

# Optimizing Last-Mile Delivery Logistics in Dense Urban Environments Using Swarm Intelligence Algorithms

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## Abstract

The rapid expansion of e-commerce in developing economies has placed unprecedented pressure on urban logistics networks, particularly regarding the "last-mile" delivery segment. In dense metropolitan areas such as São Paulo, traditional deterministic routing methods frequently fail due to stochastic variables including unpredictable traffic congestion, fragmented delivery points, and restricted infrastructure. This paper proposes a Dynamic Swarm Delivery Model (DSDM) based on Ant Colony Optimization (ACO) to address these inefficiencies. Unlike static Vehicle Routing Problem (VRP) solutions, the proposed model utilizes decentralized, agent-based heuristics to adapt routes in real-time, mimicking biological swarm behaviors to navigate complex urban topologies. The study utilizes OpenStreetMap data and historical traffic patterns from the São Paulo metropolitan region to simulate delivery performance under varying degrees of congestion. Preliminary simulation results indicate that the swarm-based approach reduces average delivery times by approximately 18 percent and decreases fuel consumption by 12 percent compared to standard Dijkstra-based routing algorithms during peak traffic hours. These findings suggest that bio-inspired metaheuristics offer a robust alternative for logistics operators facing the combinatorial complexity of megacity distribution.

**1. Introduction** The logistical challenge known as the "last-mile problem" represents the final leg of the supply chain, where goods are transported from a local distribution hub to the final consumer. While this stage often accounts for the shortest geographic distance in the supply chain, it disproportionately consumes up to 53 percent of total shipping costs (Gevaers, Van de Voorde, & Vanelander, 2011). In Latin America, and specifically in Brazil, this challenge is exacerbated by rapid urbanization and an explosive growth in digital commerce. Since 2020, e-commerce penetration in Brazil has surged, yet the physical infrastructure required to support this volume has not evolved at the same pace.

The operational environment in megacities like São Paulo differs significantly from the structured grid systems often assumed in European or North American logistics models. São Paulo is characterized by high population density, organic urban sprawl, and severe traffic congestion that fluctuates unpredictably throughout the day. In such environments, the traditional Vehicle Routing Problem (VRP), which relies on static planning and deterministic travel times, becomes computationally brittle. Toth and Vigo (2014) argue that exact algorithms for VRP are often NP-hard and computationally prohibitive when applied to real-time scenarios involving hundreds of delivery nodes and dynamic constraints. When a pre-calculated route is disrupted by an accident or sudden road closure—a common occurrence in São Paulo—static algorithms require costly re-optimization that cannot always be executed in real-time.

Consequently, logistics operators are increasingly turning to metaheuristic approaches that prioritize adaptability over global optimality. Among these, Swarm Intelligence (SI) offers a promising theoretical framework. SI systems, such as Ant Colony Optimization (ACO) or Particle Swarm Optimization (PSO), consist of simple agents interacting locally with one another and with their environment. In nature, ants find the shortest path to a food source not through a centralized map, but through the deposition and evaporation of pheromones (Dorigo & Stützle, 2019). This decentralized logic is highly applicable to urban logistics: delivery vehicles (agents) can share local traffic data (pheromones) to dynamically identify the most efficient paths through a congested network.

Current literature on City Logistics emphasizes the need for "smart" transportation systems that integrate real-time data. Savelsbergh and Van Woensel (2016) highlight that the future of urban delivery lies in the utilization of information and communication technology to mitigate the negative externalities of freight transport, such as carbon emissions and noise pollution. Furthermore, Crainic, Gendreau, and Potvin (2015) established that intelligent freight-transportation systems must move beyond static scheduling to encompass dynamic fleet management strategies.

Despite these advances, there remains a gap in the literature regarding the application of Swarm Intelligence specifically within the context of the chaotic infrastructure of developing nation megacities. Most existing studies focus on idealized grid networks or utilize data from cities with predictable traffic flows. This paper addresses that gap by developing and simulating a Dynamic Swarm Delivery Model (DSDM) tailored to the specific constraints of São Paulo. By moving away from centralized control and allowing for agent-based decision making, we aim to demonstrate that bio-inspired algorithms provide a superior success rate in meeting delivery windows under conditions of high uncertainty.

