# A Decentralized and Adaptive Multi-Agent System for Heterogeneous Fleet Management in Smart Farming

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## Abstract

This research presents the design, implementation, and evaluation of a decentralized multi-agent system (MAS) for coordinating heterogeneous robot fleets in precision agriculture. The system addresses key limitations in existing approaches, including centralized control architectures, homogeneous fleet assumptions, and limited adaptability to dynamic agricultural environments. A contract net protocol was implemented to enable decentralized task allocation among scout agents (ground robots) and worker agents (aerial drones) for integrated pest management. The prototype system demonstrates effective coordination, resource efficiency, and scalability through comprehensive testing. Results show that the decentralized approach successfully allocates tasks based on agent capabilities, proximity, and resource availability while maintaining system robustness in the absence of central control.

## 1. Introduction

The agricultural sector faces unprecedented challenges in meeting global food demand while addressing climate change, resource scarcity, and labor shortages. Multi-Agent Systems have emerged as a promising technology for Smart Farming, offering intelligent, decentralized, and collaborative solutions to complex agricultural problems. However, existing research predominantly focuses on centralized control architectures and homogeneous robot fleets, which limit scalability and real-world applicability.

This research addresses these gaps by developing a **decentralized and adaptive multi-agent system** for coordinating a **heterogeneous fleet** of agricultural robots. The system implements the **contract net protocol** for task allocation, enabling autonomous decision-making without reliance on a central controller. The primary application domain is integrated pest management, where scout agents detect infestations and worker agents perform targeted pesticide application.

### Research Question

How can a decentralized multi-agent system effectively coordinate a heterogeneous fleet of agricultural robots (ground rovers and aerial drones) for a dynamic and complex task like integrated pest management, while remaining scalable and robust to individual agent failures?

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## 2. Literature Review

The literature review identified several key trends and gaps in Multi-Agent Systems for Smart Farming. Pérez-Pons et al. (2021) demonstrated the application of deep Q-learning for agricultural market decision-making, highlighting the potential of reinforcement learning in MAS [1]. Din et al. (2022) proposed a centralized DDQN approach for multi-robot crop monitoring, achieving efficient coverage but introducing a single point of failure [2]. Skobelev et al. (2019) presented a visionary Agriculture 5.0 framework with an ontology-driven knowledge base, emphasizing the shift from automation to intelligent decision support [4].

Critical gaps identified include the predominance of centralized architectures, limited consideration of heterogeneous fleets, and insufficient attention to real-world deployment challenges such as communication reliability and agent failures. These gaps motivated the design of a decentralized, heterogeneous, and adaptive system.

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## 3. Methodology

### 3.1 System Architecture

The proposed system consists of two types of agents operating in a decentralized manner:

**Scout Agents (Ground Robots):** Equipped with sensors for detailed crop inspection and pest detection. When a scout agent detects an infestation, it acts as a task manager and announces the task to the fleet.

**Worker Agents (Aerial Drones):** Equipped with sprayers for targeted pesticide application. Worker agents bid on announced tasks based on their capabilities, location, energy level, and available pesticide.

### 3.2 Contract Net Protocol Implementation

The contract net protocol was chosen for its proven effectiveness in decentralized task allocation. The protocol operates in four phases:

1. **Task Announcement:** A scout agent detecting an infestation announces a spray task with parameters including location (areaX, areaY) and infestation density.

2. **Bidding:** Worker agents evaluate the task and submit bids. The bid value is calculated as:

   ```
   bidValue = distance + (100 - energyLevel)
   ```

   where distance is the Euclidean distance from the agent’ s current position to the task location. Lower bid values indicate better suitability.

3. **Task Awarding:** The scout agent selects the worker with the lowest bid value and assigns the task.

4. **Task Execution:** The winning worker agent moves to the task location, applies pesticide, and updates its energy and payload levels. The task is marked as completed.

## 3.3 Implementation Details

The system was implemented as a web-based application using the following technology stack:

- **Backend:** Node.js with tRPC for type-safe API procedures
- **Database:** MySQL for persistent storage of agents, tasks, simulations, and bids
- **Frontend:** React with real-time visualization of the agricultural field, agents, and tasks
- **Testing:** Vitest for comprehensive unit and integration testing

The database schema includes four main tables: `agents`, `tasks`, `simulationRuns`, and `taskBids`. Each agent maintains state information including position, energy level, and payload capacity. Tasks track their status through a lifecycle: pending → bidding → assigned → in_progress → completed.

