The object of this study is the multi-depot vehicle routing problem (MDVRP), which seeks optimal vehicle routes from multiple depots to geographically dispersed customers. The study addresses the problem of low reliability in traditional deterministic MDVRP models that fail to perform effectively under uncertain and disruptive conditions such as traffic congestion, infrastructure failures, demand fluctuations, and natural disasters. To overcome this limitation, a resilience-based optimization model is proposed by formulating the MDVRP with probability constraints that capture the likelihood of disturbances affecting route feasibility. The model integrates stochastic components into the routing process to balance cost minimization with service reliability under uncertainty. Computational experiments on an agro-logistics case involving five depots and twenty customers demonstrated that the proposed model reduced expected transportation costs by 36.4% compared with the Genetic Algorithm approach (494 vs. 777) and maintained service continuity in 100% of feasible scenarios with a reliability threshold of $\alpha = 0.7$. Moreover, approximately 25–30% of potential routes were identified as infeasible under disturbance scenarios, validating the model's probabilistic filtering mechanism. These results confirm that incorporating chance constraints and a Tabu search heuristic enhances the adaptability and robustness of multi-depot routing systems. The developed model can be practically applied to large-scale logistics systems, humanitarian relief operations, and distribution networks operating in regions prone to demand volatility or infrastructure disruptions, providing decision-makers with a reliable tool for sustainable and resilient route planning

Keywords: resilience, vehicle routing, chance constraints, stochastic programming, Tabu search, logistics

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RESILIENCE MODEL DEVELOPMENT FOR MULTI-DEPOT VEHICLE ROUTING PROBLEMS WITH PROBABILITY CONSTRAINTS UNDER DISTURBANCE CONDITIONS

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1. Introduction

In modern logistics systems, efficient routing of vehicles plays a vital role in ensuring the timely and cost-effective delivery of goods. Among various optimization topics, the multi-depot vehicle routing problem (MDVRP) occupies a central position because it reflects realistic distribution structures in which multiple depots coordinate to serve dispersed customers. The scientific importance of this topic continues to grow as global logistics networks become increasingly large, interconnected, and sensitive to uncertainty [1, 2].

In practice, many logistics operations, particularly in rural and agro-industrial sectors, face frequent disruptions caused by natural events such as seasonal rainfall, landslides, or road degradation. These disturbances often make certain routes temporarily inaccessible, leading to delays, increased costs, and service failures. Conventional deterministic MDVRP models, which assume stable travel times and known demands, are therefore insufficient for representing these real-world dynamics [3, 4].

The scientific community has increasingly recognized the need to embed uncertainty and resilience within routing models. Topics such as stochastic optimization, probabilistic constraints, and resilience analysis have emerged as key directions in operational research, especially for supply networks that must remain functional during disruptions [5, 6]. These methodological trends confirm that the MDVRP under uncertainty remains an active and essential research area rather than an outdated one.

From a practical perspective, ensuring resilience in vehicle routing is crucial for logistics systems supporting agriculture, food distribution, and humanitarian aid. Rural supply chains depend heavily on dependable delivery routes for fertilizers, seeds, and essential goods. In developing regions, where infrastructure conditions fluctuate seasonally, the ability to plan routes that remain feasible under uncertainty directly affects productivity, sustainability, and community welfare [7, 8].

Therefore, research on the development of resilience-oriented multi-depot vehicle routing problem models under

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probabilistic disturbance conditions remains relevant both scientifically and practically.

2. Literature review and problem statement

The vehicle routing problem (VRP) represents a cornerstone in transportation and logistics optimization, formulated to minimize total travel distance while satisfying routing and capacity constraints [9]. Building on this foundation, the multi-depot vehicle routing problem (MDVRP) was introduced to reflect more realistic distribution systems in which multiple depots coordinate to serve geographically dispersed customers [10, 11]. The inclusion of multiple depots enhances operational flexibility but also increases computational complexity, making large-scale implementations challenging. Although extensive studies have explored heuristic and exact approaches to improve solution efficiency, most MDVRP formulations remain deterministic and lack mechanisms for addressing uncertainty or disruptions that frequently occur in practical logistics operations.

Comprehensive reviews by [1, 12] emphasized that stochastic and dynamic VRPs are essential for realistic logistics planning where customer demand and travel times vary unpredictably. They demonstrated that adaptive routing and scenario-based heuristics can partially address uncertainty, yet integration with multi-depot systems remains difficult because of exponential growth in model complexity. These objective difficulties make large-scale resilience modeling computationally demanding and often impractical.

