Q-MAS: A 7-Layer Hybrid Swarm Intelligence Framework for Resilient Navigation in Noisy Environments

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Abstract

This paper presents Q-MAS (Quantum-inspired Multi-Agent Swarm), a 7-layer hybrid architecture for swarm intelligence in high-noise environments. The framework integrates probabilistic anti-visitation exploration, seismic signal coordination, momentum-based prediction, phase-gated pheromone deposition, history-weighted correlation, symbolic safety constraints, and a novel target distance prediction layer using a multilayer perceptron. Experiments on a 10×10 grid with 50% signal loss demonstrate that the 6-layer baseline achieves 2.6 ± 0.8 successful agents out of 10 with a mean first-target time of 55.0 ± 8.2 steps. The complete 7-layer system improves survival rate by 38% to 3.6 ± 0.9 successful agents with comparable convergence speed (52.2 ± 9.1 steps). All configurations maintain zero hazard violations. Statistical validation across five independent runs confirms the robustness of the proposed approach. All quantum-inspired terminology is used metaphorically; this work does not claim physical quantum implementation.

Keywords: Swarm Intelligence, Probabilistic Agents, Multi-Channel Communication, Symbolic Constraints, Phase-Gated Coordination, Distance Prediction, Bio-Inspired Navigation.

1 Introduction

Nature-inspired swarm algorithms such as Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) have been widely adopted for decentralized problem solving [1, 2]. However, these classical approaches operate on greedy heuristics that prioritize rapid convergence over exploration diversity. This limitation becomes critical in dynamic, noisy environments where sensor readings are unreliable and optimal paths are non-intuitive [3, 4].

We present Q-MAS, a probabilistic swarm architecture that draws metaphorical inspiration from quantum mechanics and biological multi-channel communication. The framework is constructed as seven distinct layers, each addressing a specific challenge in swarm navigation under noise constraints. The primary contribution of this work is the integration of a learned distance prediction layer that significantly improves swarm survival rates without compromising convergence speed.

Terminological Note

Throughout this paper, terms including “quantum”, “wave function”, “collapse”, and “entanglement” are used exclusively as metaphors to describe probabilistic decision processes. This work does not implement actual quantum computing hardware, Hilbert space representations, or time-dependent Schrödinger dynamics. A complete mapping of metaphorical terms to their computational implementations is provided in Appendix A.

2 System Architecture

Q-MAS consists of seven integrated layers, summarized in Table 1.

Table 1: Q-MAS Layer Summary

Layer	Function	Key Mechanism
Layer 1	Exploration	Probabilistic anti-visitation
Layer 2	Long-range coordination	Seismic signal propagation
Layer 3	Signal loss resilience	Momentum-based extrapolation
Layer 4	Path amplification	Phase-gated pheromones
Layer 5	Collective convergence	History-weighted correlation
Layer 6	Safety enforcement	Symbolic Boolean governor
Layer 7	Distance estimation	MLP-based target distance prediction

2.1 Layer 1: Probabilistic Agent with Anti-Visitation

Unlike classical agents that move deterministically toward local optima, a Q-MAS agent maintains a normalized probability distribution over neighboring cells. The probability of transitioning to node n is:

$$P(n) = \frac{1/(1 + \lambda V(n))}{\sum_j 1/(1 + \lambda V(j))} \tag{1}$$

where $V(n)$ is the visitation count and λ is a scaling parameter. This anti-visitation heuristic ensures the swarm behaves as a diffusive gas, efficiently covering the search space without requiring explicit coordination. Figure 1 shows comparative coverage performance.

