Report on

Sustainable Vehicle Routing via Hybrid IFACO: A Multi-Objective Optimization Model for Distance and Emission Minimization

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by

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CERTIFICATE

This is to *certify* that the Course Project Work Report entitled "**Sustainable Vehicle Routing via Hybrid IFACO: A Multi-Objective Optimization Model for Distance and Emission Minimization** "submitted by

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as the record of the work carried out by them, is *accepted as the B.Tech. Course Project Work report submission* in partial fulfillment of the requirement for the award of degree of Bachelor of Technology in Information Technology in the Department of Information Technology, NITK Surathkal.

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DECLARATION

I/We hereby *declare* that the Course Project Work Report entitled **"Sustainable Vehicle Routing via Hybrid IFACO: A Multi-Objective Optimization Model for Distance and Emission Minimization"**, which is being submitted to the **National Institute of Technology Karnataka, Surathkal**, for the award of the Degree of Bachelor of Technology in Information Technology, is a *bonafide report of the work carried out by me/us.* The material contained in this Course Project Report has not been submitted to any University or Institution for the award of any degree.

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ABSTRACT

This paper presents a novel hybrid metaheuristic algorithm combining the Artificial Fish Swarm Algorithm (AFSA) and Improved Ant Colony Optimization (ACO) for solving the Vehicle Routing Problem with Time Windows (VRPTW), while simultaneously minimizing both travel distance and CO_2 emissions. The proposed IFACO (Improved Fish Swarm–Ant Colony Optimization) algorithm leverages AFSA for rapid initial solution generation and ACO for refinement through pheromone-guided search. A multi-objective fitness function incorporating weighted distance and emission objectives is formulated as

$$F = \lambda 1 D + \lambda 2 E,$$

where D represents the total distance and E denotes CO_2 emissions.

Experimental results on Solomon benchmark instances(C101) demonstrate that the hybrid IFACO achieves a fitness value of 4337.06, representing a 0.06% improvement over standalone ACO (4339.72) and a 65.4% improvement over standalone AFSA (12532.30), with a total distance of 882.74 km and 3454.31 kg of CO_2 emissions. The algorithm successfully integrates environmental sustainability considerations into traditional VRPTW optimization, providing a practical and efficient framework for green logistics applications.

CHAPTER 1
INTRODUCTION

The Vehicle Routing Problem with Time Windows (VRPTW) represents a critical optimization challenge in modern logistics and supply chain management. As global concerns regarding environmental sustainability intensify, the transportation sector faces increasing pressure to reduce carbon emissions while maintaining operational efficiency. Traditional VRPTW formulations focus primarily on minimizing travel distance or operational costs, often neglecting the environmental impact of routing decisions.

Metaheuristic algorithms have emerged as the predominant approach for solving VRPTW due to the NP-hard nature of the problem. Ant Colony Optimization (ACO) has demonstrated particular effectiveness in discrete optimization problems, mimicking the foraging behavior of ant colonies through pheromone-based communication. However, ACO suffers from slow convergence and susceptibility to premature stagnation, especially in large-scale networks.

The Artificial Fish Swarm Algorithm (AFSA), inspired by the collective behavior of fish schools, offers rapid global search capabilities and flexibility in the early stages of optimization by combining AFSA's exploratory strength with ACO's exploitation abilities, hybrid algorithms can overcome the limitations of individual approaches.

CHAPTER 2
LITERATURE REVIEW

1.Ant Colony Optimization (ACO), introduced by Dorigo[2], has been successfully applied to various routing problems. The algorithm's strength lies in its ability to balance exploration and exploitation through pheromone-based communication. However, ACO requires careful parameter tuning and often suffers from slow convergence.

2.To address this limitation, Li et al.[3] proposed a hybrid AFSA–ACO routing protocol for wireless sensor networks, where AFSA was utilized during the initial route discovery phase to accelerate convergence. Their results demonstrated that AFSA's global search capabilities in the early stages effectively complement ACO's strong local refinement ability. Similarly, Zhang et al, applied the AFSA–ACO hybrid framework to UAV path planning and logistics distribution, confirming the generalizability and robustness of this combination across different optimization domains.

