Modeling and Applying Tree-Like Path Planning of Multiple Ant Colonies

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Abstract

Ant colonies exemplify rigorous and efficient distributed cognition, providing profound inspirations for understanding collective intelligence. Specifically, inter-colony competitions and foraging strategies of ants offer insights into how biological systems search resources. Although it is well-known that ants naturally create tree-like structures in foraging paths, little is investigated regarding how multiple colonies optimize these structures simultaneously under competitions. Hence, we propose MT-ACO, a Dual-Colony Competition Model driven by a Pheromone Repulsion Mechanism. In this model, agents treat the pheromone trails of competitors as dynamic environmental constraints, simulating the biological principle of Competitive Exclusion. Simulations reveal that this simple rule leads to near-optimal Edge-Disjoint Directed Trees. This emergent topology maximizes resource coverage while minimizing conflict, providing a decentralized heuristic for the NP-hard Minimal Directed Edge-Disjoint Double Tree problem. Our findings demonstrate that avoidance functions offering a computational framework to understand how swarms resolve the tragedy of the commons through adaptive niche differentiation.

Keywords: Distributed Cognition; Swarm Intelligence; Niche Differentiation; Self-Organization; Agent-Based Modeling; Competitive Exclusion

Introduction

Collective behavior shows how cognition can be distributed across many simple agents. From insect societies to human teams, complex global structure often emerges from local interaction without centralized control. This idea underlies *distributed cognition* (Hutchins, 1995), where intelligent behavior is realized through spatial organization and external representations (Kirsh, 1995), and *collective cognition*, where group-level coordination arises from simple interaction rules (Couzin, 2009). Such principles motivate computational models in swarm robotics and artificial life (Trianni and Tuci, 2011).

Ant foraging provides a canonical example. Through stigmergic communication, colonies construct efficient, often tree-like trail systems connecting nests to multiple food sources. These systems have long served as models of "superorganism" cognition (Sasaki and Pratt, 2018) and decentralized information processing (Fernández-López et al., 2025). Yet natural environments rarely host a single colony. Multiple colonies often forage in overlapping territories, and *intercolony competition* introduces a core cognitive tension: how can independent swarms explore the same environment while avoiding destructive interference? This resembles distributed search under conflict constraints (Hills et al., 2015). Despite extensive studies of single-colony foraging and its algorithmic counterparts, little is known about how *multiple* colonies can simultaneously construct efficient, *non-overlapping* tree-like structures under strict competition (Sasaki and Pratt, 2018; Trianni and Tuci, 2011).

A key modeling challenge is to connect a mechanistic local rule to a measurable system-level planning outcome (edge-disjoint connectivity) in a competitive setting. Recent work emphasizes agent-based benchmarks and structured tasks probing these capacities (Brown et al., 2024; Cross et al., 2024). However, for multi-colony foraging, we still lack a minimal mechanistic model explaining how competitive interaction yields *structural differentiation* rather than collapse into conflict. To address this, we propose **MT-ACO**, a *Dual-Colony Competition Model* driven by a *Pheromone Repulsion Mechanism*. Related deterministic baselines for constructing multiple disjoint routing structures further motivate a mechanistic competitive account (Lopez-Pajares et al., 2025). The model builds on Ant Colony Optimization (ACO) (Dorigo and Stützle, 2004; Dorigo et al., 1996), including bounded-reinforcement variants (Stützle and Hoos, 2000) and cooperative-learning formulations (Dorigo and Gambardella, 1997). MT-ACO introduces a cognitively interpretable rule: agents treat competitors' pheromone trails as dynamic environmental constraints, locally biasing movement away from contested edges, implementing a computational analogue of *competitive exclusion* without global coordination.

