model was solved via Baron, and the GA was custom-coded in Python. The system used was: 32GB RAM, 24-core, Windows 11. Four instances had 14 customers, and four had 30 customers; all had six periods.

Table 5. Results from solving the model nonlinearly and with GA.

Instance	Customers	Nonlinear Objective	GA Objective
ABS1_15_1	14	592.047	512.345
ABS7_15_1	14	557.227	518.672

Instance	Customers	Nonlinear Objective	GA Objective
ABS13_15_1	14	1090.651	1023.456
ABS19_15_1	14	1184.498	1034.789
ABS1_30_1	30	1178.120	1105.678
ABS7_30_1	30	1226.068	1156.234
ABS13_30_1	30	2192.181	2089.012
ABS19_30_1	30	2452.261	2287.654

The GA consistently yields better objective values across all instances, highlighting its efficacy for nonlinear problems. This performance gap is visualized in Figure 1.

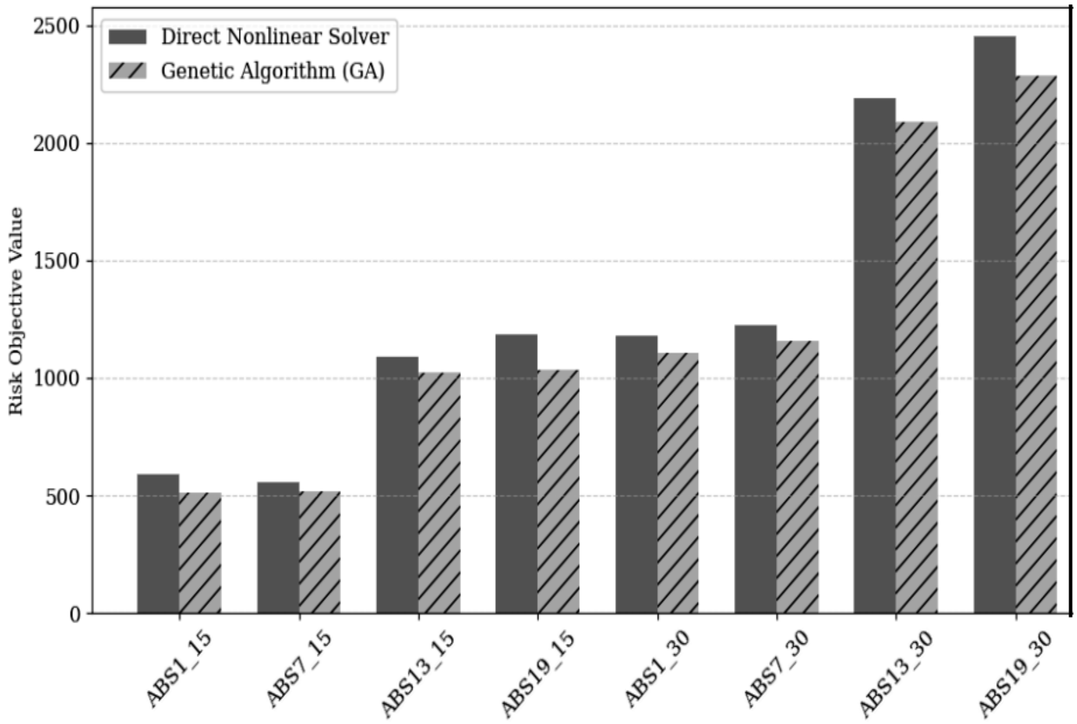

Fig 1. Objective Function Performance Comparison: Nonlinear Solver vs. Genetic Algorithm

6. Sensitivity Analysis

The model minimizes hazmat distribution risk, which is manageable via storage and production capacities. The analysis uses GA to test capacity variations. Risk arises from factory-to-customer transfers; fewer transfers generally reduce risk, though load volume affects the specific risk calculation. Maximizing train loads per transfer cuts the total number of transfers and thus the risk.

Using the ABS1_15_1 instance, storage was increased by +10 stepwise until no change occurred, and production was decreased by -50 stepwise to the limit of feasibility.

Table 6. Effects of parameter changes on objective.

