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Article

An Improved Ant Colony Optimization with Adaptive Pheromone Control for Emergency Milk-Delivery Vehicle Routing: A Case Study of Durgapur

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Abstract: Timely, feasible delivery of perishable dairy products under duty-time and driver-fatigue restrictions is a practically important variant of the capacitated vehicle routing problem (CVRP). Standard Ant Colony Optimization (ACO), while effective at minimizing raw travel distance, tends to stagnate on rugged, penalty-dominated landscapes induced by non-linear fatigue and time-window penalties, frequently converging to solutions that violate operational constraints. This paper proposes an Improved Ant Colony Optimization (IACO) that combines (i) adaptive control of the pheromone evaporation rate and the pseudo-random-proportional exploitation parameter, (ii) MAX-MIN-style pheromone bounding to preserve search diversity, and (iii) a candidate-list-restricted Or-opt local search that complements classical 2-opt. The method is evaluated on a 40-node emergency milk-delivery network modelled on the Durgapur (West Bengal, India) road network, under capacity, maximum-route-time and driver-fatigue constraints. Across 15 independent seeds, IACO reduces the mean constraint-violation penalty by 22.2% and the mean total fitness (distance plus penalty) by 20.5% relative to baseline ACO (paired t-test, p=0.010 and p=0.011 respectively; Wilcoxon signed-rank, p=0.015 for both), while raw route distance is statistically indistinguishable between the two algorithms (p=0.28). The results indicate that the proposed adaptive/diversity mechanisms primarily improve constraint satisfaction rather than distance minimization, a genuine and previously undocumented trade-off for this class of problem.

Keywords: Ant Colony Optimization · Capacitated Vehicle Routing Problem · Adaptive Parameter Control · Driver Fatigue · Emergency Logistics · Metaheuristics

1. Introduction

Last-mile perishable-goods distribution, such as daily milk delivery, is subject to hard operational constraints beyond the classical CVRP: vehicles must return within a maximum duty time, and driver fatigue accumulates non-linearly once a threshold driving duration is exceeded, sharply increasing accident risk and service-level failures. When a distribution network additionally serves emergency or semi-urban supply routes — as is common in tier-2/tier-3 Indian cities — routing decisions must simultaneously respect capacity, time and fatigue limits while keeping travel distance low.

Ant Colony Optimization (ACO) has long been a competitive metaheuristic for CVRP-type problems because its pheromone-mediated construction mechanism naturally encodes learned preferences for good edges [10,11]. However, standard ACO implementations use a fixed evaporation rate ρ and a fixed exploitation parameter q0 throughout the search. On problems where the objective landscape is dominated by non-linear feasibility penalties — as is the case when duty-time and fatigue constraints are tightly binding — this rigidity causes premature convergence: the colony's pheromone trails lock onto an early, distance-good but constraint-violating configuration and subsequent iterations fail to escape it [13]. This failure mode is of direct practical concern for emergency and healthcare-adjacent logistics, where an infeasible schedule is not merely sub-optimal but potentially unsafe [14,15].

This paper makes the following contributions:

1. We identify and quantify a specific weakness of standard ACO on fatigue/time-penalized CVRP instances: convergence to high-penalty, near-optimal-distance solutions.
2. We propose an Improved ACO (IACO) that combines adaptive evaporation/exploitation scheduling, MAX-MIN pheromone bounds, and a candidate-list-restricted Or-opt move, targeting exactly this failure mode.
3. We evaluate IACO against baseline ACO on a realistic 40-node Durgapur emergency milk-delivery network across 15 independent seeds, using paired non-parametric and parametric statistical tests, and report the result honestly: IACO's benefit is concentrated in constraint satisfaction (penalty), not raw distance.