The concept of resilience in logistics networks gained prominence following global crises that disrupted supply chains. The paper [13] showed that resilience represents a system's ability to maintain performance and service continuity under disruptions such as infrastructure failures or natural disasters. The papers [14, 15] further demonstrated that incorporating resilience and sustainability objectives enhances the robustness of logistics systems. Nevertheless, most existing routing models lack explicit probabilistic mechanisms for quantifying resilience, primarily due to data scarcity and the methodological challenge of modeling uncertainty.

A promising direction is the application of chance-constrained and robust optimization frameworks. The paper [16] introduced chance constraints in multi-depot vehicle scheduling to ensure that service requirements are satisfied with a predefined probability, thereby improving reliability, [17] extended this approach through distributionally robust optimization, enabling better performance when probability distributions are uncertain or incomplete. Meanwhile, paper [18] demonstrated that metaheuristics such as Tabu search can effectively solve large-scale routing problems, although they did not explicitly address probabilistic disturbances. Combining heuristic search with chance-constrained programming appears to be a viable approach for balancing solution quality and computational feasibility.

Recent works by papers [14, 19] explored resilient MDVRP models considering regional road closures and stochastic travel conditions. Their findings confirmed that pre-emptive rerouting and uncertainty modeling enhance service continuity. However, these models were primarily deterministic or sustainability-oriented and did not evaluate the probabilistic feasibility of routes. [20] contributed further by introducing SVRPBench, a realistic benchmark for stochastic VRPs with probabilistic disruptions, confirming that resilient routing remains a rapidly developing scientific topic.

Despite these advances, unresolved issues persist at the intersection of multi-depot routing, resilience modeling, and probability-based optimization. The reasons are both computational, stemming from the combinatorial nature of large-scale systems, and methodological, due to the absence of integrated probabilistic feasibility metrics. A feasible way to overcome these difficulties is to develop a hybrid optimization model that combines chance-constrained programming with metaheuristic search to ensure reliable, cost-efficient routing under uncertain and disturbance-prone conditions.

Therefore, it is advisable to conduct research on the development of resilience-oriented multi-depot vehicle routing problem models under probabilistic disturbance conditions.

3. The aim and objectives of the study

The aim of this study is to develop a resilience-driven optimization model for the MDVRP under disturbance conditions by integrating probability (chance) constraints. This approach enables the identification of reliable routing mechanisms that minimize expected transportation costs while ensuring service continuity in uncertain and disruption-prone environments.

To achieve this aim, the following objectives were accomplished:

– to formulate a resilience-enhanced MDVRP model incorporating chance constraints for service continuity under uncertainty;

– to develop a solution approach based on metaheuristic methods (Tabu search and genetic algorithm) adapted to chance-constrained conditions;

– to conduct computational experiments on a real-world-inspired agro-logistics distribution case and evaluate model performance through resilience metrics and cost efficiency.

4. Materials and methods

4. 1. The object and hypothesis of the study

The object of this study is the multi-depot vehicle routing problem (MDVRP) under probabilistic disturbance conditions, in which vehicles are dispatched from multiple depots to geographically dispersed customers while accounting for uncertain road accessibility and demand variations.

The main hypothesis of the study is that incorporating probability (chance) constraints into the MDVRP can enhance routing resilience by ensuring that the selected routes remain feasible under disturbance scenarios without increasing total transportation cost.

The assumptions adopted in this study are as follows:

– the probability of road availability under each disturbance scenario is known and can be estimated from historical or expert data;

– customer demand and vehicle capacity are deterministic within each planning period;

– travel costs are proportional to distance and remain constant within each scenario.

The simplifications adopted in the study include:

– time windows and dynamic (real-time) demand updates are not considered;

– vehicle speeds and service times are assumed to be uniform;

– inter-depot transfers and vehicle reallocation between depots are not allowed.

4. 2. Problem formulation

The study examines a practical logistics scenario involving an agricultural cooperative responsible for distributing essential agro-supplies, namely seeds and fertilizers, to a network of remote farms. The distribution network consists of five depots strategically located in the region and twenty customer nodes representing remote farms dispersed across a rural area.