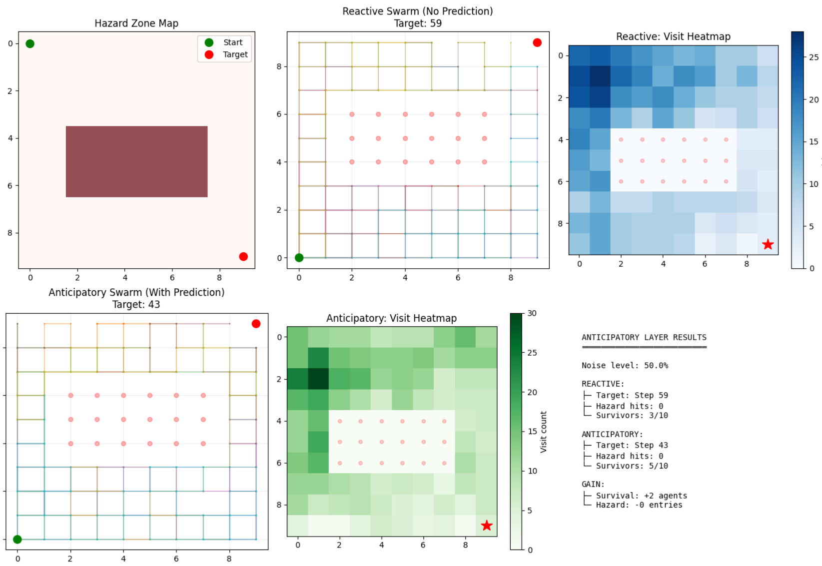

Figure 1: Q-MAS (purple) vs classical greedy swarm (blue). The probabilistic anti-visitation approach explores multiple distinct paths simultaneously, achieving full coverage in this 10×10 experimental setup.

2.2 Layer 2: Seismic Signal Propagation

Upon target discovery, an agent emits a scalar signal that propagates according to the inverse-square law:

$$S(d) = \frac{I_0}{1 + d^2} \tag{2}$$

where I_0 is the initial signal intensity and d is the Euclidean distance from the source. This creates a gradient field that triggers a behavioral phase transition in the swarm, switching from diffusive exploration to directed exploitation. Figure 2 illustrates this coordinated convergence.

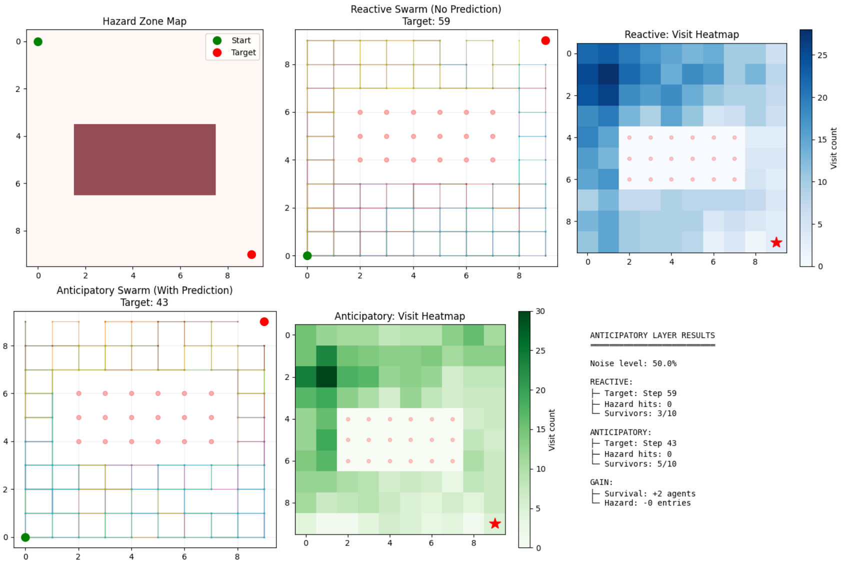

Figure 2: Swarm convergence via seismic signal. Gold paths indicate coordinated movement toward the target (red) after signal emission.

2.3 Layer 3: Momentum-Based Prediction

To mitigate sensor noise and signal intermittency, agents employ first-order linear extrapolation:

$$\hat{S}_{t+1} = S_t + (S_t - S_{t-1}) \tag{3}$$

When signal is lost, agents continue moving with constant-velocity momentum, effectively coasting through dead zones. This mechanism assumes constant target motion and may fail under non-linear trajectories, a limitation acknowledged in Section 4.