3.Zhang et al[6]. (2022) proposed a hybrid algorithm called IFACO, which combines Artificial Fish Swarm Algorithm and Ant Colony Optimization techniques, to solve the Vehicle Routing Problem with Time Windows. Their approach successfully improved solution quality and convergence speed by integrating global search and advanced local optimizations. Experiments using Solomon benchmark datasets showed that IFACO achieves better results than basic methods.

CHAPTER 3
Proposed Methodology

3.1 PROBLEM FORMULATION

3.1.1 Mathematical Model:

The VRPTW can be formally defined on a complete directed graph (V,E), where $V = \{0, 1, 2, \ldots, n\}$ is the set of nodes and $E =${(i , j): i , j belongs to v , i not equal to j} is the set of edges. Node 0 represents the depot, and nodes 1 through n represent customers. Each customer i is characterized by:

- q_i: Demand quantity
- $|e_i, l_i|$: Time window where e_i is the earliest service time and l_i is the due service time
- s_i: Service time duration
- (x_i, y_i): Geographical coordinates

A fleet of K homogeneous vehicles, each with capacity Q, is available at the depot. The distance d_{ij} between nodes i and j is calculated as:

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

Decision variables:

$$x_{ijk} = \begin{cases} 1 & amp; \text{if vehicle } k \text{ travels from } i \text{ to } j \\ 0 & amp; \text{otherwise} \end{cases}$$

$$t_{ik} = \text{Time when vehicle } k \text{ begins service at node } i$$

Objective Function:

The multi-objective fitness function is formulated as:

$$\min F = \lambda_1 \sum_{k=1}^{K} \sum_{i=0}^{n} \sum_{j=0}^{n} d_{ij} x_{ijk} + \lambda_2 \sum_{k=1}^{K} \sum_{i=0}^{n} \sum_{j=0}^{n} E_{ij}^{k}$$

where λ_1 and λ_2 are weight parameters balancing distance and emission objectives.

Constraints:

1. Each customer is visited exactly once:

$$\sum_{k=1}^{K} \sum_{j=0}^{n} x_{ijk} = \mathbf{1}, \quad \forall i \in \{1, \ldots, n\}$$

2. Vehicle flow conservation:

$$\sum_{i=0}^{n} x_{ihk} - \sum_{j=0}^{n} x_{hjk} = 0, \quad \forall h \in \{1, \ldots, n\}, k \in \{1, \ldots, K\}$$

3. Capacity constraints:

$$\sum_{i=1}^{n} q_i \sum_{j=0}^{n} x_{ijk} \leq Q, \quad \forall k \in \{1, \ldots, K\}$$

4. Time window constraints:

$$e_i \leq t_{ik} \leq l_i, \quad \forall i \in \{0, \ldots, n\}, k \in \{1, \ldots, K\}$$

5. Time consistency:

$$t_{ik} + s_i + d_{ij} \leq t_{jk} + M(1 - x_{ijk}), \quad \forall i, j \in V, k \in \{1, \ldots, K\}$$

where M is a large constant.

3.1.2 CO_2 Emission Calculation Model:

The emission model considers load-dependent fuel consumption, recognizing that heavier loads result in higher emissions. The emission for edge (i, j) with load L_{ij} is calculated as:

$$E_{ij} = \gamma \cdot d_{ij} \cdot L_{ij}$$

where:

- γ =emission factor ,kg CO2 per km unit load
- d_{ij} = distance from node i to node j (km)
- L_{ij} = load carried on edge (i, j) (units)

Typical emission factors from road transport literature [9]:

- Light Duty Vehicle (<3.5T): 0.307 kg CO_2/km base
- Medium Duty Vehicle (<12T): 0.593 kg CO_2/km base
- Heavy Duty Vehicle (>12T): 0.738 kg CO_2/km base
- Per tonne-km: 0.04-0.065 kg CO_2/tonne-km (average)

For this study, we use $\gamma = 0.05$ kg CO_2/ (km·unit load), representing a moderate estimate for freight vehicles.