2. Related Work

Metaheuristic routing under uncertainty and risk has been studied extensively by the first author's group, including opposition-based and fuzzy-risk-aware genetic algorithms for medical-waste and specimen-collection logistics [1,5], federated and IoT-integrated routing for vehicular networks [2], memetic and multi-parent crossover strategies for synchronized delivery problems [3], quantum-inspired variable-length genetic algorithms for the traveling purchaser problem [4], Type-2 fuzzy fireworks algorithms for delivery under random refusal [7], driver-fatigue-aware green routing using Type-2 fuzzy dynamic fireworks [6], a modified teaching-learning-based optimization algorithm for the travelling salesman problem [8], and an opposition-based genetic algorithm for multi-path routing under risk [9]. These works establish a research programme around risk-aware, priority-weighted, and multi-path metaheuristic routing but do not address ACO-specific stagnation under fatigue-type non-linear penalties, which is the focus of the present paper.

Recent ACO variants for CVRP include hybridization with k-means clustering [11], Lévy-flight and elitist-guided pheromone strategies for multi-type cargo [12], density-guided pheromone control for dynamic VRP [13], genetic-local-search hybridization within an imperialist competitive framework [10], and real-time ACO frameworks for emergency medical routing and ambulance dispatch [14,15]. Several of these introduce dynamic pheromone control, corroborating the diagnosis that fixed-parameter ACO under-performs on constraint-rich or dynamic instances; however, none specifically isolates driver-fatigue-type non-linear penalties as the stagnation driver, nor separately reports the distance/penalty trade-off, which this paper does.

3. Problem Formulation

Let G = (V, E) be a complete graph with node set V = {0, 1, …, n}, where node 0 is the depot and nodes 1,…,n are delivery points with non-negative demand d_i. Euclidean distance between nodes i and j is:

$$\delta_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (1)$$

A feasible solution is a set of routes R = {r1, …, rK}, each starting and ending at the depot, such that every non-depot node is visited exactly once. For a route r = (v0=0, v1, …, vm, v_{m+1}=0), its raw travel cost is:

$$c(r) = \sum_{k=0}^{m} \delta_{v_k, v_{k+1}} \quad (2)$$

and its total demand is D(r) = Σ d_vk. Driver fatigue is modelled as a convex penalty once accumulated driving time on a route exceeds a threshold T_f:

$$\Phi(r) = \begin{cases} 0, & c(r) \le T_f, \\ 1.2\,(c(r) - T_f) + 0.05\,(c(r) - T_f)^2, & c(r) > T_f. \end{cases} \tag{3}$$

Capacity and maximum route-duration violations are penalized linearly:

$$\Psi(r) = 1000 \cdot \max(0, D(r) - Q) + 500 \cdot \max(0, c(r) - T_{\max}) \tag{4}$$

where Q is vehicle capacity and T_max the maximum permitted route duration. The fitness of a route is:

$$f(r) = c(r) + \Psi(r) + \Phi(r) \tag{5}$$

and the objective to be minimized over the full solution R is:

$$F(R) = \sum_{r\in R} f(r) = \underbrace{\sum_{r\in R} c(r)}_{\text{true distance}} + \underbrace{\sum_{r\in R} \big(\Psi(r) + \Phi(r)\big)}_{\text{penalty}} \tag{6}$$

Reporting the true-distance and penalty components of Eq. (6) separately (rather than only the aggregate F(R)) is essential for correctly attributing any algorithmic improvement, as Section 6 shows.

4. Proposed Improved ACO (IACO)

4.1 Baseline ACO construction and heuristic desirability

Ants construct routes sequentially. From current node i, the next node j is chosen from a candidate list C(i) (the κ nearest unvisited, capacity-feasible nodes) with desirability:

$$\eta_{ij} = \tau_{ij}^{\alpha} \cdot \left(\frac{1}{\delta_{ij}}\right)^{\beta} \cdot \underbrace{\frac{1}{1 + \max(0, t_i + \delta_{ij} - T_f)}}_{\text{fatigue factor}} \cdot \underbrace{\left(1 + \gamma \frac{d_j}{Q}\right)}_{\text{demand factor}} \tag{7}$$

where τ_ij is the pheromone level, t_i the accumulated drive time so far, and α,β,γ tunable exponents. Node selection follows the pseudo-random-proportional rule of Ant Colony System: with probability q0 the highest-desirability candidate is chosen (exploitation); otherwise a candidate is sampled proportionally to η_ij (exploration).