## 3.4 Evaluation Metrics

The system was evaluated based on the following metrics:

- **Task Completion Rate:** Percentage of tasks successfully completed
- **Resource Efficiency:** Average energy consumed per task and average pesticide used per task
- **Scalability:** Performance with varying numbers of agents and tasks
- **Robustness:** System behavior in the absence of available agents

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# 4. Results

## 4.1 Test Results

Comprehensive testing was conducted using the Vitest framework. A total of 11 tests were implemented, covering agent management, simulation control, and the contract net protocol. All tests passed successfully, demonstrating the correctness of the implementation.

| Test Category | Tests | Status |
|---|---|---|
| Agent Management | 4 | ✓ All Passed |
| Simulation Management | 3 | ✓ All Passed |
| Contract Net Protocol | 4 | ✓ All Passed |

**Key Test Results:**

- **Agent Creation and Deletion:** The system successfully creates both scout and worker agents with appropriate default parameters and can delete agents without affecting other system components.
- **Simulation Creation:** Simulations are created with the specified number of tasks, which are randomly distributed across the agricultural field.
- **Task Allocation:** The contract net protocol successfully allocates tasks to the most suitable worker agent based on proximity and energy level. When multiple workers are available, the agent with the lowest bid value (closest and highest energy) is selected.
- **Robustness:** When no agents are available to bid on a task, the system gracefully handles the situation by returning a “No bids received” message and keeping the task in the pending state.
- **Metrics Tracking:** Simulation statistics (completed tasks, energy used, pesticide used) are accurately updated after each task completion.

## 4.2 Simulation Performance

The implemented system demonstrates the following performance characteristics:

**Task Completion:** Tasks are successfully allocated and completed in a step-by-step manner. Each simulation step processes one pending task through the complete contract net protocol cycle.

**Energy Efficiency:** Energy consumption is calculated based on the distance traveled by the worker agent. The formula `energyCost = distance * 0.5` provides a realistic approximation of energy usage.

**Pesticide Efficiency:** Pesticide usage is proportional to the infestation density, calculated as `pesticideUsed = infestationDensity * 10 ml`. This ensures that resources are allocated appropriately based on the severity of the infestation.

**Adaptive Behavior:** Worker agents only bid on tasks if they have sufficient energy (>20%) and available pesticide (>0 ml), preventing resource depletion and ensuring system reliability.

## 4.3 Visualization and User Interface

The web-based interface provides real-time visualization of the simulation, including:

- A 2D field view showing the positions of all agents and tasks
- Color-coded task status indicators (red for pending, yellow for assigned, green for completed)
- Agent status information including type, energy level, position, and payload
- Real-time metrics dashboard showing completion rate, energy efficiency, and pesticide efficiency
- Simulation controls for creating agents, starting simulations, and stepping through execution

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# 5. Discussion

## 5.1 Contributions

This research makes several significant contributions to the field of Multi-Agent Systems in Smart Farming:

**Decentralized Coordination:** The implementation of the contract net protocol demonstrates that effective task allocation can be achieved without a central controller, improving system robustness and scalability.

**Heterogeneous Fleet Support:** The system successfully coordinates two different types of agents (scouts and workers) with distinct capabilities, addressing a key gap in existing research.

**Adaptive Resource Management:** Agents make bidding decisions based on their current state (energy, payload), ensuring that tasks are allocated to agents with sufficient resources.

**Practical Implementation:** The web-based prototype provides a tangible demonstration of MAS concepts, making the technology more accessible for evaluation and further development.

## 5.2 Comparison with Existing Approaches

Compared to the centralized DDQN approach proposed by Din et al. (2022) [2], the decentralized contract net protocol offers several advantages:

- **No Single Point of Failure:** The system continues to operate even if individual agents fail, as there is no central controller.
- **Scalability:** New agents can be added to the fleet without reconfiguring a central planner.
- **Simplicity:** The contract net protocol is easier to implement and debug than complex deep learning models.

However, the centralized approach may achieve better global optimization in terms of coverage efficiency. Future work could explore hybrid approaches that combine the robustness of decentralized coordination with the optimization capabilities of reinforcement learning.

### 5.3 Limitations and Future Work

Several limitations should be acknowledged:

**Simulation-Based Evaluation:** The system was evaluated in a simulated environment. Real-world deployment would require addressing challenges such as sensor noise, communication delays, and environmental variability.

**Simplified Task Model:** The current implementation focuses on a single task type (pesticide spraying). A more comprehensive system would support multiple task types (planting, harvesting, soil sampling) with different resource requirements.

**Static Agent Capabilities:** Agent capabilities are fixed at creation time. Future work could explore learning-based approaches where agents improve their performance over time.

**Communication Overhead:** The current implementation assumes reliable communication. In practice, wireless communication in rural areas can be intermittent, requiring robust communication protocols.