We formalize this scenario as the *Minimal Directed Edge-Disjoint Double Tree* (MDEDDT) problem. Two directed tree-like structures must be constructed from a common source to a set of terminals, subject to strict edge-disjointness and minimal total cost. Within MT-ACO, this task is realized through local rules governing movement, reinforcement, evaporation, and repulsion. Despite their locality, these rules yield the spontaneous emergence of two efficient, non-overlapping directed trees. Our contributions are as follows:

- We formulate multi-colony foraging as a structured planning problem capturing the tension between efficiency and conflict under competition (Couzin, 2009; Hutchins, 1995; Sasaki and Pratt, 2018).
- We propose MT-ACO, a dual-colony model grounded in ACO (Dorigo and Gambardella, 1997; Dorigo and Stützle, 2004; Dorigo et al., 1996; Stützle and Hoos, 2000), where

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pheromone repulsion provides a mechanistic account of avoidance as *implicit cooperation*.

- Through simulations, we show that this local rule yields emergent edge-disjoint trees that *heuristically* address the NP-hard MDEDDT problem and outperform deterministic baselines, particularly in sparse environments (Sec. 4).

Cognitive Formulation of Multi-Colony Path Planning

Multi-colony foraging can be understood as a form of distributed planning under competition. Biologically, colonies consist of simple agents that perceive only local information, move incrementally, and modify the environment via pheromone deposition. There is no direct communication: coordination is mediated entirely by environmental traces, consistent with stigmergic interaction (Dorigo and Stützle, 2004; Trianni and Tuci, 2011). From a cognitive perspective, each colony performs a distributed search in a constrained environment, where pheromone trails act as externalized memory (Hutchins, 1995; Kirsh, 1995). In single-colony settings, positive feedback yields coherent trail systems. In multi-colony settings, however, the same mechanisms lead to interference: without additional constraints, competing swarms collapse onto identical high-reward paths. Empirically, such collapse is rare; colonies instead exhibit spatial segregation and avoidance (Sasaki and Pratt, 2018), suggesting that competition is resolved through local interaction rules rather than centralized negotiation.

From Foraging to Graph Abstraction

We formalize the environment as a directed graph $G = (V, E, w)$, where vertices represent spatial locations and directed edges represent feasible movements. Each edge $e \in E$ carries a nonnegative cost $w(e)$ encoding distance, energy, or traversal difficulty. A distinguished vertex $r \in V$ represents the nest, and a subset $T \subset V$ represents resource sites.

For a single colony, constructing an efficient foraging network corresponds to building a directed tree rooted at r that spans all terminals in T with minimal total cost. This abstraction is standard in network optimization and computational models of foraging (Dorigo and Stützle, 2004; Hu et al., 2006), and has also motivated alternative metaheuristics such as particle swarm optimization for Steiner and multicast variants (Ma and Liu, 2010; Qu et al., 2013).

With multiple colonies, the abstraction must encode competition. Each colony seeks such a tree, but edges cannot be shared: overlapping routes imply physical interference and ecological conflict. The environment therefore becomes a shared planning substrate in which multiple distributed agents must coordinate indirectly to avoid overlap.

MDEDDT as a Cognitive Task

We formalize this setting as the *Minimal Directed Edge-Disjoint Double Tree* (MDEDDT) problem.

Definition 1 (MDEDDT) *Given a directed graph $G = (V, E, w)$, a root $r \in V$, and a terminal set $T \subset V$, find two directed trees $\mathcal{T}_1$ and $\mathcal{T}_2$ such that:*

1. *Each $\mathcal{T}_k$ is a directed tree rooted at r spanning all vertices in T;*
2. *The two trees are* edge-disjoint*, i.e., $E(\mathcal{T}_1) \cap E(\mathcal{T}_2) = \emptyset$;*
3. *The total cost $w(\mathcal{T}_1) + w(\mathcal{T}_2)$ is minimized.*