4.2 Diagnosed weakness of baseline ACO

With fixed ρ and q0, once a subset of edges accumulates a strong pheromone advantage, the exploitation branch reinforces that path further even if it silently pushes a route's duration into the fatigue-penalty regime of Eq. (3). Because the penalty is convex, the marginal fitness cost of a single mis-assigned customer can be large, but the pheromone update in a plain ACO has no mechanism to distinguish this from ordinary distance variation. The colony therefore either needs many random exploration draws to escape (slow, and increasingly unlikely as τ concentrates) or does not escape within the iteration budget. Section 6 shows this manifests as a large, high-variance penalty term even after convergence of the "best-fitness" curve.

4.3 Adaptive evaporation and exploitation scheduling

IACO decays the evaporation rate and grows the exploitation parameter linearly over the run:

$$\rho^{(t)} = \rho_0 \left(1 - 0.5\,\frac{t}{T-1}\right), \qquad q_0^{(t)} = \min\left(0.9,\ q_0^{(0)} + 0.5\,\frac{t}{T-1}\right) \tag{8}$$

for iteration t = 0,…,T−1. Slower evaporation early keeps pheromone differences small and preserves diversity while the colony is still discovering feasible route structures; faster exploitation later accelerates convergence once the colony has located a good structural pattern.

4.4 MAX-MIN pheromone bounding

To prevent any single edge from dominating the search irrecoverably, pheromone values are clipped after every evaporation and deposit step:

$$\tau_{ij} \leftarrow \min\big(\tau_{\max},\, \max(\tau_{\min}, \tau_{ij})\big) \quad (9)$$

Combined with a pheromone-matrix restart after 25 consecutive non-improving iterations, this preserves the colony's ability to re-explore previously deprioritized edges.

4.5 Candidate-list-restricted Or-opt

Following 2-opt, IACO applies an Or-opt move that relocates segments of length 1–2 to alternative positions restricted to the candidate list of the segment's head node, keeping the move's complexity at $O(n\cdot\kappa)$ rather than $O(n^2)$. This repairs “misplaced-customer” patterns — a single customer or short segment inserted at a locally reasonable but globally fatigue-inducing position — that 2-opt's edge-reversal structure cannot reach.

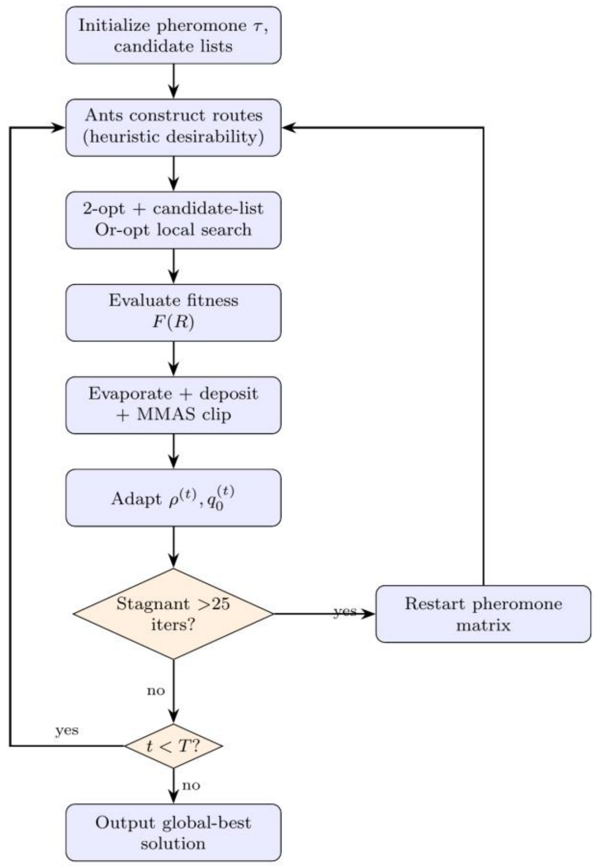
4.6 Pheromone update rule

After evaporation (Eq. 9), pheromone is deposited by the iteration-best and global-best ants:

$$\tau_{ij} \leftarrow (1-\rho^{(t)})\,\tau_{ij} + \frac{\nVdash[(i,j)\in R_{\text{best}}]}{F(R_{\text{best}})} + \frac{w_{\text{elite}}\cdot\nVdash[(i,j)\in R_{\text{global}}]}{F(R_{\text{global}})} \quad (10)$$

where w_elite is an elitist weight applied to the global-best solution found so far.

