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Dynamic Metaheuristic Optimization for Resilient Supply Chain Routing under Disruptions

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Abstract

Modern supply chains face unprecedented vulnerability to disruptions arising from natural disasters, infrastructure failures, demand volatility, and geopolitical instability. The Dynamic Multi-Depot Vehicle Routing Problem with Disruptions (DMDVRP-D) captures the complexity of real-time logistics re-optimization when such events occur, yet existing solution approaches inadequately balance computational efficiency with solution resilience. This paper proposes the Dynamic Resilient Supply-chain Optimizer (DRSO), a novel hybrid metaheuristic that integrates Adaptive Large Neighborhood Search (ALNS) with Grey Wolf Optimizer (GWO) for solving the DMDVRP-D. DRSO introduces five key innovations: 1) scenario-tree-based stochastic programming embedded within fitness evaluation to account for disruption uncertainty, 2) ALNS destroy-repair operators specialized for supply chain resilience, including Facility Substitution (FS), Emergency Re-Routing (ER), Demand Splitting (DS), and Multi-Modal Switching (MS), 3) GWO-guided intensification on promising ALNS neighborhoods to accelerate convergence, 4) real-time re-optimization triggered by disruption events with warm-start from pre-disruption solutions, and 5) a Composite Resilience Score (CRS) metric that unifies Recovery Time (RT), Service Level (SL), and Excess Cost (EC) into a single evaluative measure. We formulate the DMDVRP-D as a Mixed-Integer Linear Program (MILP) and evaluate DRSO on modified Solomon VRPTW benchmark instances extended with disruption scenarios, as well as two real-world case studies: a Nigerian pharmaceutical distribution network spanning the Lagos–Abuja–Kano corridor (45 nodes) and a Chinese manufacturing supply chain in the Yangtze River Delta (YRD) region (78 nodes). Computational experiments over 30 independent runs demonstrate that DRSO achieves 18–32% lower disruption recovery cost, 25–41% faster RT, and 15–28% fewer unserved customers compared to standalone ALNS, Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and a commercial solver (Gurobi with a time limit). Statistical significance is confirmed via the Wilcoxon signed-rank test at $p < 0.05$. The results establish DRSO as a competitive and practical approach for resilient supply chain routing under dynamic disruption conditions.

Keywords: Supply chain resilience, Vehicle routing, Metaheuristic optimization, Disruption management, Adaptive large neighborhood search, Dynamic optimization, Logistics.

1 | Introduction

Global supply chains have evolved into intricate, interdependent networks spanning multiple countries, transportation modes, and intermediary facilities. While this interconnectedness has yielded substantial efficiency gains through specialization, economies of scale, and just-in-time inventory strategies, it has simultaneously amplified vulnerability to disruptions [1]. Events such as the 2011 Tōhoku earthquake, the 2020–2022 COVID-19 pandemic, the 2021 Suez Canal obstruction, and recurring flooding across West Africa

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and Southeast Asia have demonstrated that localized failures can cascade rapidly through supply networks, generating disproportionate economic losses and service degradation [2], [3]. The World Economic Forum estimated that supply chain disruptions cost the global economy approximately USD 4.4 trillion between 2020 and 2023, underscoring the urgency of designing logistics systems capable of absorbing, adapting to, and recovering from adverse events.

At the operational level, supply chain disruptions manifest through several channels: Road closures that sever established delivery routes, facility failures that eliminate depot and warehouse capacity, sudden demand surges that overwhelm planned allocation, and vehicle breakdowns that reduce fleet availability. Each disruption type imposes distinct constraints on the routing problem, and their co-occurrence, common in large-scale disasters, compounds the combinatorial complexity of re-optimization [4]. The Vehicle Routing Problem (VRP), introduced by Dantzig and Ramser [5] as the truck dispatching problem, provides the canonical mathematical framework for optimizing delivery routes. Over six decades of research have produced a rich taxonomy of VRP variants incorporating time windows [6], multiple depots [7], heterogeneous fleets [8], pickup and delivery [9], and stochastic parameters [10]. However, explicitly integrating disruption events into VRP formulations, particularly in dynamic, multi-depot settings where disruptions unfold in real time, remains an underexplored frontier.

Supply chain resilience, defined as the ability of a supply chain to prepare for, respond to, and recover from unexpected disruptions while maintaining continuity of operations at desired performance levels [11], has emerged as a central concern in both academic research and industrial practice. Resilience extends beyond classical robustness, which focuses on withstanding known perturbations, by encompassing adaptive capacity and recovery speed [12]. Despite growing theoretical interest, translating resilience concepts into operational routing algorithms has been limited. Most existing approaches treat disruptions ex post, re-solving the routing problem from scratch after a disruption occurs, without exploiting the structure of pre-disruption solutions or incorporating anticipatory information about disruption likelihood [13].

Metaheuristic optimization methods have proven highly effective for large-scale VRP instances where exact methods become computationally prohibitive. Adaptive Large Neighborhood Search (ALNS), introduced by Ropke and Pisinger [9], has become one of the most successful frameworks for VRP variants, employing multiple destroy and repair operators whose selection is guided by historical performance. The Grey Wolf Optimizer (GWO), proposed by Mirjalili et al. [14], offers complementary strengths through its population-based search mechanism that balances exploration and exploitation via a hierarchical leadership structure inspired by wolf pack hunting behavior. While both ALNS and GWO have been applied independently to various combinatorial optimization problems, their hybridization, particularly for disruption-aware routing, has not been explored in the literature.

This paper addresses the research gap at the intersection of dynamic vehicle routing, supply chain disruption management, and hybrid metaheuristic optimization. We make the following contributions:

I. We formulate the Dynamic Multi-Depot Vehicle Routing Problem with Disruptions (DMDVRP-D) as a Mixed-Integer Linear Programming (MILP) model that explicitly incorporates road closures, facility failures, demand surges, and vehicle breakdowns as time-indexed disruption events.

II. We propose the Dynamic Resilient Supply-chain Optimizer (DRSO), a novel hybrid algorithm that integrates ALNS with GWO. DRSO features four specialized destroy-repair operator pairs designed for supply chain resilience: Facility Substitution (FS), Emergency Re-Routing (ER), Demand Splitting (DS), and Multi-Modal Switching (MS).

III. We embed scenario-tree-based stochastic programming within the fitness evaluation function, enabling DRSO to anticipate and hedge against potential disruptions during solution construction.

IV. We design a warm-start re-optimization strategy that leverages structural information from pre-disruption solutions to accelerate convergence when disruptions trigger route reconfiguration.

V. We introduce a Composite Resilience Score (CRS) metric that integrates Recovery Time (RT), Service Level (SL), and Excess Cost (EC), providing a unified measure for evaluating solution quality under disruptions.

VI. We validate DRSO through extensive computational experiments on modified Solomon VRPTW benchmarks with disruption extensions and two real-world case studies: a Nigerian pharmaceutical distribution network (45 nodes, Lagos–Abuja–Kano corridor) and a Chinese manufacturing supply chain (78 nodes, Yangtze River Delta (YRD).

The remainder of this paper is organized as follows. Section 2 reviews related work on VRP variants, supply chain disruption management, metaheuristics for VRP, and dynamic and stochastic VRP. Section 3 presents the DMDVRP-D formulation and the DRSO algorithm in detail. Section 4 describes the experimental setup, including benchmark instances and case study data. Section 5 reports and analyzes computational results. Section 6 discusses findings, managerial implications, and limitations. Section 7 concludes the paper and outlines directions for future research.

2 | Related Work

2.1 | Vehicle Routing Problem and Its Variants

The VRP, originating from the seminal work of Dantzig and Ramser [5], seeks to determine optimal routes for a fleet of vehicles serving geographically dispersed customers from one or more depots. The VRP is classified as NP-hard [15], and its practical importance has spawned an extensive taxonomy of variants. Solomon [6] introduced time window constraints, yielding the VRP with Time Windows (VRPTW), and generated benchmark instances that remain standard references nearly four decades later. The Multi-Depot VRP (MDVRP), studied by Cordeau et al. [7] and later by Montoya-Torres et al. [16], extends the problem to multiple origin points, introducing depot assignment as an additional decision dimension. Heterogeneous fleet variants [8] capture realistic fleet compositions with varying capacities, speeds, and operating costs.

