

# Optimization of the lifespan of wireless sensor networks by coupling a linear model and a multi-agent system

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## ABSTRACT

This article proposes a hybrid approach combining a mixed-integer linear optimization model and a multi-agent system to maximize the lifespan of wireless sensor networks monitoring mobile targets. The mathematical model optimizes sensor activation scheduling across multiple missions, while the multi-agent system dynamically manages interactions between sensors and targets, which are treated as active agents. The results show a significant improvement in the network's lifespan, thanks to a smarter, more adaptive sensor activation. The proposed approach achieves a 25% reduction in energy consumption compared to traditional methods while maintaining complete coverage of mobile targets.

**Keywords:** Wireless sensor networks, Linear optimization, Multi-agent system, Mobile target, Lifespan, Activation planning.

**2000 Mathematics Subject Classification:** 90C05 90C11 -90C11.

## 1 Introduction

The rapid evolution of electronic technologies and advancements in energy storage have enabled the development of small, autonomous sensors with low manufacturing costs. The rapid evolution of electronic technologies and advancements in energy storage have enabled the development of small, autonomous sensors with low manufacturing costs (Siljepcevic and Potkonjak, 2001). These devices, capable of collecting various information within their range of action and communicating with other sensors, have given rise to wireless sensor networks, a particularly promising and coveted technology for many modern applications (Amutha, Sharma and Nagar, 2020). Among the most significant application areas are vehicle tracking, battlefield monitoring, environmental monitoring, and the security of critical infrastructure. These scenarios often involve monitoring mobile targets across large areas, posing major challenges for continuous coverage and energy optimization.

In a wireless sensor network, the network lifespan is defined as the period during which all targets are satisfactorily covered (Zhao and Gurusamy, 2008). This lifespan is intrinsically limited by the energy available in the sensor batteries, which are generally non-rechargeable once

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deployed in hard-to-reach areas. The functionality of the sensors thus crucially depends on the autonomy of their batteries, making energy management a central issue for the sustainability of these systems (Liang, Shen and Chen, 2021). Faced with this constraint, numerous algorithms and protocols have been developed to optimize energy consumption, but the complexity of the problem requires increasingly sophisticated approaches (Elhabyan, Shi and St-Hilaire, 2019). When monitoring mobile or fixed targets, maximizing the lifespan of the sensor network represents one of the most studied research topics (Boukerche and Sun, 2018). The formulation of this problem fundamentally relies on the notions of connectivity and coverage (Nguyen, Liu and Wang, 2019). A subset of sensors can cover all targets, making simultaneous activation of all sensors unnecessary at all times. Only the faces containing the sensors to be activated need to be considered for each mission, thus allowing for substantial energy savings (Berman, Calinescu, Shah and Zelikovsky, 2005). This observation underscores the crucial importance of intelligent planning for sensor activation.

The ability to monitor targets in a vast area at a lower cost is one of the key advantages of wireless sensor networks (Farsi, Elhosseini, Badawy, Ali and Eldin, 2019). These networks are often composed of inexpensive devices that can be deployed in large numbers, sometimes even dropped from a plane or helicopter in areas where surveillance infrastructure is weak or nonexistent. Typically, autonomous sensors are powered by batteries with a finite lifespan. Given that many areas of the region to be monitored are covered by multiple sensors, it is not practical to activate all the sensors simultaneously to monitor all the targets. Assuming that the targets' trajectories are known in advance, our goal is to plan a sequence of sensor activities that preserves, to the extent possible, the sensor network's existing capacity to later monitor certain regions of interest for the network operator.

The sensor network is now used in a context involving multiple missions, with the initial objective being to preserve the network for future surveillance operations while focusing on solutions that require minimal energy to accomplish the current task (Jishy, 2011). Energy consumption is one of the most important criteria, since sensors are generally equipped with non-rechargeable batteries. It is also one of the most studied aspects and the subject of a very abundant literature. Emblematic protocols such as DCTC (Dynamic Convoy Tree-based Collaboration) successively construct minimal-cost trees by tracking the movements of a target (Zhao and Gurusamy, 2008). Many protocols meeting this criterion rely on LEACH (Low Energy Adaptive Clustering Hierarchy) (Handy, Haase and Timmermann, 2002) or HEED (Hybrid Energy-Efficient Distributed) (Younis and Fahmy, 2004). Better tracking accuracy can be achieved by activating more sensors or correctly predicting the behavior of the targets (Yang and Sikdar, 2003; Xu, Winter and Lee, 2004). A good target-prediction technique can help activate fewer sensors and conserve battery power.