From a computational standpoint, MDEDDT is NP-hard because it subsumes classical directed Steiner and branching variants (Chu and Liu, 1965; Dreyfus and Wagner, 1971; Edmonds, 1967; Hwang and Richards, 1992; Imase and Waxman, 1991). A minimal reduction can be sketched as follows. Consider an instance of the Directed Steiner Tree Problem (DSTP) on (V, E, w) with root r and terminals T. Construct a new directed multigraph $G' = (V, E_1 \cup E_2, w')$ where E_1 and E_2 are two *edge-disjoint copies* of E (parallel edges treated as distinct), with identical weights. Any DSTP solution S induces a feasible MDEDDT solution on G' by taking S on E_1 and S on E_2, hence $\mathrm{OPT}_{\mathrm{MDEDDT}} \leq 2\,\mathrm{OPT}_{\mathrm{DSTP}}$. Conversely, for any feasible MDEDDT pair $(\mathcal{T}_1, \mathcal{T}_2)$ on G', projecting to either copy yields a feasible DSTP, so $\mathrm{OPT}_{\mathrm{DSTP}} \leq \min\{w(\mathcal{T}_1), w(\mathcal{T}_2)\} \leq \frac{1}{2}(w(\mathcal{T}_1) + w(\mathcal{T}_2))$. Therefore $\mathrm{OPT}_{\mathrm{MDEDDT}} \geq 2\,\mathrm{OPT}_{\mathrm{DSTP}}$, and deciding whether $\mathrm{OPT}_{\mathrm{MDEDDT}} \leq 2B$ is NP-hard.

This complexity motivates decentralized heuristic mechanisms that nevertheless yield interpretable emergent structure, which aligns with recent perspectives that treat planning and world modeling as emergent properties of agent–environment interaction (Brown et al., 2024; Cross et al., 2024). Rather than assuming a centralized planner, MDEDDT frames multi-colony foraging as a collective problem in which structure must arise from decentralized dynamics.

Why Edge-Disjoint Trees Matter

Edge-disjointness has a direct cognitive interpretation. Sharing an edge corresponds to repeated physical encounters and competition over the same spatial corridor; avoiding overlap minimizes conflict and stabilizes collective behavior. Ecologically, the emergence of disjoint structures reflects *niche differentiation*, where each colony occupies a distinct subspace of the environment (Sasaki and Pratt, 2018). Cognitively, it represents implicit coordination achieved without communication: the environment itself becomes partitioned through stigmergic interaction.

Solving MDEDDT therefore models how distributed systems resolve shared-resource conflicts through local avoidance rules that reshape global structure. In the next section, we show how this cognitive task can be realized by a minimal dual-colony ant model, in which pheromone repulsion operationalizes competitive exclusion and drives the emergence of edge-disjoint tree-like foraging networks.

MT-ACO: A Dual-Colony Competition Model

MT-ACO is a minimal mechanistic model for multi-colony path planning under competition. It preserves the locality and

simplicity of classical ACO while enabling the emergence of globally edge-disjoint structures. We first recall how tree-like organization arises in single-colony foraging, then extend this mechanism to a dual-colony setting through pheromone repulsion.

Single-Colony Foraging as Tree Emergence

In classical Ant Colony Optimization (ACO), a population of agents repeatedly traverses a graph, depositing pheromone on visited edges. The probability of choosing an outgoing edge $e = (u, v)$ from node u is biased by a static heuristic and a dynamic pheromone level $\tau(e)$ (Dorigo and Stützle, 2004; Dorigo et al., 1996):

$$P(u \to v) \propto \left[\tau(u,v)\right]^{\alpha} \cdot \left[\eta(u,v)\right]^{\beta}, \tag{1}$$

where η is a heuristic desirability and α, β control the balance between learned and intrinsic preferences; the proportionality is normalized over all outgoing edges from u.

Successful tours reinforce their constituent edges, while pheromone evaporates over time. This positive feedback, coupled with decay, concentrates traffic on efficient routes. When the task is to connect a root to multiple terminals, repeated biased traversals naturally generate a sparse, tree-like subgraph. A directed tree is therefore not explicitly constructed; it *emerges* as a stable attractor of distributed exploration and reinforcement.

Cognitively, this process can be interpreted as distributed planning. Each ant acts on local information only, while the colony externalizes memory in the environment through pheromone traces (Hutchins, 1995; Kirsh, 1995).

Inter-Colony Competition via Pheromone Repulsion

In a multi-colony environment, naive application of single-colony ACO leads to collapse: both populations converge on the same high-quality edges, producing maximal interference. Biological systems avoid such outcomes through spatial segregation and avoidance (Sasaki and Pratt, 2018).