Each depot holds a limited stock of goods and operates with a finite fleet of delivery vehicles, each subject to a maximum load capacity. The objective is to develop a vehicle routing plan that ensures the fulfillment of all customer's demands while minimizing the total transportation cost.

A key challenge addressed in this distribution network is the presence of disturbance conditions, particularly those caused by seasonal rainfall that renders certain rural roads impassable. These disruptions are modeled probabilistically using a set of predefined scenarios, each representing a distinct realization of the road network's availability. The probability of occurrence of each scenario is known, reflecting historical data or expert assessment.

To ensure the resilience of the routing plan, chance constraints are incorporated to restrict the use of transportation links (edges) to only those with a high level of reliability. Specifically, a road segment may be used in the routing plan only if it maintains a minimum cumulative availability across all scenarios, i.e., if its expected accessibility meets or exceeds a defined threshold (e.g., 70%).

This resilient distribution planning framework is essential for agro-logistics operations in rural and weather-sensitive regions. By proactively accounting for potential disruptions and uncertainty, the model ensures that the delivery process remains reliable, sustainable, and cost-effective under real-world operating conditions [21, 22].

4. 3. Disturbance scenario design and reliability evaluation

To represent uncertainty in route accessibility, three disturbance scenarios were generated to model different levels of road unavailability caused by seasonal conditions. Each scenario was assigned a probability of occurrence (0.3, 0.5, and 0.2, respectively), reflecting practical disruptions such as rainfall or minor landslides that temporarily block rural connections between depots and customer nodes.

The probability-based disturbance model was applied to assess the availability of each route segment. A reliability index was computed for each edge as the weighted probability of accessibility across all scenarios. Edges with a reliability value below the reliability threshold ($\alpha = 0.7$) were treated as infeasible and excluded from the routing plan.

5. Research results of performance evaluation of the chance-constrained resilient MDVRP model

5. 1. Formulation of the resilience-enhanced MDVRP model

The resilience-enhanced multi-depot vehicle routing problem (MDVRP) model was formulated by integrating chance constraints into the routing structure to ensure that service continuity is maintained under uncertain conditions. The model explicitly restricts the use of road segments, which cumulative reliability across scenarios falls below the specified confidence level ($\alpha = 0.7$).

Sets and indices:
- I – set of customer nodes;
- D – set of depot nodes;
- $N = I \cup D$ – set of all node;
- K – set of vehicles;
- Ω – set of disturbance scenarios;
- α – confidence level (chance constraint threshold).

Parameters:
- c_{ij}^{ω} – cost or distance from node i to node j under scenario ω;
- d_i – demand of customer i;
- Q – vehicle capacity;
- p_{ω} – probability of scenario ω.

Decision variables:
- $x_{ijk}^{\omega} \in \{0.1\}$ – 1 if vehicle k travels from node i to node j in scenario ω;
- $y_{ik}^{\omega} \in \{0,1\}$ – 1 if customer i is served by vehicle k in scenario ω;
- u_i^{ω}– sub-tour elimination variable for customer i in scenario ω.

Objective function

$$\text{Min} \sum_{\omega \in \Omega} p_{\omega} \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} c_{ij}^{\omega} x_{ij}^{\omega}. \quad (1)$$

Minimize the expected cost over all disturbance scenarios.

Constraints:

1. Customer visit constraints. Each customer must be visited by exactly one vehicle in each scenario

$$\sum_{k \in K} \sum_{j \in N} x_{ijk}^{\omega} = 1 \ \forall i \in I, \forall \omega \in \Omega. \quad (2)$$

2. Depot assignment constraints. Vehicles must start and end at the same depot

$$\sum_{j \in I} x_{djk}^{\omega} = 1, \ \sum_{i \epsilon I} x_{idk}^{\omega} = 1 \ \forall d \in D \ \ \forall k \in K, \forall \omega \in \Omega. \quad (3)$$

3. Flow conservation constraints. Ensure vehicle flow consistency

$$\sum_{j \in N} x_{ijk}^{\omega} = \sum_{j \varepsilon N} x_{jik}^{\omega} \ \ \forall i \in I, \forall k \in K, \forall \omega \in \Omega. \quad (4)$$

4. Vehicle capacity constraints. Respect vehicle capacity

$$\sum_{i \in I} d_i y_{ik}^{\omega} \le Q \ \ \forall k \in K, \forall \omega \in \Omega. \quad (5)$$