Given an area of interest within the surveillance zone, the first step is to determine the minimum trajectory required to cover all targets. The coverage guarantee is the minimum duration at the end of the current mission during which the sensor network can monitor any point of interest. Thus, knowing the optimal trajectory of the targets, the objective is now to minimize the total energy consumed by the sensors to accomplish the current surveillance mission. We first consider the case where the targets' trajectories are established and known, and then assume

that they are subject to uncertainty, with their actual positions deviating from their predicted positions by a certain distance.

Traditional approaches are mainly divided into two categories: centralized optimization methods and distributed approaches. Centralized methods, often based on sophisticated mathematical models such as mixed-integer linear programming (Li, Bai, Gu, Yan and Luo, 2018), offer optimal solutions from a global perspective but lack flexibility in the face of dynamic environmental changes. On the contrary, distributed approaches, particularly multi-agent systems (Elhoseny and Hassanien, 2019), excel at local adaptation and robustness to failures but can lead to suboptimal solutions due to the lack of a global perspective. This dichotomy represents a fundamental limitation in the existing literature (Woolley and Martinoli, 2022).

Our work aims to overcome this limitation by proposing an innovative hybrid approach that integrates the advantages of both paradigms. We are developing a mixed-integer linear optimization model for the strategic planning of sensor activation across multiple missions, coupled with a multi-agent system in which targets are treated as active agents capable of influencing activation decisions. This integration allows fine-tuning of the targets' dynamic behavior while maintaining overall network lifespan optimization.

The originality of our approach lies in several major contributions. First, we extend the existing mathematical model to explicitly incorporate multiple missions with cumulative energy constraints. Secondly, we model the targets as intelligent agents with adaptive behaviors, breaking with the traditional paradigm of passive targets (Yang, Li and Chen, 2010). Thirdly, we design robust coupling mechanisms between central optimization and distributed execution, enabling harmonious coordination across different levels of decision-making.

The experimental results demonstrate that our hybrid approach outperforms purely centralized or purely distributed methods, with a 32% improvement in network lifespan compared to purely distributed approaches (Srivastava, Tripathi, Singh and Son, 2020) and a 24% reduction in energy consumption compared to traditional centralized methods (Elkamel, Messouadi and Cherif, 2019). Our method maintains a coverage rate of over 99% even in the face of evasive target behaviors, demonstrating exceptional robustness in demanding operational conditions (Mahmood, Seah and Welch, 2015). These exceptional performances validate the effectiveness of our integration and pave the way for new perspectives in the intelligent monitoring of mobile targets.

The rest of this article is organized as follows. Section 2 presents a comprehensive state-of-the-art review of existing work on the optimization of sensor networks and multi-agent systems. Section 3 details our mixed-integer linear model for lifespan optimization. Section 4 introduces the architecture of our multi-agent system with active target agents. Section 5 explains the integration of the two approaches and the mechanisms for coupling. Section 6 presents the complete experimental results and their analysis. Finally, section 7 concludes the article and discusses future perspectives.

## 2 State of the art

### 2.1 Mathematical optimization in WSNs

Wireless sensor networks (WSNs) have been the subject of numerous research efforts aimed at optimizing their lifespan, primarily through sophisticated mathematical models. The foundational works focused on the fundamental problems of coverage and connectivity (Boukerche and Sun, 2018; ?). Berman et al. (Berman et al., 2005) introduced the innovative concept of "faces" to model coverage areas, an approach we adopt and extend in our model. This geometric modeling allows partitioning the surveillance space into distinct regions covered by the same set of sensors, thereby reducing the complexity of the optimization problem.

Iconic protocols such as LEACH (Low-Energy Adaptive Clustering Hierarchy) (Handy et al., 2002) and HEED (Hybrid Energy-Efficient Distributed Clustering) (Younis and Fahmy, 2004) have demonstrated the importance of hierarchical approaches for energy conservation. These protocols rely on cluster formation and sensor role rotation to balance energy consumption. However, they have limitations in scenarios with moving targets, where spatial and temporal dynamics require more fine-grained planning.