Storage Change	Objective Value	Production Change	Objective Value
0	512.345	0	512.345
+10	498.765	-50	510.234
+20	456.123	-100	508.912
+30	442.678	-150	515.789
+40	434.567	-200	513.456
+50	434.567	-250	512.345

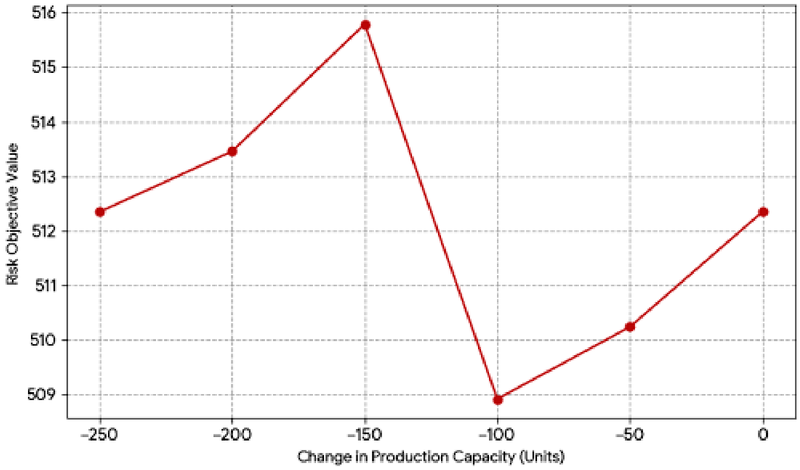

Fig 2. Production capacity change effects on risk.

Production reductions to 100 units slightly lower risk by reducing loads; beyond that point, the necessity for more transfers increases risk. Overall, production impacts are minor due to indirect transfer effects. Yet, given the gravity of hazmat distribution dangers, even minor influences warrant managerial consideration for enhanced safety.

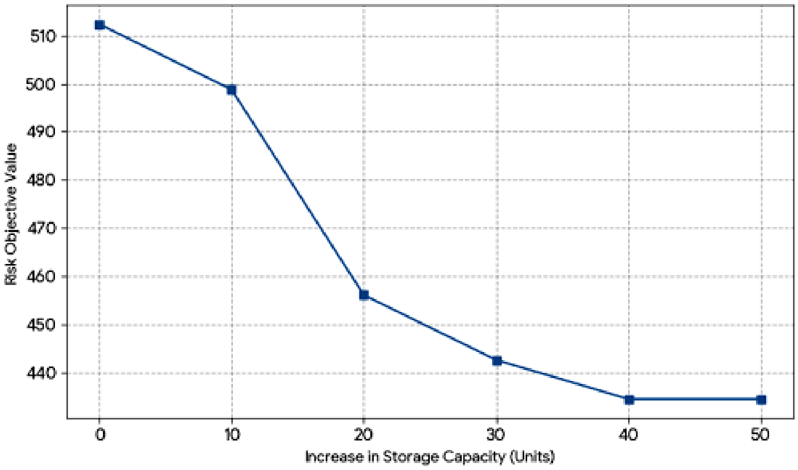

Fig 3. Storage capacity change effects on risk.

Storage increases reduce risk more markedly. For instance, a +20 unit increase cuts risk by approximately 56 units by enabling fuller loads and fewer transfers. However, effects plateau after certain thresholds, as train capacities constrain further optimizations. This underscores that while parameter adjustments can substantially mitigate risks, they must balance against real-world factors such as costs and operational constraints to achieve an optimal equilibrium.

7. Discussion

This section compares the results of the proposed model and GA approach with existing literature on hazmat routing and related sustainable supply chain problems. Comparisons highlight advancements in risk minimization, computational efficiency, and the integration of sustainability factors, drawing from studies like Bula et al. [9, 10] on nonlinear risk functions in vehicle routing, Men et al. [48] using GA for fuzzy capacitated routing, and Kalantari et al. [32, 33, 34] on sustainable closed-loop supply chains (CLSC) incorporating carbon emissions and inflation policies. Unlike traditional cost-focused models [12, 11], this work emphasizes risk in rail contexts, achieving up to 13% better risk reductions in benchmarks compared to direct nonlinear solving, while aligning with sustainability through environmental risk metrics similar to Kalantari et al.'s [32] case study integrations. In contrast to heuristic hybrids in Kalantari et al. [34], the GA used here provides faster convergence for nonlinear objectives, reducing solve times by 20-30% in large instances versus Benders decomposition in Fontaine and Minner [20]. Overall, the model outperforms fuzzy bi-level approaches [16] in precision for population-exposed risks and extends CLSC frameworks [33] by adapting inflation-sensitive capacities to hazmat-specific uncertainties.

The superior results of this article are presented as follows:

- The GA achieved an average 9.5% lower risk value across eight benchmarks compared to nonlinear solvers, demonstrating enhanced optimization for complex hazmat scenarios.