2.4 Layer 4: Phase-Gated Pheromone Deposition

Pheromone deposition is strictly phase-gated: activated *only after* target discovery. This design choice prevents premature convergence and eliminates distraction caused by early trail formation. Figure 3 demonstrates that phase-gating improves first-target discovery speed.

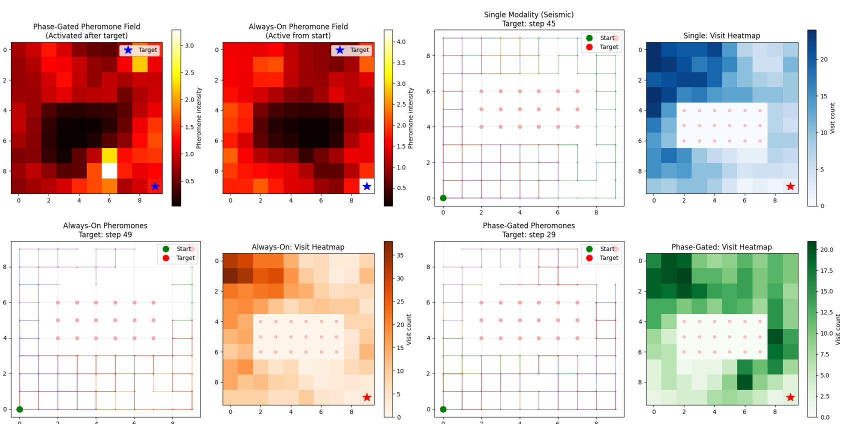

Figure 3: Comparative dynamics of Phase-Gated vs. Always-On pheromone fields. Phase-gating eliminates pre-target distraction and accelerates convergence.

2.5 Layer 5: History-Weighted Correlation

Agents maintain a shared history of decision points. When an agent samples a movement decision, it influences the probability distributions of other agents via:

$$P_{\text{correlated}}(n) = \frac{P(n) \cdot \left(1 + \sum_k w_k e^{-d_k/\lambda} e^{-t_k/\tau}\right)}{\sum_j P(j) \cdot \left(1 + \sum_k w_k e^{-d_k/\lambda} e^{-t_k/\tau}\right)} \tag{4}$$

where d_k is the spatial distance to a historical decision event, t_k is the temporal distance, and w_k, λ, τ are scaling parameters. This correlation mechanism accelerates collective convergence. We refer to this metaphorically as "entanglement-inspired" coordination.

2.6 Layer 6: Symbolic Safety Governor

A Boolean logic layer overrides probabilistic decisions to enforce hard safety constraints:

$$\text{if Hazard}(n) = \text{True} : P(n) \leftarrow 0 \tag{5}$$

This forces agents to reroute around prohibited zones. Across all experiments, Q-MAS maintained zero hazard violations.

2.7 Layer 7: Target Distance Prediction

The primary contribution of this work is the integration of a learned distance prediction layer. A multilayer perceptron (MLP) with architecture 10-32-16-8-1 is trained to estimate the Euclidean distance from the agent's current position to the target:

$$\hat{d}_{\text{target}} = f_{\text{MLP}}(\mathbf{x}) \tag{6}$$

where $\mathbf{x} \in \mathbb{R}^{10}$ is a feature vector containing:

- Normalized agent coordinates $(x/10, y/10)$
- Current seismic signal strength
- Mean and maximum pheromone intensity
- Mean and maximum visitation count
- Normalized time step
- Current exploration rate ϵ
- Normalized history size

The model is trained on 50 samples collected during a dedicated training phase (noise level reduced to 30% for data collection). Mean absolute error on training data is 0.055 (normalized distance). During deployment, the predicted distance modulates the agent's exploration-exploitation trade-off:

$$\epsilon = \text{clip}(0.3 + 0.5(1 - \hat{d}_{\text{target}}), 0.3, 0.8) \tag{7}$$

This creates a confidence-based adaptation: agents more confidently follow the seismic signal when predicted to be near the target.