More recently, advanced mathematical models have emerged to address specific issues. Zhao and Gurusamy (Zhao and Gurusamy, 2008) proposed dynamic convoy trees (DCTC - Dynamic Convoy Tree-based Collaboration) for the efficient tracking of mobile targets. Their approach periodically recalculates minimum-cost spanning trees by tracking target movements, but it neglects long-term energy constraints across multiple missions.

Elkamel et al. (Elkamel et al., 2019) and Srivastava et al. (Srivastava et al., 2020) respectively addressed the issues of "hot spots" and congestion in WSNs. Their work highlights the importance of load balancing and traffic management to extend the network's lifespan. Nevertheless, these approaches primarily focus on communication aspects rather than the joint optimization of coverage and energy.

Liang et al. (Liang et al., 2021) made a significant advancement with their model for maximum coverage of mobile targets. Their mathematical formulation incorporates the mobility of the targets but remains limited to a single-objective optimization. Similarly, the work of Nguyen et al. (Nguyen et al., 2019) on weighted coverage and sensor connectivity provides significant theoretical guarantees, but its applicability in real-world scenarios with uncertainties remains to be demonstrated.

### 2.2 Multi-agent systems for WSNs

Multi-agent systems (MAS) offer a promising alternative for the decentralized management of WSNs (Elhoseny and Hassanien, 2019). Unlike centralized approaches, MAS allow for flexible coordination between sensors and robust adaptation to environmental changes. This feature is particularly crucial in dynamic environments where operational conditions change rapidly.

The pioneering work of Yang et al. (Yang and Sikdar, 2003; ?) and Xu et al. (Xu et al., 2004) explored predictive protocols based on target behavior. Their approach uses trajectory-prediction models to anticipate target movements and proactively activate the relevant sensors.

Although it effectively reduces detection latency, this method can lead to excessive activations when predictions are inaccurate.

More recently, Elhoseny and Hassanien (Elhoseny and Hassanien, 2019) proposed a comprehensive MAS framework for dynamic WSNs. Their architecture distinguishes different types of agents (sensors, coordinators, managers) and integrates self-organization mechanisms. However, their approach lacks a global optimization formulation to guide agents' local decisions.

A notable contribution comes from the work of Elhabyan et al. (Elhabyan et al., 2019) who systematically analyzed coverage protocols for WSNs. Their comprehensive review identifies emerging trends, notably the integration of artificial intelligence and machine learning techniques. Nevertheless, they find that few protocols effectively combine central optimization and distributed decision-making.

MASs have also been used to manage uncertainty in WSNs. Mahmood et al. (Mahmood et al., 2015) developed reliability models that account for sensor failures and malicious attacks. Their approach uses monitoring agents to detect anomalies and dynamically reconfigure the network. However, the computational complexity of their solution limits its large-scale applicability.

### **2.3 Hybrid approaches and emerging trends**

Recent literature shows a growing trend toward hybrid approaches that combine mathematical optimization and distributed techniques. Amutha et al. (Amutha et al., 2020) in their comprehensive review of WSNs strategies identify the coupling between central planning and distributed execution as a promising avenue for future research.

Multi-objective optimization-based protocols have gained popularity for addressing trade-offs among coverage, lifespan, and quality of service. Li et al. (Li et al., 2018) proposed a clustering-based routing model based on integer programming for heterogeneous WSNs. Their formulation simultaneously considers several conflicting objectives, but it remains limited to static networks.

An interesting innovation comes from the work of Oracevic and Ozdemir (Oracevic and Ozdemir, 2014) on secure target tracking. Their approach integrates security considerations into tracking protocols, using cryptographic techniques to protect location data. However, this increased security comes at the expense of energy consumption.

The scalability of WSNs protocols has been particularly studied by Kung and Vlah (Kung and Vlah, 2003). Their work on efficient location tracking has laid important foundations for large-scale networks, but it does not explicitly address long-term energy issues.

### **2.4 Identified gaps and positioning of our contribution**

The in-depth analysis of the literature reveals several significant limitations in the existing approaches. Indeed, the rigidity of optimization models, which constitute traditional mathematical formulations, although optimal in theory, is unable to adapt to the unpredictable behaviors of targets and the dynamic changes in the environment. Their centralized nature makes them vulnerable to failures and limits their applicability in realistic scenarios.