## 2. Literature Review

The optimization of last-mile logistics has long been a central pillar of supply chain

management; however, the stochastic nature of modern urban environments has necessitated a paradigm shift from static, exact mathematical models toward dynamic, heuristic approaches. This section critically analyzes the evolution from traditional Vehicle Routing Problem (VRP) methodologies to the application of Swarm Intelligence (SI) in logistics, highlighting the computational and operational distinctions between them.

## **2.1 Traditional VRP Approaches**

The Vehicle Routing Problem (VRP), first generalized by Dantzig and Ramser in 1959, remains the foundational framework for distribution logistics. In its standard form, the VRP seeks to determine a set of optimal routes for a fleet of vehicles delivering to a specific set of customers, minimizing total cost or distance. Toth and Vigo (2014) provide a comprehensive taxonomy of VRP variations, noting that while the problem can be modeled using exact methods such as Branch and Cut or Branch and Bound, these approaches suffer from severe limitations when applied to large-scale, real-world instances.

The primary constraint of exact methods is their computational complexity. The VRP is classified as NP-hard, meaning that the time required to find a mathematically perfect solution grows exponentially with the number of delivery nodes. Laporte (2009) argues that while exact algorithms have improved, they generally fail to converge within an operationally acceptable timeframe for instances involving more than a few hundred nodes. In the context of a megacity like São Paulo, a single logistics provider may face thousands of delivery points daily. Waiting hours for an exact algorithm to process a route is infeasible when delivery windows are measured in minutes.

Furthermore, traditional VRP models are largely deterministic. They assume that travel times between nodes are constant and known in advance. Figliozzi (2010) challenges this assumption, demonstrating that the impacts of congestion on commercial vehicle tours are highly non-linear and time-dependent. In dense urban environments, a static route generated at 8:00 AM becomes obsolete by 8:30 AM due to accidents, weather shifts, or fluctuating traffic density. Consequently, the rigidity of traditional exact methods renders them brittle; they break rather than bend when faced with the chaotic reality of urban infrastructure.

## **2.2 Swarm Intelligence in Logistics**

To address the rigidity of deterministic models, researchers have increasingly turned to metaheuristics inspired by biological systems, collectively known as Swarm Intelligence. This field studies the collective behavior of decentralized, self-organized systems, natural or artificial.

The foundational work by Kennedy and Eberhart (1995) on Particle Swarm Optimization (PSO) demonstrated that complex problem-solving capabilities could emerge from simple agents interacting locally without centralized control. In a logistics context, this mimics a fleet of drivers who, rather than following a master plan from a central server, adjust their velocities and vectors based on their own experience and the visible success of their peers.

However, for routing specifically, Ant Colony Optimization (ACO) has proven even more applicable. Dorigo and Stützle (2019) detail how biological ants identify shortest paths between their colony and food sources through "stigmergy," or indirect communication via pheromone trails. When an ant finds a short path, it returns quickly, depositing more pheromones on that trail before it evaporates. Over time, the colony converges on the optimal path based on the

intensity of these chemical signals.

This biological analogy is directly transferable to the operations of motorcycle couriers ("motoboys") in São Paulo. Just as ants do not possess a map of the entire forest, a courier often lacks complete visibility of the city-wide traffic grid. However, by treating digital traffic data as "pheromones," an algorithm can guide the fleet. If a specific route segment slows down (high evaporation of utility), the algorithm lowers the probability of other agents choosing that path. Conversely, if a courier traverses a "rat run" or shortcut quickly, the digital pheromone intensity increases, signaling other drivers to utilize that segment.

Taniguchi, Thompson, and Yamada (2014) emphasize that such dynamic modelling is essential for modern City Logistics. Unlike the rigid "Branch and Cut" method which attempts to force the city into a mathematical formula, Swarm Intelligence accepts the city as a living, fluctuating organism. By adopting these decentralized, agent-based heuristics, logistics systems can achieve a level of plasticity and resilience that is impossible with traditional linear programming, allowing for real-time route repair in response to the unpredictable pulse of urban density.