MT-ACO introduces two interacting pheromone fields, $\tau_1(e)$ and $\tau_2(e)$, one for each colony. Each colony reinforces its own trails exactly as in standard ACO. Crucially, ants also perceive competitors' pheromone and treat it as a dynamic constraint. For an ant of colony $k \in \{1, 2\}$ at node u,

$$P_k(u \to v) \propto \left[\tau_k(u,v)\right]^{\alpha} \cdot \left[\eta(u,v)\right]^{\beta} \cdot \phi\big(\tau_{3-k}(u,v)\big), \tag{2}$$

where $\phi(\cdot)$ is a monotone decreasing repulsion function; the proportionality is normalized over all outgoing edges from u.

We instantiate $\phi(\cdot)$ as an exponential inhibition:

$$\phi(x) \;=\; \exp(-\lambda\, x), \tag{3}$$

where $\lambda \geq 0$ is a *repulsion strength* parameter. Competitors' pheromone thus acts as a graded "crowding" signal that suppresses action selection, analogous to inhibitory gating in decentralized decision systems. To ensure scale invariance, repulsion is applied to a normalized competitor field

$$\tilde{\tau}_{3-k}(u,v) \;=\; \frac{\tau_{3-k}(u,v)}{\max_{e \in E} \tau_{3-k}(e) + \epsilon}, \tag{4}$$

with $\epsilon > 0$ for numerical safety, and $\phi(\tilde{\tau}_{3-k}(u,v))$ is used in the transition rule. The normalization $\max_{e \in E} \tau_{3-k}(e)$ is computed per iteration (before sampling trajectories) to keep λ comparable across settings.

This single modification operationalizes a computational analogue of *competitive exclusion*: local avoidance suffices to partition the environment into two non-overlapping foraging structures.

Competition can be implemented either at the *action-selection* level (as above) or at the *memory-update* level via cross-inhibition in pheromone reinforcement. Both realize the same principle that "competitor traces decrease future use." We adopt the choice-level form because it is cognitively transparent: repulsion acts as a local perceptual constraint on decisions.

Algorithmic Realization

A "tree" is constructed by incremental attachment of terminals via sampled root-to-terminal trajectories. For colony k, an ant builds a candidate structure $\mathcal{T}_k^{(m)}$ by: (i) initializing $\mathcal{T} \leftarrow \{r\}$; (ii) processing terminals in random order π; (iii) for each $t \in \pi$, repeatedly sampling a trajectory from r using P_k until reaching t (or exhausting a step budget); (iv) adding trajectory edges to $\mathcal{T}$ with first-visit parents to maintain a tree-like structure; (v) discarding edges that close directed cycles; (vi) marking the construction as *failed* if t is unreachable after R restarts. The cost $w(\mathcal{T})$ is the sum of unique edges. In experiments, any run in which either colony fails to span all terminals is counted as a failure (and included in the denominator of success rate).

Algorithm 1 summarizes MT-ACO. Two ant populations repeatedly generate candidate trees, update pheromones within each colony, and evaporate globally. Repulsion is applied implicitly through the modified transition probabilities.

After selecting $\mathcal{T}_k^*$, we apply

$$\tau_k(e) \leftarrow (1-\rho)\tau_k(e) + \Delta\tau_k(e),$$

where $\Delta\tau_k(e) = Q/w(\mathcal{T}_k^*)$ if $e \in \mathcal{T}_k^*$ and 0 otherwise. Optionally, we clip $\tau_k(e) \in [\tau_{\min}, \tau_{\max}]$ as in MAX–MIN ACO (Stützle and Hoos, 2000).

The algorithm retains the modularity of standard ACO (Dorigo and Stützle, 2004; Stützle and Hoos, 2000) and is naturally compatible with GPU-parallel implementations (Zhou et al., 2017). All inter-colony interaction is mediated by the environment; no direct coupling is introduced. In the next section, we show that this minimal modification suffices to induce the spontaneous emergence of two edge-disjoint directed trees.

