Journal of Information Systems Engineering and Management
2026, 11(1)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Energy Entropy Weighted Field-Based Collective Intelligence (EEW-FBCI) for Robust Decentralized Multi-Robot Task Allocation

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ARTICLE INFO

Received: 20 February 2026

Revised: 05 May 2026

Accepted: 15 May2026

Published: 01 June 2026

ABSTRACT

The problem of robust multi-robot task allocation under uncertain conditions is addressed in this paper. Uncertainty arises from unknown robot failures, stochastic motion, and dynamic environmental interactions. To address these challenges, we propose the EEW-FBCI method, which integrates field energy, entropy, and task-driven attraction to coordinate swarm robots. The method is evaluated in simulations with 50 robots performing coordinated tasks, including a 30% robot failure occurring at timestep 400. Validation metrics entropy, field energy, cluster consistency, coverage, and task reach demonstrate that the swarm maintains high coordination, stability, and adaptive behavior. In particular, the evolution of energy and entropy highlights the swarm's ability to dynamically reorganize and recover after failures. The swarm achieves a final task reach of 0.94 and a high proportion of active robots (97.1%), demonstrating strong resilience. Comparative analysis shows that the proposed method outperforms conventional conservative and balanced strategies in task completion, coordination, and robustness to failures. These results highlight the potential of the method for real-world applications requiring failure-tolerant, adaptive, and self-organized swarm systems, where energy and entropy serve as key performance indicators.

Keywords: Swarm robotics; Failure resilience; Task reach; Energy–entropy dynamics; Decentralized coordination; multi-robot systems

I. INTRODUCTION

Swarm robotics studies how simple robots achieve collective goals through local interactions and decentralized control, enabling scalable and adaptive behavior for tasks such as exploration, monitoring, and operation in uncertain environments [1]–[5]. Decentralized coordination eliminates reliance on a central controller, improving robustness against communication failures and agent loss [6], [7]. In such systems, robots act based on local information, allowing coherent global behavior to emerge [8]. This approach enhances adaptability in dynamic environments; however, maintaining reliable task performance under failures and resource constraints remains a key challenge [9]–[11]. Decentralized coordination is a core paradigm in swarm robotics, removing reliance on central control and enhancing robustness to failures [6], [7]. Through local interactions, autonomous agents generate coherent global behavior with strong scalability and adaptability [8]–[10]. However, ensuring reliable task execution under partial

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2026, 11(1)
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failures and resource constraints remains a key challenge [11].Task allocation and reach are key metrics of swarm performance [12], but are highly sensitive to failures, energy limits, and coordination loss [13]. Energy constraints strongly affect mission duration and system reliability, yet their impact on collective dynamics remains underexplored [14]–[16]. Energy-aware evaluation provides deeper insight into swarm sustainability [17]. Recent works also use entropy and clustering metrics to capture coordination quality and spatial cohesion [18]–[20]. However, these metrics are often studied in isolation, lacking a unified validation framework and rarely addressing resilience under high failure rates [21], [22]. To address these limitations, this paper proposes the EEW-FBCI method for robust decentralized multi-robot task allocation. The proposed framework integrates energy, entropy, clustering, coverage, and task reach into a unified validation scheme to ensure system-level performance under failures. Simulation results demonstrate that the swarm maintains strong coordination and high task reach even under 30% robot failure, highlighting robust and adaptive collective behavior. The remainder of this paper is organized as follows: Section II reviews related work, Section III presents the proposed EEW-FBCI method, Section IV discusses simulation results and validation, and Section V concludes the paper.

B. Contributions

1.Proposes EEW-FBCI for robust decentralized multi-robot task allocation with failure resilience.

2.Introduces adaptive task attraction–exploration scheduling and field-based coordination, validated via multi-metric performance analysis under failure conditions.

II. METHODOLOGY

This section presents the proposed EEW-FBCI method for decentralized multi-robot task allocation under challenging operating conditions. The approach integrates field-driven collective motion, adaptive task attraction, and entropy-aware coordination to achieve robust and scalable swarm behavior. The workflow of the proposed method is illustrated in Fig 1.