Route Emission Calculation:

For a given route $R = \{0, c_1, c_2, \ldots, c_m, 0\}$, the total emission is:

$$E_R = \gamma \left[d_{0,c_1} \cdot L_{0,c_1} + \sum_{i=1}^{m-1} d_{c_i,c_{i+1}} \cdot L_{c_i,c_{i+1}} + d_{c_m,0} \cdot L_{c_m,0} \right]$$

where the load decreases sequentially:

$$L_{c_i,c_{i+1}} = \sum_{j=i+1}^{m} q_{c_j}$$

This formulation ensures that emissions reflect the actual load carried at each segment, decreasing as deliveries are made.

3.1.3 Multi-Objective Weight Selection

The weight parameters λ_1 and λ_2 allow decision-makers to balance competing objectives:

- **Balanced**: $\lambda_1 = 1.0, \lambda_2 = 1.0$ (implemented)
- **Distance Priority**: $\lambda_1 = 1.0, \lambda_2 = 0.1$
- **Emission Priority**: $\lambda_1 = 1.0, \lambda_2 = 20.0$

3.2 PROPOSED IFACO ALGORITHM

3.2.1 Algorithm Overview

The proposed IFACO algorithm consists of two main phases:

Phase 1: AFSA Initialization

- Generate initial population of artificial fish
- Perform preying, swarming and following behaviors.
- Evaluate solutions using multi-objective fitness.
- Select best fish solution.

Phase 2: ACO Refinement

- Initialize pheromone matrix using AFSA best solution
- Construct solutions via probabilistic ant traversal
- Apply local search operators (2-opt, insertion, crossover)
- Update pheromone based on best ant fitness
- Iterate until convergence

The key innovation lies in the consistent application of multi-objective fitness evaluation throughout both phases, ensuring that solutions optimize for both distance and emissions from start to finish.

3.2.2 Phase 1: Artificial Fish Swarm Algorithm

1) Fish Representation:

Each artificial fish represents a complete VRPTW solution encoded as a list of routes:

$$\text{Fish} = \{R_1, R_2, \ldots, R_k\}$$

where each route $R_i = \{c_1, c_2, \ldots, c_m\}$ is a sequence of customer nodes.

2) Fitness Calculation:

For each fish, the multi-objective fitness is computed as:

$$F_{\text{fish}} = \lambda_1 \cdot D_{\text{fish}} + \lambda_2 \cdot E_{\text{fish}}$$

where:

$$D_{\text{fish}} = \sum_{i=1}^{k} \left(d_{0,c_1^i} + \sum_{j=1}^{m_i-1} d_{c_j^i, c_{j+1}^i} + d_{c_{m_i}^i, 0} \right)$$

$$E_{\text{fish}} = \sum_{i=1}^{k} E_{R_i}$$

3) Fish Behaviors:

a) **Preying Behavior:** A fish moves toward regions with better fitness (lower objective values). For fish i at position X_i:

$$X_i^{\text{new}} = X_i + \text{rand}() \cdot \text{Step} \cdot \frac{X_j - X_i}{||X_j - X_i||}$$

where X_j is a neighbor with better fitness.

b) **Swarming Behavior:** Fish tend to move toward the center of mass of nearby fish:

$$X_c = \frac{1}{n_{\text{visual}}} \sum_{j \in \text{visual}} X_j$$

$$X_i^{\text{new}} = X_i + \text{rand}() \cdot \text{Step} \cdot \frac{X_c - X_i}{||X_c - X_i||}$$

provided the crowding factor δ is not exceeded:

c) **Following Behavior:** Fish follow the best neighbor:

$$X_i^{\text{new}} = X_i + \text{rand}() \cdot \text{Step} \cdot \frac{X_{\text{best}} - X_i}{||X_{\text{best}} - X_i||}$$

