Antelligence: LLM-Powered Emergence in a Simulated Foraging Ant Colony

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Introduction

Antelligence demonstrates that complex systems thrive through decentralized coordination. Ant colonies achieve resilience and efficiency without centralized control, relying on stigmergy and emergent behavior.
Antelligence extends this principle by integrating Large Language Models (LLMs) into Agent-Based Models (ABMs), enabling ants to reason dynamically with language prompts instead of fixed heuristics. Agents communicate through pheromone-inspired signals and maintain blockchain-verified memory, achieving adaptive, intelligent foraging strategies.
This framework bridges biological swarm intelligence and cognitive AI reasoning, offering new pathways for autonomous swarms, distributed AI, and human–AI collaboration.

Theoretical Foundation

Swarm Intelligence. Ant colonies achieve resilience through *stigmergy*—indirect signaling via pheromone trails. Simple local rules create global behaviors such as efficient foraging and adaptive pathfinding.

Distributed AI. Antelligence extends agent-based models (ABMs) with large language models (LLMs). Unlike static heuristics, LLM “cyber-ants” interpret prompts in context, injecting cognitive diversity into swarm dynamics.

Emergence. Local interactions among LLM- and rule-based agents yield colony-level properties: division of labor, robust coordination, and adaptive responses to dynamic environments.

Sociotechnical Perspective. Combining biological heuristics with cognitive AI reasoning provides a hybrid architecture for studying governance, auditability, and self- organization in decentralized systems.

Key Insight. Language-driven ants, guided by pheromone-inspired signals and blockchain-logged memory, illustrate how collective intelligence can be amplified without central control.

Models & Methods (Part 1)

Agent Architecture. The colony integrates three complementary agent classes to probe trade-offs between adaptability, cost, and robustness:

LLM-Powered Workers: Real-time decisions via IO Intelligence API prompts. Agents parse local state (neighbor cells, food signal, pheromone vector, risk cues) and colony context to choose *move, harvest, return, or wait*. They reroute around obstacles, reprioritize high-yield patches, and modify exploration–exploitation balance based on recent outcomes and Queen guidance—demonstrating cognitive flexibility beyond fixed heuristics.

Rule-Based Workers: Deterministic baseline with stochastic exploration, gradient-following toward food, and shortest-path return once loaded. No adaptive re-planning. Provides a control for measuring the marginal benefit and cost of LLM reasoning and for constructing hybrid swarms.

Queen Overseer: Meta-agent issuing strategic interventions under heuristic or LLM mode. Capabilities include anomaly handling (API failures, congestion), worker reallocation (reinforce/retreat), and policy nudges (expand search radius, increase recruitment). Enables experiments on centralized oversight layered over stigmergic coordination.

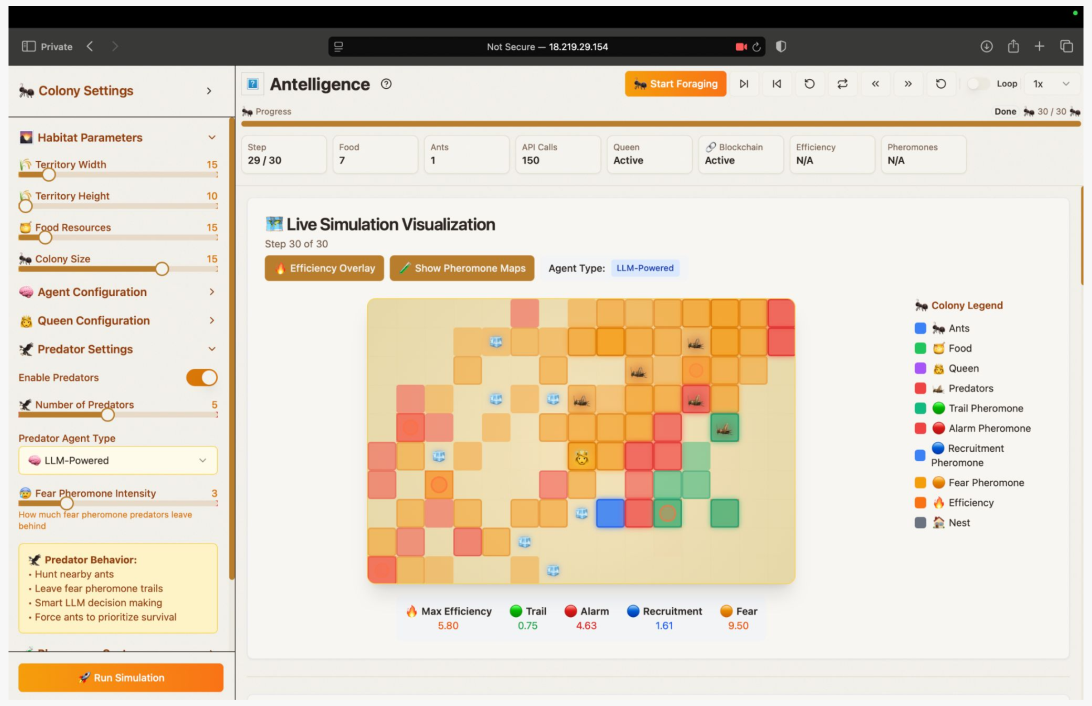
Communication System. Indirect coordination occurs on a pheromone grid with exponential decay:

Trail — reinforces successful paths to food; guides return and future traffic.