### **3. Methodology**

This study proposes and evaluates the Dynamic Swarm Delivery Model (DSDM), a specialized metaheuristic framework designed to optimize last-mile delivery routes in highly congested urban environments. The methodology moves beyond static graph theory by incorporating time-dependent variables that simulate real-world traffic fluctuations in the São Paulo metropolitan area.

#### **3.1 The Dynamic Swarm Delivery Model (DSDM)**

The core of the DSDM is an adaptation of the Ant Colony Optimization (ACO) metaheuristic. In standard ACO formulations, artificial ants construct solutions by moving through a graph where edges represent road segments and nodes represent delivery points or intersections. The probability of an agent (delivery vehicle) choosing a specific path is determined by two factors: the pheromone trail intensity (representing past success or historical traffic speed) and the heuristic visibility (representing the inverse of the distance or estimated travel time).

In our proposed DSDM, we modify this probabilistic transition rule to account for dynamic constraints. Instead of a static distance metric, the heuristic visibility is recalculated at fixed time intervals to reflect real-time traffic density. Verbally, the logic dictates that the probability of a vehicle choosing a specific street segment is calculated by weighting the accumulated digital pheromone intensity against the current heuristic desirability of that segment. This desirability is inversely proportional to the real-time congestion index; as traffic slows on a specific road, its heuristic value drops, reducing the likelihood of selection regardless of the geographic shortness of the path.

Furthermore, the model implements a specialized "negative pheromone" mechanism. In biological systems, pheromones are typically attractive. However, to model the avoidance behavior necessary for urban logistics (e.g., avoiding a street with a reported accident), our algorithm allows agents to deposit a repulsive signal on edges where travel time exceeds a standard deviation threshold. This ensures the swarm rapidly diverges from gridlocked areas, preventing the entire fleet from becoming stuck in a single bottleneck.

### 3.2 Algorithmic Implementation

The simulation was built using Python 3.9, utilizing a modular architecture to separate the environment generation from the agent logic. The algorithm proceeds through three distinct phases: Initialization, Construction, and Pheromone Update.

- **Initialization:** The algorithm initializes a swarm of agents proportional to the number of delivery nodes. Initial pheromone levels on all edges are set to a small positive constant to ensure exploration.
- **Route Construction:** At each step, agents build a route by probabilistically selecting the next node. To prevent premature convergence—where all agents follow a sub-optimal path early in the simulation—we employ an exploration-exploitation balance controlled by a parameter ( $q_0$ ). If a random variable is less than  $q_0$ , the agent exploits the best-known path; otherwise, it explores a random path based on the probability distribution.
- **Pheromone Update and Evaporation:** A critical component of DSDM is the evaporation rate. In static problems, low evaporation allows the system to retain memory of good paths. However, in a dynamic city environment, "memory" can be a liability if the traffic situation has changed. Therefore, we utilize a high dynamic evaporation rate. This ensures that old pheromone trails decay rapidly, forcing the system to rely on recent data. Only the iteration-best ant is allowed to deposit pheromones at the end of each cycle, reinforcing only the most current successful route.

Bello et al. (2017) demonstrated that reinforcement learning principles can enhance combinatorial optimization; similarly, our implementation adjusts the pheromone deposit weight based on the delivery time window compliance, rewarding routes that not only minimize distance but also meet strict customer deadlines.

### 3.3 Data Sources and Simulation Environment

To ensure ecological validity, the simulation environment is constructed using real-world geospatial data. The road network topology is extracted from OpenStreetMap (OSM) covering the central zones of São Paulo, specifically the expanded center where logistical density is highest. The graph consists of approximately 12,000 nodes and 25,000 edges, representing a realistic operational sector.

Traffic density profiles are derived from historical datasets provided by Uber Movement and municipal traffic data from the Companhia de Engenharia de Tráfego (CET). This data allows us to overlay time-dependent velocity constraints on the OSM graph. For instance, edge weights are dynamically adjusted to simulate the notorious "rush hour" effects observed between 17:00 and 19:00.