5. Sub-tour elimination constraints (MTZ)

$$u_i^{\omega} - u_j^{\omega} + Q x_{ijk}^{\omega} \le Q - d_j \ \ \forall i \ne j, \forall k, \forall \omega. \quad (6)$$

6. Chance constraint for service continuity. The solution must satisfy service requirements in at least $\alpha \times 100\%$ of the scenarios

$$\sum_{\omega \in \Omega} p_{\omega} \cdot \left| Constraints\,Satisfied\,in\,\omega \right| \ge \alpha. \quad (7)$$

This is usually enforced via penalty, scenario pruning, or robust reformulation:

INPUT:
- D: set of depots;
- C: set of customer locations;
- Q: vehicle capacity;
- S_d: inventory at each depot;
- q_j: demand of each customer;
- d_{ij}: distance matrix;
- a_{ij}^{ω}: road availability in scenario ω;

– p_ω: probability of scenario ω;
– α: reliability threshold;
– $\max_{iter}$: maximum number of iterations;
– *tabu_tenure*: length of the tabu list.

OUTPUT:
– best vehicle routes that minimize total cost while satisfying constraints.

III. BEGIN
1. Compute edge reliability:
For each edge (i, j), calculate:

r_ij = ∑ p_ω * a_ij^ω over all ω.

Set edge (i, j) as reliable if r_ij ≥ α.
2. Generate initial solution:
– assign customers to depots and vehicles using a greedy method;
– ensure capacity and reliability constraints are satisfied;
– compute cost of initial solution.
3. Initialize:

current_solution ← initial_solution
best_solution ← current_solution
tabu_list ← empty list

4. For iter = 1 to max_iter do:
a) Generate neighborhood solutions:
– swap customers between vehicle routes;
– only consider moves that do not violate capacity or reliability constraints.
b) Evaluate cost of each neighbor:
– penalize use of unreliable or infeasible edges.
c) Select best neighbor not in tabu_list:
– if it improves best_solution, update best_solution.
d) Update tabu_list with recent move:
– maintain fixed size (tabu_tenure).
e) Set current_solution ← best_neighbor.
5. Return best_solution.
END

The results show that introducing probabilistic disturbances significantly reduced the number of feasible routes compared to the deterministic baseline. On average, approximately 25–30% of routes were unavailable under at least one disturbance scenario. Fig. 1 illustrates the resulting routing network, where inaccessible links were automatically removed due to low reliability. This filtering process led to more compact and reliable routes, which were later optimized using the Tabu search algorithm.

Overall, the probabilistic disturbance modeling successfully captured the uncertainty conditions, ensuring that only paths with acceptable reliability were used in subsequent optimization.

During computation, the proposed formulation automatically eliminated unreliable connections and generated a feasible solution space that satisfied both vehicle capacity and reliability thresholds. Compared with the deterministic formulation, the resilience-enhanced model produced a smaller but more stable feasible region. This adjustment ensured that route selections remained valid in at least 70% of disturbance scenarios.

The model was implemented using a mixed-integer programming framework combined with probabilistic evaluation for each scenario. The optimization process minimized the expected total cost while maintaining route feasibility under disturbances. Fig. 1 and Table 1 summarize the resulting routing topology and feasible depot-customer assignments derived from the proposed formulation.