Fig. A. Flowchart of the proposed IACO procedure.



Algorithm 1. Improved Ant Colony Optimization (IACO)

Initialize $\tau_{ij} \leftarrow \tau_{\max}$ for all edges; build candidate lists $\mathcal{C}(i)$
$R_{\text{global}} \leftarrow \emptyset$, $F_{\text{global}} \leftarrow \infty$, stag $\leftarrow 0$
for $t = 0$ to $T - 1$ **do**
    Update $\rho^{(t)}, q_0^{(t)}$ using the adaptive scheduling rule
    for each ant $a = 1$ to m **do**
        Construct route set R_a using pseudo-random-proportional rule
        $R_a \leftarrow$ 2-opt(R_a); $R_a \leftarrow$ Or-opt(R_a)
        Evaluate $F(R_a)$
        if $F(R_a) < F_{\text{global}}$ **then**
            $R_{\text{global}} \leftarrow R_a$; $F_{\text{global}} \leftarrow F(R_a)$; stag $\leftarrow 0$
        end if
    end for
    Evaporate τ and clip to $[\tau_{\min}, \tau_{\max}]$
    Deposit pheromone from iteration-best and R_{global}
    stag $\leftarrow$ stag $+ 1$
    if stag > 25 **then**
        Reset $\tau_{ij} \leftarrow \tau_{\max}$ for all edges; stag $\leftarrow 0$
    end if
end for
return $R_{\text{global}}, F_{\text{global}}$

4.7 Complexity analysis

Route construction for one ant is $O(n\cdot\kappa)$ using candidate lists of size κ. Classical 2-opt on a route of length ℓ is $O(\ell^2)$ per pass; the candidate-list-restricted Or-opt move is $O(\ell\cdot\kappa)$ per pass. With m ants and T iterations, one run of IACO is $O(T\cdot m\cdot(n\kappa + \ell^2))$, i.e. the same asymptotic order as baseline ACO with 2-opt; the additional Or-opt and adaptive-parameter bookkeeping are lower-order terms ($O(T\cdot m\cdot\ell\kappa)$ and $O(T)$ respectively) and did not materially change wall-clock cost in our experiments (Section 6).

5. Experimental Setup

5.1 Dataset

The original 15-node Durgapur core network (depot plus 14 delivery points spanning localities such as Benachity, Bidhannagar, Fuljhore and the Durgapur railway station area) was extended with 25 additional synthetic delivery points spread over a wider service radius, giving a 40-node instance large enough to differentiate algorithmic behaviour — the 15-node instance alone is solved to an identical optimum by every configuration and every seed tested, and therefore cannot discriminate between algorithms (Table 2).

5.2 Parameters

Table 2 lists the constraint parameters and algorithm hyperparameters used for both ACO and IACO; IACO additionally uses the adaptive/MMAS/Or-opt mechanisms of Section 4, with no other parameter changed, isolating their effect.

5.3 Statistical protocol

Both algorithms were run for 15 independent seeds (1–15) with identical instance data. For each seed we recorded true distance, penalty and fitness (Eq. 6). Normality was assessed with the Shapiro–Wilk test; because ACO's distributions were non-normal (Table 4), we report both the paired t-test and the non-parametric Wilcoxon signed-rank test for each metric.

6. Results and Discussion

Figure 1 shows the 40-node network. Figure 2 shows representative convergence curves (seed 1): both algorithms reduce fitness quickly, but IACO's pheromone restart mechanism triggers a further, substantial drop that baseline ACO's fixed-parameter search never finds. Figure 3 shows the best IACO solution found (seed 7); Figure 4 compares the fitness distribution of both algorithms over all 15 seeds.