Alarm — signals predators or API anomalies to rapidly de-prioritize zones.

Recruitment — in a scenario where the Ant needs help, it uses recruitment pheromone

System Overview & Live Screens



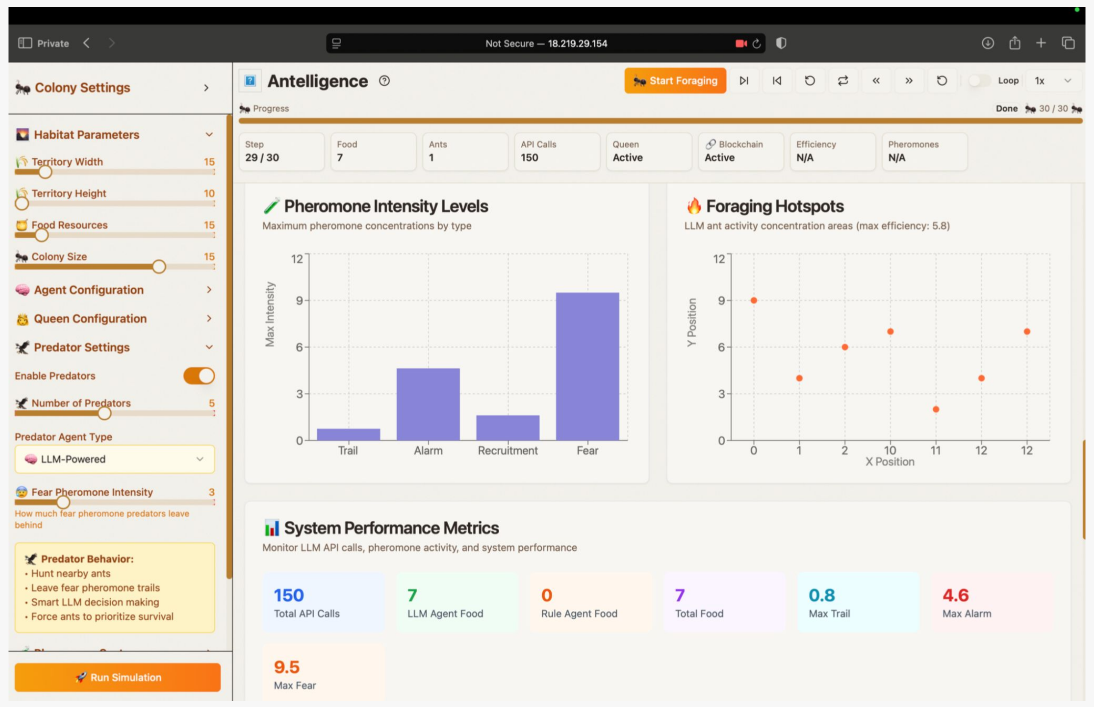
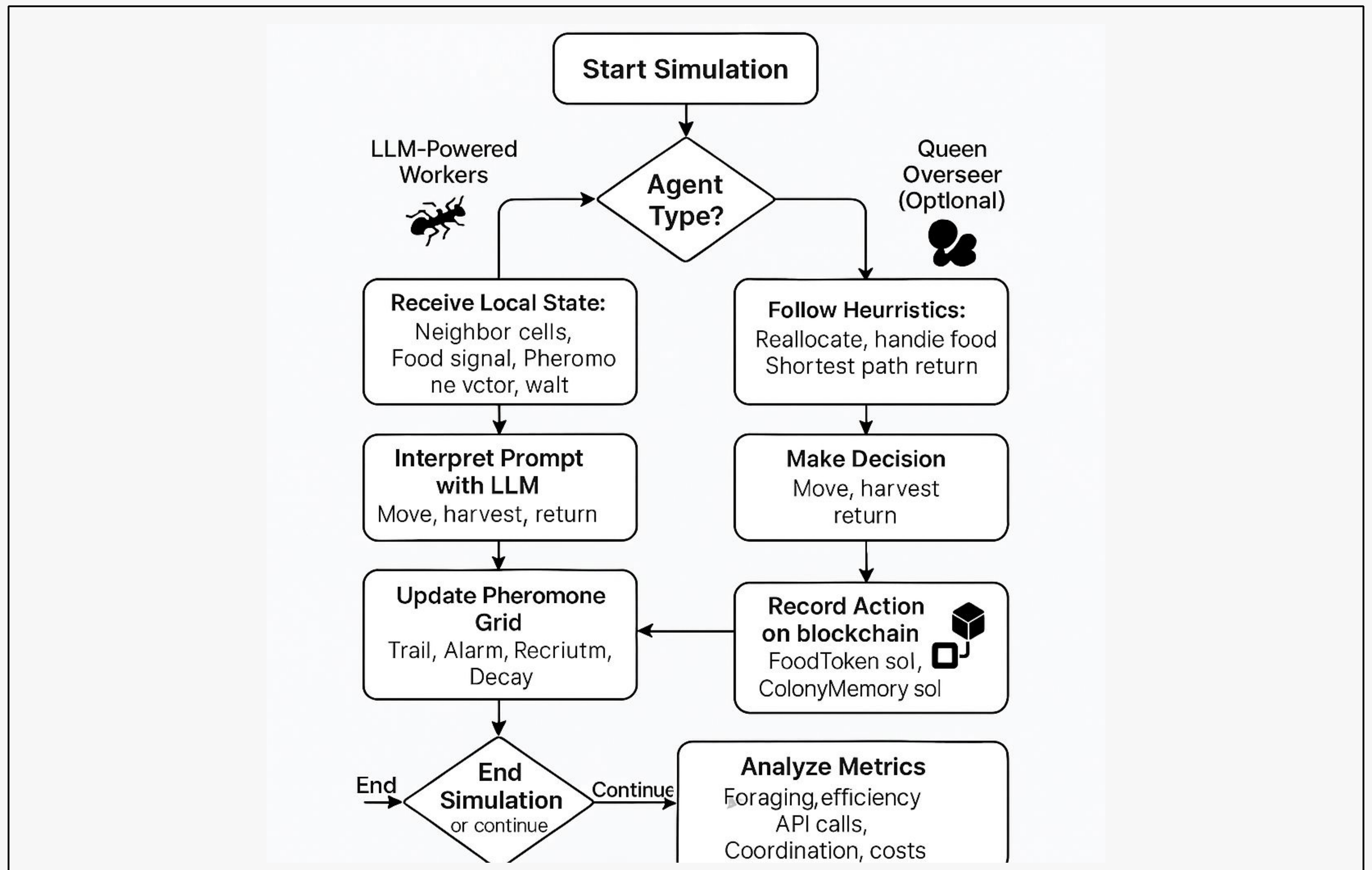