Recent reviews by Braekers et al. [17] and Elshaer and Awad [18] provide comprehensive classifications of VRP variants and solution methodologies. The rich VRP framework proposed by Caceres-Cruz et al. [19] emphasizes that real-world routing problems typically involve multiple complicating features simultaneously time windows, heterogeneous fleets, multiple depots, and dynamic information yet most solution methods address these features in isolation. Our work contributes to this stream by incorporating disruption events as a first-class modeling construct within the multi-depot, time-windowed routing context.

2.2 | Supply Chain Disruption Management

The study of supply chain disruptions has expanded substantially since the early 2000s, driven by high-profile events that exposed fragilities in global logistics networks. Snyder et al. [4] provided a comprehensive review of OR/MS models for supply chain disruptions, categorizing nearly 150 scholarly works into strategic decisions, sourcing, contracts, inventory, and facility location. They identified a persistent gap in operational-level disruption management, particularly in routing and scheduling contexts. Tomlin [20] analyzed dual-sourcing strategies under disruption risk, demonstrating that tailored mitigation approaches outperform generic contingency planning. Sheffi and Rice [12] articulated the concept of supply chain resilience as encompassing redundancy, flexibility, and velocity of recovery, laying conceptual foundations that subsequent quantitative work has sought to operationalize.

Ivanov [2] introduced the concept of “viability” in supply chain management, arguing that disruptions induced by pandemics and ripple effects require models that go beyond traditional resilience to consider survival and adaptation. Hosseini et al. [3] proposed a Bayesian network approach for quantifying supply chain resilience, incorporating disruption probability, vulnerability, and recoverability as interconnected factors. While these contributions provide valuable strategic and analytical frameworks, the translation into routing-level algorithms that can execute in real-time operational settings remains limited. Our work addresses this gap by embedding disruption modeling directly within the routing optimization algorithm.

2.3 | Metaheuristics for the Vehicle Routing Problem

Metaheuristic methods dominate the practical solution landscape for VRP variants due to the computational intractability of exact approaches for realistic instance sizes. Gendreau et al. [21] provided an early taxonomy of metaheuristics for VRP, covering tabu search, simulated annealing, and Genetic Algorithms (GA). Tabu search, applied to VRP by Gendreau et al. [22] and further refined by Cordeau et al. [23] for multi-depot variants, has produced many best-known solutions on benchmark instances. GAs have been successfully applied to VRPTW by Berger and Barkaoui [24] and to MDVRP by Vidal et al. [25], whose Unified Hybrid Genetic Search (UHGS) represents a landmark contribution in the field.

ALNS, proposed by Ropke and Pisinger [9], has emerged as one of the most versatile and effective frameworks for VRP. ALNS maintains a portfolio of destroy and repair operators, adaptively selecting among them based on historical performance using a roulette-wheel mechanism. Pisinger and Ropke [26] demonstrated ALNS on five VRP variants simultaneously, establishing its generalizability. Subsequent extensions include the work of Demir et al. [27] on the pollution-routing problem, Ribeiro and Laporte [28] on the cumulative VRP, and Grangier et al. [29] on the electric VRPTW and nonlinear charging. The flexibility of the ALNS framework makes it particularly suitable for incorporating disruption-specific operators, a strategy we exploit in DRSO.

Particle Swarm Optimization (PSO), introduced by Kennedy and Eberhart [30], has been adapted for discrete VRP variants through various encoding schemes [31]. The GWO by Mirjalili et al. [14] is a more recent swarm intelligence algorithm that has shown competitive performance on continuous optimization benchmarks. Extensions to discrete optimization, including GWO for TSP [32] and hybrid GWO for scheduling [33], suggest potential for VRP applications, though limited work has explored this direction. Our hybridization of GWO with ALNS is, to our knowledge, the first such combination proposed for any VRP variant.

2.4 | Dynamic and Stochastic Vehicle Routing Problem

Dynamic VRP (DVRP) settings involve information that is revealed or changes during route execution. Pillac et al. [13] provided a comprehensive classification of dynamic and stochastic VRP variants, distinguishing between problems with dynamic customer requests, dynamic travel times, and dynamic vehicle availability. Psaraftis et al. [34] surveyed dynamic vehicle routing with an emphasis on real-time information and the role of communication technologies. Ulmer et al. [35] addressed anticipatory routing in the DVRP, demonstrating that policies incorporating future information significantly outperform myopic re-optimization.

Stochastic VRP (SVRP) models uncertainty through probability distributions over problem parameters. Gendreau et al. [10] introduced the stochastic VRP with random demands, solved via an integer L-shaped method. Laporte et al. [36] provided exact and heuristic solutions for SVRP variants with stochastic demands and customers. More recently, scenario-based approaches have gained traction: Bent and Van Hentenryck [37] proposed a scenario-based online stochastic VRP, while Saint-Guillain et al. [38] developed a sample-average approximation method for the dynamic stochastic VRP.

Despite substantial progress in both dynamic and stochastic VRP research, few studies simultaneously address dynamic information revelation and disruption events within a unified framework. Notable exceptions include the work of Li et al. [39] on the VRP with disruptions and the contribution of Mu et al. [40] on disruption management for the VRPTW. However, these works do not incorporate multi-depot settings, heterogeneous disruption types, or resilience-oriented performance metrics. Our DMDVRP-D formulation and DRSO algorithm fill this gap by providing a comprehensive framework that addresses multiple disruption types, multiple depots, stochastic scenario modeling, and resilience evaluation within a single algorithmic architecture.

3 | Methodology

3.1 | Problem Formulation

We formulate the DMDVRP-D as a MILP. Let G = (N, A) be a directed graph where N = D ∪ C is the set of nodes comprising depots $D = \{d_1, d_2, \ldots, d_{|D|}\}$ and customers $C = \{c_1, c_2, \ldots, c_{|C|}\}$, and $A = \{(i, j): i, j \in N, i \neq j\}$ is the set of arcs. Let $K = \{k_1, k_2, \ldots, k_{|K|}\}$ denote the set of vehicles, and $T = \{t_0, t_1, \ldots, t_{|T|}\}$ denote discrete time periods within the planning horizon.

We define the following parameters:

I. qi: demand of customer i ∈ C.

II. Qk: capacity of vehicle k ∈ K.

III. cij: travel cost on arc (i, j) ∈ A.

IV. τij: travel time on arc (i, j) ∈ A.

V. [ei, li]: time window for node i ∈ N.

VI. si: service time at node i ∈ C.

VII. δRij,t ∈ {0, 1}: road closure indicator for arc (i, j) at time t.

VIII. δFd,t ∈ {0, 1}: facility failure indicator for depot d at time t.

IX. δDi,t ≥ 0: demand surge multiplier for customer i at time t.

X. δVk,t ∈ {0, 1}: vehicle breakdown indicator for vehicle k at time t.

Decision variables:

I. xijk ∈ {0, 1}: equals 1 if vehicle k traverses arc (i, j), 0 otherwise.

II. yik ∈ {0, 1}: equals 1 if customer i is assigned to vehicle k, 0 otherwise.

III. wi ≥ 0: arrival time of the vehicle at node i.

IV. ui ∈ {0, 1}: equals 1 if customer i is unserved, 0 otherwise.

V. zid ∈ {0, 1}: equals 1 if customer i is reassigned to backup depot d.

VI. fi ≥ 0: fraction of demand for customer i fulfilled through DS.

The objective function minimizes a weighted combination of routing cost, penalty for unserved customers, and disruption recovery cost:

$$\text{Minimize } Z = \alpha \sum_{k\in K} \sum_{(i,j)\in A} c_{ij}\, x_{ijk} + \beta \sum_{i\in C} p_i\, u_i + \gamma \sum_{i\in C} \sum_{d\in D} r_{id}\, z_{id}, \tag{1}$$

where p_i is the penalty for leaving customer i unserved, r_{id} is the reassignment cost for redirecting customer i to backup depot d, and α, β, γ are weighting parameters reflecting the decision maker's priorities.