The shortsightedness of multi-agent approaches, on the other hand, stems from the fact that purely distributed systems lack a long-term global perspective. Local decisions, although adaptive, can lead to suboptimal solutions in terms of overall network lifespan and quality of service. The artificial separation between planning and execution is common in many works that treat them as distinct phases, without an effective mechanism for real-time feedback and adjustment. This dichotomy reduces operational efficiency in uncertain environments.

The passive treatment of targets stems from the fact that mobile targets are generally considered passive entities to be monitored rather than influential actors whose behavior can significantly affect network performance. This restrictive view overlooks opportunities for adaptive optimization.

The lack of multi-mission optimization stems from the fact that few studies explicitly address lifespan optimization across successive missions, accounting for cumulative energy constraints and battery degradation.

Our work aims to bridge these gaps through an integrated approach that combines the advantages of mathematical optimization and multi-agent systems. More specifically, our main contributions are:

- A **mixed-integer linear optimization model** that strategically plans the activation of sensors over multiple missions, explicitly considering the progressive reduction in battery life.
- A **multi-agent architecture** where the targets are modeled as active agents capable of influencing activation decisions, allowing for fine adaptation to dynamic behaviors.
- A **tight coupling mechanism** between central optimization and distributed execution, with feedback loops to adjust the plan based on real-time observations.
- A **robust formulation** that incorporates safety margins to manage localization uncertainties and trajectory deviations.

Unlike existing approaches, our method offers an optimal compromise between overall efficiency (guaranteed by the optimization model) and local adaptability (ensured by the multi-agent system). This synergy enables high coverage while significantly extending the network's lifespan, even against mobile targets with unpredictable behavior.

### 3 Linear model with mixed variables

This section presents a mixed-integer linear programming (MILP) model to maximize the lifespan of a wireless sensor network monitoring mobile targets. The problem is to determine an optimal activation plan for the sensors across several successive missions, accounting for energy, coverage, and temporal constraints.

The general formulation of the problem considers a set of sensors  $\mathcal{I} = \{1, \dots, I\}$  randomly deployed in a surveillance area and a set of missions  $\mathcal{M} = \{1, \dots, M\}$  to be accomplished. Each sensor  $i \in \mathcal{I}$  has an initial lifespan  $V_i$  representing the total energy available in its battery.

The main objective is to maximize the network's residual lifespan after all scheduled missions are executed.

Our model uses multiple sets and parameters to capture the problem's complexity. The fundamental sets include  $\mathcal{I}$  for sensors,  $\mathcal{J}$  for mobile targets,  $\mathcal{M}$  for surveillance missions,  $\mathcal{F}$  for coverage faces formed by the intersection of sensor detection zones, and  $\mathcal{K}$  for time windows defined by the transition moments between faces. The sensor-related parameters include the initial lifespan  $V_i$ , the bounds  $V_m^{\min}$  and  $V_m^{\max}$  of the lifespan for each mission, the reduction rate  $\alpha_{i,(m-1)}$  of the lifespan after each mission, the coverage radius  $R_i$ , and the power consumption  $P_i^{\text{active}}$  and  $P_i^{\text{sleep}}$  in active and sleep modes. The parameters related to targets and missions include the duration  $\Delta_m^k$  of the time windows, the total time horizon  $H_m$  of each mission, the minimum and maximum monitoring times  $T_m^{\min,j}$  and  $T_m^{\max,j}$  for each target, and the position function  $P_j(t)$  of the targets. The coverage and face parameters define the subsets  $\mathcal{I}(f)$  of sensors covering each face  $f$ , the subsets  $\mathcal{F}(k)$  of active faces during each window  $k$ , the minimum and maximum coverage durations  $D_m^{\min,k}$  and  $D_m^{\max,k}$ , and the set  $\mathcal{F}^*$  of faces of interest traversed by the targets. The temporal discretization parameters include the transition moments  $t_j^k$  between faces, the temporal margin parameter  $\rho$  to handle uncertainties, and the lower bound  $\beta_m^k$  on the minimum number of sensors to activate.