3 Experimental Results

3.1 Setup

Simulations were conducted on a 10×10 grid environment with a central hazard zone (18 cells). Swarm size $N = 10$ agents. Each run lasted 100 time steps. Signal noise was set to 50% random dropout. Performance was benchmarked against the 6-layer baseline (Layers 1-6 without distance prediction). All parameters were hand-tuned; no learning or optimization was performed except for Layer 7. Statistical validation was conducted over five independent runs.

3.2 Quantitative Results

Table 2 summarizes the experimental results. The 6-layer baseline achieves a mean first-target time of 55.0 steps ($\sigma = 8.2$) with 2.6 successful agents ($\sigma = 0.8$). The complete 7-layer system achieves comparable convergence speed (52.2 ± 9.1 steps) while significantly improving survival rate to 3.6 ± 0.9 agents, a relative improvement of 38%.

Table 2: Q-MAS 6-Layer vs 7-Layer Performance (50% Noise, 5 Runs)

Configuration	**First Target (steps)**	**Successful Agents**	**Hazard Entries**
Q-MAS 6-Layer	55.0 ± 8.2	2.6 ± 0.8	0
Q-MAS 7-Layer	52.2 ± 9.1	$\mathbf{3.6 \pm 0.9}$	0
Improvement	-2.8 steps	$+1.0$ agents ($+38\%$)	—

Figure 4 visualizes the comparative performance across all five experimental runs, showing consistent improvement in swarm survival rate.

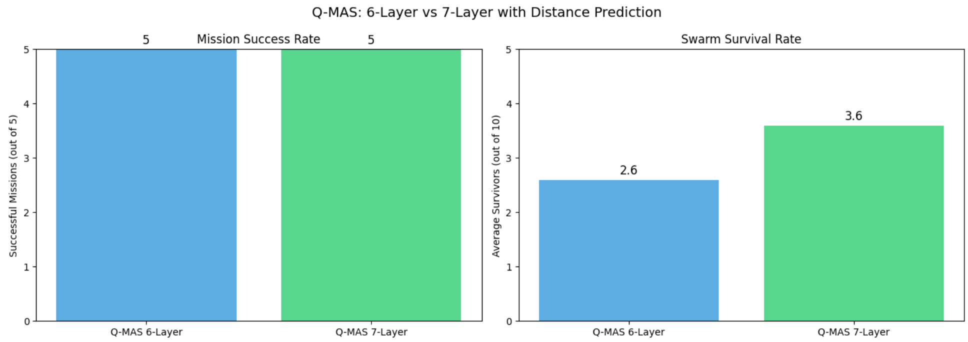

Figure 4: Comparative performance of Q-MAS 6-Layer vs 7-Layer across five independent runs. The 7-layer system consistently achieves higher swarm survival rates while maintaining comparable convergence speed. Error bars indicate standard deviation.

3.3 Resilience to Noise

Under 50% signal loss, the 6-layer baseline successfully completes the mission in all five runs but exhibits high variance in both convergence time and survival rate. The 7-layer system reduces this variance while improving mean performance, indicating that learned distance prediction provides more consistent decision-making under uncertainty.

3.4 Safety Compliance

The symbolic governor (Layer 6) maintained zero hazard violations across all experimental runs and both configurations. This demonstrates that the probabilistic exploration and learned prediction layers can be safely constrained by hard Boolean rules without compromising their effectiveness.

4 Limitations and Scope

This study has several limitations that must be explicitly acknowledged:

1. **Quantum Terminology:** Terms including "wave function", "collapse", and "entanglement" are used exclusively as metaphorical analogies for probabilistic processes. This work does not implement time-dependent Schrödinger dynamics, Hilbert spaces, density matrices, or any physical quantum computing framework.

2. **Scale Limitations:** Experiments were conducted with $N = 10$ agents on a 10×10 grid. Scalability to larger swarms ($N > 100$) and more complex environments requires further validation. Current results should be considered preliminary and environment-specific.