Emergence and Quantitative Evaluation

We evaluate MT-ACO from two complementary perspectives. First, we test whether (i) tree-like connectivity in a single colony and (ii) edge-disjoint differentiation in two competing colonies can emerge from local rules alone. Second, we quantify reliability and efficiency on the MDEDDT task as environmental constraint varies. Together, these experiments assess both qualitative emergence and quantitative robustness.

Algorithm 1 MT-ACO (Dual-Colony Ant Model)

Initialize $\tau_1(e) \leftarrow \tau_0$, $\tau_2(e) \leftarrow \tau_0$ for all $e \in E$
for $t = 1$ to T **do**
  Compute normalized competitor fields $\tilde{\tau}_k(e) = \tau_k(e)/(\max_{e' \in E} \tau_k(e') + \epsilon)$ for $k \in \{1, 2\}$
  for $k \in \{1, 2\}$ **do**
    for $m = 1$ to M **do**
      Construct a candidate tree $\mathcal{T}_k^{(m)}$ using transition rule on $P_k(u \to v)$ and normalized over all outgoing edges from u as

$$P_k \propto [\tau_k(u, v)]^\alpha \, [\eta(u, v)]^\beta \, \phi(\tilde{\tau}_{3-k}(u, v)).$$

    end for
    Select best $\mathcal{T}_k^*$ among $\{\mathcal{T}_k^{(m)}\}$ by minimal cost
    Update pheromones for colony k:

$$\tau_k(e) \leftarrow (1 - \rho)\tau_k(e) + \Delta\tau_k(e)$$

    where

$$\Delta\tau_k(e) = \begin{cases} Q/w(\mathcal{T}_k^*), & e \in \mathcal{T}_k^*, \\ 0, & \text{otherwise.} \end{cases}$$

  end for
end for
return $(\mathcal{T}_1^*, \mathcal{T}_2^*)$

All experiments use a single, fixed parameter configuration to isolate the role of the competitive mechanism and ensure comparability across conditions. Unless otherwise stated, we set $\alpha = 1, \beta = 2, \rho = 0.02, Q = 1$, which follow standard ACO practice and provide a balanced trade-off between exploitation and exploration.

Each colony deploys $M = 100$ ants per iteration, and the algorithm runs for $T = 100$ iterations. Pheromone values are initialized uniformly as $\tau_k(e) = \tau_0$ with $\tau_0 = 1$ for all edges and both colonies.

For trajectory construction, each terminal is reached via repeated root-to-terminal sampling. If a terminal cannot be reached after $R = 20$ restarts, the current tree construction is marked as a failure. A trial is counted as successful only if *both* colonies construct valid structure spanning all terminals.

The heuristic term $\eta(u, v)$ is defined as the inverse edge cost,

$$\eta(u, v) = \frac{1}{w(u, v) + \epsilon},$$

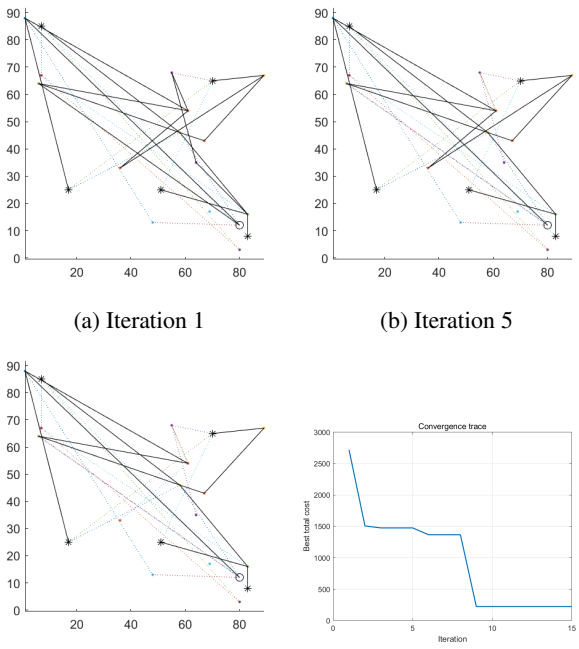
with $\epsilon = 10^{-8}$ for numerical stability, favoring shorter edges during exploration.