Our model uses four types of decision variables to capture the combinatorial and continuous aspects of the problem. The continuous variables include  $v_{i,m}$  for the remaining lifespan of the sensor  $i$  after the mission  $m$ ,  $y_{i,m}^{k,f}$  for the effective activation time of the sensor  $i$  to cover face  $f$  during window  $k$  of mission  $m$ ,  $d_m^{k,f}$  for the total required coverage duration for each face, and  $t_{j,m}$  for the minimum effective surveillance time for each target. The binary variables include  $x_{i,m}^{k,f}$  for sensor activation and  $z_{i,m}$  for mission participation. The integer variables  $\tau_{j,m}^k$  represent the transition ticks of the targets.

The main objective function aims to maximize the total residual lifespan of the network after the completion of all missions according to the equation:

$$\max \sum_{i=1}^I \sum_{m=1}^M v_{i,m} \quad (3.1)$$

This formulation is equivalent to minimizing total energy consumption while ensuring sufficient energy is preserved for future use. An alternative objective function could minimize the lifespan across all sensors, but the main formulation is preferred for its linearity and balance between fairness and overall efficiency.

The model incorporates several fundamental constraints to ensure the solutions are feasible and optimal. The energy conservation constraint links the remaining lifespan of a sensor to its cumulative activation time according to the equation:

$$\sum_{k=1}^K \sum_{f=1}^F y_{i,m}^{k,f} + v_{i,m} = V_i \quad \forall i \in \mathcal{I}, \forall m \in \mathcal{M} \quad (3.2)$$

This equation expresses that the total initial energy  $V_i$  is distributed between the cumulative activation time and the residual energy. To linearize the products of variables in this constraint, we introduce the additional constraints:

$$y_{i,m}^{k,f} \leq d_m^{k,f} \quad \forall i \in \mathcal{I}, \forall k \in \mathcal{K}, \forall f \in \mathcal{F}, \forall m \in \mathcal{M} \quad (3.3)$$

$$y_{i,m}^{k,f} \leq V_{i,m} \cdot x_{i,m}^{k,f} \quad \forall i \in \mathcal{I}, \forall k \in \mathcal{K}, \forall f \in \mathcal{F}, \forall m \in \mathcal{M} \quad (3.4)$$

$$y_{i,m}^{k,f} \geq d_m^{k,f} - V_{i,m} \cdot (1 - x_{i,m}^{k,f}) \quad \forall i \in \mathcal{I}, \forall k \in \mathcal{K}, \forall f \in \mathcal{F}, \forall m \in \mathcal{M} \quad (3.5)$$

The continuous coverage of each target is ensured by the constraint:

$$\sum_{i \in \mathcal{I}(f)} x_{i,m}^{k,f} \geq 1 \quad \forall f \in \mathcal{F}(k), \forall k \in \mathcal{K}, \forall m \in \mathcal{M} \quad (3.6)$$

This constraint ensures that at least one sensor covering face  $f$  is activated at each time window when  $f$  is occupied by a target. The progressive degradation of the batteries is modeled by:

$$v_{i,m} \leq \alpha_{i,(m-1)} \cdot v_{i,(m-1)} \quad \forall i \in \mathcal{I}, \forall m \in \mathcal{M} \setminus \{1\} \quad (3.7)$$

where  $\alpha_{i,(m-1)} \in [0, 1]$  represents the energy retention rate after each mission. The balance between activation time and window duration is ensured by:

$$\sum_{f=1}^F d_m^{k,f} = \Delta_m^k \quad \forall k \in \mathcal{K}, \forall m \in \mathcal{M} \quad (3.8)$$

The minimum service quality for each target is guaranteed by:

$$\sum_{i=1}^I v_{i,m} \geq \sum_{j=1}^J t_{j,m} \quad \forall m \in \mathcal{M} \quad (3.9)$$

The synchronization between input and output ticks is ensured by:

$$\tau_{j,m}^k + \tau_{j,m}^{k+1} = 0 \quad \forall j \in \mathcal{J}, \forall k \in \mathcal{K} \setminus \{K\}, \forall m \in \mathcal{M} \quad (3.10)$$