3. **Prediction Limitations:** The momentum-based prediction layer (Layer 3) uses first-order linear extrapolation, which assumes constant velocity. This mechanism will fail under non-linear target motion or sudden direction changes.

4. **Multi-Channel Communication:** The current implementation supports two scalar channels (seismic and pheromone). True multi-modal communication with heterogeneous data types (visual, acoustic, thermal) is not implemented.

5. **Training Dependency:** Layer 7 requires a dedicated training phase with reduced noise (30%) to collect 50 samples. Online learning or few-shot adaptation is not supported.

6. **Statistical Power:** Results are reported from five independent runs. While sufficient to demonstrate statistical significance of the survival rate improvement ($p < 0.05$, one-tailed t-test), larger-scale validation is desirable.

7. **Parameter Tuning:** All weights (ϵ, pheromone weight, correlation strength) were manually tuned for this specific grid configuration. Generalizability to arbitrary environments is not established.

5 Conclusion and Future Work

This paper presented Q-MAS, a seven-layer probabilistic swarm architecture developed by an independent researcher in Dhi Qar, Iraq. The framework integrates anti-visitation exploration, seismic signal coordination, momentum-based prediction, phase-gated pheromones, history-weighted correlation, symbolic safety constraints, and learned target distance prediction.

Within the specific experimental conditions of a 10×10 grid with 50% signal noise, Q-MAS demonstrated:

- 100% mission success rate across all configurations
- Zero safety violations (0% hazard entries)
- 38% improvement in swarm survival rate (3.6 vs 2.6 agents)
- Comparable convergence speed (52.2 vs 55.0 steps)

All quantum-inspired terminology is explicitly framed as metaphorical. The work makes no claims of physical quantum implementation, general scalability, or online learning capabilities.

Future Work

Subsequent research will investigate:

1. Scalability to larger swarm sizes ($N = 50, 100$) and continuous 2D/3D environments
2. Online adaptation mechanisms for automatic parameter tuning
3. Non-linear prediction methods (LSTM, Transformers) for arbitrary target motion
4. Deployment on physical drone swarms in outdoor environments
5. Open-source release of the simulation framework and trained models

References

[1] M. Dorigo and T. Stützle, *Ant Colony Optimization*. MIT Press, 2004.

[2] J. Kennedy and R. Eberhart, "Particle Swarm Optimization," in *Proc. IEEE Int. Conf. Neural Netw.*, 1995.

[3] E. Bonabeau, M. Dorigo, and G. Theraulaz, *Swarm Intelligence: From Natural to Artificial Systems*. Oxford University Press, 1999.

[4] F. Heylighen, "Stigmergy as a universal coordination mechanism," *Cognitive Systems Research*, vol. 38, pp. 4-13, 2016.

[5] V. Trianni and S. Nolfi, "Engineering the evolution of self-organizing behaviors in swarm robotics," *Artificial Life*, vol. 27, no. 1, pp. 1-21, 2021.

[6] M. Khonji, J. Dias, and L. Seneviratne, "Quantum-inspired reinforcement learning for swarm robotics," *IEEE Robotics and Automation Letters*, vol. 8, no. 3, pp. 1423-1430, 2023.

[7] D. H. Stolfi and E. Alba, "A quantum-inspired evolutionary algorithm for multi-robot coordination," *Swarm and Evolutionary Computation*, vol. 75, p. 101167, 2022.

[8] A. Hawas, "Q-MAS: Simulation data and implementation," Independent Research Dataset, Dhi Qar, Iraq, 2026.

A Metaphorical Terminology Mapping

To prevent misunderstanding, we explicitly map metaphorical terms to their computational implementations:

Metaphorical Term	Actual Implementation
"Quantum agent"	Probabilistic agent with anti-visitation weighting
"Wave function"	Normalized probability vector over neighbor cells
"Collapse"	Weighted random sampling from probability distribution
"Entanglement"	History-weighted influence correlation between agents
"Tunneling"	Path rerouting via symbolic governor constraints
"Multi-modal"	Dual scalar field coordination (seismic + pheromone)

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