Subject to the following constraints:

$$\sum_{k\in K} y_{ik} + u_i = 1, \quad \forall\, i \in C, \tag{2}$$

$$\sum_{i\in C} q_i \left(1 + \delta^{D}_{i,t}\right) y_{ik} \leq Q_k, \quad \forall\, k \in K, \tag{3}$$

$$\sum_{j\in N} x_{ijk} = y_{ik}, \quad \forall\, i \in C, \forall\, k \in K, \tag{4}$$

$$\sum_{j\in N} x_{ijk} = \sum_{j\in N} x_{jik}, \quad \forall\, i \in N, \forall\, k \in K, \tag{5}$$

$$x_{ijk} \leq 1 - \delta^{R}_{ij,t}, \quad \forall\, (i,j) \in A, \forall\, k \in K, \forall\, t \in T, \tag{6}$$

$$\sum_{j \in N} x_{djk} \leq 1 - \delta^{F}_{d,t}, \quad \forall\, d \in D, \forall\, k \in K, \forall\, t \in T, \tag{7}$$

$$\sum_{(i,j) \in A} x_{ijk} \leq M\,(1 - \delta^{V}_{k,t}), \quad \forall\, k \in K, \forall\, t \in T, \tag{8}$$

$$w_i + s_i + \tau_{ij} - M(1 - x_{ijk}) \leq w_j, \quad \forall\, (i,j) \in A, \forall\, k \in K, \tag{9}$$

$$e_i \leq w_i \leq l_i, \quad \forall\, i \in N. \tag{10}$$

Constraints (2) ensure each customer is either served by exactly one vehicle or marked as unserved. *Constraints (3)* enforce capacity limits adjusted for demand surges. *Constraints (4)* and *(5)* are assignment and flow conservation constraints. *Constraint (6)* prohibits traversal of arcs affected by road closures. *Constraint (7)* prevents route origination from failed depots. *Constraint (8)* deactivates broken-down vehicles. *Constraints (9)* and *(10)* enforce time window feasibility via big-M linearization.

The DMDVRP-D is NP-hard, as it generalizes the classical VRP. Moreover, the dynamic nature of disruption parameters and the stochastic uncertainty in their occurrence render exact solution intractable for realistic instance sizes, motivating the metaheuristic approach developed in Section 3.2.

3.2 | Dynamic Resilient Supply-chain Optimizer Algorithm: Adaptive Large Neighborhood Search + Grey Wolf Optimizer Hybrid

The DRSO combines the neighborhood-based intensification capabilities of ALNS with the population-based exploration strengths of GWO. The algorithm operates in two interleaved phases: an ALNS phase that generates and refines candidate solutions through destroy-repair cycles, and a GWO phase that guides population-level search toward promising regions of the solution space.

3.2.1 | Solution representation

A solution S is represented as a set of routes $R = \{r_1, r_2, \ldots, r_{|K|}\}$, where each route $r_k = (d_k, v_{k1}, v_{k2}, \ldots, v_{km}, d_k)$ specifies the sequence of customer visits for vehicle k, originating from and returning to its assigned depot d_k. Each solution maintains an associated disruption state vector $\Delta(t) = (\delta^R(t), \delta^F(t), \delta^D(t), \delta^V(t))$ encoding the active disruptions at time t. The fitness of solution S under disruption state $\Delta(t)$ is evaluated using the *Objective Function (1)* augmented by the stochastic component described in Section 3.3.

3.2.2 | Adaptive large neighborhood search component

The ALNS component employs eight destroy operators and eight repair operators, including four standard operators and four resilience-specific operators. Standard destroy operators include random removal, worst removal, Shaw [41] removal, and historical node-pair removal. Standard repair operators include greedy insertion, regret-2 insertion, regret-3 insertion, and noise-perturbed greedy insertion.

The four resilience-specific destroy-repair operator pairs are:

FS: the destroy operator removes all customers currently assigned to a disrupted depot. The repair operator reassigns these customers to the nearest operational depot, attempting insertion into existing routes at that depot before creating new routes.

ER: The destroy operator removes customers whose routes traverse closed road segments. The repair operator constructs alternative paths using a modified Dijkstra's algorithm on the residual network, reinserting affected customers at minimum cost positions.

DS: The destroy operator identifies customers with surge-inflated demands exceeding vehicle capacity. The repair operator splits such demands across multiple vehicles, creating partial delivery visits that collectively satisfy the full (surged) demand.

MS: The destroy operator removes customers in regions where the primary transportation mode is disrupted. The repair operator evaluates alternative modes (e.g., rail, air freight, inland waterway) with adjusted cost and time parameters, reinserting customers using the most cost-effective available mode.

Operator selection follows the adaptive weight adjustment mechanism of Ropke and Pisinger [9]. Each operator ω maintains a weight w_ω updated at the end of each segment of ψ iterations:

$$w_\omega \leftarrow (1-\lambda)\, w_\omega + \lambda\, (\pi_\omega / \max(1, \theta_\omega)), \tag{11}$$

where $\lambda \in [0, 1]$ is the reaction factor, π_ω is the accumulated score of operator ω in the current segment, and θ_ω is the number of times operator ω was used. Scores are assigned as follows: σ_1 if the operator found a new global best solution, σ_2 if it found a solution better than the current solution, and σ_3 if it found an accepted but non-improving solution.

3.2.3 | Grey wolf optimizer component

The GWO component maintains a population of N_w wolf solutions, hierarchically ranked as alpha (α), beta (β), delta (δ), and omega (ω) wolves based on fitness. Position update in GWO, originally designed for continuous spaces [14], is adapted for discrete VRP solutions through a crossover-based position update mechanism.

At each GWO iteration, omega wolves update their positions by constructing new solutions that combine route segments from the alpha, beta, and delta wolves. Specifically, for each omega wolf solution S_ω, a new solution is constructed as:

$$S_\omega' = \text{CrossoverSelect}(S_\alpha, S_\beta, S_\delta, a(t)), \tag{12}$$

where $a(t) = 2(1 - t/T_{max})$ is the linearly decreasing convergence parameter. The CrossoverSelect operation randomly selects route segments from the three leader wolves with probabilities proportional to their fitness ranks, adjusted by a(t) to shift from exploration (diverse segment selection) to exploitation (preference for alpha segments) as the search progresses.

The coefficient vectors A and C, central to GWO's position update, are reinterpreted in the discrete context as perturbation operators:

$$A = 2a \cdot \text{rand} - a, \quad C = 2 \cdot \text{rand}. \tag{13}$$

When $|A| < 1$, the update favors exploitation (local ALNS refinement on segments near the leader wolves); when $|A| \geq 1$, the update favors exploration (random destroy-repair operations generating diverse solutions).

3.2.4 | Hybrid integration

The ALNS and GWO components are integrated through a cooperative scheme. In each major iteration of DRSO: 1) the GWO component performs one position update cycle across the wolf population, generating a set of candidate solutions; 2) the ALNS component applies destroy-repair cycles to each candidate solution for a fixed number of inner iterations N_{ALNS}; and 3) improved solutions are fed back to the GWO population, potentially updating the alpha, beta, and delta positions. This integration exploits ALNS's strength in local refinement while leveraging GWO's ability to maintain population diversity and guide search toward globally promising regions.

3.3 | Disruption Scenario Modeling

To account for uncertainty in disruption occurrence, DRSO employs scenario-tree-based stochastic programming within its fitness evaluation. A scenario tree T is constructed with branching points at discrete time epochs $t_1, t_2, \ldots, t_H$ within the planning horizon. Each branch represents a possible disruption realization characterized by its type (road closure, facility failure, demand surge, vehicle breakdown), location, severity, and duration.

Let $\Omega = \{\omega_1, \omega_2, \ldots, \omega_{|\Omega|}\}$ denote the set of scenarios generated from the scenario tree, with associated probabilities p_ω satisfying $\sum_{\omega\in\Omega} p_\omega = 1$. The stochastic fitness of a solution S is:

$$F(S) = (1 - \eta)\, Z(S, \Delta_0) + \eta \sum_{\omega\in\Omega} p_\omega\, Z(S, \Delta_\omega), \tag{14}$$

where $Z(S, \Delta_0)$ is the objective value under the nominal (disruption-free) scenario, $Z(S, \Delta_\omega)$ is the objective value under disruption scenario ω, and $\eta \in [0, 1]$ controls the trade-off between nominal optimality and disruption preparedness. Larger values of η produce solutions that are more resilient but potentially suboptimal under normal conditions.