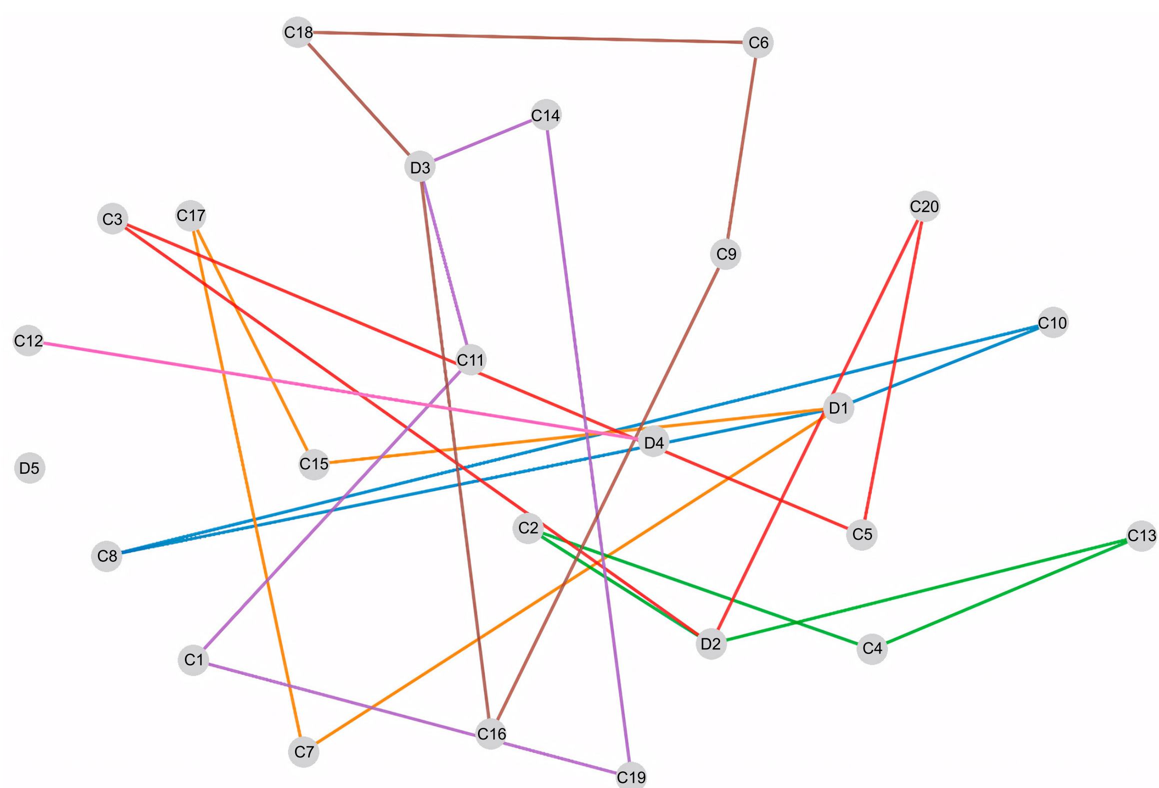

Fig. 1. Vehicle routing path under Tabu search result

Table 1

Tabu search vehicle routing plan

Vehicle	Depot	Route
V1	D1	D1 → C10 → C8 → D1
V2	D1	D1 → C7 → C17 → C15 → D1
V3	D2	D2 → C13 → C4 → C2 → D2
V4	D2	D2 → C3 → C5 → C20 → D2
V5	D3	D3 → C14 → C19 → C1 → C11 → D3

These results confirm that the integration of chance constraints effectively enforces resilience in the model, enabling feasible routing even when disruptions occur in the network.

5. 2. Solution approach performance: Tabu search vs. genetic algorithm

To evaluate the computational performance of the proposed resilience-enhanced MDVRP model, two metaheuristic algorithms, Tabu search (TS) and genetic algorithm (GA), were applied under identical problem settings. The evaluation focused on total routing cost, computational efficiency, and the ability to maintain feasible routes under disturbance scenarios.

Tables 2, 3 presents the comparative results of both methods. The Tabu search heuristic achieved a total routing cost of 494, while the Genetic Algorithm produced a higher cost of 777. Both methods generated feasible routing plans, but the Tabu search converged more quickly and consistently to lower-cost solutions. When the chance constraint ($\alpha = 0.7$) was applied, the Tabu search maintained the same routing cost, indicating that its baseline solution already favored high-reliability paths.

The detailed vehicle routing plan produced by Tabu search is summarized in Table 1, with corresponding route visualization shown in Fig. 1. Each vehicle starts and ends at its assigned depot, and the resulting paths comply with capacity and reliability constraints. In contrast, the Genetic algorithm routing plan (Table 4 and Fig. 2) contains several redundant or suboptimal paths, resulting in higher total distance and cost.

