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Reconfigurable Mobile Wireless Sensor Network Coordination for Simultaneous Multi-Target Tracking

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Abstract

This paper presents a distributed coordination framework for simultaneous multi-target tracking using a mobile wireless sensor network (MWSN) based on discrete-event-system principles. The proposed framework employs a finite-state-machine architecture, where autonomous mobile sensors sequentially process detection and tracking events. Unlike passive tracking approaches that react to target loss after it occurs, the proposed strategy implements predictive handover through Extended-Kalman-Filter-based uncertainty propagation. This enables sensors to anticipate target loss and to reposition auxiliary sensors in advance, acquiring targets along their predicted trajectories. A bidding-based allocation mechanism coordinates sensor assignments by evaluating four competing objectives: network preservation, spatial proximity to handover points, temporal mission feasibility, and estimation uncertainty. The proposed framework integrates four components: EKF-convergence-triggered proactive handover, multi-objective competitive bidding, distributed min-max conflict resolution, and fusion-driven proportional navigation. Unlike existing methods, auxiliary sensors navigate using confidence-weighted EKF estimates shared by neighboring sensors rather than their own measurements. An ablation study over ten Monte Carlo trials confirms that each component contributes independently, with EKF-based predictive triggering identified as the dominant performance driver.

Keywords: multi-target tracking; mobile wireless sensor networks; discrete-event-system control; navigation guidance; predictive tracking; distributed coordination

1. Introduction

Autonomous simultaneous tracking of multiple mobile targets represents a fundamental challenge in distributed robotic systems, with applications spanning surveillance [1], search and rescue [2,3], and environmental monitoring [4]. Mobile wireless sensor networks (MWSNs), where each node is an autonomous mobile platform such as an uncrewed ground vehicle (UGV) or uncrewed aerial vehicle (UAV), offer a scalable solution for multi-target tracking. In these networks, spatially distributed sensors cooperate to detect and track targets moving through the monitored region [5,6]. However, maintaining continuous target observation in such environments remains problematic when individual sensors possess limited detection ranges and mobility constraints that restrict their operational displacement from designated home positions [7].

Traditional WSN tracking approaches use passive handover strategies where sensors track targets individually until detection is lost and then rely on opportunistic encounters with neighboring sensors to reacquire the target [8]. This reactive paradigm results



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in frequent target loss events, particularly when target velocities exceed sensor mobility capabilities or when targets traverse sparsely covered regions [9]. A passive approach fails to leverage the distributed sensing and communication capabilities inherent in networked systems, treating the WSN as a collection of independent agents rather than a coordinated system [10]. Furthermore, such methods cannot predict when current trackers will lose target observation, preventing proactive positioning of additional sensors to ensure continuous tracking [8].

This paper presents a distributed coordination framework that implements predictive active handover, where sensors use Extended Kalman Filter (EKF)-based uncertainty propagation to anticipate target loss and proactively position auxiliary sensors to reach predicted handover points along target trajectories using guidance-theory principles [11,12]. The proposed discrete-event system (DES) architecture coordinates autonomous sensors through finite-state machines (FSMs), enabling dynamic role transitions among detection, tracking, repositioning, and return states based on target behavior and network conditions.

The main contributions of this work are (1) a proactive handover mechanism triggered by EKF velocity-estimate convergence, enabling sensor replacement to begin while the primary sensor still has contact with the target; (2) a multi-objective bidding mechanism balancing network preservation, spatial proximity, temporal feasibility, and estimation uncertainty for distributed auxiliary sensor allocation; (3) a distributed min-max conflict resolution strategy that guarantees equitable sensor team allocation across simultaneously contested targets without centralized coordination; and (4) a fusion-driven proportional navigation law in which auxiliary sensors navigate to predicted handover points using confidence-weighted EKF state estimates shared by neighboring sensors rather than their own measurements. While each underlying technique is individually established, the contribution of this work lies in the predictive pre-loss handover problem itself and in its distributed solution. In this problem, a sensor that has not yet detected the target must reach a predicted handover point using only state estimates shared by its neighbors. This requirement is what motivates the two component-level adaptations introduced above: EKF-convergence-triggered handover initiation and fusion-driven proportional navigation.

The remainder of this paper is organized as follows. Section 2 reviews related work in multi-target tracking. Section 3 formulates the problem. Section 4 presents the proposed DES architecture. Section 5 presents simulation results demonstrating tracking performance. Section 6 concludes with discussion of key findings and future research directions.

2. Related Work

This section surveys work in three areas directly relevant to the proposed framework: predictive target tracking in distributed sensor networks (Section 2.1), distributed coordination and task allocation in multi-robot systems (Section 2.2), and guidance-based target pursuit (Section 2.3). For each area, we identify the gap that motivates the corresponding component of the proposed approach.

2.1. Predictive Target Tracking

Multi-target tracking in distributed sensor networks has evolved from reactive detection-based approaches to predictive frameworks that anticipate tracking failures before they occur. Active tracking algorithms with provable approximation bounds for handling sensor failures and occlusions demonstrate that proactive failure detection outperforms reactive recovery [13]. Distributed tracking architectures have been extended to autonomous vehicle fleets [14] and heterogeneous mobile sensing networks [15], where normalized unused sensing capacity metrics enable automatic load balancing to prevent coverage gaps.

Adaptive deployment strategies further support continuous tracking: directional-sensor network deployment [16] and dynamic deployment for expanding search areas [17] enable coverage optimization as targets move, while hybrid strategies combining static and mobile sensors [18] with spatiotemporal optimization [19] improve detection through coordinated adaptive sensing.

Maintaining continuous observation under limited sensing ranges has motivated research in collision-free tracking with localization uncertainty [20] and interactive Kalman filtering for multi-vehicle coordination [21]. Distributed state estimation frameworks improve tracking robustness through modified distributed unscented Kalman filters in fading channel environments [22] and joint tracking with uncertain anchor positions [23]. Variational Bayesian distributed filtering frameworks address maneuvering target tracking in networked sensor systems with nonlinear measurements [24]. Multi-target data association consensus algorithms further extend distributed tracking to scenarios involving non-overlapping sensor fields of view [25].

Recent advances in vision-based reactive planning incorporate predictive horizons for occlusion handling [26], and heterogeneous limited-range sensor frameworks use cooperative coverage prediction to prevent tracking gaps [5]. However, these approaches primarily focus on state estimation quality rather than explicitly predicting when and where a tracker will lose a target to trigger proactive repositioning, which is the core problem addressed in this paper.

2.2. Distributed Coordination and Task Allocation

Task allocation in multi-robot systems has transitioned from centralized optimization to distributed mechanisms that enable scalable coordination without global knowledge. Group-based distributed auction algorithms address time-window constraints and conflict resolution through competitive bidding [27], while factor graph formulations with maximum algorithms enable fully decentralized task allocation [28]. Resource-oriented auction mechanisms consider energy constraints and limited communication ranges, demonstrating that distributed bidding outperforms centralized allocation in communication-constrained environments [29]. Similarly, active-vision-based multi-sensor surveillance systems demonstrate effective coordination for multi-target monitoring in dynamic environments [30].

Beyond task allocation, maintaining network topology during coordination has received attention through control barrier function approaches for network connectivity preservation [31] and multi-robot coordination with task precedence relationships [32]. Conflict resolution, when multiple tasks compete for limited resources, has been addressed through optimization-based task allocation frameworks [33] and finite-state machine architectures (FSMs) for priority-based behavior coordination [34]. Connectivity recovery methods use distributed coordination to identify critical nodes and restore network connectivity [35], while consensus-based bundle algorithms enable task allocation in teams with severely limited communication [36]. Reconfigurable coordination frameworks provide virtual coordinator architectures for discrete-event control systems, enabling dynamic role transitions without centralized supervisors [37]. DES supervisory control has also been applied to multi-robot coordination, providing formal event-driven frameworks for concurrent motion scheduling [38].

However, existing task-allocation methods typically optimize a single objective or use fixed-priority schemes. None simultaneously balance network topology preservation, spatial mission costs, temporal feasibility, and information quality. All four are critical for maintaining persistent tracking coverage while minimizing network disruption, and addressing them jointly is the focus of the bidding mechanism proposed in Section 4.5. Furthermore, while auction-based methods such as [27,29] distribute the bidding process,

assignment decisions in those frameworks are, typically, resolved by a designated auctioneer node, introducing a single point of coordination and an additional communication round-trip for conflict resolution.

2.3. Target Pursuit

Guidance theory has been successfully adapted to robotic systems for target interception and pursuit-evasion scenarios. Navigation-guidance-based approaches [39] and augmented proportional navigation techniques [40] have demonstrated effective robotic pursuit of moving objects. Extending proportional navigation to robotic systems, PNG has been adapted for target pursuit with final velocity control [41], enabling smooth rendezvous with moving targets.

Optimal guidance strategies for UAV swarms integrate pure pursuit laws with formation maintenance [42], and bio-inspired cooperative hunting behaviors demonstrate mixed guidance approaches combining biological pursuit strategies with distributed multi-agent coordination [43]. Pursuit-evasion frameworks for multi-robot systems with limited sensing have adopted deep reinforcement learning for decentralized control [44]. Three-dimensional guidance laws for UAV target following incorporate EKF-based state estimation to handle noisy bearing measurements under stochastic conditions [45], while hierarchical graph structures enable asymptotically optimal multi-robot pursuit-evasion coordination [46].

However, existing guidance-based approaches focus on direct pursuit or rendezvous, where each agent navigates using its own measurements. None address the problem of proactive handover in sensor networks, where an auxiliary sensor must reach a predicted handover point before the current tracker loses the target and must do so using EKF state estimates shared by neighbors, since it has not yet detected the target itself.

3. Problem Formulation

This section formulates the multi-target tracking problem for reconfigurable MWSNs. We consider a system of mobile sensors with limited detection ranges tracking multiple targets with unknown trajectories. The objective is to maximize target tracking coverage while minimizing total sensor displacement from designated home positions, as pursuing fast-moving targets requires sensors to displace significantly from their home positions.

3.1. System Model and Assumptions

Let us consider an MWSN comprising N mobile sensors deployed in a hexagonal grid configuration (chosen for optimal area coverage) with inter-node spacing d . Although the system may operate in three dimensions (e.g., using UAVs), only planar motion is considered herein.

All parameters (positions, distances, ranges) are expressed in arbitrary spatial units, with temporal quantities in corresponding time units. The notation $|\cdot|$ denotes the Euclidean norm (L_2 distance) in two-dimensional space.

Each sensor, $i = 1, \dots, N$, has a designated home position $\mathbf{h}_i \in \mathbb{R}^2$ and current position $\mathbf{s}_i(t) \in \mathbb{R}^2$. Sensors possess identical capabilities: detection radius, r_d ; maximum velocity, v_s ; and communication range, r_c .

To preserve network topology, each sensor is constrained to operate within a maximum distance, d_{max} , from its home position. Multiple targets, $k = 1, \dots, K$, enter the monitored region with unknown entry times and locations. Each target follows a piecewise linear trajectory defined by waypoints $W_k = \{\omega_1, \omega_2, \dots, \omega_m\}$, moving at constant speed between consecutive waypoints. The state of target k at time t is represented as

$$\mathbf{x}_k(t) = [\mathbf{p}_k(t), \mathbf{v}_k(t)]^T, \quad (1)$$

where $\mathbf{p}_k(t) = [p_k^x, p_k^y]^T$ denotes the target position and $\mathbf{v}_k(t) = [v_k^x, v_k^y]^T$ denotes the velocity vector.