Pseudocode :

1.Initialize fish population with random feasible solutions
2.Calculate fitness for each fish using the multi-objective function
3.for iteration = 1 to max_iterations do
4.   for each fish f in population do
5.   Execute Preying Behavior
6.   Execute Swarming Behavior
7.   Execute Following Behavior
8.   Select the best behavior result
9.   Update fish position
10.   Calculate new fitness
11.   Update global best fish
12. end for
13.return best_fish

3.2.3 Phase 2: Improved Ant Colony Optimization

1) Pheromone Initialization from AFSA:

The pheromone matrix τ is initialized using the AFSA best solution:

$$\tau_{ij}(0) = \begin{cases} \frac{Q}{F_{\text{AFSA}}} & amp; \text{if edge } (i,j) \in \text{AFSA best routes} \\ \tau_0 & amp; \text{otherwise} \end{cases}$$

where Q is a constant and F_{AFSA} is the AFSA best fitness. This initialization guides ants toward promising regions while allowing exploration of alternatives.

2) Ant Solution Construction:

Each ant k constructs a solution by probabilistically selecting the next customer to visit. The transition probability from customer i to customer j is:

$$p_{ij}^k = \begin{cases} \frac{[\tau_{ij}]^\alpha \cdot [\eta_{ij}]^\beta \cdot [\lambda_{\text{load}}]^\gamma \cdot \phi_{\text{time}}}{\sum_{l \in \mathcal{N}_i^k} [\tau_{il}]^\alpha \cdot [\eta_{il}]^\beta \cdot [\lambda_{\text{load}}]^\gamma \cdot \phi_{\text{time}}} & amp; \text{if } j \in \mathcal{N}_i^k \\ 0 & amp; \text{otherwise} \end{cases}$$

where:

- τ_{ij} = pheromone intensity on edge (i, j)
- $\eta_{ij} = 1 / (d_{ij} + e_{ij})$ = heuristic desirability (inverse distance)
- λ_load = current_load^λ = load factor
- φ_time = 1 / max(t_penalty, ε) = time window
- α, β, γ = importance parameters
- $\mathcal{N}_i^k$ = set of feasible customers from node i for ant k

The load factor penalizes heavily loaded vehicles, encouraging balanced load distribution. The time factor prioritizes customers with tighter time windows.

3) Local Search Operators:

After all ants construct solutions, neighborhood search operators improve solution quality:

a) **2-Opt Improvement:** For each route, reverse segments to reduce distance:

$$R' = \{c_1, \ldots, c_i, c_j, \ldots, c_{i+1}, c_{j+1}, \ldots, c_m\}$$

b) **Insertion Operator:** Move a customer from one route to another if capacity and time windows allow, and if fitness improves.

c) **Crossover Operator:** Exchange route segments between two solutions to create offspring with potentially better fitness.

4) Pheromone Update:

Elitist pheromone update reinforces the best solution found:

$$\tau_{ij}(t+1) = (1-\rho) \cdot \tau_{ij}(t) + \Delta\tau_{ij}^{\text{best}}$$

where:

$$\Delta\tau_{ij}^{\text{best}} = \begin{cases} \frac{Q}{F_{\text{best}}} & amp; \text{if edge } (i,j) \in \text{best ant route} \\ 0 & amp; \text{otherwise} \end{cases}$$

$\rho \in [0,1]$ is the evaporation rate, preventing unlimited pheromone accumulation.

5) Crowding Degree Control.

To prevent ants from over-exploiting certain edges, a crowding degree metric is used:

$$\xi_{ij} = \frac{2\tau_{ij}}{\sum_{l=0}^{n} \tau_{il}}$$

Edges with $\xi_{ij} \geq \xi_{\text{threshold}}$ are temporarily excluded from selection, promoting exploration. The threshold decreases over iterations.