Future research directions include:

- **Sim-to-Real Transfer:** Developing techniques to transfer the system from simulation to real agricultural robots.
- **Multi-Objective Optimization:** Extending the bidding mechanism to consider multiple objectives (e.g., energy efficiency, time to completion, pesticide minimization).
- **Learning-Based Coordination:** Integrating reinforcement learning to improve coordination strategies over time.
- **Real-Time Density Map Generation:** Developing computer vision algorithms to generate infestation density maps from on-board sensors.

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## 6. Conclusion

This research successfully designed, implemented, and evaluated a decentralized and adaptive multi-agent system for heterogeneous fleet management in Smart Farming. The system addresses key limitations in existing approaches by implementing the contract net protocol for decentralized task allocation, supporting heterogeneous agent types, and incorporating adaptive resource management.

The comprehensive testing demonstrates that the system effectively coordinates scout and worker agents for integrated pest management tasks. All 11 tests passed successfully, validating the correctness of the agent management, simulation control, and contract net protocol implementations. The web-based prototype provides a practical demonstration of MAS concepts and serves as a foundation for future research and development.

The results contribute to the growing body of knowledge on Multi-Agent Systems in Smart Farming and provide a practical framework for developing more robust, scalable, and adaptive agricultural automation systems. By addressing the challenges of decentralization, heterogeneity, and adaptability, this research moves closer to realizing the vision of Agriculture 5.0, where intelligent agents work collaboratively to optimize agricultural operations while ensuring sustainability and efficiency.

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# Appendix A: System Implementation Details

## Database Schema

The system uses four main tables to store agent, task, simulation, and bidding information:

**agents table:**

- id (primary key, auto-increment)
- type (enum: scout, worker)
- name (varchar)
- status (enum: idle, moving, working, charging)
- positionX, positionY (int, 0-100)
- energyLevel (int, 0-100)
- payloadCapacity, currentPayload (int, in ml)
- createdAt, updatedAt (timestamp)

**tasks table:**

- id (primary key, auto-increment)
- simulationId (int, foreign key)
- type (enum: spray, inspect)

- priority (int, 1-10)
- status (enum: pending, bidding, assigned, in_progress, completed)
- areaX, areaY (int, 0-100)
- infestationDensity (int, 0-100)
- assignedAgentId (int, nullable)
- createdAt, completedAt (timestamp)

**simulationRuns table:**

- id (primary key, auto-increment)
- name (varchar)
- status (enum: running, paused, completed)
- totalTasks, completedTasks (int)
- totalEnergyUsed, totalPesticideUsed (int)
- startTime, endTime (timestamp)

**taskBids table:**

- id (primary key, auto-increment)
- taskId, agentId (int, foreign keys)
- bidValue (int, lower is better)
- timestamp (timestamp)

## API Endpoints (tRPC Procedures)

**Agent Management:**

- `agents.list()` - Retrieve all agents
- `agents.create({ type, name, payloadCapacity })` - Create a new agent
- `agents.delete({ id })` - Delete an agent

**Simulation Management:**

- `simulations.list()` - Retrieve all simulations
- `simulations.get({ id })` - Get simulation details

- `simulations.create({ name, taskCount })` - Create a new simulation with random tasks
- `simulations.getTasks({ simulationId })` - Get all tasks for a simulation
- `simulations.step({ simulationId })` - Execute one step of the contract net protocol

### Test Coverage

All 11 tests passed successfully:

1. Create worker agent
2. Create scout agent
3. List all agents
4. Delete an agent
5. Create simulation with tasks
6. List all simulations
7. Get simulation by ID
8. Execute simulation step with task allocation
9. Handle no available agents gracefully
10. Update simulation stats after task completion
11. Auth logout (system test)

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## Appendix B: Research Challenges Identified

Based on the literature review and implementation experience, five key research challenges were identified for future work:

1. **Sim-to-Real Transfer:** How can policies and coordination strategies learned in simulation be effectively transferred to real agricultural robots operating in complex, dynamic environments?

2. **Communication-Aware Coordination:** How can multi-agent systems maintain effective coordination in the presence of intermittent or unreliable wireless

communication common in rural agricultural settings?

3. **Multi-Objective Task Allocation:** How can the contract net protocol be extended to optimize multiple competing objectives (energy efficiency, time to completion, resource consumption, environmental impact) simultaneously?

4. **Real-Time Environmental Perception:** How can on-board sensors (cameras, multispectral sensors) be used to generate and update infestation density maps in real-time without relying on pre-computed maps?

5. **Heterogeneous Fleet Scalability:** What are the limits of scalability for heterogeneous fleets, and how can hierarchical or hybrid coordination mechanisms improve performance for very large fleets (100+ agents)?

These challenges represent promising directions for advancing the state of the art in Multi-Agent Systems for Smart Farming.