Competitive exclusion is controlled by the repulsion strength λ in

$$\phi(x) = \exp(-\lambda x).$$

In all reported experiments we fix $\lambda = 1$ to isolate the qualitative effect of repulsion. The ablation ON/OFF corresponds to enabling or disabling this term. As discussed earlier, sweeping λ yields a continuous family of behaviors from independent planning ($\lambda \to 0$) to strong territorial segregation (large λ), providing a mechanistic control knob for future studies.

This unified configuration ensures that all reported differences arise from the presence or absence of competitive repulsion, rather than from incidental parameter tuning.



(a) Iteration 1 (b) Iteration 5

(c) Iteration 9 (d) Convergence trace

Figure 1: Single-colony emergence of a tree-like foraging structure. (a–c) Selected edges at representative iterations, illustrating progressive sparsification and stabilization. (d) Best objective value over iterations, showing convergence as reinforcement accumulates.

Emergent Tree Structures in Single-Colony Foraging

We first verify that arborescent structure can arise in a single-colony setting without any explicit global planner. Starting from stochastic exploration, biased traversal and reinforcement gradually concentrate traffic onto a sparse subset of edges that connects the source to terminals.

Figure 1 shows representative snapshots across iterations together with the convergence trace of the best objective value. Here the objective is the tree cost $w(\mathcal{T})$ (sum of unique edge weights), and we select the best candidate by minimal $w(\mathcal{T}_k^{(m)})$ among successful constructions.

Early iterations exhibit dispersed exploration and frequent structural change, whereas later iterations stabilize into a sparse tree-structure as pheromone information accumulates, consistent with emergent tree formation from local reinforcement.

This single-colony result motivates the central hypothesis of MT-ACO: if tree-like organization can emerge from local positive feedback, then structural differentiation between

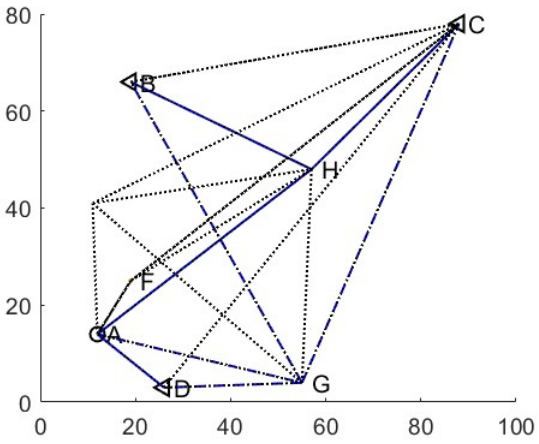


Figure 2: Representative dual-colony outcome under pheromone repulsion. Two colonies construct complementary directed trees rooted at the same source, with near-zero edge overlap, illustrating emergent structural differentiation.

colonies may emerge from an equally local competitive (negative) feedback.

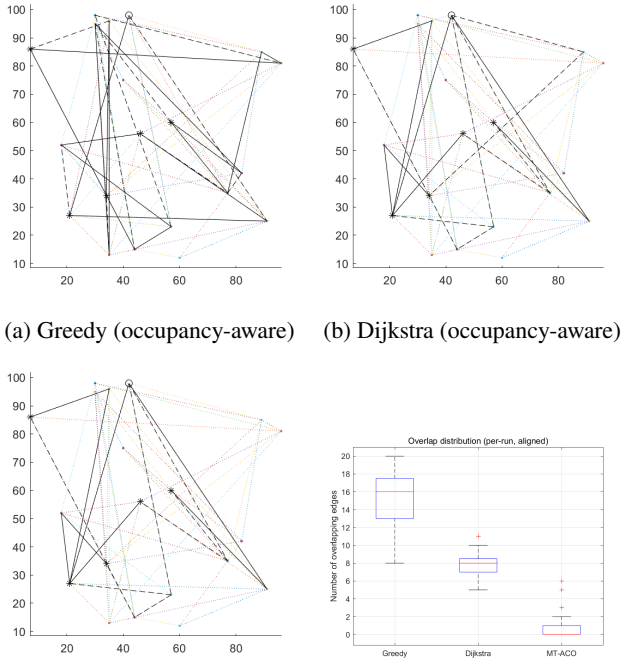
Edge-Disjoint Differentiation Under Inter-Colony Competition

We next consider the dual-colony setting, where both colonies must connect the same source to the same terminal set. MT-ACO induces differentiation via a minimal local rule: competitor pheromone acts as a dynamic constraint, making edges strongly reinforced by one colony progressively unattractive to the other. This produces niche differentiation without centralized coordination.