Sensor i detects target k when $|\mathbf{s}_i(t) - \mathbf{p}_k(t)| \leq r_d$. Upon detection, the sensor obtains noisy position measurements:

$$\mathbf{z}_{i,k}(t) = \mathbf{p}_k(t) + \mathbf{n}(t), \quad (2)$$

where $\mathbf{n}(t) \sim \mathcal{N}(0, \mathbf{R})$ represents Gaussian measurement noise with covariance $\mathbf{R}$. In the assumed platform (Section 5.1 below), this measurement model corresponds to a downward-facing camera or time-of-flight sensor providing target position fixes, with the noise covariance capturing the associated ranging error.

A representative deployment is illustrated in Figure 1 (Section 4.1), showing the hexagonal sensor grid with inter-node spacing d , detection radius r_d , communication range r_c , and an example target position.

3.2. Problem Statement

Given N sensors with home positions $\{\mathbf{h}_i\}_{i=1}^N$ and K targets with trajectories $\{\mathbf{x}_k(t)\}_{k=1}^K$, the objective is to maximize target tracking coverage while minimizing total sensor displacement from home positions:

$$\text{minimize } J = -\omega_1 \cdot C(t) + \omega_2 \cdot \sum_{i=1}^N \|\mathbf{s}_i(t) - \mathbf{h}_i\|^2, \quad (3)$$

where $C(t) = \frac{1}{K} \sum_{k=1}^K 1[\exists i : |\mathbf{s}_i(t) - \mathbf{p}_k(t)| \leq r_d]$ is the instantaneous tracking coverage fraction, and $\omega_1, \omega_2 > 0$ are weighting coefficients.

The optimization is subject to the following constraints:

- (1) **Displacement Constraint:** Each sensor must respect the maximum displacement constraint: $|\mathbf{s}_i(t) - \mathbf{h}_i| \leq d_{max}$, which preserves network topology and limits energy consumption.
- (2) **Measurement Noise:** Tracking decisions must account for noisy position measurements $\mathbf{z}_{i,k}(t)$ to determine target velocity $\mathbf{v}_k$ and predict future positions.

3.3. Sub-Problems

To address the overall problem stated above, four critical sub-problems must be solved: tracking loss prediction, proactive positioning, distributed sensor allocation, and conflict resolution. They are detailed below:

- (1) **Tracking Loss Prediction:** Determine when current tracking sensors will lose target observation, given limited detection range, r_d , and target mobility. Specifically, for each tracking sensor and target, the predicted loss time τ must be determined such that

$$\tau = \min\{\tau > 0 : |\mathbf{s}_i(t + \tau) - \mathbf{p}_k(t + \tau)| > r_d\} \quad (4)$$

This computation must account for (i) target velocity uncertainty arising from noisy measurements, (ii) sensor pursuit capability constraints when $|\mathbf{v}_k| > v_s$, and (iii) state-estimation convergence requirements for reliable prediction.

- (2) **Proactive Positioning:** Determine the repositioning locations for auxiliary sensors before tracking loss occurs. Specifically, predict handover points, $\mathbf{p}_{handover}$, where auxiliary sensors can acquire targets before current trackers lose detection. The calculations must account for sensor travel time to ensure auxiliary sensors arrive at $\mathbf{p}_{handover}$ before τ with sufficient lead time for detection and state estimation.

Additionally, auxiliary sensors must navigate to $\mathbf{p}_{\text{handover}}$ using EKF state estimates shared by the current tracker, since they have not yet detected the target themselves, requiring confidence-weighted state fusion to generate reliable guidance inputs.

- (3) **Distributed Sensor Allocation:** Determine which sensors should be allocated to handover tasks while balancing competing objectives: (i) network topology preservation, by minimizing $|\mathbf{s}_i - \mathbf{h}_i|$ to maintain the original hexagonal grid configuration; (ii) spatial efficiency, by minimizing distance to handover points; (iii) temporal feasibility, by ensuring arrival before predicted target loss; and (iv) information quality, by prioritizing sensors with high EKF estimation confidence (low state covariance). The allocation must be determined in a distributed manner without centralized control, with each sensor evaluating its own suitability based on local information.
- (4) **Conflict Resolution:** Resolve resource allocation when multiple tracking sensors require auxiliary sensor assistance while prior handover requests are still being processed. Specifically, determine (i) when handover calls from different tracking sensors occur within overlapping time windows, (ii) how to allocate non-overlapping auxiliary sensor teams to competing targets, and (iii) how to ensure no target is disproportionately disadvantaged in resource allocation.

4. Proposed Approach

This section presents the proposed DES-based coordination framework. Section 4.1 describes the system architecture. Sections 4.2–4.4 detail the FSM architecture and EKF-based predictive handover. Sections 4.5 and 4.6 present the bidding and conflict resolution mechanisms. Sections 4.7 and 4.8 cover information sharing and proportional navigation guidance. Sections 4.9 and 4.10 address the dual-tracker configuration and post-loss search. The proposed framework assumes sensors are battery-powered mobile platforms; energy consumption is approximated implicitly through the displacement constraint $d_{\max}$, which bounds the distance each sensor travels per mission. Explicit energy modeling is reserved for future work involving hardware validation.

4.1. System Architecture and Configuration

As described in Section 3.1, for simplicity, it is assumed herein that the optimal MWSN configuration is a $n_{\text{grid}} \times n_{\text{grid}}$ hexagonal grid with $N = n_{\text{grid}}^2$ sensors and inter-node spacing d . While our solution framework allows for any optimal network configuration, we select the hexagonal topology as it provides optimal two-dimensional coverage without directional bias, minimizing the number of sensors required for complete area monitoring [47,48]. The staggered hexagonal geometry simplifies distributed coordination algorithms and enables predictable communication patterns.

Although the present analysis assumes a regular hexagonal grid, the coordination mechanism is topology-agnostic: the bidding costs (Section 4.5) are determined from sensor positions and Euclidean distances only, with no assumption about grid regularity, so the framework extends directly to irregular or non-uniform sensor deployments. Partial node failures are handled passively: a failed sensor stops broadcasting and is consequently excluded from the bidder pool at the next handover call. The remaining sensors continue executing the coordination protocol without architectural change, though tracking coverage degrades proportionally. The impact of progressive node failures and irregular initial deployments on coverage is identified as a future research direction (Section 6).

As shown in Figure 1, the displacement constraint is set to $d_{\max} = d$, ensuring sensors remain within communication range, r_c , of their neighbors, while providing sufficient mobility for handover repositioning. With communication range $r_c > d$, sensors at home positions maintain connectivity with their neighbors. This connectivity is preserved during

repositioning as the constraint $d_{max} = d$ prevents sensors from moving beyond the communication range of the network. Grid parameters balance sensor utilization: larger spacing d reduces redundancy but risks coverage gaps, while smaller spacing increases robustness at the cost of sensor density.

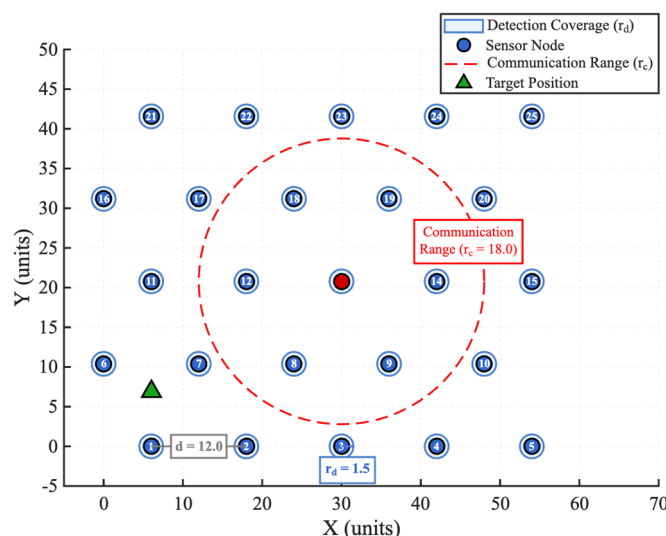


Figure 1. Hexagonal-grid WSN deployment. The red filled circle indicates the reference sensor used to illustrate the communication range r_c .

4.2. DES Architecture and Coordination Framework

The proposed framework addresses the four sub-problems identified in Section 3.3 through a discrete-event system (DES) architecture. Specifically,

- *Sub-problem 3.3.1* (Tracking Loss Prediction) is solved through EKF-based uncertainty propagation (Sections 4.3 and 4.4).
- *Sub-problem 3.3.2* (Proactive Positioning) is solved through predictive handover point computation and adaptive guidance (Sections 4.4 and 4.8).
- *Sub-problem 3.3.3* (Distributed Sensor Allocation) is solved through multi-objective competitive bidding (Section 4.5).
- *Sub-problem 3.3.4* (Conflict Resolution) is solved through min-max optimization for simultaneous requests (Section 4.6).

Supporting mechanisms include information sharing between neighboring sensors (Section 4.7), dual-tracker configuration for robustness (Section 4.9), and EKF-based search contour generation for post-loss reacquisition (Section 4.10).

The framework operates as a DES where state transitions occur in response to well-defined events rather than continuous time updates. This architecture enables efficient coordination by processing discrete tracking events (target detections, predicted losses, handover requests) while minimizing computational overhead.

Each sensor operates according to a finite-state machine (Figure 2) with five states $S = \{IDLE, DETECTING, TRACKING, REPOSITIONING, RETURNING_HOME\}$. State transitions are event-driven:

- $IDLE \rightarrow DETECTING$ occurs upon target detection within range.
- $DETECTING \rightarrow TRACKING$ occurs when fewer than two sensors are currently tracking the target (dual-tracker configuration has available slots).
- $IDLE \rightarrow REPOSITIONING$ occurs when an idle sensor wins bidding for a handover call.

- *REPOSITIONING* → *TRACKING* occurs upon successfully acquiring the target during handover.
- *TRACKING* → *RETURNING_HOME* occurs when the sensor loses target detection or upon successful handover completion.
- *REPOSITIONING* → *RETURNING_HOME* occurs when the sensor cannot acquire the target at the handover point.
- *Any state* → *RETURNING_HOME* occurs when the sensor exceeds $d_{\max}$ while neither tracking nor repositioning.
- *RETURNING_HOME* → *DETECTING* occurs if the sensor detects a target while en route home and fewer than two trackers are currently assigned to that target, allowing opportunistic re-engagement without wasting a displaced sensor.

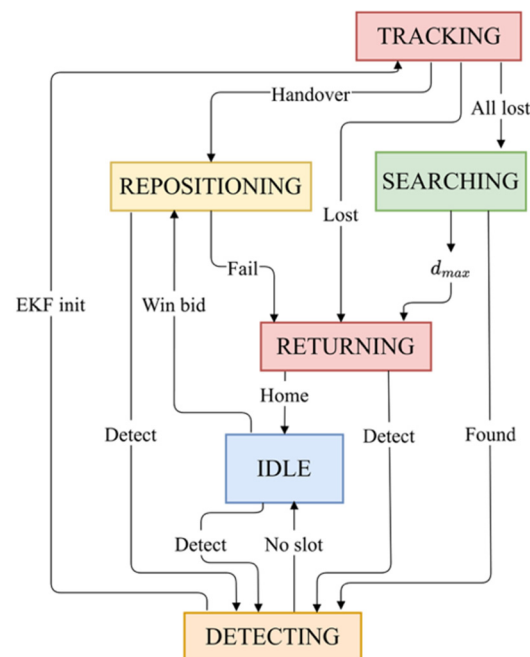


Figure 2. Proposed sensor finite-state-machine architecture.