Disruption probabilities are estimated from historical data and expert judgment. For the Nigerian case study, disruption probabilities are calibrated using five-year records of road closures (rainy season flooding, security incidents), facility outages (power failures, regulatory shutdowns), and demand surges (disease outbreaks, seasonal spikes). For the Chinese case study, probabilities are derived from logistics disruption databases maintained by the Shanghai Maritime University and publicly available incident reports from the YRD transportation authority.

3.4 | Re-Optimization Strategy

When a disruption event occurs during route execution, DRSO triggers a re-optimization procedure that exploits the structure of the pre-disruption solution to accelerate convergence. The re-optimization strategy operates as follows:

Disruption detection: the system monitors real-time data feeds for disruption signals. Upon detection, the current disruption state vector Δ(t) is updated.

Solution partitioning: the pre-disruption solution Spre is partitioned into an unaffected component SU (routes not impacted by the disruption) and an affected component SA (routes requiring modification).

Warm-start initialization: the GWO population is initialized with the unaffected component SU fixed, and the affected component SA is replaced with solutions generated by the resilience-specific destroy-repair operators. This warm-start reduces the search space substantially compared to re-solving from scratch.

Focused ALNS: the ALNS component is restricted to operate only on the affected component, with resilience-specific operators receiving elevated initial weights proportional to the disruption type (e.g., FS receives higher weight for depot failures).

Convergence and deployment: the re-optimization runs for a reduced iteration budget Nreopt < Nmax, reflecting the real-time nature of the response. The best solution found is deployed, and its structure is cached for potential subsequent re-optimization.

The complete DRSO algorithm is presented in *Algorithm 1*.

Algorithm 1. DRSO.

Input: Graph G=(N, A), vehicles K, disruption scenarios Ω, parameters

Output: Best solution S_{best}, Composite Resilience Score CRS

1: **Initialize** GWO population $P = \{S_1, S_2, \ldots, S_{Nw}\}$ // *nearest-neighbor + random*

2: **Initialize** ALNS operator weights $w_\omega = 1$ for all operators ω

Evaluate $F(S_i)$ for all $S_i \in P$ using Eq. (14)

Rank wolves: identify S_α, S_β, S_δ

$S_{best} \leftarrow S_\alpha$

for iter = 1 **to** N_{max} **do**

  if DisruptionDetected(t) **then**

    Update disruption state $\Delta(t)$

    Partition S_{best} into S_U and S_A

    WarmStartPopulation(P, S_U, S_A)

    BoostResilienceOperators($\Delta(t)$)

  end if

  Update convergence parameter: $a = 2(1 - iter/N_{max})$

  for each wolf $S_i \in P$ **do**

    // GWO position update

    $S_i' \leftarrow$ CrossoverSelect(S_α, S_β, S_δ, a)

    // ALNS refinement

    for j = 1 **to** N_{ALNS} **do**

      Select destroy operator d^- by roulette wheel on weights

      Select repair operator d^+ by roulette wheel on weights

      $S_{temp} \leftarrow d^+(d^-(S_i'))$

      if Accept(S_{temp}, S_i', T_{SA}) **then**

$S_i' \leftarrow S_{temp}$

end if

UpdateOperatorScores(π_ω)

end for

if $F(S_i') < F(S_i)$ **then** $S_i \leftarrow S_i'$

end for

Rank wolves: update S_α, S_β, S_δ

if $F(S_\alpha) < F(S_{best})$ **then** $S_{best} \leftarrow S_\alpha$

UpdateOperatorWeights(w_ω) using Eq. (11) every ψ iterations

Cool SA temperature: $T_{SA} \leftarrow \phi \cdot T_{SA}$

end for

Compute CRS(S_{best}) using Eq. (15)–(18)

return S_{best}, CRS

3.5 | Resilience Metrics

To enable comprehensive evaluation of solution quality under disruptions, we introduce the CRS, a multi-criteria metric that integrates three dimensions of supply chain resilience.

RT: the time elapsed between disruption occurrence and the point at which the re-optimized solution achieves a SL within ε of the pre-disruption level:

$$RT = \min\{t' - t_{dis} : SL(S(t')) \geq (1-\varepsilon) \cdot SL(S_{pre})\}, \tag{15}$$

where t_{dis} is the disruption time, $S(t')$ is the solution at time t', and $SL(\cdot)$ is the SL function.

SL: the proportion of total demand satisfied within time windows after re-optimization:

$$SL = \sum_{i \in C} q_i f_i (1 - u_i) \,/\, \sum_{i \in C} q_i (1 + \delta^D_{i,t}). \tag{16}$$

EC: the additional cost incurred due to disruption response, normalized by the pre-disruption cost:

$$EC = (Z(S_{post}, \Delta(t)) - Z(S_{pre}, \Delta_0)) \,/\, Z(S_{pre}, \Delta_0). \tag{17}$$

The CRS integrates these dimensions using a weighted geometric mean:

$$\mathrm{CRS} = (\mathrm{RT}_{\mathrm{norm}})^{w1} \cdot (\mathrm{SL})^{w2} \cdot (1 - \mathrm{EC}_{\mathrm{norm}})^{w3}, \quad (18)$$

where RT_{norm} and EC_{norm} are min-max normalized values, and $w_1 + w_2 + w_3 = 1$. Higher CRS values indicate greater resilience. Default weights are set as $w_1 = 0.3$, $w_2 = 0.4$, $w_3 = 0.3$, reflecting the primacy of SL in supply chain performance.

4 | Experimental Setup

4.1 | Benchmark Instances

We evaluate DRSO on two categories of test instances: modified Solomon VRPTW benchmarks and real-world case studies.

4.1.1 | Modified Solomon instances with disruptions

We extend the Solomon [6] VRPTW benchmark instances (C1, C2, R1, R2, RC1, RC2 classes with 100 customers) to multi-depot settings with disruption scenarios. Each original instance is transformed as follows: 1) three depots are placed at strategically selected locations, replacing the single depot, 2) vehicle fleets are distributed across depots proportionally to nearby customer density, and 3) disruption scenarios are generated using the parameters in *Table 1*.

Table 1. Disruption scenario parameters for modified Solomon instances.

Parameter	Value/Range	Description
Number of disruption types	4	Road closure, facility failure, demand surge, vehicle breakdown
Disruptions per scenario	1–5	Uniformly distributed
Road closure probability	0.05–0.15 per arc	Higher for long-distance arcs
Facility failure probability	0.02–0.08 per depot	Independent across depots
Demand surge multiplier	1.2–2.5	Log-normally distributed
Vehicle breakdown probability	0.03–0.10 per vehicle	Age-dependent
Disruption duration	10–50 time units	Exponentially distributed
Scenarios per instance (Ω)	20	Scenario tree with 3 branching points

For each of the six Solomon instance classes, we select five representative instances, yielding 30 base instances. Each is paired with three disruption severity levels (low, medium, high), producing 90 test configurations in total.

4.1.2 | Nigerian pharmaceutical distribution network

The first real-world case study models a pharmaceutical distribution network spanning the Lagos–Abuja–Kano corridor in Nigeria. The network comprises 45 nodes: 3 distribution centers (Lagos, Abuja, Kano) serving as depots, and 42 pharmacy/hospital locations distributed across 12 states. Disruptions are calibrated from five years (2019–2024) of operational records provided by a major Nigerian pharmaceutical logistics provider (anonymized). Key disruption characteristics include seasonal flooding (June–October) causing road closures on 15–25% of major highways, power-related facility outages averaging 3.2 days per month per depot, security-related route diversions in the North-East and North-Central geopolitical zones, and demand surges during malaria (April–July) and meningitis (December–March) seasons.

Table 2. Nigerian case study network characteristics.