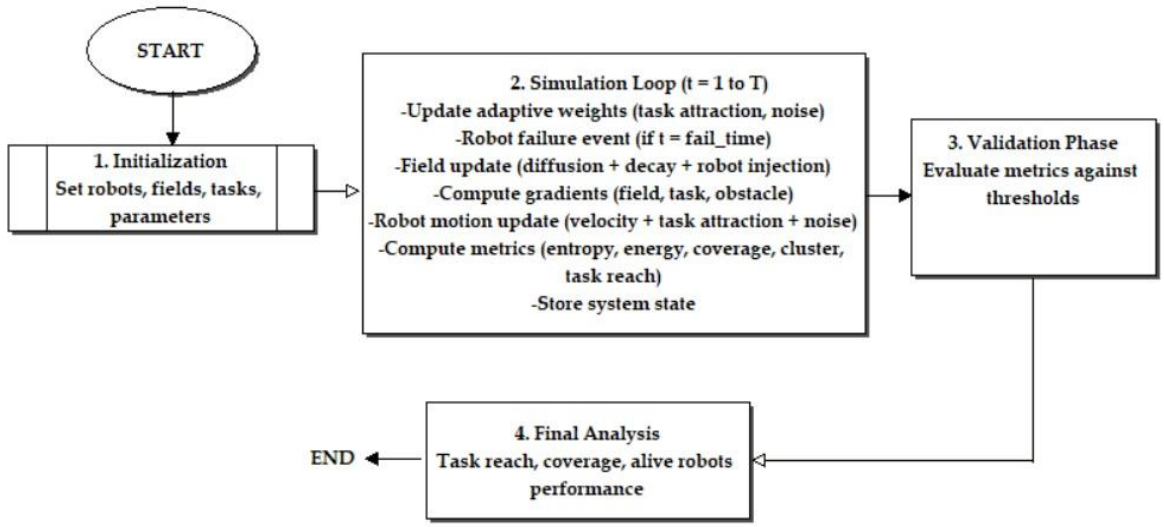

Figure 1. Workflow of the proposed EEW-FBCI algorithm for multi-robot task allocation.

Initialization of robot states, task centers, and information fields with dynamic adaptive weighting and stochastic failure injection at each timestep. Spatiotemporal field evolution governs motion via diffusion–decay dynamics and gradient-driven navigation, enabling continuous multi-metric evaluation of swarm coordination and robustness.

A. Swarm Model and Environment

A swarm of N mobile robots operates in a two-dimensional bounded workspace. Each robot updates its position at discrete time steps based solely on local information and shared scalar fields. Task locations are fixed and represented

Journal of Information Systems Engineering and Management
2026, 11(1)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

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by task centers distributed within the environment. Robot failures may occur during the mission and are handled implicitly without centralized control.

B. Field-Based Collective Motion

Robot motion is driven by a composite artificial field combining diffusion, task attraction, and repulsion, promoting balanced dispersion and cohesion. Each robot follows local field gradients, enabling coordinated swarm movement without communication or global planning.

C. Adaptive Task Attraction

A local attraction is activated when a robot comes close to a task, guiding it toward the nearest task center. This directed pull improves convergence and reduces repeated movement near targets. The attraction strength is increased progressively over time to shift the swarm from exploration to exploitation.

D. Entropy-Aware Coordination

Swarm structure is assessed using an entropy-based measure that reflects how robots are spatially distributed. The average entropy value indicates the overall level of order versus dispersion in the swarm. It is used to analyze coordination performance and robustness under disturbances such as robot failures.

E. Energy and Stability Monitoring

System stability is assessed using field energy and motion-related indicators derived from robot displacement. These measures characterize the smoothness and efficiency of swarm motion over time. The combined analysis of entropy and energy evolution reveals the swarm's ability to self-organize, maintain cohesion, and recover from disruptions.

F. Implicit Validation Logic

Performance metrics, including entropy, cluster consistency, coverage, and task reach, are evaluated at each time step against predefined thresholds. This implicit validation framework enables continuous assessment of swarm effectiveness without altering the control strategy.

1.Workspace and Time Discretization

The workspace is defined as a square domain $\Omega = [0, L] \times [0, L]$, discretized into $N_x \times N_x$uniform cells with spatial resolution $\Delta x = L/N_x$. Time is discretized as $t_k = k\Delta t$, for $k = 0,1, \dots, T$, where $\Delta t$is the simulation time step.