Figure: Live Simulation Visualization



Models & Methods (Part 2)

Blockchain Memory. Persistent, auditable memory is achieved with Ethereum-compatible smart contracts:

FoodToken.sol: Mints ERC-20 style tokens upon food retrieval events.

ColonyMemory.sol: Records agent-level actions and colony events, ensuring transparency and post-hoc analysis.

Deployed on the Sepolia testnet, accessed securely via web3.py.

Simulation Platform. The environment is implemented in Python, integrating:

Node JS and React for real-time dashboards and visualization.

NumPy, Matplotlib, PIL for grid dynamics, plots, and GIF generation.

asyncio/aiohttp for parallel LLM querying at scale.

NetLogo ant-foraging model as a baseline for benchmarking colony efficiency.

Key Methodological Contribution. This hybrid architecture combines LLM reasoning with stigmergic coordination, bridging symbolic prompt-driven cognition and emergent swarm intelligence in a unified, auditable framework. We have integrated a Queen Ant which oversees the whole process and guides the worker ant in collecting food in an efficient manner. While the Queen LLM does this, all of the food particles are recorded as transactions on blockchain and they are visible to both- the Queen Ant LLM and the Worker Ant LLM which creates a transparent layer for them to approach the nearest food particle in most efficient manner possible.

Discussion & Outlook

Key Findings. Antelligence shows that Large Language Model (LLM) agents adaptively re-route under shifting food distributions, coordinate through pheromone-inspired signaling, and recover more effectively with Queen oversight. Hybrid colonies achieve the best trade-off between foraging efficiency and computational cost, while blockchain-backed logging ensures transparent, auditable memory.

Novel Contributions. This work pioneers the integration of LLM-driven cognition into Python-based Agent-Based Models, introduces a digital pheromone coordination framework, and establishes persistent blockchain memory for agent account- ability. Together, these innovations bridge symbolic reasoning with emergent swarm intelligence.

Outlook. Future directions include multi-modal prompting,reinforcement or memory-based adaptation, and distributed deployments across multi-node clusters. Potential applications span autonomous drone swarms, large-scale logistics, and resilient disaster-response networks. Ongoing challenges include ensuring robustness against adversarial prompts and maintaining safe, predictable emergent behaviors.

References

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