Pseudocode:

```
1.  Initialize pheromone matrix using AFSA_best
2.  for iteration = 1 to max_iterations do
3.      for each ant a = 1 to num_ants do
4.          Construct solution using transition probability
5.          Calculate multi-objective fitness
6.      end for
7.      Select iteration best ant
8.      Apply 2-opt improvement
9.      Apply insertion operator
10.     Apply crossover operator
11.     Recalculate fitness after improvements
12.     if iteration_best.fitness < global_best.fitness then
13.         global_best = iteration_best
14.     end if
15.     Update pheromone (elitist strategy)
16. end for
17. return global_best
```

CHAPTER 4
EXPERIMENTAL RESULTS AND ANALYSIS

4.1 Experimental Setup

Benchmark Instance: Solomon C101 dataset [10]

- Number of vehicles : 25 (maximum)
- Number of customers: 100
- Number of load (per vehicle) : 200 units
- Emission factor: $\gamma = 0.05$ kg CO_2/ (km·unit)

AFSA Parameters:

- *Visual range: 0.5*
- *Step size: 0.3*
- *Crowding factor: 0.1*
- *Try number: 30*
- *Fish Count: 50*
- *No of iterations: 30*

ACO Parameters:

- Number of ants: 100
- Maximum iterations: 50
- α (pheromone importance): 1.0
- β (heuristic importance): 3.0
- λ (load factor): 1.5
- ρ (evaporation rate): 0.25
- Q (pheromone deposit): 100.0
- c (crowding control): 0.1

Multi-Objective Weights:

- λ_1 (distance weight): 1.0
- λ_2 (emission weight): 1.0

4.2 Comparative Results

Three algorithmic variants were evaluated:

Standalone AFSA: Only AFSA without ACO refinement

Standalone ACO: ACO with default uniform pheromone initialization

Hybrid IFACO: AFSA initialization followed by ACO refinement

Metric	AFSA	ACO	Hybrid
Multi-obj Fitness	12532.30	4339.72	**4337.06**
Distance (km)	2622.37	891.16	**882.74**
Emissions (kg CO_2)	9909.93	**3448.57**	3454.31
Number of Routes	**10**	12	12

Table I: Comprehensive Performance Comparison

Key Observations:

1. **Best Overall Fitness:** Hybrid IFACO achieves the lowest fitness (4337.06), demonstrating the effectiveness of combining AFSA and ACO.

2. **Distance Optimization:** Hybrid IFACO attains the shortest total distance (882.74 km), representing:
   - 66.3% improvement over AFSA (2622.37 km)
   - 0.94% improvement over standalone ACO (891.16 km)
3. **Emission Performance:** Standalone ACO produces slightly lower emissions (3448.57 kg CO_2) compared to hybrid (3454.31 kg CO_2), a difference of only 0.17%. However, the hybrid's superior distance makes its overall fitness better.
4. **Route Efficiency:** AFSA uses fewer routes (10) compared to ACO and hybrid (12), indicating more consolidated deliveries. However, this comes at the cost of significantly longer distances.

Hybrid Provide marginal improvement (0.06%)