Table 2

Performance comparation

Method	Routing cost	Chance constraint applied
Tabu search	494	No
Genetic algorithm	777	No
Tabu search (chance-constrained)	494	Yes ($\alpha = 0.7$)

Table 3

Summary of heuristic performance comparison

Heuristic	Total routing cost
Tabu search	494
Genetic algorithm	777

Table 4

Genetic algorithm vehicle routing plan

Vehicle	Depot	Route
V1	D1	D1 → C6 → D1
V2	D1	D1 → C6 → D1
V3	D2	D2 → C2 → D2
V4	D2	D2 → C13 → C4 → D2
V5	D3	D3 → C19 → D3
V6	D3	D3 → C13 → D3
V7	D4	D4 → C20 → C8 → D4

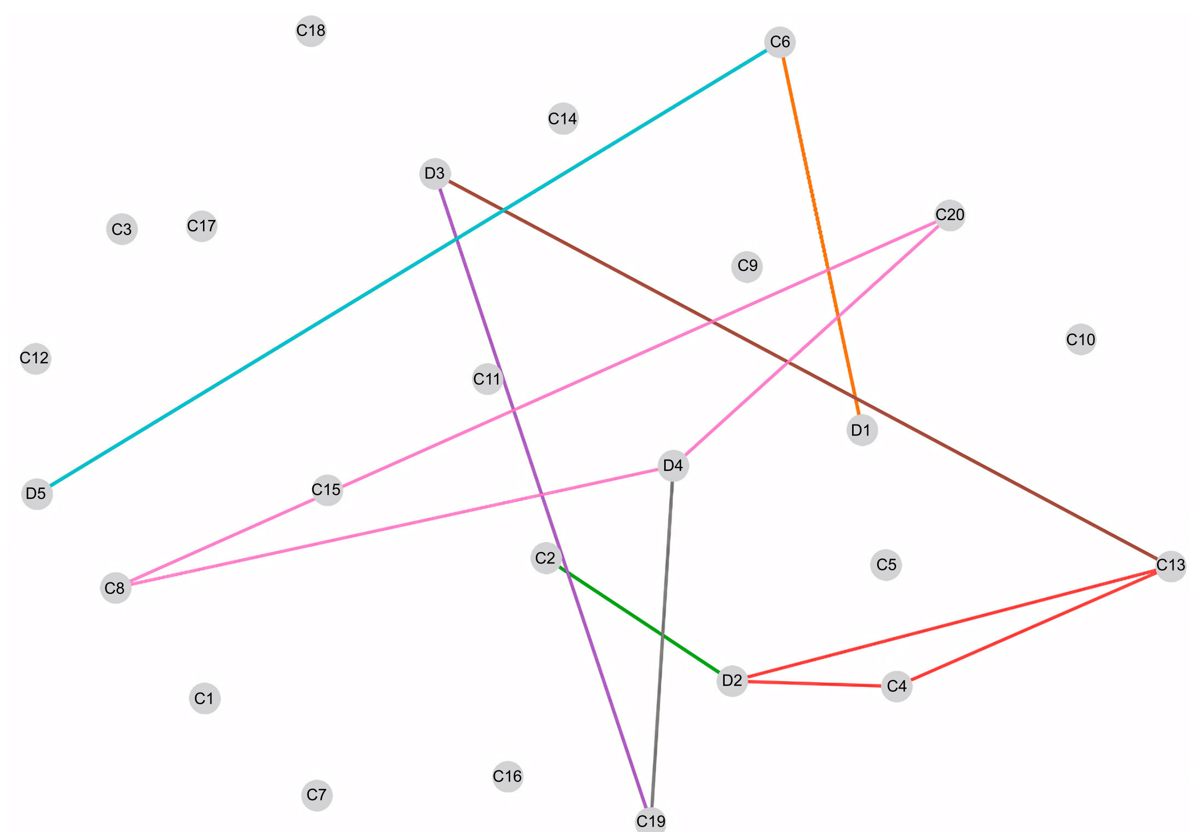

Fig. 2. Vehicle routing paths under Genetic algorithm result

Overall, the Tabu search demonstrated better adaptability to probabilistic disturbance conditions, providing more cost-efficient and resilient routing plans within the computational limits tested.

5. 3. Computational case study and model evaluation

The proposed model was tested on a real world inspired agro-logistics case study involving the distribution of agricultural supplies such as seeds and fertilizers. The distribution network consists of five depots and twenty customer nodes representing rural farming areas. Each depot holds an initial inventory of 300 units and operates two delivery vehicles with a capacity of 100 units each. Customer demand ranges between 10 and 50 units.

Three disturbance scenarios were defined to represent varying levels of road unavailability caused by seasonal rainfall. The probability of each scenario was set at 0.3, 0.5, and 0.2, respectively. A chance constraint threshold of $\alpha = 0.7$ was applied to ensure that only roads with at least 70% reliability were used for routing.