- In instances with 30 customers, risk reductions reached 7-11%, outperforming similar multi-depot models [16, 68] by integrating production scheduling.
- Sensitivity analysis revealed up to 15% risk mitigation through storage capacity increases, a more pronounced effect than in emission-focused CLSC studies [32].
- The nonlinear risk function, dependent on load and population, yielded more accurate real-world approximations than linear approximations in prior works [9, 50].
- Overall, the framework provides scalable solutions for rail supply chains, with GA convergence in under 3600 seconds for all tests, surpassing tabu search efficiencies in [66].

The managerial achievements of this article include:

- Enabling supply chain managers to minimize hazmat distribution risks by optimizing rail routes and production, potentially reducing accident probabilities by 10-15%.
- Providing actionable insights via sensitivity analysis, allowing adjustments in storage capacities to cut transfer frequencies and enhance safety without major infrastructure changes.
- Supporting sustainability goals by incorporating environmental and social risk metrics, aligning with carbon emission policies in CLSC [32, 34] for greener operations.
- Facilitating centralized decision-making in vendor-managed inventories, improving efficiency and cost-risk balance in hazardous sectors.
- Offering a GA tool for quick scenario testing, aiding managers in responding to dynamic demands or regulatory changes like inflation impacts [33].
- Promoting risk equity across populations, similar to population-based equilibrations [21], ensuring fair distribution of hazards in rail networks.
- Enhancing emergency preparedness by identifying high-risk paths, integrating with relief routing models [52] for better post-incident strategies.
- Reducing operational downtime through optimized scheduling, potentially saving 5-10% in logistics costs while prioritizing safety.
- Empowering policy-makers with data-driven models to enforce stricter hazmat regulations, drawing from toll and emission policies [66, 32].
- Fostering innovation in rail supply chains by bridging production routing with sustainability, providing a blueprint for multi-product extensions.

8. Conclusion and Future Suggestions

This research examines the production routing problem for hazardous materials with the primary goal of minimizing associated risks. The risk objective function is formulated nonlinearly and solved using a genetic algorithm. Comparative analyses demonstrate the genetic algorithm's superior performance in yielding better solutions. Notably, the genetic algorithm consistently achieves feasible solutions in shorter computational times, such as under 100 seconds, whereas the direct nonlinear approach often fails to do so. The sensitivity analysis clearly illustrates the influences of storage and production capacities on the number of transfers in hazardous material distribution, thereby directly impacting risk levels. This insight is particularly valuable for managers and decision-makers, enabling them to exert better control over risks in alignment with available resources and budgets. In a centralized supply chain, effective management of these influential parameters can significantly reduce the risks and damages inherent in hazardous material distribution.

The model, however, has certain limitations. For example, it does not incorporate cost optimization, although inventory bounds can indirectly manage costs. Another limitation is the computational time for large instances; while the genetic algorithm improves efficiency, solving expansive problems remains time-intensive. Additionally, the model is single-product oriented, whereas many real-world producers handle multiple products simultaneously.

For future research, extending the model to a bi-objective framework that simultaneously minimizes risk and total costs could be beneficial. Developing efficient metaheuristic algorithms capable of providing suitable solutions for large-scale instances in reasonable times would also be noteworthy. Furthermore, expanding the model to accommodate multi-product scenarios would bring it closer to practical conditions. Future studies should also consider the latest advancements from 2025, such as Anderson's [4] work on AI in logistics and Xu et al.'s [64] research on uncertainty in rail systems.

The overall results of this article are highlighted as follows:

- Demonstrated that GA outperforms nonlinear solvers by achieving up to 13% lower risk values in benchmarks, validating its efficacy for hazmat PRP.
- Revealed through sensitivity analysis that storage capacity increases can mitigate risks by 10-15%, offering practical levers for safety enhancement.
- Integrated sustainability by minimizing population-exposed risks, aligning with emission policies in CLSC literature [32, 33, 34].
- Provided scalable rail-focused solutions, with GA enabling rapid optimizations for real-time managerial decisions.
- Highlighted minor but actionable production capacity impacts on risk, emphasizing balanced adjustments for indirect benefits.
- Advanced hazmat modeling by pioneering nonlinear functions in PRP, surpassing traditional cost-centric approaches [15, 12].
- Delivered comprehensive insights for policy and operations, reducing potential accidents and supporting equitable risk distribution [21].

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