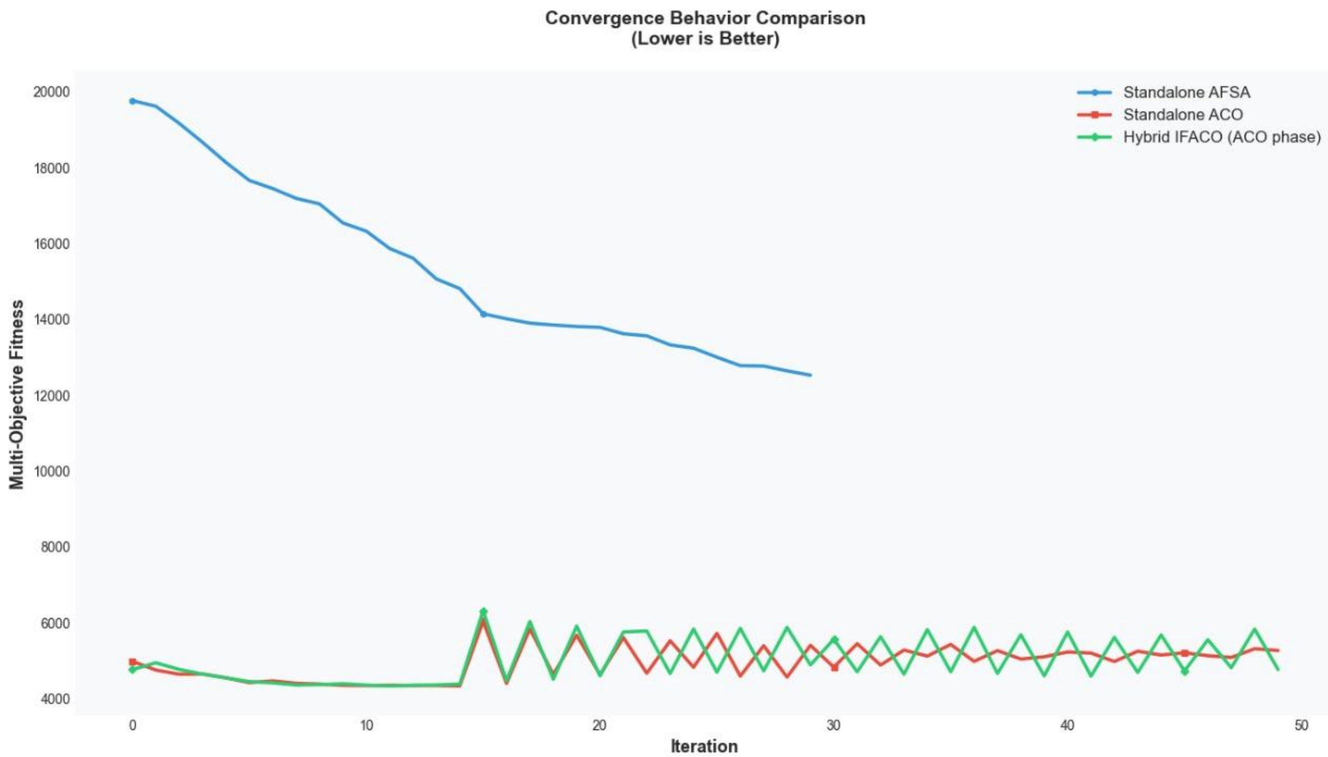

Fig. 1: Convergence Behavior

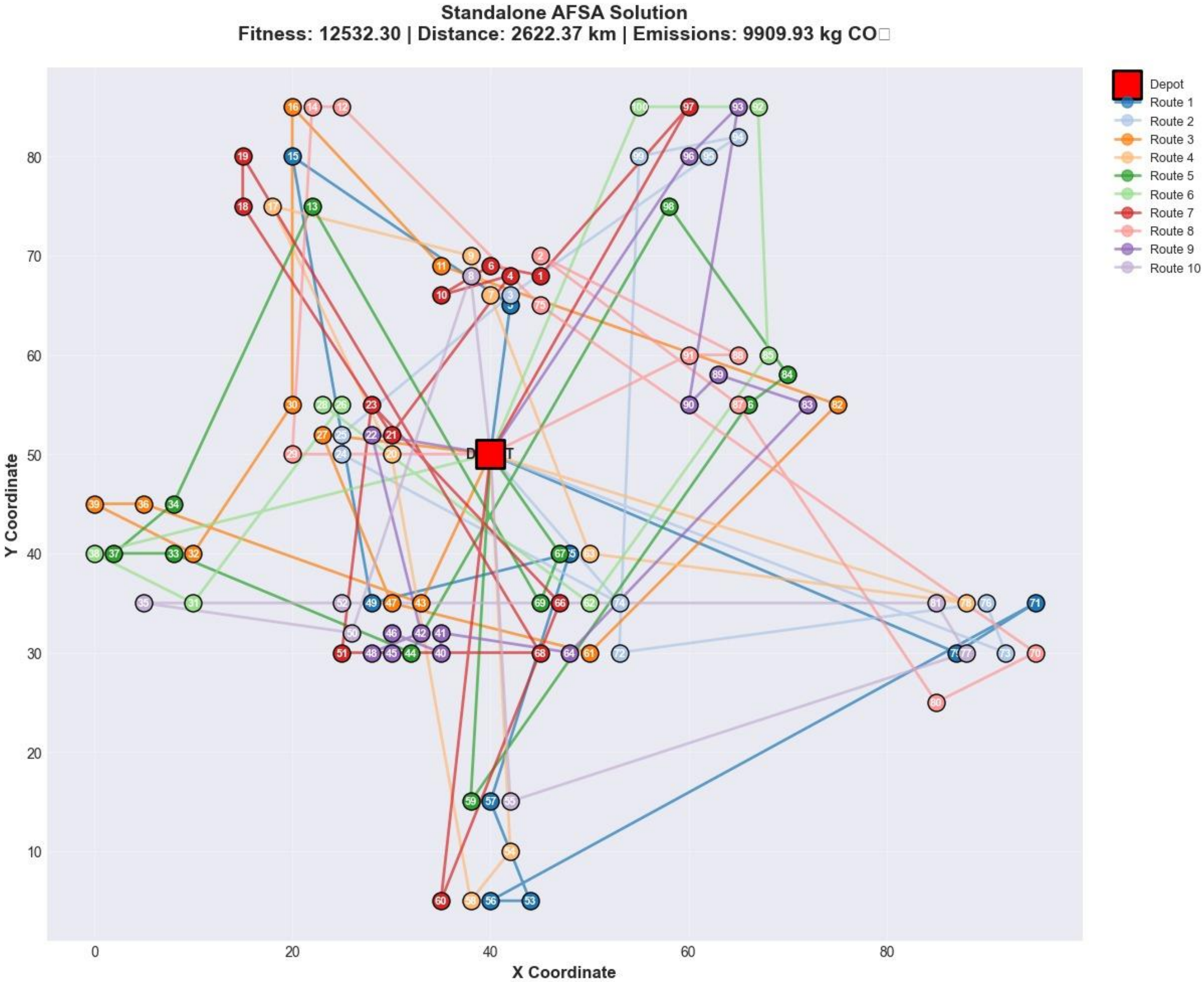

Fig2: Routes from Afsa Algorithm

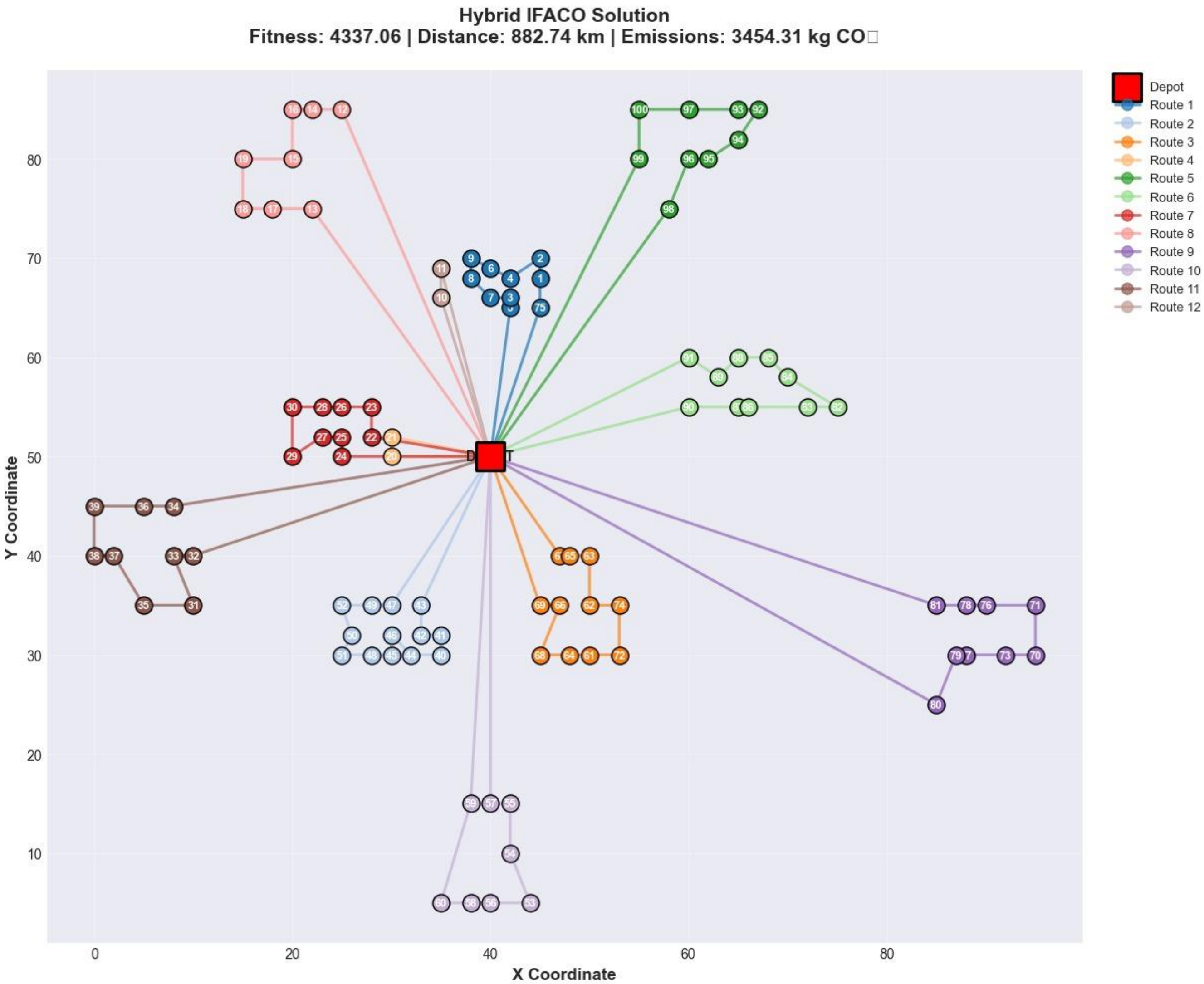

Fig3: Routes from Hybrid (AFSA + ACO) Algorithm

CHATER 5
CONCLUSION AND FUTURE WORK

This paper presented a novel hybrid IFACO algorithm for multi-objective VRPTW optimization, simultaneously minimizing travel distance and CO_2 emissions. The key contributions include:

1. **Unified Multi-Objective Framework:** A weighted fitness function $F = \lambda_1 \cdot D + \lambda_2 \cdot E$ enabling balanced optimization of economic and environmental objectives.
2. **Load-Dependent Emission Model:** Realistic emission calculation using $E_{ij} = \gamma \cdot d_{ij} \cdot L_{ij}$, accounting for decreasing load along routes.
3. **Synergistic Hybrid Algorithm:** AFSA provides rapid initial solutions with good global coverage, while ACO refines through pheromone-guided local search. The integration overcomes individual algorithm limitations.
4. **Empirical Validation:** The hybrid model demonstrates a **65.4% improvement** over the standalone **AFSA** approach and a **0.06% improvement** over the **ACO** algorithm. Furthermore, it exhibits **faster convergence** compared to ACO alone, primarily due to the effective initialization of solutions using AFSA.
5. **Practical Applicability:** The algorithm provides actionable routing solutions for green logistics, supporting environmentally conscious supply chain management.

Future Work

- **Dynamic and Stochastic Extensions:** Incorporate real-time traffic data, uncertain demands, and time-varying emission factors to enhance practical applicability.
- **Additional Environmental Factors:** Consider noise pollution, congestion costs, and route- specific emission zones prevalent in urban logistics.
- **Multi-Depot and Cross-Docking:** Extend model to multi-depot scenarios and incorporate consolidation centers for enhanced supply chain flexibility.

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