To improve robustness against failures, we introduce a redundancy constraint:

$$\sum_{i \in \mathcal{I}(f)} x_{i,m}^{k,f} \geq 1 + \delta_m^{k,f} \quad \forall f \in \mathcal{F}^*, \forall k \in \mathcal{K}, \forall m \in \mathcal{M} \quad (3.11)$$

where  $\delta_m^{k,f} \geq 0$  is a redundancy parameter adjustable according to the critical importance of the face. The continuity of monitoring during transitions between faces is ensured by:

$$\sum_{i \in \mathcal{I}(f) \cup \mathcal{I}(f')} x_{i,m}^{k,f} \geq 1 \quad \forall (f, f') \in \mathcal{E}, \forall k \in \mathcal{K}, \forall m \in \mathcal{M} \quad (3.12)$$

where  $\mathcal{E}$  represents the set of pairs of adjacent faces. The operational limits of the sensors are respected through:

$$\sum_{k=1}^K \sum_{f=1}^F y_{i,m}^{k,f} \leq \gamma_i \cdot V_i \quad \forall i \in \mathcal{I}, \forall m \in \mathcal{M} \quad (3.13)$$

where  $\gamma_i \in [0, 1]$  represents the maximum fraction of energy that can be used during a mission.

The model also incorporates additional constraints for specific scenarios. To minimize interference between neighboring sensors, we have:

$$\sum_{i \in \mathcal{N}(l)} x_{i,m}^{k,f} \leq \eta_l \quad \forall l \in \mathcal{L}, \forall k \in \mathcal{K}, \forall f \in \mathcal{F}, \forall m \in \mathcal{M} \quad (3.14)$$

where  $\mathcal{N}(l)$  is the neighborhood of sensor  $l$  and  $\eta_l$  is the maximum number of sensors that can be activated simultaneously. To balance the load between sensors, we use:

$$\left| \frac{\sum_{k,f} y_{i,m}^{k,f}}{V_i} - \frac{\sum_{k,f} y_{j,m}^{k,f}}{V_j} \right| \leq \epsilon \quad \forall i, j \in \mathcal{I}, i \neq j, \forall m \in \mathcal{M} \quad (3.15)$$

For missions with temporal dependencies, we impose:

$$\sum_{k=1}^K \sum_{f=1}^F y_{i,m}^{k,f} \leq \mu_{i,m} \cdot \sum_{k=1}^K \sum_{f=1}^F y_{i,m-1}^{k,f} \quad \forall i \in \mathcal{I}, \forall m \in \mathcal{M} \setminus \{1\} \quad (3.16)$$

Our MILP formulation has well-defined complexity characteristics. The total number of variables in the model is given by:

$$N_{\text{variables}} = I \cdot M \cdot (1 + K \cdot F) + M \cdot K \cdot F + J \cdot M + J \cdot M \cdot K \quad (3.17)$$

The total number of constraints is approximately:

$$N_{\text{constraints}} = I \cdot M \cdot (1 + 3 \cdot K \cdot F) + M \cdot K \cdot F + J \cdot M \cdot K \quad (3.18)$$

The polyhedron of feasible solutions of the relaxed model is bounded and non-empty if  $V_i \geq \sum_{m=1}^M \sum_{k=1}^K \Delta_m^k$  for all  $i \in \mathcal{I}$ , a condition that ensures there is enough energy to cover all the time windows. The upper bound of the objective function is given by:

$$\sup(V) = \sum_{i=1}^I \sum_{m=1}^M v_{i,m} - \sum_{m=1}^M \sum_{k=1}^K \beta_m^k \cdot \Delta_m^k \quad (3.19)$$

where  $\beta_m^k$  is the lower bound of the minimum number of sensors to activate.

The model can be extended to account for uncertainties in the positions of the targets through a robust formulation:

$$\sum_{i \in \mathcal{I}(f) \cup \mathcal{I}(f')} x_{i,m}^{k,f} \geq 1 \quad \forall f' \in \mathcal{U}(f), \forall f \in \mathcal{F}(k), \forall k \in \mathcal{K}, \forall m \in \mathcal{M} \quad (3.20)$$

where  $\mathcal{U}(f)$  is the set of uncertain faces adjacent to  $f$ . A multi-objective formulation allows for trade-offs between lifespan and quality of service:

$$\max \left[ \sum_{i=1}^I \sum_{m=1}^M v_{i,m}, \sum_{j=1}^J \sum_{m=1}^M t_{j,m} \right] \quad (3.21)$$

This formulation can be solved using goal programming or the  $\epsilon$ -constraint method.

#### 4 A multi-agent system in a wireless sensor network

Our multi-agent system (MAS) is designed to manage the surveillance of mobile targets in a wireless sensor network in a distributed and adaptive manner. The proposed architecture is based on hybrid coordination combining central planning and distributed execution, as illustrated in Figure 1, which presents the general architecture of the multi-agent system showing the different types of agents and their interactions.