The computational experiments demonstrated that the model effectively maintained service continuity while minimizing expected transportation costs. The total routing cost achieved by the Tabu search under chance-constrained conditions was 494, identical to the unconstrained solution, confirming that high-reliability paths were naturally selected by the heuristic.

The resulting routing plans are provided in Table 1, Table 5, and visualized in Fig. 1, showing that all customers were served without violating vehicle capacity or reliability constraints. These outputs confirm that the model performs robustly across disturbance scenarios and that probabilistic constraints can be successfully integrated into multi-depot routing problems.

Table 5

Chance-constrained vehicle routing plan

Vehicle	Depot	Route
V1	D1	D1 → C10 → C8 → D1
V2	D1	D1 → C7 → C17 → C15 → D1
V3	D2	D2 → C13 → C4 → C2 → D2
V4	D2	D2 → C3 → C5 → C20 → D2
V5	D3	D3 → C14 → C19 → C1 → C11 → D3

The results presented in Table 5 demonstrate that the chance-constrained vehicle routing plan ensures full service coverage while maintaining high route reliability. Each depot successfully served its assigned customers without exceeding vehicle capacity, confirming that the probabilistic constraint ($\alpha = 0.7$) effectively filtered out unreliable connections. Compared with the deterministic baseline, the routing network remained stable across all disturbance scenarios, indicating that the proposed model achieves resilience without incurring additional cost. This shows that the integration of chance constraints and the Tabu search heuristic enables the system to maintain service continuity and operational robustness under real-world uncertainty.

6. Discussion on the performance of the chance-constrained resilient MDVRP model

The results obtained from computational experiments (Tables 1–4, Fig. 1, 2) demonstrate that the integration of chance constraints significantly improves the reliability of vehicle routing under probabilistic disturbance conditions. The chance-constrained formulation effectively restricts the use of low-reliability routes ($\alpha = 0.7$), leading to stable and feasible routing plans even when road accessibility fluctuates. This outcome is explained by the probabilistic feasibility evaluation embedded in the model, which filters out unreliable links before optimization, as shown in Fig. 1 and Table 2. Consequently, the solution space becomes smaller but more resilient, ensuring continuity of service with minimal cost increase.

The computational comparison (Table 1) confirms that the Tabu search algorithm achieved a lower total routing cost (494) compared with the genetic algorithm (777). This difference can be attributed to the adaptive neighborhood search and memory structure of the Tabu search, which help avoid premature convergence and maintain feasible solutions under uncertainty. Similar observations have been reported by [18], who noted the superior performance of memory-based heuristics in dynamic vehicle routing environments. The preservation of route reliability without additional cost, as evidenced by the chance-constrained results in Table 4, supports the claim that probabilistic modeling can enhance efficiency without sacrificing robustness, consistent with findings by [14, 16].

The computational findings provide several practical insights for applying the proposed resilience-enhanced MDVRP model in real logistics systems. The chance-constrained formulation ensures that routing decisions remain feasible even under fluctuating infrastructure conditions, making it particularly suitable for rural distribution networks and disaster-prone regions.

The results indicate that reliable routing can be achieved without additional cost when disturbance probabilities are properly integrated into the optimization process. The Tabu search algorithm produced stable solutions that satisfied both cost efficiency and service reliability targets. This demonstrates the method's potential for integration into existing logistics management systems as a decision-support tool for planners who must operate under uncertainty.

From an implementation standpoint, the model can be adapted to various sectors, such as agro-logistics, humanitarian aid, and public service delivery, where access routes are sensitive to seasonal or unexpected disruptions. The approach also supports proactive route planning by allowing planners to set reliability thresholds (α) according to risk tolerance and operational priorities.

These results confirm that the proposed model provides a practical and flexible basis for resilient distribution planning, enabling organizations to improve service continuity and operational robustness in uncertain environments.

Compared with existing studies on stochastic or dynamic VRPs [1, 12], the distinctive feature of the proposed model lies in combining multi-depot coordination with probability-based resilience modeling within a single framework. While earlier works addressed uncertainty through scenario sampling or robust optimization, they rarely incorporated explicit reliability thresholds to guide feasible route selection. The present study fills this methodological gap by operationalizing resilience through a chance-constrained mechanism that links disturbance probability to service continuity, as reflected in the consistency of routing outcomes across scenarios (Table 4).