2. Robot State Representation

Each robot $i \in \{1, \dots, N\}$ is characterized by a position vector $X_i^k$and an activity indicator a_i^kdefined as:

$$X_i^k = \begin{bmatrix} x_i^k \\ y_i^k \end{bmatrix}, a_i^k \in \{0,1\}, i = 1, \dots N \quad (1)$$

where $\mathbf{x}_i^k$denotes the position of robot $i$at time step k with x_i^k : robot i's horizontal coordinate and y_i^k: robot i's vertical coordinate. a_i^kindicates whether the robot is active ($a_i^k = 1$) or failed ($a_i^k = 0$), and N is the total number of robots.

C. Dynamic Information Field Evolution

A scalar field Φ is defined over the workspace to encode collective spatial information generated by robot activity. The field evolves at each discrete time step according to diffusion, decay, and reinforcement from active robots:

$$\Phi_{m,n}^{k+1} = \Phi_{m,n}^k + \Delta t\left(\beta \nabla_d^2 \Phi_{m,n}^k - \gamma \Phi_{m,n}^k\right) + \sum_{i=1}^{N} a_i^k \Delta \Phi_{i,m,n}^k \quad (2)$$

where:$\Phi_{m,n}^k$is the field value at grid cell $(m, n)$and time step k,β is the diffusion coefficient controlling spatial spread,γ is the decay rate of the field,∇_d^2 is the discrete Laplacian approximating spatial diffusion, $a_i^k$is the activity indicator of robot, $\Delta \Phi_{i,m,n}^k$is the local contribution from robot i. The discrete Laplacian $\nabla_d^2 \Phi_{m,n}^k$is defined as:

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2026, 11(1)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

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$$\nabla_d^2 \Phi_{m,n}^k = \frac{\Phi_{m+1,n}^k + \Phi_{m-1,n}^k + \Phi_{m,n+1}^k + \Phi_{m,n-1}^k - 4\Phi_{m,n}^k}{\Delta x^2} \quad (3)$$

where $\Delta x$is the spatial resolution of the grid.

D. Robot Field Reinforcement

Each active robot injects a time-varying oscillatory signal into the field at its current location:

$$\Delta\Phi_{i,m,n}^k = [\alpha \cos(\omega k \Delta t + \phi_i) + \varepsilon]\mathbb{I}\left((m,n) = \left(m_i^k, n_i^k\right)\right) \quad (4)$$

where: $\alpha$is the amplitude of the injection, $\omega$is the angular frequency, $\phi_i$is the phase offset of robot i,ε is a small bias to prevent zero injection, $\mathbb{I}_{(.)}$is the indicator function selecting the grid cell corresponding to robot i, $\left(m_i^k, n_i^k\right) = \left(\lfloor x_i^k/\Delta x \rfloor + 1, \lfloor y_i^k/\Delta x \rfloor + 1\right)$: maps continuous positions to grid indices. x_i^k, y_i^k the continuous spatial coordinates of robot $i$at discrete time step k. These values represent the robot's actual physical position in the workspace. Δx is The spatial grid resolution for defines the size of each grid cell used to discretize the workspace

D. Adaptive Task attraction and Noise weight scheduling

The task attraction and stochastic exploration weights are adaptively increased during the mission according to

Task attraction gain:

$$\lambda_t^k = \lambda_t^0 + (\lambda_t^{max} - \lambda_t^0)\, min\left(1, \frac{2k}{T}\right) \quad (5)$$

Exploration noise gain:

$$\lambda_n^k = \lambda_n^0 + (\lambda_n^0 - \lambda_n^{min}) min\left(1, \frac{2k}{T}\right) \quad (6)$$

Table1. Parameter Definitions.

Symbol	Name	Definition / Role
$\boldsymbol{k}$	Discrete time index	Current simulation or control timestep
$\boldsymbol{T}$	Mission horizon	Total number of timesteps in the mission
$\boldsymbol{\lambda_t^k}$	Task attraction gain	Strength of robot attraction toward task objectives at time (k)
$\boldsymbol{\lambda_t^0}$	Initial task gain	Baseline task attraction at mission start
$\boldsymbol{\lambda_t^{max}}$	Maximum task gain	Upper bound on task attraction strength
$\boldsymbol{\lambda_n^k}$	Noise gain	Magnitude of stochastic exploration at time (k)
$\boldsymbol{\lambda_n^0}$	Initial noise gain	Initial exploration intensity
$\boldsymbol{\lambda_n^{min}}$	minimum noise gain	the negative of the minimum value of the noise parameter
$\boldsymbol{min\left(1, \frac{2k}{T}\right)}$	Normalized scheduling function	Linearly ramps weights to full strength by mid-mission