Figure 2 shows a representative outcome on one instance: two colonies self-organize into complementary directed trees rooted at the same source with negligible edge overlap. Separation arises during construction as repulsion reshapes effective transition probabilities over time.

To contextualize the competitive mechanism, we compare MT-ACO to two non-competitive but occupancy-aware constructions that approximate how independent planners might avoid direct edge reuse: (i) a greedy baseline with local occupancy bias, and (ii) a Dijkstra-based baseline that builds shortest-path connections. These baselines do not implement adaptive mutual repulsion during learning, and thus serve as descriptive references.

Figure 3(a–c) shows representative constructions on the same instance. While occupancy-aware baselines may reduce overlap, they often do so with higher length cost or less stable separation. Figure 3(d) aggregates overlap statistics across environments to provide a distributional view beyond a single example.



(a) Greedy (occupancy-aware) (b) Dijkstra (occupancy-aware)

(c) MT-ACO (competitive) (d) Overlap distribution

Figure 3: Qualitative constructions and overlap statistics under competition. (a–c) Two-tree solutions on the same instance for occupancy-aware baselines versus MT-ACO. (d) Distribution of overlapping-edge counts across environments (lower is better), highlighting more reliable separation under MT-ACO.

Mechanistic Test: Removing Repulsion

A core claim of MT-ACO is that repulsion is a *causal mechanism* for differentiation. We therefore run a controlled ablation where ON and OFF conditions share the same implementation (initialization, sampling, evaporation, and deposition) and differ only in whether competitive pheromone repulsion is enabled.

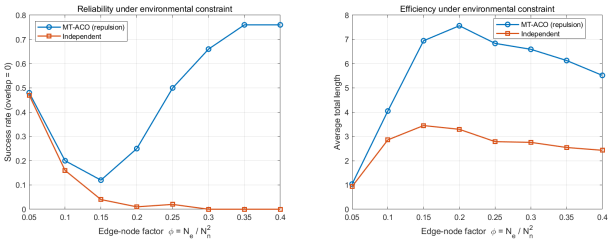
Beyond the ON/OFF ablation, Eq. 3 defines a continuous mechanism parameter λ. Here we keep λ fixed to isolate the causal role of repulsion, but the model yields testable predictions: increasing λ should (i) reduce overlap and increase the probability of fully edge-disjoint outcomes, while (ii) increasing total length by discouraging traversal of short shared corridors. As $\lambda \to 0$, MT-ACO should smoothly recover the independent-planner regime with low cost but persistent overlap. These predictions can be tested by sweeping λ while holding (α, β, ρ) fixed and reporting the joint curve of success rate, mean overlap, and mean total length.

The two conditions correspond to different ecological interpretations. With repulsion ON, overlap represents conflict and is treated as the primary failure signal. With repulsion OFF, each colony behaves as an independent planner optimizing its own cost, and overlap is recorded as an observational outcome.

Table 1 summarizes 100 trials. Without repulsion, solutions

Table 1: Controlled ablation of pheromone repulsion (ON vs. OFF) over 100 trials. Success Rate is the fraction of trials with zero overlap; Mean Overlap is the number of shared edges; Mean Total Length is $w(\mathcal{T}_1) + w(\mathcal{T}_2)$.