The proposed architecture integrates three coordinating modules within each sensor via message passing (Figure 3): the Tracking Coordinator manages tracker assignments and immediate handover requests, the Handover Coordinator processes predictive handover calls through distributed bidding and conflict resolution, and the Recovery Protocol manages return-to-home operations and generates iso-probability contours for future search operations. This separation enables independent processing of distinct tracking tasks while ensuring coordinated resolution of resource conflicts. Specifically, each target is handled by an independent set of FSM instances, one per sensor, so tracking, handover, and recovery operations for different targets proceed without blocking or interfering with each other. The number of targets that can be tracked without architectural limitation is bounded only by the number of available sensors. The three coordinator modules (*Tracking*, *Handover*, *Recovery*) communicate via message passing rather than shared state, so events for different targets trigger independent state transitions within the simulation event queue.

Importantly, decision-making is distributed: each sensor executes local decisions based on its finite state machine (Figure 2) using information from coordinating modules. The system employs a hybrid communication model where global broadcast enables all sensors to participate in competitive bidding for handover coordination, while local peer-to-peer communication within range r_c handles routine tracking information exchange (detailed

in Section 4.7). The framework assumes trusted communication channels; resilience to adversarial jamming or spoofing is outside the current scope and is left for future work.

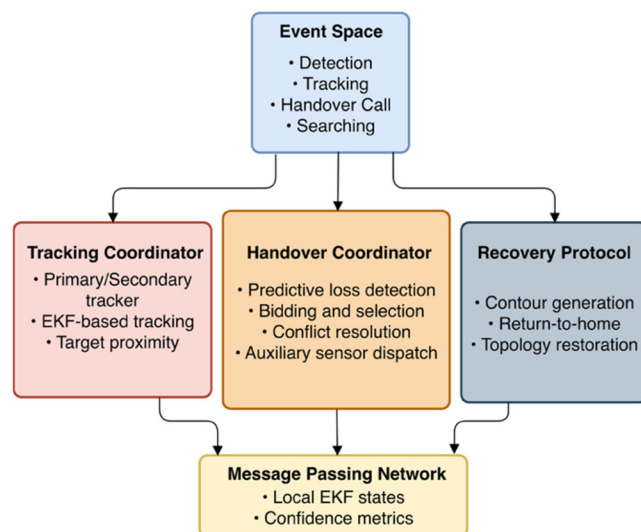


Figure 3. DES architecture.

4.3. EKF-Based Target State Estimation

To solve Sub-problem 3.3.1 (Tracking Loss Prediction), each tracking sensor maintains an EKF estimating target state $\hat{\mathbf{x}}_k(t)$ with covariance $\mathbf{P}_k(t)$. Although the state transition and measurement models are linear, the EKF framework is adopted to accommodate nonlinear target dynamics arising from stochastic trajectory perturbations applied during simulation. The discrete-time state transition model with time step Δt is

$$\mathbf{x}_k(t + \Delta t) = \mathbf{F}\mathbf{x}_k(t) + \mathbf{G}\mathbf{w}(t), \quad (5)$$

where $\mathbf{F}$ is the state transition matrix, $\mathbf{G}$ is the process noise gain, and $\mathbf{w}(t) \sim \mathcal{N}(0, \mathbf{Q})$ represents unit process noise. The matrices are defined as

$$\mathbf{F} = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \mathbf{G} = \begin{bmatrix} \Delta t^2/2 & 0 \\ 0 & \Delta t^2/2 \\ \Delta t & 0 \\ 0 & \Delta t \end{bmatrix}, \quad (6)$$

$$\mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}, \mathbf{Q} = \sigma_w^2 \mathbf{I}_2,$$

where σ_w^2 represents process noise covariance. The EKF prediction step propagates state and covariance:

$$\hat{\mathbf{x}}_k^- = \mathbf{F}\hat{\mathbf{x}}_k, \mathbf{P}_k^- = \mathbf{F}\mathbf{P}_k\mathbf{F}^T + \mathbf{G}\mathbf{Q}\mathbf{G}^T. \quad (7)$$

Upon receiving measurement $\mathbf{z}_{i,k}$, the update step determines the Kalman gain $\mathbf{K}$ and updates:

$$\mathbf{K} = \mathbf{P}_k^- \mathbf{H}^T (\mathbf{H}\mathbf{P}_k^- \mathbf{H}^T + \mathbf{R})^{-1}, \quad (8)$$

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \mathbf{K}(\mathbf{z}_{i,k} - \mathbf{H}\hat{\mathbf{x}}_k^-), \text{ and } \mathbf{P}_k = (\mathbf{I} - \mathbf{K}\mathbf{H})\mathbf{P}_k^-. \quad (9)$$

Convergence is detected when velocity covariance components satisfy $[\mathbf{P}_k]_{3,3} < \sigma_{v,thresh}^2$ and $[\mathbf{P}_k]_{4,4} < \sigma_{v,thresh}^2$, indicating sufficient velocity estimation quality for loss prediction. Here, indices (3,3) and (4,4) correspond to the v_x and v_y components of the state vector $\mathbf{x}_k = [p_x, p_y, v_x, v_y]^T$ defined in Equation (1); the subscript k indexes the discrete time step,

while the bracketed indices denote matrix elements, confirming that velocity estimation has converged before handover is triggered. The threshold $\sigma_{v,thresh}^2 = 0.006$ was selected based on the sensitivity analysis presented in Section 5.5, which shows it achieves the best balance between handover lead time and prediction accuracy.

4.4. Predictive Loss Detection Using EKF Convergence

Upon EKF convergence, tracking sensors address Sub-problem 3.3.1 by predicting when target loss will occur. The sensor forward propagates the target state. Given the tracker position $\mathbf{s}_i(t)$ and estimated target state $\hat{\mathbf{x}}_k(t) = [\hat{\mathbf{p}}_k(t), \hat{\mathbf{v}}_k(t)]^T$, the predicted distance at future time $t + \tau$ is

$$d(\tau) = |\mathbf{s}_i(t) + v_s \hat{\mathbf{u}}\tau - (\hat{\mathbf{p}}_k(t) + \hat{\mathbf{v}}_k(t)\tau)|. \quad (10)$$

where $\hat{\mathbf{u}} = (\hat{\mathbf{p}}_k(t) - \mathbf{s}_i(t)) / |\hat{\mathbf{p}}_k(t) - \mathbf{s}_i(t)|$ is the unit vector from sensor toward target.

When target velocity exceeds sensor capability $|\hat{\mathbf{v}}_k| > v_s$, loss is inevitable and τ_{loss} is determined by when the distance first exceeds r_d given sensor pursuit at maximum velocity toward the target, as illustrated in Figure 4. When $|\hat{\mathbf{v}}_k| \leq v_s$, the sensor can keep up with the target but is eventually stopped by the displacement constraint d_{max} . At that boundary position $s_{boundary}$, τ_{loss} is determined by Equation (4) evaluated from $s_{boundary}$ rather than the current sensor position.

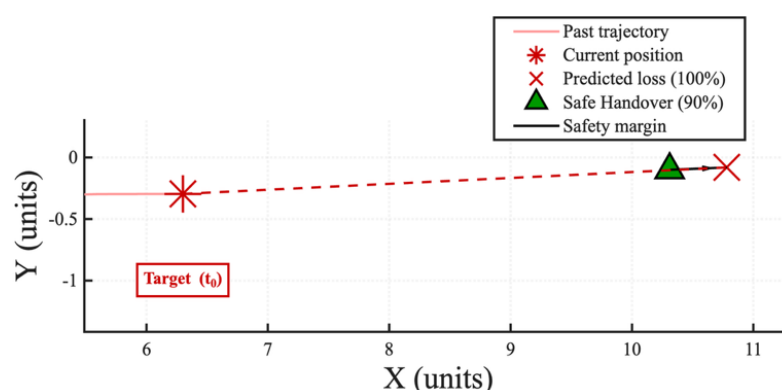


Figure 4. Predictive loss detection and handover mechanism.

To ensure sensors arrive before tracking loss, a safety margin is applied: the handover point is set to $\mathbf{p}_{handover} = \hat{\mathbf{p}}_k(t) + \hat{\mathbf{v}}_k(t)\tau_{safe}$ where $\tau_{safe} < \tau_{loss}$ provides a temporal safety margin (greater values increase robustness but require earlier sensor commitment). Figure 5 shows a detailed view of the safety margin application during the handover process.

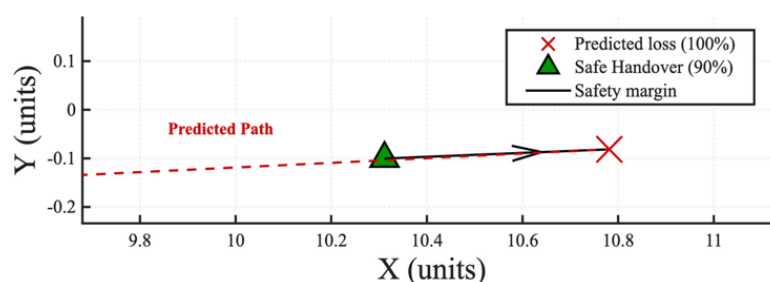


Figure 5. Close-up view of safety margin application.

4.5. Multi-Objective Bidding for Sensor Assignment

To solve Sub-problem 3.3.3 (Distributed Sensor Allocation), we propose a competitive bidding mechanism where each available sensor evaluates its suitability for handover

tasks. Upon receiving a handover call, each available sensor i (one not currently tracking, repositioning or detecting, i.e., in IDLE or RETURNING_HOME state) computes a bid reflecting four competing objectives. Let $\mathbf{s}_i$ denote the current position, $\mathbf{h}_i$ home position, and $\mathbf{p}_{\text{handover}}$ the predicted handover point. The monitoring region has width W and height H , giving a network diagonal $D_{\max} = \sqrt{(W^2 + H^2)}$ used for normalization. The bid components are as follows.

(1) Network Topology Preservation (Objective (i) of sub-problem 3.3.3) quantifies displacement from home position:

$$\text{penalty}_{\text{network}}(i) = \frac{|\mathbf{s}_i - \mathbf{h}_i|}{D_{\max}}, \quad (11)$$

(2) Spatial Efficiency (Objective (ii) of sub-problem 3.3.3) measures distance to handover point:

$$\text{penalty}_{\text{spatial}}(i) = \frac{|\mathbf{s}_i - \mathbf{p}_{\text{handover}}|}{D_{\max}}. \quad (12)$$

(3) Temporal Feasibility (Objective (iii) of sub-problem 3.3.3) evaluates sensor arrival time relative to target arrival at the handover point.

Let $t_{\text{sensor}} = |\mathbf{s}_i - \mathbf{p}_{\text{handover}}|/v_s$ be the sensor's travel time, and let

$$t_{\text{target}} = \frac{|\hat{\mathbf{p}}_k(t) - \mathbf{p}_{\text{handover}}|}{|\hat{\mathbf{v}}_k|}, \quad (13)$$

be the target's estimated time to reach the handover point. The temporal penalty is

$$\text{penalty}_{\text{temporal}}(i) = \min\left(1, \max\left(0, \frac{t_{\text{sensor}} - t_{\text{target}}}{t_{\text{target}}}\right)\right). \quad (14)$$

This penalty is zero when the sensor arrives before the target, increases linearly with late arrival, and is capped at 1 to maintain comparable scales with other penalties.