Attribute	Value
Total nodes	45 (3 depots + 42 customers)
Total corridor length	~1,100 km (Lagos–Abuja–Kano)
Fleet size	18 vehicles (6 per depot)
Vehicle capacity	2,500 kg (refrigerated) / 4,000 kg (ambient)
Planning horizon	12 hours
Average demand per customer	180–650 kg
Time windows	Hospital deliveries: 2-hour windows; pharmacies: 4-hour windows
Historical disruption frequency	2.8 events per week (averaged over 5 years)

4.1.3 | Chinese manufacturing supply chain

The second real-world case study models a manufacturing supply chain in the YRD region of China, encompassing parts of Shanghai, Jiangsu, Zhejiang, and Anhui provinces. The network comprises 78 nodes: 5 distribution centers (Shanghai, Suzhou, Nanjing, Hangzhou, Hefei) serving as depots, and 73 manufacturing plants and assembly facilities as customers. The network supports the distribution of automotive components and electronic parts.

Table 3. Chinese case study network characteristics.

Attribute	Value
Total nodes	78 (5 depots + 73 customers)
Network coverage area	~120,000 km²
Fleet size	32 vehicles (4–8 per depot)
Vehicle types	3 types: light (5t), medium (10t), heavy (20t)
Transportation modes	Road, rail, inland waterway (Yangtze River)
Planning horizon	24 hours
Average demand per customer	1.2–8.5 tonnes
Time windows	JIT deliveries: 1-hour windows; standard: 4-hour windows
Historical disruption frequency	1.6 events per week (averaged over 3 years)

Disruptions in the YRD network include typhoon-induced road and port closures (July–October), Yangtze River flooding affecting inland waterway transport, factory shutdowns due to power rationing during peak summer demand, and traffic congestion on the G2/G40/G50 expressway corridors causing significant travel time variability.

4.2 | Compared Algorithms

DRSO is compared against five baseline approaches:

ALNS-only: standard ALNS with the same operator portfolio but without GWO-guided search or resilience-specific operators.

GA: GA with order crossover, mutation, and elitism, calibrated following Vidal et al. [25].

PSO: discrete PSO with swap-sequence encoding, following Ai and Kachitvichyanukul [31].

GWO-only: standalone GWO adapted for VRP with the discrete position update of Section 3.2.3 but without ALNS refinement.

Gurobi (TL): the MILP formulation (Section 3.1) solved using Gurobi 10.0 with a time limit equal to the wall-clock time consumed by DRSO on the same instance.

4.3 | Parameter Settings

DRSO parameters are calibrated through preliminary experiments on a subset of 10 Solomon-derived instances not included in the final test set. *Table 4* summarizes the parameter settings.

Table 4. DRSO parameter settings.

Parameter	Symbol	Value
GWO population size	N_w	30
Maximum iterations	N_{max}	5,000
ALNS inner iterations per wolf	N_{ALNS}	200
Re-optimization iteration budget	N_{reopt}	500
ALNS segment length	ψ	100
Reaction factor	λ	0.15
Score parameters	$\sigma_1, \sigma_2, \sigma_3$	33, 9, 3
SA initial temperature	T_{SA}	100
SA cooling rate	φ	0.9997
Stochastic weight	η	0.35
Objective weights	α, β, γ	1.0, 50.0, 5.0
Resilience weights	w_1, w_2, w_3	0.3, 0.4, 0.3
Recovery threshold	ε	0.05
Number of scenarios	$\|\Omega\|$	20
Removal percentage (destroy)		10–40% of customers

4.4 | Computational Environment and Statistical Testing

All experiments are conducted on a workstation equipped with an Intel Xeon E5-2690 v4 processor (2.60 GHz, 14 cores) and 128 GB RAM, running Ubuntu 22.04 LTS. DRSO and all metaheuristic baselines are implemented in Python 3.11 with NumPy 1.26 and compiled Cython extensions for performance-critical operations. Gurobi 10.0.3 is used for MILP solving with default settings except for the imposed time limit.

Each metaheuristic algorithm is executed 30 independent times per instance with different random seeds. Statistical significance of pairwise differences is assessed using the Wilcoxon signed-rank test at a significance level of $p < 0.05$. Effect sizes are reported using the Vargha-Delaney A-measure [42], where $A > 0.71$ indicates a large effect. We also report the Interquartile Range (IQR) of results to characterize solution consistency.

5 | Results

5.1 | Results on Modified Solomon Instances

Table 5 presents the aggregated results across all 90 modified Solomon configurations, reporting mean values over 30 independent runs for each algorithm. DRSO consistently outperforms all baseline methods across the three primary metrics: disruption recovery cost, RT, and percentage of unserved customers.

Table 5. Aggregated results on modified Solomon instances (mean over 30 runs, 90 configurations).

Algorithm	Recovery Cost	Cost Implication (%)	RT (TU)	Time Implication (%)	Unserved (%)	Unserved Implication (%)	CRS
DRSO	4,287.3		12.4		3.8		0.847
ALNS-only	5,418.6	20.9	17.8	30.3	5.6	32.1	0.712
GA	5,891.4	27.2	20.1	38.3	6.4	40.6	0.663
PSO	6,122.7	30.0	21.0	41.0	7.1	46.5	0.631
GWO-only	5,745.2	25.4	19.3	35.8	6.0	36.7	0.686
Gurobi (TL)	5,194.8	17.5	16.2	23.5	5.2	26.9	0.738

DRSO achieves mean improvements of 20.9% over ALNS-only, 27.2% over GA, 30.0% over PSO, 25.4% over GWO-only, and 17.5% over Gurobi (TL) in recovery cost. RT improvements range from 23.5% (vs. Gurobi) to 41.0% (vs. PSO). The reduction in unserved customers is particularly notable, ranging from 26.9% to 46.5% across baselines. All pairwise differences are statistically significant at $p < 0.05$ via the Wilcoxon signed-rank test.

Table 6 presents results disaggregated by disruption severity level, revealing that DRSO's advantage increases with disruption severity.

Table 6. DRSO improvement over ALNS-only by disruption severity (modified Solomon instances).

Severity Level	Cost Implication (%)	Time Implication (%)	Unserved Implication (%)	CRS (DRSO)	CRS (ALNS)
Low (1–2 disruptions)	14.3	18.7	15.2	0.912	0.823
Medium (3 disruptions)	21.6	31.4	28.7	0.841	0.702
High (4–5 disruptions)	28.1	41.5	48.4	0.788	0.611

Under high disruption severity, DRSO achieves 28.1% cost reduction and 41.5% faster recovery compared to ALNS-only. This escalating advantage under severe conditions confirms the effectiveness of the scenario-tree stochastic evaluation and resilience-specific operators in anticipating and adapting to complex disruption patterns.

5.2 | Results on Nigerian Pharmaceutical Network

Table 7 presents results on the Nigerian pharmaceutical distribution network across three representative disruption profiles: rainy-season flooding (Profile A), combined flooding and security disruptions (Profile B), and compound disruptions including demand surge from disease outbreak (Profile C).

Table 7. Results on the Nigerian pharmaceutical network (45 nodes, mean over 30 runs).

Algorithm	Profile A Cost (₦×10³)	Profile B Cost (₦×10³)	Profile C Cost (₦×10³)	Average Recovery (Minutes)	Average SL (%)	CRS
DRSO	2,847	3,912	5,134	38.2	96.4	0.871
ALNS-only	3,524	5,087	6,843	58.6	89.7	0.723
GA	3,815	5,491	7,328	64.3	86.5	0.681
PSO	3,972	5,698	7,615	68.1	84.9	0.658
GWO-only	3,643	5,234	7,084	61.7	88.2	0.701
Gurobi (TL)	3,198	4,876	6,592	52.4	91.3	0.751

DRSO demonstrates substantial advantages across all profiles, with cost reductions of 19.2% (Profile A), 23.1% (Profile B), and 25.0% (Profile C) compared to ALNS-only. Under the most challenging compound disruption, Profile C, DRSO maintains a 96.4% average SL, compared to 89.7% for ALNS-only and 84.9% for PSO. The RT advantage (38.2 minutes vs. 58.6–68.1 minutes for baselines) is critical in the pharmaceutical context, where delayed deliveries of temperature-sensitive medications can result in spoilage and patient harm.

5.3 | Results on Chinese Manufacturing Supply Chain

Table 8 summarizes results on the YRD manufacturing network across four disruption profiles: typhoon-induced closures (Profile D), river flooding with modal disruption (Profile E), factory shutdowns with demand redistribution (Profile F), and compound multi-type disruptions (Profile G).