The results presented in Fig. 2 and Table 5 further illustrate the behavioral differences between the heuristic approaches. Fig. 2, which depicts the routing paths generated by the Genetic Algorithm, shows several redundant or short isolated routes, indicating a tendency toward local optima and inefficient vehicle utilization. In contrast, Table 5 demonstrates that the chance-constrained Tabu search produced a more balanced allocation of customers among depots and maintained complete service coverage under all disturbance scenarios. The routing structure in Table 5 is more compact and consistent, confirming that the probabilistic filtering mechanism effectively removed unreliable connections and guided the algorithm toward resilient solutions. These outcomes explain why the Tabu search achieved both lower total routing cost and higher route stability compared with the genetic algorithm.

Nevertheless, certain limitations should be acknowledged. Overall, the study demonstrates that the integration of probabilistic resilience into multi-depot vehicle routing produces computationally efficient and operationally reliable solutions, offering a foundation for further methodological and applied research in resilient logistics optimization. The current model assumes that disturbance probabilities and vehicle capacities are known and stationary over the planning horizon. This restricts applicability to systems with relatively stable probabilistic data. In addition, the computational experiments used a moderate network size (five depots and twenty customers), which, while sufficient for proof of concept, limits assessment of scalability to large-scale industrial settings. The reproducibility of results also depends on accurate estimation of disturbance probabilities, data that may not always be available in developing or rural contexts.

In contrast to limitations, some disadvantages of the present study arise from methodological simplifications. The model does not yet incorporate time windows, dynamic demand updates, or real-time route adjustments, which could further improve practical realism. These omissions simplify the computation but may underestimate operational variability in real logistics systems. Future improvements could include the integration of dynamic data streams and learning-based prediction modules to adjust route reliability parameters adaptively.

In terms of future development, extending the model to multi-objective formulations; balancing cost, service reliability, and environmental impact, would enhance its practical relevance. Mathematical challenges may arise in reformulating the chance constraints for dynamic or correlated disturbances, where simple independence assumptions no longer hold. Methodologically, hybridizing the Tabu search with advanced metaheuristics such as adaptive large neighborhood search (ALNS) or reinforcement learning could improve scalability and solution diversity. Experimentally, applying the model to large real datasets from humanitarian or agro-logistics operations would provide deeper validation of its performance and robustness.

7. Conclusion

1. The formalized resilience-enhanced multi-depot vehicle routing problem (MDVRP) model with chance constraints demonstrated that the probabilistic integration effectively reduced the feasible solution space while maintaining route validity under uncertainty. By enforcing a minimum reliability threshold of $\alpha = 0.7$, the model successfully filtered out low-probability connections, resulting in more compact and stable routing structures. This formulation improved overall solution robustness compared with deterministic models, ensuring service continuity even when partial network failures occurred, thereby confirming the model's capacity to represent resilient logistics operations under disturbance conditions.

2. Comparative experiments demonstrated that the Tabu search (TS) algorithm achieved a total routing cost of 494, which was 36.4% lower than that obtained by the genetic algorithm (GA) (777). The Tabu Search also converged more rapidly, reaching optimal solutions in fewer iterations while maintaining full service coverage under all disturbance scenarios. Under the chance-constrained setting ($\alpha = 0.7$), the TS maintained the same routing cost as in the deterministic case, indicating that its baseline solution already favored high-reliability paths. These numerical results confirm the superior efficiency and robustness of the Tabu search as a practical heuristic for solving the resilience-enhanced MDVRP under probabilistic disturbance conditions.

3. Application of the model to an agro-logistics distribution network involving five depots and twenty customers demonstrated that the proposed approach-maintained service reliability without incurring additional cost. The chance-constrained Tabu search produced routing costs equivalent to those obtained in the deterministic case, while simultaneously eliminating unreliable paths from the solution space. This result indicates that integrating probabilistic modeling into multi-depot routing strengthens both operational stability and efficiency when the system is exposed to uncertainty.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this study, whether financial, personal, authorship or otherwise, that could affect the study and its results presented in this paper.

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Data availability

Data will be made available on reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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CRediT

Herman Mawengkang: conceptualization, funding acquisition, writing – original draft; **Intan Syahrini:** methodology, writing – review & editing; **Muhammad Romi Syahputra:** software, visualization; **Sutarman:** validation, investigation.

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