(4) Information Quality (Objective (iv) of sub-problem 3.3.3) reflects the reliability of shared target information available to the repositioning sensor. Based on information age and spatial proximity to active trackers, each sensor computes a confidence metric $\alpha_i \in [0, 1]$ (see Section 4.7 for details). The uncertainty penalty is

$$\text{penalty}_{\text{uncertainty}}(i) = 1 - \alpha_i, \quad (15)$$

where lower confidence in shared information increases the penalty, discouraging assignment when available information is stale or unreliable.

The total bid combines these components through a weighted summation:

$$\text{bid}(i) = w_n \cdot p_n(i) + w_s \cdot p_s(i) + w_t \cdot p_t(i) + w_u \cdot p_u(i), \quad (16)$$

where $p_n = \text{penalty}_{\text{network}}$, $p_s = \text{penalty}_{\text{spatial}}$, $p_t = \text{penalty}_{\text{temporal}}$, $p_u = \text{penalty}_{\text{uncertainty}}$, and $w_n + w_s + w_t + w_u = 1$. Sensors with lower bids are preferable.

As shown in Figure 6, the winner selection follows a distributed self-selection protocol: each bidder broadcasts its bid to all sensors in the network via global broadcast, independently ranks itself against all received bids, and transitions to REPOSITIONING if its rank is 2 or lower. No central coordinator collects or processes bids; the global broadcast ensures every bidder receives the same complete bid set, guaranteeing identical self-selection outcomes across all nodes. Ties are broken deterministically by sensor ID, requiring no central authority. The two selected sensors maintain redundancy against prediction errors or sensor failures.

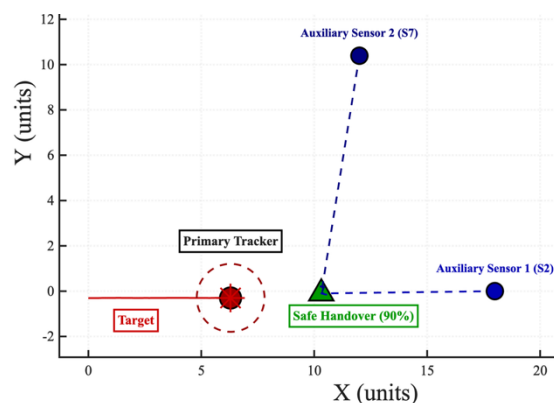


Figure 6. Successful multi-objective bidding.

4.6. Conflict Resolution for Simultaneous Handover Requests

To solve Sub-problem 3.3.4 (Conflict Resolution), a min–max optimization approach is proposed for situations in which multiple tracking sensors require auxiliary sensor assistance while prior handover requests are still being processed within the same DES cycle. Rather than allocating auxiliary sensors independently to each request, the system enters conflict resolution mode to minimize the maximum team cost across all simultaneous handover requests. Since auction bids are broadcast globally (Section 4.5), every sensor in the network independently receives the complete bid set for all concurrent requests and runs the same min–max algorithm locally. Since the inputs and algorithm are identical at every node, all sensors arrive at the same assignment decision without a central coordinator.

Let $\mathcal{T} = \{k_1, k_2, \dots, k_n\}$ denote the targets requiring handovers, and let $S_{\text{available}} = \{i_1, i_2, \dots, i_m\}$ denote available sensors (excluding active trackers). For each assignment $A : \mathcal{T} \rightarrow S_{\text{available}} \times S_{\text{available}}$ mapping targets to sensor pairs, the cost is

$$\text{cost}(A) = \max_{k \in \mathcal{T}} \sum_{i \in A(k)} \text{bid}_i(k), \quad (17)$$

subject to $A(k) \cap A(k') = \emptyset$ for all $k \neq k'$, where $\text{bid}_i(k)$ is sensor i 's bid for target k 's handover mission and $A(k)$ denotes the two-sensor team assigned to target k . The non-overlapping constraint ensures each sensor is committed to at most one target. The optimal assignment $A^* = \underset{A}{\text{argmincost}}$ minimizes the worst-case team cost, ensuring no target is disproportionately disadvantaged in resource allocation.

For two-target conflicts, all valid non-overlapping sensor team combinations (s_1, s_2, s_3, s_4) where $s_i \in S_{\text{available}}$ and teams share no common sensors are evaluated to find the min–max solution. Exhaustive search has complexity $O(|S_{\text{available}}|^4)$. To reduce this, only the top k bidders per target are considered, reducing complexity to $O(k^4)$, where $k \ll |S_{\text{available}}|$ while maintaining near-optimal solutions. When no conflicts exist, sensors are assigned independently based on lowest individual bids without min–max optimization.

4.7. Information Sharing During Tracking

While handover calls are broadcast globally to all sensors in the network (using a network-wide flood reaching all N sensors regardless of distance), target state information is shared locally via direct peer-to-peer unicast between sensors within communication range r_c . Each tracking sensor shares its current EKF state estimate:

$$\hat{x}_j = [\hat{p}_j^x, \hat{p}_j^y, \hat{v}_j^x, \hat{v}_j^y]^T, \quad (18)$$

with neighbors. Receiving sensors compute a confidence-weighted fusion of estimates from all trackers within range:

$$\hat{\mathbf{x}}_{\text{shared}} = \frac{\sum_{j \in \mathcal{N}_i} w_j \hat{\mathbf{x}}_j}{\sum_{j \in \mathcal{N}_i} w_j}, \quad (19)$$

where $\mathcal{N}_i$ denotes sensors within communication range of Sensor i , and the weight assigned to each neighbor j is

$$w_j = \frac{e^{-\lambda_t \Delta t_j}}{1 + \lambda_s d_{ij}}, \quad (20)$$

where Δt_j is the time since Sensor j 's last detection, and d_{ij} is the inter-sensor distance.

The two factors penalize estimates that are temporally stale ($\lambda_t = 0.1$) and spatially distant ($\lambda_s = 0.1$). The aggregate weight determines the confidence metric used in bidding:

$$\alpha_i = \min(1, \sum_{j \in \mathcal{N}_i} w_j), \quad (21)$$

This metric is used in the bidding mechanism (Section 4.5, objective (iv) of Sub-problem 3.3.3) to penalize assignments when available information is stale or spatially distant from active trackers, enabling auxiliary sensors to use shared estimates for guidance without requiring direct target detection.

The proactive design provides a natural resilience window against broadcast failures: because handover initiation begins at $\tau_{\text{safe}} < \tau_{\text{loss}}$ (Section 4.4), the primary tracker retains the target for the duration of the interval $[\tau_{\text{safe}}, \tau_{\text{loss}}]$ even after the handover call is issued. A missed or delayed broadcast therefore does not immediately result in tracking failure, and coordination may be re-attempted within this window. Full state-recovery mechanisms for repeated or cascading broadcast failures under adverse channel conditions are identified as future work (Section 6).

4.8. Fusion-Driven Proportional Navigation for Sensor Repositioning

Upon winning the handover bid, idle sensors transition to the *REPOSITIONING* state to reach the predicted handover point $\mathbf{p}_{\text{handover}}$ calculated in Section 4.4 (addressing Sub-problem 3.3.2). The sensor employs a distance-dependent adaptive guidance strategy.

(1) Phase 1: Adaptive Guidance (distance > δ_{switch})

When far from the handover point, sensors retrieve shared target information (Section 4.7) from neighboring trackers, obtaining confidence $\alpha \in [0, 1]$. Three scenarios arise:

- *Low Confidence* ($\alpha \leq \alpha_{\text{threshold}}$): The sensor aborts repositioning and transitions to *RETURNING_HOME*, as unreliable target information renders the predicted handover point invalid.
- *Target Not Yet Passed*: When geometric analysis indicates the target has not moved beyond $\mathbf{p}_{\text{handover}}$, the sensor navigates directly toward the handover point:

$$\mathbf{v}_{\text{command}} = v_s \frac{\mathbf{p}_{\text{handover}} - \mathbf{s}_i}{\|\mathbf{p}_{\text{handover}} - \mathbf{s}_i\|}. \quad (22)$$

- *Target Passed Handover Point*: When geometric analysis indicates the target has moved beyond $\mathbf{p}_{\text{handover}}$ and $\alpha > \alpha_{\text{threshold}}$, PNG is employed. PNG commands a lateral acceleration perpendicular to the sensor's velocity vector at a rate proportional to the line-of-sight (LOS) rotation rate [49]:

$$a_{\text{PNG}} = N' \cdot v_s \cdot \theta_{\text{LOS}} \cdot \hat{n}_{\perp}, \quad (23)$$

where $N' = 2$ is the navigation constant, θ_{LOS} is the LOS rotation rate between sensor and target, and $\hat{n}_{\perp}$ is the unit normal to the sensor's current velocity. Unlike

standard PNG, which relies on direct measurements, the guidance input is derived from the confidence-weighted fusion of EKF estimates shared by neighboring trackers (Section 4.7). The PNG direction is blended with the sensor's current heading proportionally to confidence:

$$\hat{e}_{new} = \text{normalize}((1 - \beta) \cdot \hat{e}_{cur} + \beta \cdot \hat{e}_{PNG}), \quad (24)$$

where $\beta = 0.1\alpha$, $\hat{e}_{cur}$ is the current heading direction, and $\hat{e}_{PNG} = a_{PNG}/|a_{PNG}|$. Higher confidence produces a more curved repositioning trajectory bending toward the target.

(2) *Phase 2: Final Approach (distance $\leq \delta_{switch}$ units)*

When within δ_{switch} units of $\mathbf{p}_{handover}$, the sensor reverts to direct navigation (Equation (22)) regardless of shared information quality, committing to the last known handover point.

Upon reaching $\mathbf{p}_{handover}$, the sensor transitions to TRACKING if target acquisition is successful or to RETURNING_HOME if acquisition fails.

4.9. Dual-Tracker Configuration and Immediate Handover

The Tracking Coordinator maintains up to two active trackers per target for robustness against individual sensor failure or detection loss. This objective of “up to two active trackers per target” is an upper bound per target, not a system-wide limit: a target is tracked with one sensor under normal conditions and a second is added only when available for redundancy. Each sensor makes this decision locally using its own cache, independently for each target. The network's multi-target capability is demonstrated with three targets in Section 5.3 and four targets in Section 5.4. This reactive mechanism complements the predictive handover of Section 4.4 by handling cases where a new sensor enters detection range of an already-tracked target. Active trackers periodically broadcast their target ID and tracking status as part of the information-sharing protocol (Section 4.7), so every sensor maintains a local cache of current tracker assignments and can immediately determine whether a newly detected target is already being tracked.

When a new sensor detects a target with fewer than two active trackers, it is accepted directly without releasing any existing tracker. If the target already has two active trackers, the newly detecting sensor identifies, using its local cache of tracker assignments, the tracker farthest from its home position:

$$i_{\text{release}} = \underset{i \in \mathcal{S}_k}{\text{argmax}} |\mathbf{s}_i - \mathbf{h}_i|, \quad (25)$$

where $\mathcal{S}_k$ denotes the set of sensors currently tracking target k . The tracker with maximum home displacement i_{release} is released and transitions to RETURNING_HOME, allowing the new detecting sensor to assume tracking responsibility. This policy balances tracking redundancy with network topology preservation.