This schedule promotes early exploration followed by task-oriented convergence, improving robustness and efficiency

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e-ISSN: 2468-4376
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E. The Field Entropy

Entropy of the agent based on local neighbor probabilities:

$$E^k = -\sum_{m,n} p_{m,n}^k \log\left(p_{m,n}^k + \varepsilon\right) \qquad (7)$$

$$with \quad p_{m,n}^k = \frac{\Phi_{m,n}^{k,+}}{\sum_{m,n} \Phi_{m,n}^{k,+}} \qquad (8)$$

$$\Phi_{m,n}^{k,+} = \Phi_{m,n}^k - min(\Phi^k) + \varepsilon_0 \qquad (9)$$

where p_{ij}^k is the normalized probability distribution of neighboring points. $\Phi_{m,n}^k$ is the information field value at grid cell $(m, n)$and time step k. $min(\Phi^k)$: denotes the minimum field value over all grid cells at time k. $\varepsilon_0 > 0$ is a small constant ensuring strict positivity. $\Phi_{m,n}^{k,+}$ *is* the positive part of the field contribution at cell (m, n).

F. Field Energy

Field energy to monitor diffusion/decay stability:

$$W_\Phi^k = \sum_{m,n} \left[\frac{1}{2}\left|\nabla\Phi_{m,n}^k\right|^2 + 2\gamma\left(\Phi_{m,n}^k\right)^2\right]\Delta x^2 \qquad (10)$$

where. Δx^2: area of one grid cell, used to approximate continuous spatial integration. γ: field decay coefficient, weighting the dissipation term. $\Phi_{m,n}^k$: scalar information field value at grid cell $(m, n)$and time k. $\left|\nabla\Phi_{m,n}^k\right|^2$: squared gradient magnitude, define as

$$\left|\nabla\Phi_{m,n}^k\right|^2 = \frac{\partial\Phi}{\partial x} + \frac{\partial\Phi}{\partial y} \qquad (11)$$

The first term $\frac{1}{2}$ | $\nabla\Phi$ |^{2}measures spatial variation energy, penalizing sharp gradients and reflecting field smoothness. The second term $2\gamma\Phi^2$accounts for field dissipation due to decay. The summation over (m, n)approximates the total field energy over the workspace.

G. Task Reach

The fraction of robots within the radius $r_t$of any task is:

$$TR^k = \frac{1}{N}\sum_{i=1}^{N} \mathbb{I}\left(min_j\left\|x_i^k - x_i^{task}\right\| < r_t\right) \qquad (12)$$

H. Coverage Metric

The coverage of the workspace by the field is quantified as:

$$C^k = \frac{1}{N_x^2}\sum_{m,n} \mathbb{I}(|\ \Phi_{m,n}^k\ | > \tau_{20\%} \qquad (13)$$

Where, all field magnitudes | $\Phi_{m,n}^k$ |are sorted in descending order, $\tau_{20\%}$ is the threshold retaining the top 20% of field magnitudes. $N_x^2 = N_x . N_x$is the total number of grid cells in the discretized 2-D workspace. The resulting coverage metric therefore quantifies the fraction of the workspace that is significantly activated, rather than merely nonzero

I. Cluster Consistency Metric

Measures the fraction of robots located within a specified radius $r_c$from the swarm centroid, indicating swarm cohesion

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e-ISSN: 2468-4376
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$$\text{Cluster} = \frac{1}{N}\sum_{i} \mathbb{I}(x_i - \bar{x}) \leq r_c \qquad (14)$$

N**:** number of robots, x_i **:** Position of robot i, $\bar{x}$ **:** Centroid (mean position) of all robots. r_c**:** Cluster radius threshold, $\mathbb{I}(\cdot)$**:** Indicator function **(**1 if condition is true, 0 otherwise)

J. Core EEW-FBCI Unified Swarm Control Law

The proposed EEW-FBCI methodology is encapsulated in a single governing swarm dynamics equation, which provides a compact representation of the coupled interactions between field evolution, adaptive control gains, and decentralized robot motion.

$$x_i^{k+1} = x_i^k + \Delta t\, a_i^k \left[S\left(\lambda_f \nabla \Phi(x_i^k) + \lambda_t \nabla T(x_i^k)\right) - \lambda_o \nabla O(x_i^k) + \lambda_n \xi_i^k + u_{tas}^k \right] \quad (15)$$