Table 8. Results on the Chinese manufacturing supply chain (78 nodes, mean over 30 runs).

Algorithm	Profile D Cost (¥×10³)	Profile E Cost (¥×10³)	Profile F Cost (¥×10³)	Profile G Cost (¥×10³)	Average RT (Minutes)	Average SL (%)	CRS
DRSO	187.4	214.8	198.3	267.5	22.7	97.1	0.883
ALNS-only	231.6	278.4	252.1	348.2	34.8	91.8	0.746
GA	248.9	302.7	271.4	382.6	39.5	88.4	0.698
PSO	257.3	318.5	283.9	401.8	42.1	86.7	0.672
GWO-only	239.7	287.6	260.8	361.4	36.9	90.3	0.724
Gurobi (TL)	218.4	261.3	238.6	327.1	30.2	93.5	0.771

On the larger Chinese network (78 nodes), DRSO's advantages are even more pronounced, with cost reductions of 19.1% to 23.2% compared to ALNS-only across disruption profiles. The MS operator proves particularly effective in the YRD context, where inland waterway alternatives along the Yangtze River provide viable backup routes when road or rail links are disrupted. DRSO achieves a 97.1% average SL, critical for just-in-time automotive manufacturing where line stoppages due to missing components incur costs of approximately ¥500,000–2,000,000 per hour.

5.4 | Statistical Significance and Effect Size

Table 9 presents the Wilcoxon signed-rank test results and Vargha-Delaney A-measure effect sizes for pairwise comparisons between DRSO and each baseline, aggregated across all test instances.

Table 9. Statistical significance and effect sizes (DRSO vs. baselines, all instances).

Comparison	Metric	W-Statistic	p-value	Significant?	A-Measure	Effect
DRSO vs. ALNS-only	Cost	42	<0.001	Yes	0.84	Large
DRSO vs. ALNS-only	RT	38	<0.001	Yes	0.87	Large
DRSO vs. ALNS-only	SL	51	<0.001	Yes	0.82	Large
DRSO vs. GA	Cost	28	<0.001	Yes	0.91	Large
DRSO vs. GA	RT	31	<0.001	Yes	0.89	Large
DRSO vs. PSO	Cost	19	<0.001	Yes	0.93	Large
DRSO vs. PSO	RT	22	<0.001	Yes	0.92	Large
DRSO vs. GWO-only	Cost	35	<0.001	Yes	0.86	Large
DRSO vs. Gurobi (TL)	Cost	64	0.003	Yes	0.76	Large
DRSO vs. Gurobi (TL)	RT	58	0.008	Yes	0.74	Large

All comparisons yield $p < 0.05$, confirming statistical significance. The A-measure values (0.74–0.93) consistently indicate large effect sizes, demonstrating that DRSO's superiority is not merely statistically significant but practically meaningful. The smallest effect size is observed against Gurobi (TL), which benefits from the optimality guarantees of exact methods for the portion of the solution it can compute within the time limit.

5.5 | Operator Performance Analysis

Table 10 reports the average usage frequency and contribution of each ALNS operator across all DRSO runs, providing insight into the algorithm's adaptive behavior.

Table 10. ALNS operator usage frequency and contribution analysis (averaged across all runs).

Operator	Type	Usage Frequency (%)	New Best (%)	Improvement (%)	Final Weight
Random removal	Standard destroy	11.2	4.3	18.6	0.82
Worst removal	Standard destroy	13.8	7.1	24.3	1.14
Shaw removal	Standard destroy	14.1	8.6	27.1	1.21
Historical removal	Standard destroy	9.4	5.8	20.7	0.93
FS	Resilience destroy	15.7	12.4	34.8	1.58
ER	Resilience destroy	14.2	11.7	32.1	1.47
DS	Resilience destroy	10.8	9.3	28.5	1.31
MS	Resilience destroy	10.8	8.9	26.4	1.22
Greedy insertion	Standard repair	14.6	6.2	22.4	1.04
Regret-2 insertion	Standard repair	16.3	9.8	30.6	1.38
Regret-3 insertion	Standard repair	15.1	10.4	31.2	1.42
Noise greedy insertion	Standard repair	12.7	5.1	19.8	0.91

The resilience-specific operators consistently achieve higher final weights than standard operators, indicating their effectiveness in the disruption context. FS achieves the highest contribution rate (34.8% of uses leading to improvement), followed by ER (32.1%). These results confirm that domain-specific destroy-repair operations provide substantially greater search guidance than generic operators when the problem involves disruption-induced structural changes to the solution.

5.6 | Computational Time Analysis

Table 11 reports average wall-clock computation times across instance categories.

Table 11. Average computation time (seconds) across instance categories.

Instance Category	DRSO	ALNS-only	GA	PSO	GWO-only	Gurobi (TL)
Solomon (100 cust.)	124.3	67.8	89.4	72.1	58.3	124.3
Nigeria (45 nodes)	86.7	42.1	61.3	48.6	37.4	86.7
China (78 nodes)	218.5	108.2	147.6	119.4	92.7	218.5
Re-optimization (Average)	18.4	32.6	47.8	39.1	28.3	

DRSO requires approximately 1.8–2.4 times the computation time of standalone methods for initial solution construction due to the overhead of GWO population management and scenario evaluation. However, the warm-start re-optimization mechanism delivers a critical advantage in dynamic settings: DRSO's re-optimization time (18.4 seconds average) is 44–62% faster than baseline metaheuristics, which must re-solve the disrupted problem without structural guidance from the pre-disruption solution. Re-optimization speed is operationally significant, as re-optimization speed directly determines the delay between disruption detection and route adjustment deployment.

5.7 | Ablation Study

Table 12 presents an ablation study isolating the contribution of each DRSO component. Five variants are tested: DRSO without GWO (ALNS with resilience operators only), DRSO without resilience operators (ALNS+GWO with standard operators only), DRSO without scenario-tree evaluation (deterministic fitness), DRSO without warm-start re-optimization (cold restart), and the full DRSO.

Table 12. Ablation study results (aggregated over all instances, mean over 30 runs).

Variant	Average Cost	Average RT (TU)	Average SL (%)	CRS	Cost Gap (%)
Full DRSO	4,287.3	12.4	96.8	0.847	
w/o GWO	4,812.6	14.1	94.7	0.798	12.3
w/o Resilience Operators	5,134.8	16.8	92.1	0.741	19.8
w/o Scenario-tree Eval.	4,923.4	15.6	93.4	0.772	14.8
w/o Warm-start Reopt.	4,641.7	18.2	95.6	0.814	8.3

The ablation study reveals that resilience-specific operators contribute the largest individual improvement (19.8% cost gap when removed), followed by scenario-tree evaluation (14.8%), GWO integration (12.3%), and warm-start re-optimization (8.3%). The warm-start mechanism, while having the smallest cost impact, has a disproportionately large effect on RT (18.2 TU without vs. 12.4 TU with), confirming its critical role in dynamic settings where rapid response is essential.

6 | Discussion

6.1 | Analysis of Dynamic Resilient Supply-chain Optimizer Performance

The computational results provide strong evidence for the effectiveness of the DRSO framework across diverse problem settings. Several factors contribute to DRSO's superior performance. First, the hybridization of ALNS and GWO creates a synergistic search mechanism where GWO's population-based exploration prevents premature convergence, a known weakness of standalone ALNS [26], while ALNS's destroy-repair cycles provide the fine-grained neighborhood exploitation that pure population-based methods lack. The ablation study confirms this complementarity: removing either component degrades performance, but removing both would reduce DRSO to a basic heuristic.

Second, the resilience-specific operators encode domain knowledge about supply chain disruption response strategies into the search mechanism. Unlike generic VRP operators that treat solution modification as purely topological (rearranging visit sequences), the FS, ER, DS, and MS operators operate on the structural level of supply chain configuration. This semantic richness accelerates the discovery of high-quality solutions in disrupted scenarios, as evidenced by the operators' consistently higher adaptive weights and improvement rates compared to standard operators (*Table 10*).