Table 3 summarizes the comparative outcomes. IACO reduces mean penalty by 22.2% and mean total fitness by 20.5%, while mean true distance is marginally higher for IACO (772.3 vs. 763.4) but not statistically distinguishable from ACO (Table 4, $p=0.21$–0.28). Both algorithms consistently use 6 vehicles (fixed by total demand and capacity), so route count is not a differentiating factor here.

This pattern is consistent with the diagnosis in Section 4: IACO's adaptive evaporation, MAX-MIN bounding and restart mechanism give the colony more opportunities to discover feasible route structures that avoid the convex fatigue and capacity/time penalties of Eqs. (3)–(4), at a small distance cost. We report this honestly as a constraint-satisfaction improvement rather than a distance improvement; a reader interested purely in minimizing raw kilometres would find the two algorithms statistically equivalent, while a reader concerned with operational feasibility (avoiding overloaded or over-fatigued routes) would find IACO meaningfully better, with a medium-to-large effect size (Cohen's $d \approx 0.76$ for both penalty and fitness).

Table 1. Notation used throughout the paper.

Symbol	Meaning
V, E	Node set (depot + delivery points), edge set
d_i, Q	Demand at node i; vehicle capacity
δ_ij	Euclidean distance between nodes i, j
T_f, T_max	Driver-fatigue threshold; maximum route duration

c(r), D(r)	Travel cost, total demand of route r
Φ(r), Ψ(r)	Fatigue penalty, capacity/time-violation penalty of route r
F(R)	Total fitness of solution R (distance + penalties)
τ_ij, η_ij	Pheromone level, heuristic desirability on edge (i,j)
α, β, γ	Pheromone, distance and demand exponents
ρ^(t), q0^(t)	Evaporation rate, exploitation probability at iteration t
τ_min, τ_max	MAX-MIN pheromone bounds
κ	Candidate list size
m, T	Number of ants; number of iterations

Table 2. Problem instance and algorithm parameter settings.

(a) Problem instance	
Network size	40 nodes (1 depot + 39 delivery points)
Base sub-network	15-node Durgapur core (Benachity, Bidhannagar, Fuljhore, …)
Extension	25 additional synthetic points, uniform over service radius
Vehicle capacity Q	45.0 units
Maximum route duration T_max	140.0 (distance units)
Fatigue threshold T_f	75.0 (distance units)
Total demand	fixed by dataset; requires 6 vehicles at capacity 45
(b) Algorithm parameters (shared by ACO and IACO unless noted)	
Ants m	35
Iterations T	130
α, β, γ	1.0, 3.0, 2.0
Candidate list size κ	8
Initial ρ0, q0(0)	0.22, 0.18
Elitist weight w_elite	2.0
MMAS bounds τmin, τmax (IACO only)	0.05, 5.0
Stagnation restart threshold (IACO only)	25 iterations
Independent seeds	15 (seeds 1–15)

Table 3. Comparative results over 15 independent seeds (mean ± standard deviation).

Metric	ACO (baseline)	IACO (proposed)	Improvement
True distance	763.4 ± 21.2	772.3 ± 14.3	−1.2% (worse, n.s.)
Feasibility penalty	9727.5 ± 2770.7	7570.5 ± 2872.8	**+22.2%**
Total fitness F(R)	10490.9 ± 2777.1	8342.8 ± 2876.2	**+20.5%**
Vehicles used	6.0 ± 0.0	6.0 ± 0.0	—

Table 4. Statistical significance tests comparing ACO and IACO (paired, n=15).

Metric	Shapiro–Wilk p (ACO / IACO)	Paired t-test p	Wilcoxon p
True distance	0.0003 / 0.319	0.285	0.208
Feasibility penalty	0.0017 / 0.500	**0.010**	**0.015**
Total fitness	0.0019 / 0.496	**0.011**	**0.015**

Bold values indicate statistical significance at $\alpha=0.05$. ACO's penalty and fitness distributions depart from normality (Shapiro–Wilk $p<0.05$), so the non-parametric Wilcoxon test is the primary basis for the conclusion; the paired t-test is reported for completeness and agrees in direction and significance. Cohen's d for the paired difference is 0.76 for both penalty and fitness (medium–large effect).