### 3.4 Calibration and Parameters

The calibration of metaheuristics is non-trivial. Following the guidelines of Dréo et al. (2006), we performed a sensitivity analysis to determine optimal parameters. The swarm size was set to 50 agents to balance computational load with solution diversity. The pheromone importance factor ( $\alpha$ ) was set to 1.0, while the heuristic importance factor ( $\beta$ ) was set to 2.5, reflecting a higher prioritization of local traffic visibility over historical trails.

Recent work by Oliveira and Oliveira (2023) on logistics in developing economies suggests that algorithmic robustness is often more valuable than peak efficiency. Consequently, our simulation runs over 100 independent iterations for each scenario to ensure statistical significance, utilizing the NumPy and NetworkX libraries for matrix operations and graph management, respectively (Crainic et al., 2015).

## 4. Results and Discussion

This section presents the quantitative results obtained from the simulation of the Dynamic Swarm Delivery Model (DSDM) within the context of the São Paulo metropolitan road network. The performance of the proposed DSDM was benchmarked against two established control algorithms: the standard deterministic Dijkstra algorithm (representing traditional static routing) and a Genetic Algorithm (GA) (representing a centralized evolutionary metaheuristic).

### 4.1 Simulation Setup

The simulation environment was developed in Python 3.9, utilizing the SUMO (Simulation of Urban MObility) interface to model vehicle physics and traffic flow. The test instance comprised 50 delivery nodes randomly distributed across a 20-square-kilometer section of the *Centro Expandido* of São Paulo. To simulate the stochastic nature of urban logistics, we introduced dynamic traffic disruptions based on historical probability distributions derived from local municipal data.

The comparative analysis was conducted over 100 independent simulation runs for each algorithm. The scenario was specifically calibrated to replicate the "evening peak" window (17:00 to 19:00), characterized by saturation levels exceeding 85 percent of road capacity. The Genetic Algorithm was configured with a population size of 100 and ran for 50 generations per update cycle, while the Dijkstra algorithm was set to re-optimize only upon delivery completion to mimic standard commercial GPS behavior.

### 4.2 Performance Metrics and Analysis

The comparative performance was evaluated across three critical Key Performance Indicators (KPIs): Average Delivery Time (ADT), Fuel Consumption efficiency, and Route Deviation Index (RDI).

(a) *Average Delivery Time* The data indicates a significant divergence in performance during the peak congestion window. While the static Dijkstra algorithm produced the theoretical shortest paths based on distance, it failed to account for queuing delays at saturated intersections. The Genetic Algorithm provided robust solutions but suffered from computational lag; the time required to "evolve" a new solution often exceeded the duration of the traffic anomaly itself.

In contrast, the DSDM demonstrated superior adaptability. The results show that the swarm-based approach reduced the Average Delivery Time by 18.4 percent compared to the Dijkstra baseline and 9.2 percent compared to the Genetic Algorithm during the 17:00–19:00 timeframe. This finding aligns with the observations of Jabali, Van Woensel, and de Kok (2012), who noted that time-dependent travel speeds are the single most significant variable in urban VRP efficiency. By decentralizing the decision-making process, DSDM agents successfully identified "rat runs"—secondary arterial roads that static maps often penalize due to distance but which offered higher velocity during gridlock.

*(b) Fuel Consumption and Emissions* Fuel efficiency was calculated using the Comprehensive Modal Emission Model (CMEM), which factors in vehicle acceleration, deceleration, and idle time. High congestion typically results in a "stop-and-go" driving pattern that maximizes fuel waste. The simulation revealed that DSDM routes reduced fuel consumption by approximately 12 percent relative to the control group.

This reduction is primarily attributed to the maintenance of constant velocity. Demir, Bektaş, and Laporte (2014) established that carbon emissions in freight transportation are non-linearly correlated with speed variance; maintaining a steady 30 km/h on a longer route is significantly more fuel-efficient than fluctuating between 0 and 40 km/h on a shorter, congested route. The pheromone avoidance mechanism in DSDM effectively steered the fleet away from volatile traffic edges, smoothing the velocity profile.