Each new tracker initializes its EKF with state $\hat{\mathbf{x}}_k = [\mathbf{z}_{i,k}, \mathbf{0}]^T$ using the current position measurement and zero initial velocity. When a target exits the monitored region, assigned trackers transition to RETURNING_HOME and remove the target from their tracking list.

4.10. EKF-Based Iso-Probability Search Contour Generation

Upon confirmed target loss (target exits detection range as defined in Section 4.4), the last tracking sensor generates search regions based on its final EKF state estimate, represented as iso-probability contours connecting points of equal probability density. Existing methods that use such contours typically compute full probability density distributions over discretized spatial grids [3,50,51]. The proposed approach instead derives the contours

analytically from the EKF covariance matrix already maintained during tracking, adding no computational overhead.

The position covariance submatrix $\mathbf{P}_{pos} = \mathbf{P}_k(1:2, 1:2)$ defines a 2D Gaussian distribution over target location. Eigenvalue decomposition $\mathbf{P}_{pos} = \mathbf{V}\mathbf{\Lambda}\mathbf{V}^T$ yields principal axis directions (columns of $\mathbf{V}$) and uncertainty magnitudes (diagonal of $\mathbf{\Lambda} = \text{diag}(\lambda_1, \lambda_2)$). For confidence level p , the corresponding chi-square value $\chi_p^2(2)$ scales the uncertainty ellipse. The contour parameterization is

$$c(\theta) = [\hat{p}_k^x, \hat{p}_k^y]^T + \sqrt{(\chi_p^2)} \cdot \mathbf{V} \cdot [\sqrt{\lambda_1} \cos \theta, \sqrt{\lambda_2} \sin \theta]^T, \quad (26)$$

for $\theta \in [0, 2\pi]$. For a 2D Gaussian distribution, n-sigma ellipses correspond to chi-squared values with two degrees of freedom, yielding confidence levels of 39.35 for 1σ , 86.47 for 2σ , and 98.89 for 3σ , as illustrated in Figure 7.

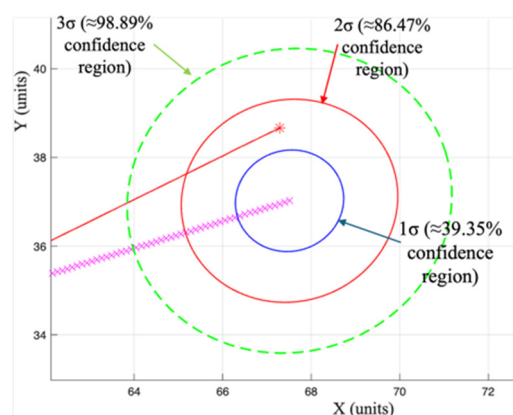


Figure 7. EKF-based probabilistic search contours generated after target loss.

These nested elliptical contours enclose regions of increasing cumulative probability and provide spatial search regions for subsequent search operations, though full search algorithm implementation is reserved for future work.

5. Simulated Experiments

5.1. Simulation Setup

Numerous simulations were conducted to evaluate the proposed framework's performance in multi-target tracking scenarios with varying target velocities and simultaneous handover demands. Two representative scenarios demonstrate key system capabilities: (1) conflict resolution when multiple targets require auxiliary sensors while prior handover requests are still being processed and (2) scalable coordination among three targets with progressive velocities and staggered entry times. Section 5.4 presents an ablation study isolating the contribution of each system component, and Section 5.5 examines sensitivity to the EKF convergence threshold. Performance is evaluated through tracking coverage duration, sensor engagement rates, handover success rates, and network topology preservation.

The simulation scenario is grounded in a concrete physical deployment: a team of $N = 25$ battery-powered nano-quadrators arranged in a 5×5 hexagonal grid with inter-node spacing $d = 12$ m over a $60 \text{ m} \times 52 \text{ m}$ outdoor area, tasked with monitoring multiple moving targets simultaneously. Each UAV, such as the Crazyflie 2.1 (Bitcraze) [52], has a detection radius of $r_d = 1.5$ m via a downward-facing camera or time-of-flight sensor and a cruising velocity of $v_s = 0.75$ m/s. When a target moves faster than a single UAV can follow, or when a UAV reaches the boundary of its allowable operating zone, continuous tracking requires proactive handover to a neighboring UAV. Energy constraints compound

this challenge: with a battery life of approximately 7 min [53], unnecessary repositioning must be minimized, motivating the displacement constraint $d_{max} = 12$ m that bounds each sensor's energy expenditure per mission. Target velocities of 1.0–1.2 m/s represent a walking person or slow-moving ground vehicle. The $60 \text{ m} \times 52 \text{ m}$ deployment area is consistent with the practical outdoor operating envelope of the Crazyflie 2.1, and all simulation scenarios in Sections 5.2–5.4 are parameterized for this physical scale.

The DES simulation assumes global message broadcasting for handover coordination, implemented as a network-wide flood over the 2.4 GHz Crazyradio PA link. The Crazyradio PA provides reliable connectivity at ranges up to 80 m outdoors, well exceeding the maximum inter-sensor distance in the $60 \text{ m} \times 52 \text{ m}$ deployment area. Handover auction messages are small, containing only sensor ID, target state estimate, and intercept point, and are well within the radio payload limit. Broadcast latency across the network is negligible relative to the 0.1 s simulation time step, justifying the instantaneous broadcast assumption used in the DES model.

EKF parameters include process noise covariance $\mathbf{Q} = \text{diag}(0.01, 0.01)$ and measurement noise covariance $\mathbf{R} = \text{diag}(0.0025, 0.0025)$. Velocity convergence is detected when variance components satisfy $\mathbf{P}_k(3, 3)$, and $\mathbf{P}_k(4, 4)$, both fall below $\sigma_{v,thresh}^2 = 0.006$ (selected in Section 4.3), typically achieved within 1 time unit of continuous tracking.

The bidding weights prioritize network topology preservation ($w_n = 0.4$) to ensure long-term operational sustainability, followed by spatial efficiency ($w_s = 0.3$) to minimize travel distance, temporal feasibility ($w_t = 0.2$) to ensure timely arrival, and information quality ($w_u = 0.1$) to account for tracking uncertainty. This allocation reflects the dual objectives stated in Section 3.2. The weights were selected based on sensitivity analysis across multiple scenarios. The system maintains effective coordination when individual weights are varied by ± 0.1 from the nominal values, confirming that overall performance is driven by the relative ordering of priorities rather than the precise weight magnitudes.

The reactive baseline used for comparison disables EKF-predictive auction triggering: sensors begin seeking a replacement only after the target leaves their detection radius. All other components such as bidding, conflict resolution, and navigation remain identical to the full system. This isolates the contribution of predictive handover from the other components, which are evaluated independently in Section 5.4.

Table 1 summarizes the simulation parameters, their values, and the physical or empirical basis for each, grounding the simulation in the assumed nano-quadrotor platform.

Table 1. Simulation parameters, values, and physical justifications.

Parameter	Symbol	Value	Justification/Source
Number of sensors	N	25 (5×5)	Bounded outdoor deployment; hexagonal grid covers the 60×52 m area at spacing d
Inter-node spacing	d	12 m	Detection footprints tile the region without gaps; defines grid extent
Detection radius	r_d	1.5 m	Footprint of a downward camera/time-of-flight sensor (Crazyflie 2.1) [52]
Communication range	r_c	link reliable to ~ 80 m	2.4 GHz Crazyradio PA; exceeds max inter-sensor distance [52]
Displacement bound	d_{max}	12 m (=d)	Keeps sensors within r_c of neighbors; bounds per-mission energy (~ 7 min battery) [53]

Table 1. Cont.

Parameter	Symbol	Value	Justification/Source
Sensor velocity	v_s	0.75 m/s	Crazyflie 2.1 cruising speed [52]; below target speed (regime where reactive handover fails)
Target velocity	$ v_k $	1.0–1.2 m/s	Walking person/slow ground vehicle
Process noise cov.	Q	diag(0.01, 0.01)	Moderate process noise for stochastic trajectory perturbation
Measurement noise cov.	R	diag(0.0025, 0.0025)	$\sigma \approx 0.05$ m, consistent with short-range time-of-flight/visual ranging
EKF conv. threshold	$\sigma_{v,thresh}^2$	0.006	Best coverage/prediction-accuracy trade-off (Section 5.5)
Bidding weights	w_n, w_s, w_t, w_u	0.4, 0.3, 0.2, 0.1	Priority ordering; robust to ± 0.1 variation (Section 5.1)
Navigation constant	N'	2	Standard proportional-navigation value [49]
Simulation time step	Δt	0.1 s	Below broadcast latency; justifies instantaneous-broadcast assumption
Confidence threshold	$\alpha_{threshold}$	0.2	A repositioning sensor aborts when the shared-information confidence falls below this value (Section 4.8)
Handover safety margin	τ_{safe}	0.1	Fractional temporal margin placing τ_{safe} below the predicted loss time τ_{loss} (Section 4.4)
Guidance switch distance	δ_{switch}	1.5 m ($= r_d$)	Final-approach/acquisition radius ($= r_d$): an interceptor lacking shared target information travels to within this distance of the predicted handover point and either acquires the target or, if it is absent, returns home (Section 4.8)

5.2. Example 1: Conflict Resolution Under Simultaneous Handover Calls

Figure 8 illustrates the system's conflict resolution mechanism when multiple sensors require handover resources. At $t = 57.1$ – 57.2 time units, two tracking sensors, each monitoring a separate target, detect imminent target loss through EKF-based prediction and issue handover calls within the conflict detection window (Section 4.6). This triggers the DES conflict resolution mode, which processes the competing requests to allocate non-overlapping sensor teams.

The min–max algorithm processes the competing requests at $t = 57.3$ – 57.6 time units. Rather than evaluating all possible sensor–target assignments, the algorithm limits the search space to the top k bidders per target ($k = 8$) based on initial bid calculations. This reduces computational complexity from $O(|S_{available}|^4)$ exhaustive search to $O(k^4)$ where $k \ll |S_{available}|$, enabling efficient conflict resolution while maintaining near-optimal assignment quality.

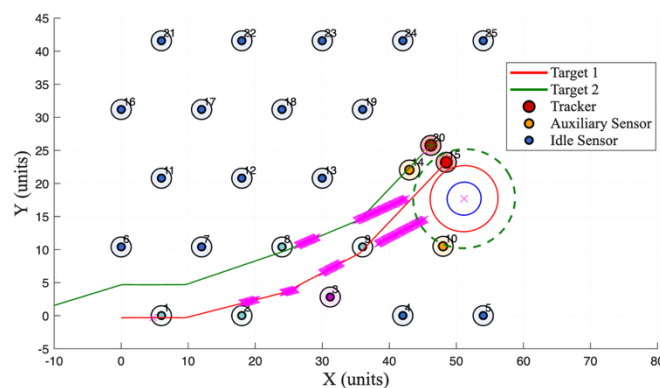


Figure 8. Conflict resolution demonstration.