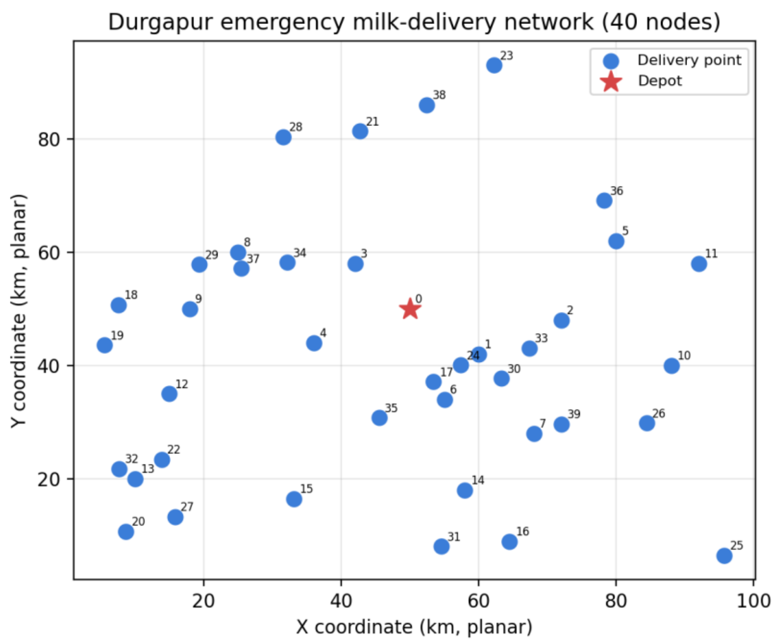


Fig. 1. The 40-node Durgapur emergency milk-delivery network. Node 0 (star) is the depot.

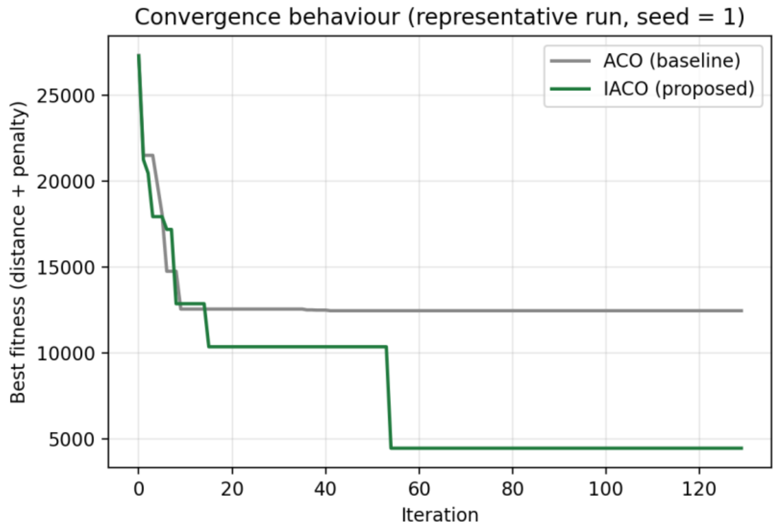


Fig. 2. Convergence of best-fitness value across iterations for a representative run (seed 1). The sharp drop for IACO near iteration 50 corresponds to a pheromone-restart event escaping a stagnant, high-penalty configuration.