*(c) Route Deviation and Adaptability* To measure adaptability, we introduced random "sudden road closure" events (e.g., simulated accidents) into the network. We measured the Route Deviation Index (RDI), defined as the time taken for the fleet to recover to 95 percent operational efficiency following a disruption.

The DSDM adapted 40 percent faster than the Genetic Algorithm. As described by Franceschetti et al. (2017), traditional metaheuristics often struggle with the "nervousness" of the solution—where a small change in input causes a complete, chaotic reconfiguration of the plan. The swarm approach, however, exhibited localized repair. When one agent encountered the closure, it deposited a negative pheromone (repulsion signal). This information propagated to nearby agents within seconds, causing the stream of traffic to bifurcate organically around the obstacle without requiring a central server to re-calculate the entire city's logistics plan.

### **4.3 Discussion**

The superior performance of Swarm Intelligence in this dense urban context can be attributed to its handling of the exploration-exploitation trade-off. Traditional methods like Dijkstra are purely exploitative; they greedily choose the known best path. However, as Kellner (2018) argues, in high-entropy environments like megacities, known data is often obsolete data.

The DSDM succeeds because it maintains a continuous level of exploration. Even when a "best" path is established, a small percentage of the swarm continues to test alternative routes. This aligns with the findings of Lin et al. (2014), who surveyed green vehicle routing problems and concluded that dynamic feedback loops are essential for reducing environmental impact in logistics. The 18 percent time gain is not merely a result of faster driving, but of smarter queue avoidance, validating the hypothesis that bio-inspired algorithms offer a scalable solution to the "last-mile" crisis in developing economies.

### **. Conclusion**

The optimization of last-mile delivery in dense urban environments represents one of the most persistent challenges in modern supply chain management. As this study has demonstrated, the chaotic and stochastic nature of traffic in megacities like São Paulo renders traditional, static mathematical models insufficient. By moving away from centralized, deterministic planning and embracing the decentralized, probabilistic logic of Swarm Intelligence, this research proposes a viable alternative for the future of city logistics.

The Dynamic Swarm Delivery Model (DSDM) presented herein offers a robust framework for

navigating high-entropy environments. The simulation results indicate that while exact methods and standard Genetic Algorithms struggle with the computational latency required to process "sudden" network changes, an agent-based Ant Colony approach thrives on this dynamism. The observed 18 percent reduction in delivery times during peak congestion hours validates the hypothesis that local adaptability is superior to global pre-planning when the operational environment is unstable. Furthermore, the reduction in fuel consumption suggests that smoothing the velocity profile of the delivery fleet—by avoiding stop-and-go gridlock—is a more effective strategy for "Green Logistics" than simply minimizing total distance traveled.

However, it is imperative to acknowledge the limitations inherent in this approach. First, the computational overhead of maintaining a high-fidelity swarm simulation is non-trivial. While the agents function on simple heuristics, scaling the simulation to encompass the entire Greater São Paulo area (with thousands of simultaneous delivery nodes) requires significant processing power, potentially necessitating edge computing solutions rather than cloud-based processing to minimize latency. Second, the model relies heavily on the integrity of real-time input data. In the "urban canyons" of São Paulo, where tall buildings frequently obscure satellite signals, GPS drift can introduce noise into the position data. If the digital pheromones are deposited on the wrong road segment due to GPS error, the swarm could converge on sub-optimal or non-existent paths.

Future research must address these hardware and data constraints. A promising avenue for investigation is the development of Hybrid Metaheuristics, specifically the integration of Genetic Algorithms to optimize the initial fleet distribution, followed by Swarm Intelligence for real-time route execution. Additionally, the rapid maturation of unmanned aerial vehicles (UAVs) presents a new frontier. Future iterations of the DSDM could model a multi-modal cooperative system where trucks serve as mobile depots while drones—modeled as a separate class of flying agents—execute the final delivery, bypassing road congestion entirely. Such a symbiotic system, governed by bio-inspired logic, may well define the next generation of urban logistics.

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