Figure 9 shows the post-resolution assignments at $t = 57.6$ time units. The algorithm successfully allocated non-overlapping handover sensor pairs: Sensors 10 and 14 are assigned to Target 1, while Sensors 19 and 25 are assigned to Target 2. The assigned sensors navigate from the left portion of the grid, demonstrating that the temporal feasibility component of the bidding mechanism correctly selects sensors capable of arriving before target loss. The min-max objective ensures balanced resource allocation by minimizing the maximum team cost across both targets, preventing one target from receiving disproportionately suboptimal auxiliary sensors. Both handovers complete successfully at $t = 63.4$ time units (Target 1) and $t = 64.1$ time units (Target 2), maintaining continuous tracking throughout the conflict resolution process.

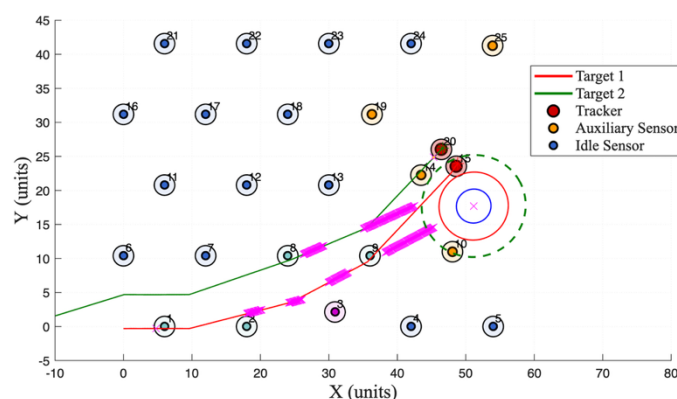


Figure 9. Post-resolution assignments at $t = 57.6$ time units.

5.3. Example 2: Three-Target Coordination with Progressive Velocities

Figure 10 shows system scalability through coordination of three targets with progressively increasing velocities and staggered entry times. Target 1 (red trajectory) enters at $t = 0$ time units with velocity 1.0 units/time unit, Target 2 (green trajectory) enters at $t = 4.0$ time units with velocity 1.1 units/time unit, and Target 3 (blue trajectory) enters at $t = 6.5$ time units with velocity 1.2 units/time unit. This configuration tests the framework's ability to maintain tracking performance under increasing speed demands and temporal complexity arising from overlapping target trajectories and concurrent tracking operations.

The system successfully maintained dual-tracker configurations for all three targets throughout the simulation despite overlapping sensor coverage areas. Distributed EKF estimation converged for all targets within one time unit of initial detection, with final velocity variance components satisfying $P_k(3,3) < 0.006$ and $P_k(4,4) < 0.006$. Figure 11 illustrates this convergence for a representative sensor–target pair, showing both variance components decaying rapidly after initial detection (dotted vertical line). Once both

components drop below the $\sigma_{v,thresh}^2 = 0.006$ (dashed vertical line), the loss prediction becomes active and the handover trigger fires shortly after (solid vertical line). The figure confirms that EKF convergence reliably precedes the handover call, validating the use of covariance-based convergence detection as the trigger condition. The converged estimates enabled stable loss predictions, triggering handover calls with sufficient lead time for successful handovers even at the highest target velocity of 1.2 units/time unit.

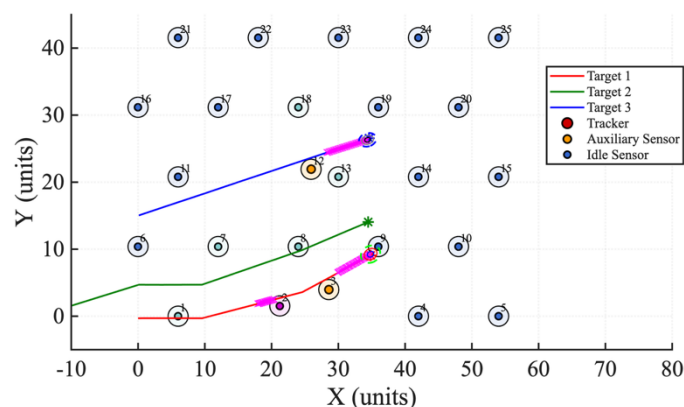


Figure 10. Three-target tracking with progressive velocity increases.

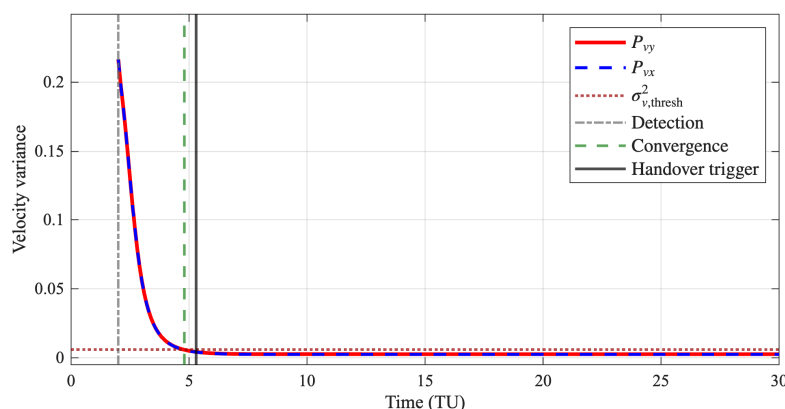


Figure 11. EKF velocity variance convergence for a representative sensor–target pair.

Figure 12 demonstrates the PNG guidance behavior for Sensor 25 during a repositioning mission for Target 3 (velocity 1.2 units/time unit). Three distinct phases are visible:

- *Direct Pursuit Phase:* Upon transitioning to REPOSITIONING state, the sensor moves directly toward the predicted safe handover point using the direct navigation law from Section 4.8, Phase 1.
- *PNG Engagement:* As shared information indicates the target has passed the predicted handover point, the sensor activates PNG guidance (Section 4.8). The trajectory curves show the characteristic smooth pursuit path as PNG nullifies the line-of-sight rate, adapting to the target's actual motion rather than rigidly following the initial prediction.
- *Abort and Return:* Confidence in shared target information drops below $\alpha_{threshold}$ during PNG engagement, triggering the fault-tolerance condition in Section 4.8. The sensor transitions to RETURNING_HOME (blue “Return” trajectory), abandoning the mission and returning to its home position to preserve network topology.

The curved pursuit trajectory demonstrates PNG's ability to compensate for prediction errors and target motion deviations. This adaptive guidance capability contributed to the 76.5% reacquisition success rate among mobilized sensors in the three-target scenario.

Eight successful handovers were executed across the three-target scenario. Of the 25 sensors, 17 (68%) were mobilized for repositioning missions: 13 sensors successfully reacquired targets while four reached the handover vicinity but failed reacquisition due to target trajectory deviations. The 76.5% success rate highlights effective predictive accuracy while acknowledging the inherent uncertainty in forecasting fast-moving target positions. The four unsuccessful missions transitioned to *RETURNING_HOME*, preserving network topology without compromising ongoing tracking operations.

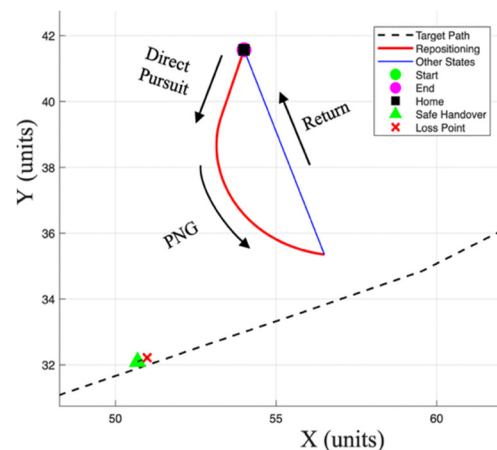


Figure 12. Sensor 25 trajectory during handover mission for Target 3.

This high utilization rate demonstrates effective distributed coordination, with sensors dynamically transitioning between *IDLE*, *DETECTING*, *TRACKING*, *REPOSITIONING*, and *RETURNING_HOME* states based on bidding outcomes and tracker assignments. No sensor exceeded the displacement constraint $d_{max} = d = 12$ units from its home position, confirming that the network preservation penalty ($w_n = 0.4$) successfully balanced mission effectiveness with topology maintenance.

5.4. Ablation Study

To quantify the individual contribution of each system component, five variants are evaluated across ten independent Monte Carlo trials in a four-target scenario. The variants are Full System, No Prediction (reactive handover only: auction triggers after target loss rather than before), No Bidding (nearest-sensor selection replaces multi-objective bidding), No Conflict Resolution (greedy first-come-first-served (FCFS) replaces min-max), and Direct Pursuit (sensor navigates directly to the originally predicted handover point without adapting its trajectory using shared EKF estimates from neighboring trackers). Results are summarized in Table 2 and Figure 13.

Table 2. Ablation Study Results.

Variant	Coverage (%)	Handover Success (%)	Engagement (%)
Full System (Proposed)	75.7 ± 5.8	69.9 ± 5.6	74.0 ± 2.1
No Prediction	49.7 ± 0.5	0.0 ± 0.0	36.0 ± 0.0
No Bidding	59.0 ± 3.1	28.3 ± 4.3	56.8 ± 1.7
No Conflict Res.	75.7 ± 5.8	69.9 ± 5.6	74.0 ± 2.1
Direct Pursuit	71.7 ± 6.5	50.4 ± 6.0	66.4 ± 3.9

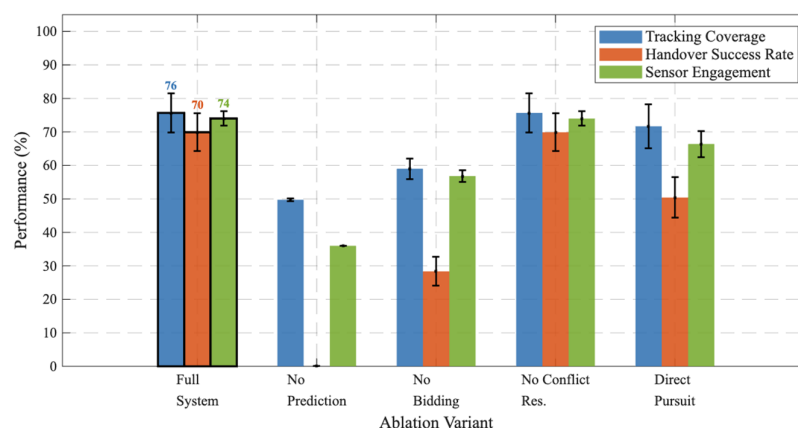


Figure 13. Ablation Bar Chart.

Removing EKF-predictive triggering reduces mean coverage from about 76% to 50% (−26%) and eliminates handover success entirely. In the reactive case, the auction fires only after target loss, leaving insufficient time for any auxiliary sensor to travel to the target’s new position before it exits the monitored region. This confirms that proactive auction initiation is the single largest contributor to system performance. Replacing the multi-objective bid with nearest-sensor selection reduces coverage by about 17% and handover success rate by 42% (70% to 28%), demonstrating that network-aware allocation is critical when targets pass through sensor boundary regions. Replacing shared-EKF adaptive navigation with direct pursuit to the original handover point reduces handover success rate by 20% (70% to 50%), validating that fusion-driven adaptive guidance provides a measurable advantage over fixed-point navigation. No Conflict Resolution produces results identical to the Full System, since the four-target scenario with staggered entry times generates infrequent overlapping Phase 3 conflicts; the min–max guarantee is most consequential in Scenario 1 (Section 5.2), where overlapping conflicts are by design.