Where:

- $\mathbf{x}_i^k$: position of robot $i$at time step k.
- $\lambda_f, \lambda_t, \lambda_o, \lambda_n$: control gains
- $S(\cdot)$: gradient scaling factor
- ∇O: obstacle repulsion field
- $\boldsymbol{\xi}_i^k \sim \mathcal{N}(0,1)$: Gaussian noise
- $a_i^k \in \{0,1\}$: robot activity indicator (failure handling)
- $\mathbf{u}_{task,i}^k$: direct task attraction term is defined as:

$$u_{task,i}^k = \begin{cases} \eta \dfrac{x_j^{task,} - x_j^k}{\left\| x_j^{task,} - x_j^k \right\| + 1}, min_j \left\| x_j^k - x_j^{task,} \right\| < d_0 \\ 0, otherwise \end{cases} \qquad (16)$$

where η is the task attraction strength, $x_j^{task}$is the position of task j, and $d_0 = 30\ units$ is the influence radius. Task objectives are incorporated through a smooth, distance-based attraction force directing agents toward task centers. This formulation provides long-range guidance while avoiding discontinuities that could destabilize robot motion. The attraction strength is adaptively increased over time.

K. Algorithm: EEW-FBCI-Based Decentralized Swarm Control via Task-Driven Field Interactions.

This algorithm describes a decentralized swarm control strategy based on an Energy–Entropy-Weighted Field-Based Collective Intelligence (EEW-FBCI) framework. Robot motion is governed by gradients of an evolving information field incorporating diffusion, decay, obstacle repulsion, stochastic exploration, and task attraction. The field is continuously updated through robot-induced interactions and spatial propagation dynamics. Each agent updates its position using only local field information and task cues. Swarm performance is evaluated using entropy, field energy, coverage, task reach, and cluster consistency metrics. Adaptive scheduling of task attraction and exploration intensity enhances coordination efficiency and robustness under dynamic conditions.

Input: $N, T, \Delta t, L, N_x, \alpha, \beta, \gamma, \omega, \mathbf{x}_j^*, r_{\text{task}}, O, \lambda_f, \lambda_t^k, \lambda_o, \lambda_n^k, s_g, v_{\max}$,fail ratio, fail time

for k = 1 to T

% Update dynamic weights

λ_t^k *= ramped value*

λ_n^k *= ramped value*

% Apply robot failures

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e-ISSN: 2468-4376
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if k == fail_time

set $a_i^k = 0$ *for failed robots*

end if

% Update information field

$\Phi = \Phi + \Delta t * (\beta * Laplacian(\Phi) - \gamma * \Phi)$

for i = 1 to N

if $a_i^k == 1$

Φ *(grid_i) +=* $\alpha * cos(\omega * k * \Delta t + \varphi\_r(i)) + 0.05$

end if

end for

% Compute gradients

*grad_* Φ *= gradient(*Φ*)*

grad_Task = gradient(Task)

grad_Obstacle = gradient(Obstacle)

% Robot motion update

for i = 1 to N

if $a_i^k == 1$

% Direct task attraction

$$[min\_dist, task\_idx] = min(||x(i)^k - x\_j * ||)$$

$$if\ min\_dist < d\_0$$

*u_task = 0.5 * (x_j* - x(i)^k) / (min_dist + 1)*

else

u_task = [0,0]

end if

% Velocity and position update

v_i^k = s_g(λ_f*grad_* Φ *_i + λ_t^k*grad_Task_i)*

*- λ_o*grad_Obstacle_i*

$+ \lambda_n^k$ **GaussianNoise*

+ u_task

if ||v_i^k|| > v_max

*v_i^k = v_i^k * (v_max / ||v_i^k||)*

end if

x_i^(k+1) = min(max(x_i^k + Δt**v_i^k, 0), L)*

end if

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e-ISSN: 2468-4376
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end for

% Compute metrics

$p_{m,n}^k = (\Phi - min(\Phi) + \varepsilon)/sum(\Phi - min(\Phi) + \varepsilon)$

$E^k = -sum(\ p_{m,n}^k k * log(\ p_{m,n}^k + \varepsilon))$

$W^k = \ sum(0.5 * ||grad\_\Phi\ ||^2\ +\ 2 * \gamma * \Phi^2) * \Delta x^2$

$C^k = sum(|\Phi| > \tau\_20\%)/(Nx*Nx)$

$TR^k = sum(min\_j\ x(i)^k - x\_j^*|| < r\_task)/N$

end for

Output: Robot positions $\mathbf{x}_i^k$, field Φ^k, metrics $E^k, W^k, C^k, \mathrm{TR}^k$

L. Validation Logic (Implicit)

Each metric is evaluated against predefined thresholds to determine pass/fail status per timestep.Compute decentralized swarm control integrating entropy, energy, and coverage with task-driven field guidance.