Third, the scenario-tree stochastic fitness evaluation enables DRSO to construct solutions that inherently hedge against potential disruptions, even before they occur. This proactive resilience contrasts with purely reactive approaches that optimize for the nominal scenario and rely on re-optimization after disruptions. The value of anticipatory optimization is particularly evident under high-severity disruption conditions (*Table 6*), where DRSO's advantage over deterministic approaches is most pronounced.

6.2 | Practical Implications

The two real-world case studies demonstrate DRSO's applicability to distinct supply chain contexts with fundamentally different disruption profiles. The Nigerian pharmaceutical case study highlights the algorithm's value in infrastructure-constrained environments where disruptions are frequent, diverse, and often compound (e.g., simultaneous flooding and security incidents). The ability to maintain 96.4% SLs under compound disruptions is particularly significant for pharmaceutical logistics, where delivery failures can have direct health consequences. The 38.2-minute average re-optimization time is well within the operational decision window for pharmaceutical delivery managers who typically have 1–2 hours between disruption detection and route commitment.

The Chinese manufacturing case study illustrates DRSO's scalability to larger, more complex networks with multi-modal transportation options. The MS operator's effectiveness in the YRD context, where Yangtze River waterways provide natural backup for disrupted road and rail links, demonstrates the importance of embedding mode-specific knowledge into the optimization framework. The 97.1% SL and 22.7-minute average re-optimization time meet the stringent requirements of JIT manufacturing supply chains where component delays translate directly to production line stoppages.

From a managerial perspective, DRSO's CRS metric provides decision-makers with a single, interpretable measure of solution resilience that balances the competing objectives of rapid recovery, service continuity, and cost control. The configurable weights (w_1, w_2, w_3) allow organizations to tailor the metric to their specific priorities; for example, pharmaceutical distributors may weight SL more heavily, while cost-sensitive manufacturers may emphasize EC minimization.

6.3 | Comparison with Exact Methods

DRSO's consistent superiority over Gurobi (TL) merits discussion. Gurobi, as a state-of-the-art commercial solver, provides optimality guarantees for the portion of the MILP it can solve within the time limit. However, the dynamic, stochastic, and multi-objective nature of the DMDVRP-D challenges exact methods in several ways: 1) the scenario-tree evaluation increases the effective problem size by a factor of $|\Omega|$, 2) the dynamic re-optimization requirement demands rapid solution generation that exceeds Gurobi's warm-start capabilities for modified MILPs, and 3) the non-linear resilience metric (CRS) cannot be directly optimized within the MILP framework. These observations align with the broader finding in the metaheuristic literature that well-designed heuristics outperform exact methods under time constraints for large-scale, structurally complex optimization problems [43].

6.4 | Limitations

Several limitations of this study should be acknowledged. First, the disruption scenarios, while calibrated from real data, are generated synthetically and may not capture the full complexity of real-world disruption dynamics, including cascading effects and interdependencies between disruption types. Second, the scenario-tree approach with $|\Omega| = 20$ scenarios represents a trade-off between computational tractability and disruption coverage; larger scenario sets may improve hedging quality at the cost of increased computation time. Third, the real-world case studies, while based on authentic network topologies and disruption patterns, use partially simulated demand data due to confidentiality constraints. Fourth, DRSO's computational overhead compared to standalone methods (*Table 11*) may limit its applicability in extremely time-critical settings where sub-second re-optimization is required. Fifth, the current formulation assumes complete and accurate disruption detection; in practice, disruption information may be partial, delayed, or noisy, requiring robust optimization extensions.

6.5 | Threats to Validity

Internal validity is supported by the use of 30 independent runs with controlled random seeds and non-parametric statistical testing. However, parameter sensitivity analysis, while conducted informally during calibration, is not reported exhaustively. External validity is enhanced by testing on both standardized benchmarks and real-world instances from two continents and two industry sectors, though generalizability to other supply chain types (e.g., cold chain, humanitarian logistics) remains to be demonstrated. Construct validity of the CRS metric depends on the appropriateness of the weight settings; while default weights are justified by supply chain management literature, alternative weighting schemes may be more suitable for specific applications.

7 | Conclusion

This paper has introduced the DRSO, a hybrid metaheuristic combining ALNS with GWO for solving the DMDVRP-D. DRSO incorporates five innovations: scenario-tree stochastic fitness evaluation, resilience-specific ALNS operators (FS, ER, DS, MS), GWO-guided population-level search, warm-start re-optimization from pre-disruption solutions, and a CRS metric integrating RT, SL, and EC.

Extensive computational experiments on 90 modified Solomon benchmark configurations and two real-world case studies a Nigerian pharmaceutical distribution network (45 nodes) and a Chinese manufacturing supply chain (78 nodes) demonstrate that DRSO achieves 18–32% lower disruption recovery cost, 25–41% faster RT, and 15–28% fewer unserved customers compared to ALNS-only, GA, PSO, GWO-only, and time-limited Gurobi. All improvements are statistically significant at $p < 0.05$ with large effect sizes. The ablation study confirms that each DRSO component contributes meaningfully to overall performance, with resilience-specific operators providing the largest individual contribution.

Future research directions include: 1) extending DRSO to handle cascading disruptions with interdependency modeling, 2) incorporating machine learning for real-time disruption prediction and adaptive scenario generation, 3) exploring multi-objective formulations with Pareto-based optimization for simultaneously optimizing cost, resilience, and environmental sustainability, 4) developing distributed and parallel implementations for large-scale networks exceeding 500 nodes, 5) integrating DRSO with digital twin platforms for real-time simulation-optimization in smart supply chain management, and 6) validating the approach through controlled field experiments with industry partners in both the Nigerian and Chinese logistics sectors.

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Authors' Contributions

All aspects of the research and manuscript preparation were carried out by the author. The author has read and approved the final version of the manuscript.

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All data supporting the reported findings in this research paper are provided within the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Consent for Publication

The author confirms consent for the publication of this work.

Ethics Approval and Consent to Participate

This article does not contain any studies with human participants performed by the author.

References

[1] Christopher, M., & Peck, H. (2004). Building the resilient supply chain available to purchase. *The international journal of logistics management*, *15*(4), 1–14. https://doi.org/10.1108/09574090410700275

[2] Ivanov, D. (2022). Viable supply chain model: Integrating agility, resilience and sustainability perspectives—lessons from and thinking beyond the COVID-19 pandemic. *Annals of operations research*, *319*(1), 1411–1431. https://doi.org/10.1007/s10479-020-03640-6

[3] Hosseini, S., Ivanov, D., & Dolgui, A. (2019). Review of quantitative methods for supply chain resilience analysis. *Transportation research part e: Logistics and transportation review*, *125*, 285–307. https://doi.org/10.1016/j.tre.2019.03.001

[4] Snyder, L. V, Atan, Z., Peng, P., Rong, Y., Schmitt, A. J., & Sinsoysal, B. (2016). OR/MS models for supply chain disruptions: A review. *Iie transactions*, *48*(2), 89–109. https://doi.org/10.1080/0740817X.2015.1067735

[5] Dantzig, G. B., & Ramser, J. H. (1959). The truck dispatching problem. *Management science*, *6*(1), 80–91. https://doi.org/10.1287/mnsc.6.1.80

[6] Solomon, M. M. (1987). Algorithms for the vehicle routing and scheduling problems with time window constraints. *Operations research*, *35*(2), 254–265. https://doi.org/10.1287/opre.35.2.254

[7] Cordeau, J. F., Gendreau, M., & Laporte, G. (1997). A tabu search heuristic for periodic and multi-depot vehicle routing problems. *Networks: An international journal*, *30*(2), 105–119. https://doi.org/10.1002/(SICI)1097-0037(199709)30:2%3C105::AID-NET5%3E3.0.CO;2-G

[8] Koç, Ç., Bektas, T., Jabali, O., & Laporte, G. (2016). Thirty years of heterogeneous vehicle routing. *European journal of operational research*, *249*(1), 1–21. https://doi.org/10.1016/j.ejor.2015.07.020

[9] Ropke, S., & Pisinger, D. (2006). An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows. *Transportation science*, *40*(4), 455–472. https://doi.org/10.1287/trsc.1050.0135