Condition	Success Rate (overlap= 0)	Mean Overlap Edges	Mean Total Length
ON	0.77	0.40	4.26
OFF	0.00	7.62	1.98



(a) Reliability (b) Efficiency

Figure 4: Reliability and efficiency under varying environmental constraint quantified by the edge-node factor N_e/N_n^2. (a) Success rate of producing edge-disjoint solutions. (b) Average total length $w(\mathcal{T}_1) + w(\mathcal{T}_2)$.

remain short but heavily reuse high-quality corridors, and fully edge-disjoint outcomes are absent. With repulsion, overlap is markedly reduced and edge-disjoint solutions occur with high probability, at a moderate length increase consistent with conflict avoidance. Success rate is computed over all trials, counting any construction failure (either colony fails to span all terminals) as a failure.

Reliability and Efficiency Under Varying Environmental Constraint

Finally, we quantify reliability and efficiency as environmental constraint varies. To normalize across graph densities, we define an *edge-node factor* $\frac{N_e}{N_n^2}$, where N_e and N_n are the numbers of directed edges and nodes, respectively, providing a scale-normalized measure of environmental richness (higher) versus sparsity (lower).

We fix $N_n = 20$ and vary $N_e/N_n^2 = 0.05 : 0.05 : 0.4$. For each setting, we run 100 trials with 5 terminals, $M = 100$ ants, and $T = 100$ iterations. We report (i) **success rate** (fraction of trials with edge-disjoint solutions) and (ii) **average total length** $w(\mathcal{T}_1) + w(\mathcal{T}_2)$.

Figure 4 summarizes the trends. As environments become richer, repulsion supports more reliable differentiation (higher success rates). Without repulsion, solutions remain shorter but overlap persists. In extremely sparse environments, both conditions can fail due to insufficient routing alternatives, consistent with increased constraint.

Overall, the results support two conclusions. First, tree-like and edge-disjoint double-tree structures are not imposed as hard constraints; they arise from local competitive updates. Second, repulsion provides a mechanistic explanation for when differentiation emerges: it converts competitors' traces into negative constraints, redistributes exploration away from shared corridors, and prevents collapse onto a single dominant route. Therefore, avoidance functions as *implicit cooperation*: agents do not coordinate explicitly, yet the collective outcome exhibits coherent niche differentiation and reduced conflict.

Discussion and Conclusion

MT-ACO shows how *avoidance* can function as *implicit cooperation* for efficient distributed cognition. No agent coordinates explicitly and no colony accesses a global plan; each ant reacts only to local pheromone cues, reinforcing its own successful paths while avoiding competitor-dominated edges.

Yet this local rule converts conflict into an informational signal that redistributes exploration and yields a coherent partition of the environment. The resulting edge-disjoint trees constitute a shared solution: both colonies obtain high-quality connectivity while minimizing repeated interference.

This mechanism aligns with *distributed cognition* accounts in which cognition is realized across agents and environmental structure (Hutchins, 1995; Kirsh, 1995). Pheromone fields act as externalized memory, and repulsion turns that memory into a constraint that shapes subsequent decisions. Importantly, the model illustrates how planning and world-structuring can emerge without internal symbolic representations: no ant represents a tree, territory, or partition, yet these constructs arise as stable population-level patterns (Couzin, 2009; Sasaki and Pratt, 2018; Trianni and Tuci, 2011). Thus MT-ACO provides a minimal computational instantiation of competitive exclusion yielding niche differentiation under stigmergic interaction.

Recent CogSci work has emphasized agent-based benchmarks and structured tasks for probing world modeling, search, and planning (Brown et al., 2024; Cross et al., 2024). In this sense, MDEDDT operationalizes a planning problem in which a global world structure (two disjoint trees) must be constructed without any agent ever representing that structure explicitly. By formalizing multi-colony foraging as the MDEDDT problem, we provide a task where global structure must arise from decentralized interaction under constraint, and MT-ACO offers a mechanistic solution that links local decision rules to emergent organization.

The present study is limited to two colonies in static environments and does not exhaustively map parameter regimes. Future work can extend MT-ACO to multiple interacting populations, dynamic resources, and heterogeneous roles, and can test mechanistic predictions by sweeping repulsion strength to quantify trade-offs between differentiation and efficiency.

Overall, MT-ACO demonstrates how competition can generate organization for efficient distributed cognition: avoidance becomes cooperation, and local sensitivity to interference produces globally structured plans.

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