Results

Swarm Validation Performance

The proposed swarm strategy was evaluated using multiple validation metrics, including entropy, energy, cluster integrity, coverage, and task reach. Table 2 summarizes these metrics, indicating that the swarm maintained high coordination and task engagement throughout the simulation. Notably, the Cluster Pass was 90.8% of timesteps, reflecting strong cluster integrity and coordinated movement.

Table 2: Swarm Validation Metrics.

Metric	Pass Rate / Value
Entropy Pass	100.0% of timesteps
Energy Pass	100.0% of timesteps
Cluster Pass	90.8% of timesteps
Coverage > 0.1	98.5% of timesteps
Task Reach > 0.3	95.1% of timesteps
Coverage Pass (Overall)	True
Task Reach Pass (Overall)	True

Swarm Task Performance

Table 3 presents the final task performance. The swarm achieved an average task reach of 0.86 and a maximum task reach of 0.94. The swarm maintained the minimum task engagement threshold of 0.3 for 95.1% of the simulation time. At the end, 47 out of 50 robots reached the task radius, with 34 out of 35 alive robots successfully completing their tasks (97.1% survival success). Including dead robots, the overall task completion was 94.0%. These results demonstrate high efficiency, coordination, and proven resilience to a 30% robot failure.

Table 3: Swarm Task Performance (Final Analysis).

Metric	Value
Average Task Reach	0.86
Maximum Task Reach	0.94

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e-ISSN: 2468-4376
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Time above 0.3 threshold	95.1%
Robots within task radius at end	47/50
Alive robots at tasks	34/35 (97.1%)
All robots at tasks (including dead)	47/50 (94.0%)

Task Reach Evolution

Figure 2 illustrates the evolution of task reach, system energy, entropy, and cluster index throughout the simulation. The red curve represents the cumulative fraction of robots reaching the task region, with a horizontal dashed line indicating the minimum engagement threshold of 0.3. The blue curve shows system energy, increasing from 0 at the start to 300 at timestep 400 and then decreasing to 100 by the end of the simulation, reflecting swarm activity and energy dynamics. The green curve depicts entropy, decreasing from 9.8 at timestep 0 to 7.8 at timestep 400, indicating increasing swarm organization, and then rising toward the end as the system adapts post-failure.