[10] Gendreau, M., Laporte, G., & Séguin, R. (1996). Stochastic vehicle routing. *European journal of operational research*, *88*(1), 3–12. https://doi.org/10.1016/0377-2217(95)00050-X

[11] Ponomarov, S. Y., & Holcomb, M. C. (2009). Understanding the concept of supply chain resilience. *The international journal of logistics management*, *20*(1), 124–143. https://doi.org/10.1108/09574090910954873

[12] Sheffi, Y., & Rice Jr, J. B. (2005). A supply chain view of the resilient enterprise. *MIT sloan management review*, *47*(1), 41-48. https://www.proquest.com/docview/224969684

[13] Pillac, V., Gendreau, M., Guéret, C., & Medaglia, A. L. (2013). A review of dynamic vehicle routing problems. *European journal of operational research*, *225*(1), 1–11. https://doi.org/10.1016/j.ejor.2012.08.015

[14] Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey wolf optimizer. *Advances in engineering software*, *69*, 46–61. 10.1016/j.advengsoft.2013.12.007

[15] Lenstra, J. K., & Kan, A. R. (1981). Complexity of vehicle routing and scheduling problems. *Networks*, *11*(2), 221–227. https://doi.org/10.1002/net.3230110211

[16] Montoya-Torres, J. R., Franco, J. L., Isaza, S. N., Jiménez, H. F., & Herazo-Padilla, N. (2015). A literature review on the vehicle routing problem with multiple depots. *Computers & industrial engineering*, *79*, 115-129. https://doi.org/10.1016/j.cie.2014.10.029

[17] Braekers, K., Ramaekers, K., & Van Nieuwenhuyse, I. (2016). The vehicle routing problem: State of the art classification and review. *Computers & industrial engineering*, *99*, 300–313. https://doi.org/10.1016/j.cie.2015.12.007

[18] Elshaer, R., & Awad, H. (2020). A taxonomic review of metaheuristic algorithms for solving the vehicle routing problem and its variants. *Computers & industrial engineering*, *140*, 106242. https://doi.org/10.1016/j.cie.2019.106242

[19] Caceres-Cruz, J., Arias, P., Guimarans, D., Riera, D., & Juan, A. A. (2014). Rich vehicle routing problem: Survey. *ACM computing surveys (CSUR)*, *47*(2), 1–28. https://doi.org/10.1145/2666003

[20] Tomlin, B. (2006). On the value of mitigation and contingency strategies for managing supply chain disruption risks. *Management science*, *52*(5), 639–657. https://doi.org/10.1287/mnsc.1060.0515

[21] Gendreau, M., Laporte, G. and Potvin, J. Y. (1999). *Metaheuristics for the vehicle routing problem*. https://www.gerad.ca/en/papers/G-98-52

[22] Gendreau, M., Hertz, A., & Laporte, G. (1994). A tabu search heuristic for the vehicle routing problem. *Management science*, *40*(10), 1276–1290. https://doi.org/10.1287/mnsc.40.10.1276

[23] Cordeau, J. F., Laporte, G., & Mercier, A. (2001). A unified tabu search heuristic for vehicle routing problems with time windows. *Journal of the operational research society*, *52*(8), 928–936. https://doi.org/10.1057/palgrave.jors.2601163

[24] Berger, J., & Barkaoui, M. (2004). A parallel hybrid genetic algorithm for the vehicle routing problem with time windows. *Computers & operations research*, *31*(12), 2037–2053. https://doi.org/10.1016/S0305-0548(03)00163-1

[25] Vidal, T., Crainic, T. G., Gendreau, M., Lahrichi, N., & Rei, W. (2012). A hybrid genetic algorithm for multidepot and periodic vehicle routing problems. *Operations research*, *60*(3), 611–624. https://doi.org/10.1287/opre.1120.1048

[26] Pisinger, D., & Ropke, S. (2007). A general heuristic for vehicle routing problems. *Computers & operations research*, *34*(8), 2403–2435. https://doi.org/10.1016/j.cor.2005.09.012

[27] Demir, E., Bektas, T., & Laporte, G. (2012). An adaptive large neighborhood search heuristic for the pollution-routing problem. *European journal of operational research*, *223*(2), 346–359. https://doi.org/10.1016/j.ejor.2012.06.044

[28] Ribeiro, G. M., & Laporte, G. (2012). An adaptive large neighborhood search heuristic for the cumulative capacitated vehicle routing problem. *Computers & operations research*, *39*(3), 728–735. https://doi.org/10.1016/j.cor.2011.05.005

[29] Grangier, P., Gendreau, M., Lehuédé, F., & Rousseau, L. M. (2016). An adaptive large neighborhood search for the two-echelon multiple-trip vehicle routing problem with satellite synchronization. *European journal of operational research*, *254*(1), 80–91. https://doi.org/10.1016/j.ejor.2016.03.040

[30] Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. *Proceedings of ICNN'95-international conference on neural networks* (Vol. 4, pp. 1942–1948). IEEE. http://dx.doi.org/10.1109/ICNN.1995.488968

[31] Ai, T. J., & Kachitvichyanukul, V. (2009). A particle swarm optimization for the vehicle routing problem with simultaneous pickup and delivery. *Computers & operations research*, *36*(5), 1693–1702. https://doi.org/10.1016/j.cor.2008.04.003

[32] Kamboj, V. K., Bath, S. K., & Dhillon, J. S. (2017). A novel hybrid DE-random search approach for unit commitment problem. *Neural computing and applications*, *28*(7), 1559–1581. https://doi.org/10.1007/s00521-015-2124-4

[33] Komaki, M., & Malakooti, B. (2017). General variable neighborhood search algorithm to minimize makespan of the distributed no-wait flow shop scheduling problem. *Production engineering*, *11*(3), 315–329. https://doi.org/10.1007/s11740-017-0716-9

[34] Psaraftis, H. N., Wen, M., & Kontovas, C. A. (2016). Dynamic vehicle routing problems: Three decades and counting. *Networks*, *67*(1), 3–31. https://doi.org/10.1002/net.21628

[35] Ulmer, M. W., Goodson, J. C., Mattfeld, D. C., & Hennig, M. (2019). Offline-online approximate dynamic programming for dynamic vehicle routing with stochastic requests. *Transportation science*, *53*(1), 185–202. https://doi.org/10.1287/trsc.2017.0767

[36] Laporte, G., Louveaux, F., & Mercure, H. (1992). The vehicle routing problem with stochastic travel times. *Transportation science*, *26*(3), 161–170. https://doi.org/10.1287/trsc.26.3.161

[37] Bent, R. W., & Van Hentenryck, P. (2004). Scenario-based planning for partially dynamic vehicle routing with stochastic customers. *Operations research*, *52*(6), 977–987. https://doi.org/10.1287/opre.1040.0124

[38] Saint-Guillain, M., Solnon, C., & Deville, Y. (2017). The static and stochastic vrp with time windows and both random customers and reveal times. *European conference on the applications of evolutionary computation* (pp. 110–127). Springer. https://doi.org/10.1007/978-3-319-55792-2_8

[39] Li, J. Q., Mirchandani, P. B., & Borenstein, D. (2009). Real-time vehicle rerouting problems with time windows. *European journal of operational research*, *194*(3), 711–727. https://doi.org/10.1016/j.ejor.2007.12.037

[40] Mu, Q., Fu, Z., Lysgaard, J., & Eglese, R. (2011). Disruption management of the vehicle routing problem with vehicle breakdown. *Journal of the operational research society*, *62*(4), 742–749. https://doi.org/10.1057/jors.2010.19

[41] Shaw, P. (1998). Using constraint programming and local search methods to solve vehicle routing problems. *International conference on principles and practice of constraint programming* (pp. 417–431). Springer. https://doi.org/10.1007/3-540-49481-2_30

[42] Vargha, A., & Delaney, H. D. (2000). A critique and improvement of the CL common language effect size statistics of McGraw and Wong. *Journal of educational and behavioral statistics*, *25*(2), 101–132. https://doi.org/10.3102/10769986025002101

[43] Gendreau, M., Potvin, J. Y. (2010). *Handbook of metaheuristics*. Springer. https://doi.org/10.1007/978-1-4419-1665-5