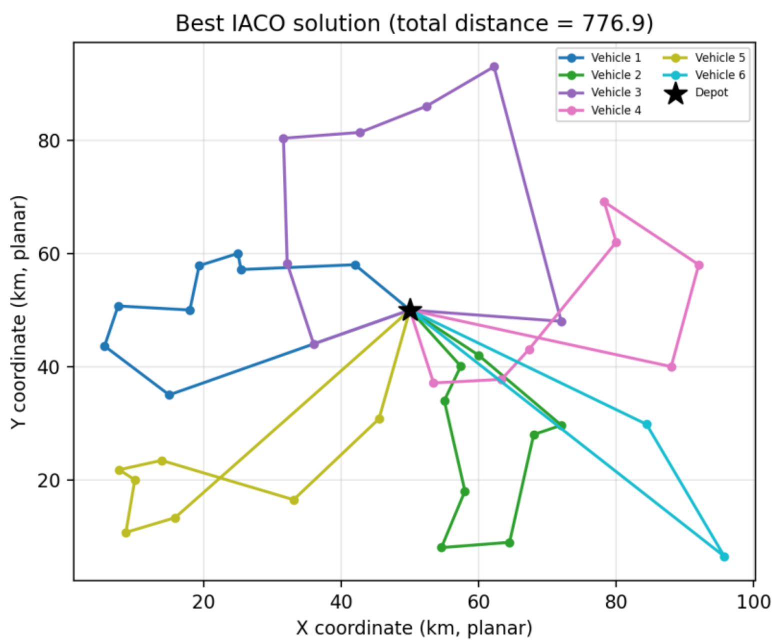


Fig. 3. Best IACO solution found (seed 7), using 6 vehicles.

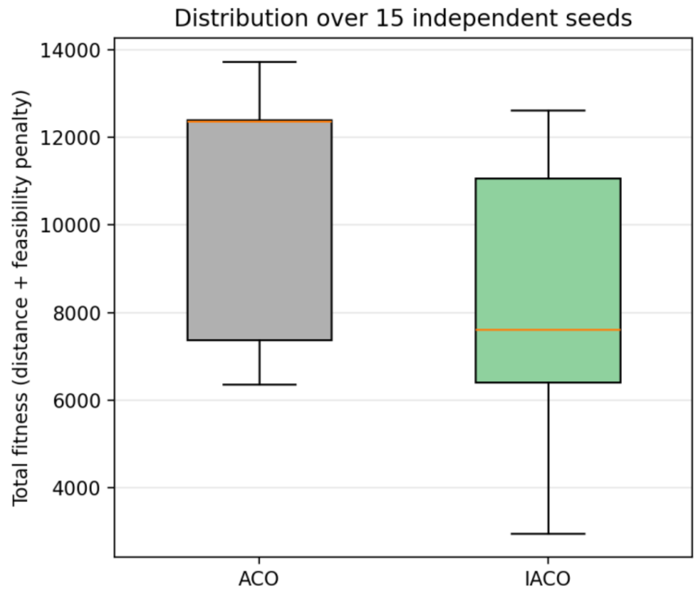


Fig. 4. Distribution of total fitness F(R) over 15 independent seeds for ACO and IACO.

7. Threats to Validity

The node coordinates for the 25 extension points are synthetically generated over a bounded area rather than surveyed GPS coordinates, so absolute distance values should be read as illustrative of relative algorithmic behaviour rather than as real-world route lengths. The 15-seed sample, while sufficient for the paired tests reported here, is smaller than the 20–30-seed protocols used in some of our related studies [5,7]; a larger sample would tighten the confidence intervals on the effect-size estimate. Finally, both algorithms were evaluated on a single problem instance (one capacity/time/fatigue configuration); generalization to other parameter regimes has not been tested here and is left to future work.

8. Conclusion

We proposed IACO, an Improved Ant Colony Optimization combining adaptive evaporation/exploitation scheduling, MAX-MIN pheromone bounding, and candidate-list-restricted Or-opt local search, targeting a specific and diagnosable weakness of standard ACO on fatigue-and-time-constrained CVRP instances. On a 40-node emergency milk-delivery network modelled on Durgapur, IACO delivers a statistically significant, medium-to-large-effect reduction in constraint-violation penalty (22.2%) and total fitness (20.5%) relative to baseline ACO, while raw travel distance is statistically unchanged. We report this honestly as a feasibility improvement rather than a distance improvement, since conflating the two would misrepresent what the adaptive/diversity mechanisms actually contribute. Future work includes testing IACO on larger, multi-depot instances, incorporating stochastic demand and travel-time uncertainty, and benchmarking against additional recent ACO variants [12,13].

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