5.5. EKF Threshold Sensitivity

Figure 14 plots tracking coverage and handover success rate as functions of $\sigma_{v,thresh}^2$ over the range [0.001, 0.05]. At low values, the system waits for very tight EKF convergence before triggering an auction, which delays handover initiation and reduces coverage, although tighter convergence improves handover prediction quality, as reflected in the higher handover success rate at $\sigma_{v,thresh}^2 = 0.001$. At high values, auctions trigger on poorly converged velocity estimates, producing inaccurate handover predictions and reducing handover success rate. The nominal value of 0.006 is the last stable point before handover success drops further, while maintaining near-peak coverage, making it the best trade-off between early auction triggering and prediction accuracy.

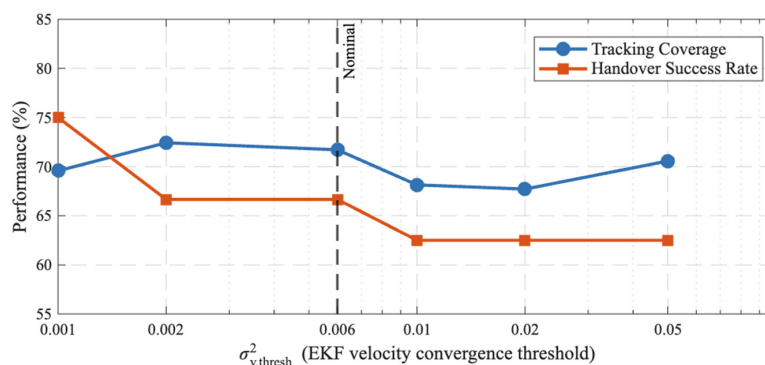


Figure 14. EKF Threshold Sensitivity.

5.6. Robustness to Broadcast Packet Loss

The DES model assumes reliable broadcast of handover calls (Section 5.1). To test robustness to broadcast packet loss, each handover broadcast is dropped independently with probability p_{loss} . This probability is swept over $\{0, 0.1, 0.2, 0.3, 0.4, 0.5\}$, with ten Monte Carlo trials at each value, using the four-target scenario of Section 5.4. At $p_{loss} = 0$, the framework reproduces the full-system results reported in Section 5.4 (about 75% coverage and about 70% handover success), which confirms that the loss model leaves the nominal dynamics unchanged. A dropped call does not reach the affected bidder, so that sensor does not bid in that round, and the auction proceeds with whichever bidders received the call.

Figure 15 reports tracking coverage and handover success rate as a function of p_{loss} , averaged over the ten trials, with error bars showing one standard deviation. Coverage barely changes, holding near 70% to 75% at every loss level. Handover success declines gradually, from 70% with perfect communication to about 45% at a packet loss probability of $p_{loss} = 0.5$ and remains above 60% for $p_{loss} \leq 0.2$. A reactive scheme has no such margin, since any delay in replacement causes an immediate target loss. Two factors explain this tolerance. First, the handover call is broadcast to all sensors; thus, many eligible bidders receive it; an auction loses every candidate only if all of them miss the call at once, which is very unlikely when many sensors are within reach. Second, the target stays tracked through the resilience window (Section 4.7); thus, a lost call does not end tracking right away. A fresh call soon follows: it is issued by a co-tracker when two trackers are active (Section 4.9) or by the next tracker as the target moves on. Each sensor acts on local information only, with no central retry.

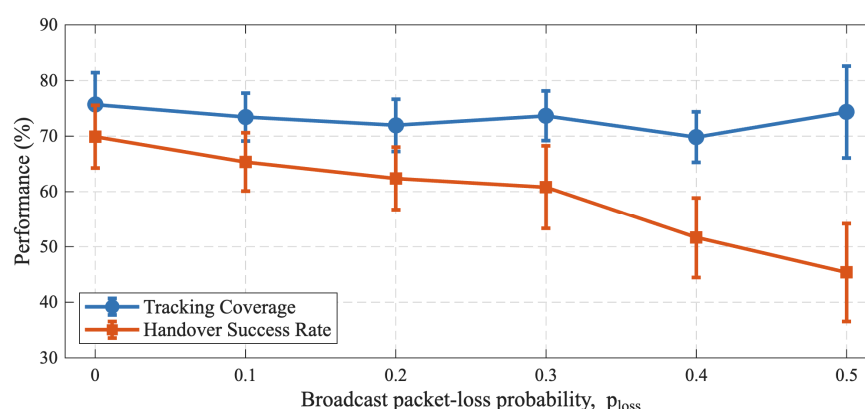


Figure 15. Tracking coverage and handover success rate versus broadcast packet-loss probability p_{loss} (mean $\pm$ one standard deviation over ten Monte Carlo trials).

5.7. Performance Summary

The simulation results collectively demonstrate four key system capabilities. First, the conflict resolution mechanism successfully manages concurrent multi-target handover demands through min-max optimization, as shown in Section 5.2. Second, the dual-tracker configuration provides robustness against individual sensor failures and transient detection losses, supporting continuous tracking throughout all scenarios. Third, the predictive handover framework scales effectively to multiple concurrent targets under progressive velocity increases, achieving 75.7% tracking coverage and 76.5% handover success in the three-target scenario. Fourth, the ablation study confirms that each component contributes independently, as detailed in Section 5.4, while the network preservation component of the bidding mechanism ensures sensors remain within displacement constraints.

6. Conclusions

This paper has presented a distributed coordination framework for proactive multi-target tracking in mobile wireless sensor networks, grounded in discrete-event-system theory. Unlike passive approaches that respond only after detection is lost, the framework anticipates tracking failures through EKF-based uncertainty propagation and proactively repositions auxiliary sensors to predicted handover points before detection is lost.

The framework integrates four complementary components: EKF-convergence-triggered handover initiation, multi-objective competitive bidding with network topology preservation, distributed min–max conflict resolution for concurrent handover demands, and fusion-driven proportional navigation, in which auxiliary sensors navigate on state estimates shared by their neighbors. Simulation results across multiple scenarios demonstrate a 26-percentage-point improvement in tracking coverage over a reactive baseline (75.7% versus 49.7%) and a 76.5% handover success rate under three-target coordination with progressive velocities.

A ten-trial Monte Carlo ablation study isolates the contribution of each component. Removing predictive triggering reduces coverage by 26 percentage points and eliminates handover success entirely, confirming that proactive auction initiation is the dominant performance driver. Nearest-sensor selection in place of multi-objective bidding reduces handover success by 41.6 percentage points, confirming that network-aware allocation is critical when targets traverse sensor boundaries. Replacing shared-EKF adaptive navigation with direct pursuit to the original handover point reduces handover success by 19.5 percentage points, validating the contribution of fusion-driven guidance under uncertain target motion.

One can note that the evaluation of our proposed framework is conducted in a simulation environment with piecewise-linear target trajectories and planar sensor motion and does not model full platform dynamics (attitude, drag, and actuation lag). Communications are assumed to be reliable and with low-latency, justified for the assumed Crazyradio PA link but not representative of congested or adversarial channels. Obstacle avoidance and inter-sensor collision avoidance are not modeled, as the deployment assumes an open monitored region. These simplifications define the scope of the results: open-area, short-range sensing deployments with reliable local communication.

Future work may focus on hardware validation using physical ground robots and UAVs. Key open problems could include the effect of communication latency on auction synchronization (beyond the independent-loss study of Section 5.6); actuator constraints on trajectory-tracking accuracy; energy consumption under extended multi-target missions; and robustness under non-uniform sensor deployments and progressive node failures. A quantitative comparison with alternative multi-target tracking methods, including reactive handover, auction-based allocation, and centralized coordination, with ANOVA-based statistical analysis, could be carried out as the primary objective of a follow-up study.

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References

1. Verma, J.K.; Chhabra, J.K.; Ranga, V. Track Consensus-Based Labeled Multi-Target Tracking in Mobile Distributed Sensor Network. *IEEE Trans. Mob. Comput.* **2024**, *23*, 7351–7362. [\[CrossRef\]](#)
2. Wang, Z.; Benhabib, B. Concurrent Multi-Robot Search of Multiple Missing Persons in Urban Environments. *Robotics* **2025**, *14*, 157. [\[CrossRef\]](#)
3. Kashino, Z.; Nejat, G.; Benhabib, B. Aerial Wilderness Search and Rescue with Ground Support. *J. Intell. Robot. Syst.* **2020**, *99*, 147–163. [\[CrossRef\]](#)
4. Fascista, A. Toward Integrated Large-Scale Environmental Monitoring Using WSN/UAV/Crowdsensing: A Review of Applications, Signal Processing, and Future Perspectives. *Sensors* **2022**, *22*, 1824. [\[CrossRef\]](#) [\[PubMed\]](#)
5. Chen, J.; Abugurain, M.; Dames, P.; Park, S. Distributed Multirobot Multitarget Tracking Using Heterogeneous Limited-Range Sensors. *IEEE Trans. Robot.* **2025**, *41*, 1755–1772. [\[CrossRef\]](#)
6. Dames, P.; Kumar, V. Autonomous Localization of an Unknown Number of Targets without Data Association Using Teams of Mobile Sensors. *IEEE Trans. Autom. Sci. Eng.* **2015**, *12*, 850–864. [\[CrossRef\]](#)
7. Peng, B.; Zhang, Z.; Song, Y. Dynamic Coverage Control for Constrained Mobile Sensor Networks. *IEEE Trans. Autom. Control* **2024**, *69*, 2131–2142. [\[CrossRef\]](#)
8. Zhang, H.; Zhou, X.; Wang, Z.; Yan, H.; Sun, J. Adaptive Consensus-Based Distributed Target Tracking with Dynamic Cluster in Sensor Networks. *IEEE Trans. Cybern.* **2019**, *49*, 1580–1591. [\[CrossRef\]](#) [\[PubMed\]](#)
9. Liang, D.; Shen, H.; Chen, L. Maximum Target Coverage Problem in Mobile Wireless Sensor Networks. *Sensors* **2021**, *21*, 184. [\[CrossRef\]](#) [\[PubMed\]](#)
10. Zhang, C.; Qin, J.; Li, H.; Wang, Y.; Wang, S.; Zheng, W.X. Consensus-Based Distributed Two-Target Tracking over Wireless Sensor Networks. *Automatica* **2022**, *146*, 110593. [\[CrossRef\]](#)
11. Yao, W.; de Marina, H.G.; Sun, Z.; Cao, M. Guiding Vector Fields for the Distributed Motion Coordination of Mobile Robots. *IEEE Trans. Robot.* **2023**, *39*, 1119–1135. [\[CrossRef\]](#)
12. Kumar, A.; Ojha, A.; Yadav, S.; Kumar, A. Real-Time Interception Performance Evaluation of Certain Proportional Navigation Based Guidance Laws in Aerial Ground Engagement. *Intell. Serv. Robot.* **2022**, *15*, 95–114. [\[CrossRef\]](#)
13. Zhou, L.; Tzoumas, V.; Pappas, G.J.; Tokekar, P. Resilient Active Target Tracking with Multiple Robots. *IEEE Robot. Autom. Lett.* **2019**, *4*, 129–136. [\[CrossRef\]](#)
14. Shorinwa, O.; Yu, J.; Halsted, T.; Koufos, A.; Schwager, M. Distributed Multi-Target Tracking for Autonomous Vehicle Fleets. In Proceedings of the 2020 IEEE International Conference on Robotics and Automation (ICRA), Paris, France, 31 May–August 2020; pp. 3495–3501.
15. Chen, J.; Dames, P. Distributed Multi-Target Tracking for Heterogeneous Mobile Sensing Networks with Limited Field of Views. In Proceedings of the 2021 IEEE International Conference on Robotics and Automation (ICRA), Xi'an, China, 30 May–5 June 2021; pp. 9058–9064.
16. Wasim, S.; Kashino, Z.; Nejat, G.; Benhabib, B. Directional-Sensor Network Deployment Planning for Mobile-Target Search. *Robotics* **2020**, *9*, 82. [\[CrossRef\]](#)
17. Vilela, J.; Kashino, Z.; Ly, R.; Nejat, G.; Benhabib, B. A Dynamic Approach to Sensor Network Deployment for Mobile-Target Detection in Unstructured, Expanding Search Areas. *IEEE Sens. J.* **2016**, *16*, 4405–4417. [\[CrossRef\]](#)
18. Kashino, Z.; Nejat, G.; Benhabib, B. A Hybrid Strategy for Target Search Using Static and Mobile Sensors. *IEEE Trans. Cybern.* **2020**, *50*, 856–868. [\[CrossRef\]](#) [\[PubMed\]](#)
19. Kashino, Z.; Kim, J.Y.; Nejat, G.; Benhabib, B. Spatiotemporal Adaptive Optimization of a Static-Sensor Network via a Non-Parametric Estimation of Target Location Likelihood. *IEEE Sens. J.* **2017**, *17*, 1479–1492. [\[CrossRef\]](#)
20. Chen, J.; Dames, P. Collision-Free Distributed Multi-Target Tracking Using Teams of Mobile Robots with Localization Uncertainty. In Proceedings of the 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Las Vegas, NV, USA, 24 October 2020–24 January 2021; pp. 6968–6974.
21. Khalkhali, M.B.; Vahedian, A.; Sadoghi Yazdi, H. Multi-Target State Estimation Using Interactive Kalman Filter for Multi-Vehicle Tracking. *IEEE Trans. Intell. Transp. Syst.* **2020**, *21*, 1131–1144. [\[CrossRef\]](#)
22. Tang, M.; Liu, M.; Zhang, S.; Zheng, R.; Dong, S. Distributed Target Tracking with Fading Channels Over Underwater Acoustic Sensor Networks. *IEEE Internet Things J.* **2024**, *11*, 13980–13994. [\[CrossRef\]](#)
23. Zhu, H.; Luo, J.; Luo, M.; Minane, J. A Recursive Robust Set-Membership Estimator for WSN-Assisted Moving Targets Tracking with UBB Anchor Location Uncertainty. *IEEE Trans. Veh. Technol.* **2023**, *72*, 6547–6557. [\[CrossRef\]](#)
24. Hu, Y.; Pan, Q.; Deng, B.; Guo, Z.; Li, M.; Chen, L. Variational Bayesian Algorithms for Maneuvering Target Tracking with Nonlinear Measurements in Sensor Networks. *Entropy* **2023**, *25*, 1235. [\[CrossRef\]](#) [\[PubMed\]](#)
25. Kamal, A.T.; Bappy, J.H.; Farrell, J.A.; Roy-Chowdhury, A.K. Distributed Multi-Target Tracking and Data Association in Vision Networks. *IEEE Trans. Pattern Anal. Mach. Intell.* **2016**, *38*, 1397–1410. [\[CrossRef\]](#) [\[PubMed\]](#)