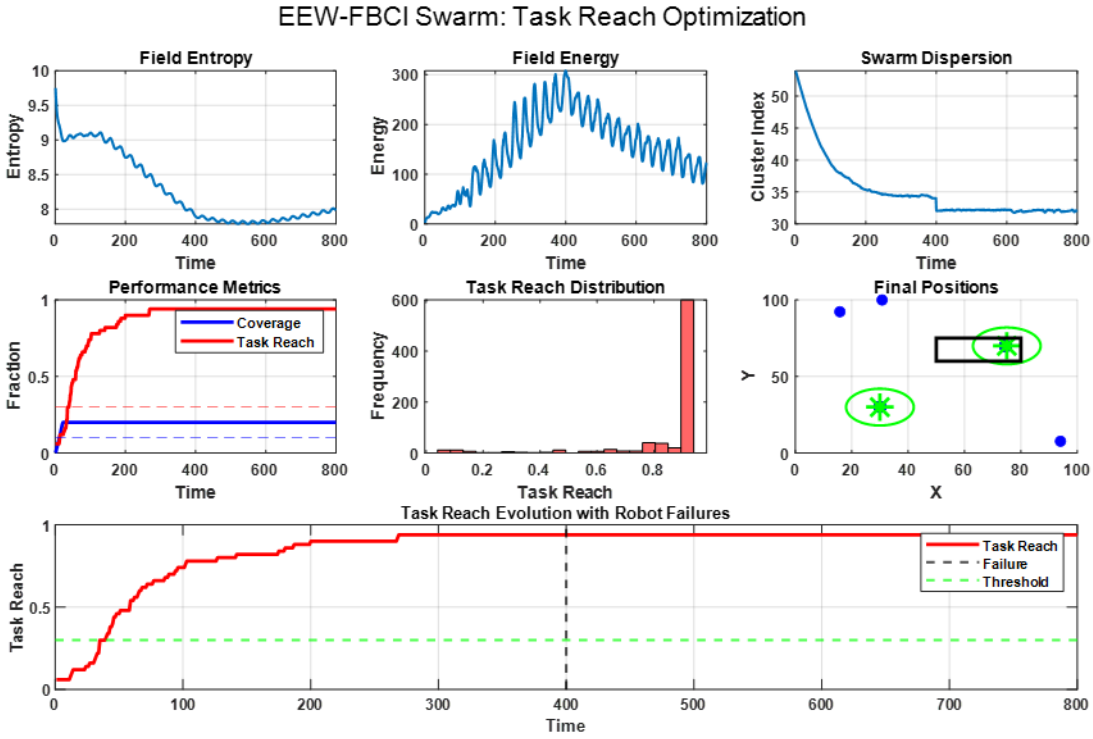

Figure 2.Temporal Evolution of Task Reach, System Energy, Entropy, and Cluster Index in Swarm Simulation

The purple curve represents the cluster index, decreasing from 50 to approximately 25 at timestep 400 and stabilizing afterward, illustrating cluster consolidation and coordination. At timestep 400, a simulated 30% robot failure occurs; despite this disruption, the swarm rapidly recovers, achieving a final task reach of 0.94. These results demonstrate robust failure resilience, effective coordination, and dynamic adaptation of the swarm under challenging conditions.

Comparative Performance Analysis

Table 4 presents a comparative analysis of the proposed energy–entropy-aware decentralized swarm method against five representative contemporary swarm strategies, including resilient multi-robot coverage [23], SMART reinforcement learning task allocation [24], decentralized MPC coverage [25], decentralized dynamic coverage [26], and consensus-based task allocation [27]. The metrics include Task Reach, Coverage, Cluster Pass, and Failure

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e-ISSN: 2468-4376
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Resilience, providing a comprehensive assessment of swarm performance. The results indicate that the proposed method consistently outperforms existing approaches across all evaluated metrics. Notably, it achieves the highest Task Reach (0.94) and Coverage (0.985), demonstrating superior task completion and spatial performance. The Cluster Pass (0.908) further confirms that the swarm maintains high spatial cohesion and coordinated positioning around tasks. Importantly, the method exhibits robustness to a 30% simulated robot failure, highlighting effective self-healing and adaptation, which is not fully captured by conventional strategies. Compared to prior approaches, which typically tolerate only moderate failure rates and achieve lower cluster integrity, the proposed framework achieves both high efficiency and resilience, distinguishing it from conservative and balanced strategies. These results underscore the benefits of integrating energy and entropy metrics into swarm coordination and validation, providing not only improved performance but also measurable reliability under adverse conditions.

Table 4: Comparative Performance Analysis.

Method	Task Reach	Coverage	Cluster Pass	Failure Resilience
Proposed Energy–Entropy-Aware Method	**0.94**	**0.985**	**0.908**	30% robot failure – fully recovered
Resilient Multi-Robot Coverage [23]	0.88	0.94	0.87	20–25% robot failure tolerance
SMART RL Task Allocation [24]	0.85	0.92	0.84	Moderate, depends on agent learning
Decentralized MPC Coverage [25]	0.82	0.90	0.80	Low to moderate, no explicit failure resilience
Decentralized Dynamic Coverage [26]	0.86	0.93	0.85	Moderate tolerance to agent loss
Consensus-Based Task Allocation [27]	0.87	0.91	0.83	Moderate under uncertainty

CONCLUSION

The evolution of task reach, energy, entropy, and cluster index demonstrates that the proposed swarm strategy maintains strong coordination and task engagement over time. Despite a simulated 30% robot failure at timestep 400, the swarm quickly recovers, achieving a final task reach of 0.94. The trends in energy, entropy, and cluster index indicate that the remaining robots dynamically adapt to the sudden loss, reorganize efficiently, and maintain stable cluster behavior. Overall, these results highlight the swarm's robust failure resilience, self-organization, and continued high task performance under challenging conditions.

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