26. Penin, B.; Giordano, P.R.; Chaumette, F. Vision-Based Reactive Planning for Aggressive Target Tracking While Avoiding Collisions and Occlusions. *IEEE Robot. Autom. Lett.* **2018**, *3*, 3725–3732. [\[CrossRef\]](#)
27. Bai, X.; Fielbaum, A.; Kronmüller, M.; Knoedler, L.; Alonso-Mora, J. Group-Based Distributed Auction Algorithms for Multi-Robot Task Assignment. *IEEE Trans. Autom. Sci. Eng.* **2023**, *20*, 1292–1303. [\[CrossRef\]](#)
28. Chen, Y.; Rosolia, U.; Ames, A.D. Decentralized Task and Path Planning for Multi-Robot Systems. *IEEE Robot. Autom. Lett.* **2021**, *6*, 4337–4344. [\[CrossRef\]](#)
29. Lee, D.-H.; Zaheer, S.A.; Kim, J.-H. A Resource-Oriented, Decentralized Auction Algorithm for Multirobot Task Allocation. *IEEE Trans. Autom. Sci. Eng.* **2015**, *12*, 1469–1481. [\[CrossRef\]](#)
30. Bakhtari, A.; Naish, M.D.; Eskandari, M.; Croft, E.A.; Benhabib, B. Active-Vision-Based Multisensor Surveillance—An Implementation. *IEEE Trans. Syst. Man Cybern. Part C (Appl. Rev.)* **2006**, *36*, 668–680. [\[CrossRef\]](#)
31. Ong, P.; Capelli, B.; Sabattini, L.; Cortés, J. Nonsmooth Control Barrier Function Design of Continuous Constraints for Network Connectivity Maintenance. *Automatica* **2023**, *156*, 111209. [\[CrossRef\]](#)
32. Gosrich, W.; Mayya, S.; Narayan, S.; Malencia, M.; Agarwal, S.; Kumar, V. Multi-Robot Coordination and Cooperation with Task Precedence Relationships. In Proceedings of the 2023 IEEE International Conference on Robotics and Automation (ICRA), London, UK, 29 May–2 June 2023; pp. 5800–5806.
33. Notomista, G.; Mayya, S.; Emam, Y.; Kroninger, C.; Bohannon, A.; Hutchinson, S.; Egerstedt, M. A Resilient and Energy-Aware Task Allocation Framework for Heterogeneous Multirobot Systems. *IEEE Trans. Robot.* **2022**, *38*, 159–179. [\[CrossRef\]](#)
34. Ghzouli, R.; Berger, T.; Johnsen, E.B.; Wasowski, A.; Dragule, S. Behavior Trees and State Machines in Robotics Applications. *IEEE Trans. Softw. Eng.* **2023**, *49*, 4243–4267. [\[CrossRef\]](#)
35. Khalilpour Akram, V.; Akusta Dagdeviren, Z.; Dagdeviren, O.; Challenger, M. PINC: Pickup Non-Critical Node Based k-Connectivity Restoration in Wireless Sensor Networks. *Sensors* **2021**, *21*, 6418. [\[CrossRef\]](#) [\[PubMed\]](#)
36. Sanni, O. Advanced Teaming with the Consensus-Based Bundle Algorithm. In Proceedings of the 2021 7th International Conference on Control, Automation and Robotics (ICCAR), Singapore (Virtual), 23–26 April 2021; pp. 65–70.
37. Zhang, J.; Khalgui, M.; Li, Z.; Frey, G.; Mosbahi, O.; Salah, H.B. Reconfigurable Coordination of Distributed Discrete Event Control Systems. *IEEE Trans. Control Syst. Technol.* **2015**, *23*, 323–330. [\[CrossRef\]](#)
38. Roszkowska, E.; Makowski-Czerski, P.; Janiec, L. Multi-Level Control for Multiple Mobile Robot Systems. *Discret. Event Dyn. Syst.* **2023**, *33*, 425–453. [\[CrossRef\]](#)
39. Borg, J.M.; Mehrandezh, M.; Fenton, R.G.; Benhabib, B. Navigation-Guidance-Based Robotic Interception of Moving Objects in Industrial Settings. *J. Intell. Robot. Syst.* **2002**, *33*, 1–23. [\[CrossRef\]](#)
40. Mehrandezh, M.; Sela, N.M.; Fenton, R.G.; Benhabib, B. Robotic Interception of Moving Objects Using an Augmented Ideal Proportional Navigation Guidance Technique. *IEEE Trans. Syst. Man Cybern. Part A Syst. Hum.* **2000**, *30*, 238–250. [\[CrossRef\]](#)
41. Ghaderi, H.; Yadegar, M.; Meskin, N.; Noorizadeh, M. A Novel Proportional Navigation Based Method for Robotic Interception Planning with Final Velocity Control. *IEEE Access* **2021**, *9*, 106428–106440. [\[CrossRef\]](#)
42. Wang, X.; Tan, G.; Dai, Y.; Lu, F.; Zhao, J. An Optimal Guidance Strategy for Moving-Target Interception by a Multirotor Unmanned Aerial Vehicle Swarm. *IEEE Access* **2020**, *8*, 121650–121664. [\[CrossRef\]](#)
43. Tong, B.; Liu, J.; Duan, H. Multi-UAV Interception Inspired by Harris’ Hawks Cooperative Hunting Behavior. In Proceedings of the 2021 IEEE International Conference on Robotics and Biomimetics (ROBIO), Sanya, China, 27–31 December 2021; pp. 1656–1661.
44. de Souza, C.; Newbury, R.; Cosgun, A.; Castillo, P.; Vidolov, B.; Kulić, D. Decentralized Multi-Agent Pursuit Using Deep Reinforcement Learning. *IEEE Robot. Autom. Lett.* **2021**, *6*, 4552–4559. [\[CrossRef\]](#)
45. Li, J.; Ning, Z.; He, S.; Lee, C.-H.; Zhao, S. Three-Dimensional Bearing-Only Target Following via Observability-Enhanced Helical Guidance. *IEEE Trans. Robot.* **2023**, *39*, 1509–1526. [\[CrossRef\]](#)
46. Stiffler, N.M.; O’Kane, J.M. Asymptotically-Optimal Multi-Robot Visibility-Based Pursuit-Evasion. In Proceedings of the 2024 IEEE International Conference on Robotics and Automation (ICRA), Yokohama, Japan, 13–17 May 2024; pp. 10366–10373.
47. Li, J.; Tao, Y.; Yuan, K.; Tang, R.; Hu, Z.; Yan, W.; Liu, S. Fruchterman–Reingold Hexagon Empowered Node Deployment in Wireless Sensor Network Application. *Sensors* **2022**, *22*, 5179. [\[CrossRef\]](#) [\[PubMed\]](#)
48. Yinjun, Z. An Adaptive Hexagonal Deployment Model for Resilient Wireless Sensor Networks in Precision Agriculture. *Sci. Rep.* **2024**, *14*, 24078. [\[CrossRef\]](#) [\[PubMed\]](#)
49. Zarchan, P. *Tactical and Strategic Missile Guidance*, 6th ed.; American Institute of Aeronautics and Astronautics, Inc.: Reston, VA, USA, 2012. [\[CrossRef\]](#)
50. Macwan, A.; Nejat, G.; Benhabib, B. Target-Motion Prediction for Robotic Search and Rescue in Wilderness Environments. *IEEE Trans. Syst. Man Cybern. Part B (Cybern.)* **2011**, *41*, 1287–1298. [\[CrossRef\]](#) [\[PubMed\]](#)
51. Ku, S.Y.; Nejat, G.; Benhabib, B. Wilderness Search for Lost Persons Using a Multimodal Aerial-Terrestrial Robot Team. *Robotics* **2022**, *11*, 64. [\[CrossRef\]](#)

52. Pichierri, L.; Testa, A.; Notarstefano, G. CrazyChoir: Flying Swarms of Crazyflie Quadrotors in ROS 2. *IEEE Robot. Autom. Lett.* **2023**, *8*, 4713–4720. [[CrossRef](#)]
53. Bitcraze, A.B. *Crazyflie 2.1 Datasheet, Rev. 3*; Bitcraze AB: Malmö, Sweden, 2024.

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