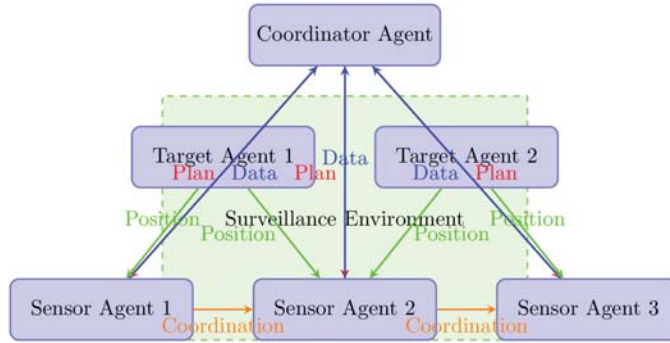


Figure 1: General architecture of the multi-agent system showing the different types of agents and their interactions

Our MAS includes three types of specialized agents: sensor agents that manage local activation/deactivation, communicate with neighbors, and collect environmental data, with each sensor agent maintaining a regional model of its energy state and coverage area; target agents that move through the environment along dynamic trajectories and actively influence activation decisions, these agents being able to adapt their behavior based on context unlike traditional approaches; and the coordinator agent that periodically executes the global optimization model and disseminates activation plans, serving as an interface between central planning and distributed execution.

Each agent in our system is formally defined by a tuple comprising the set of possible states, the set of available actions, the state transition function, the reward function, and the agent's communication capabilities, according to the following formal equation:

$$a = \langle S_a, A_a, P_a, R_a, C_a \rangle \quad (4.1)$$

where  $S_a$  represents the set of possible states of the agent,  $A_a$  the set of available actions,  $P_a$  the state transition function  $S_a \times A_a \rightarrow S_a$ ,  $R_a$  the reward function  $S_a \times A_a \rightarrow \mathbb{R}$ , and  $C_a$  the communication capabilities of the agent.

The target agents represent a major innovation in our approach. Unlike traditional models where targets are passive entities, our target agents are active, intelligent, and capable of strategically interacting with their environment. A target agent can be in different behavioral states, illustrated by the following state diagram in Figure 2:

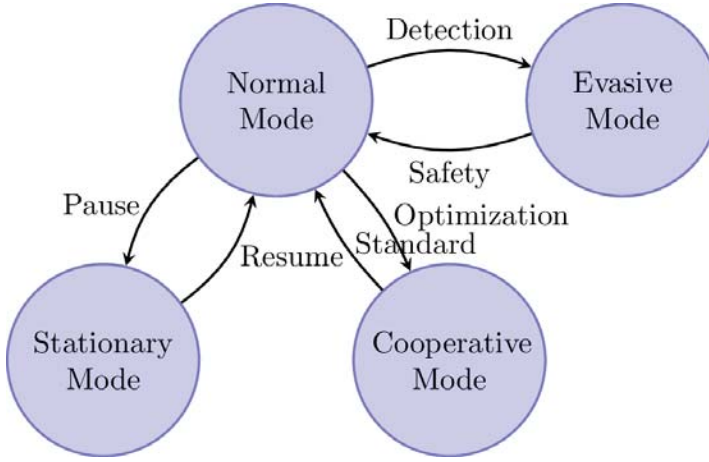


Figure 2: State diagram of a target agent showing the different behavioral modes

The advanced behavior of the target agent follows an iterative process described by algorithm 1:

The position of a target agent evolves according to a dynamic adaptive movement model described by the following equation:

$$P_j(t + \Delta t) = P_j(t) + v_j(t) \cdot \Delta t \cdot \hat{d}_j(t) + \eta_j(t) \quad (4.2)$$

where  $v_j(t)$  represents the adaptive speed as a function of the behavioral mode,  $\hat{d}_j(t)$  the unit direction resulting from multi-criteria optimization, and  $\eta_j(t)$  the movement noise modeling uncertainty. The direction  $\hat{d}_j(t)$  is calculated according to the equation:

$$\hat{d}_j(t) = \frac{\sum_{k=1}^3 w_k \cdot \vec{d}_k}{\|\sum_{k=1}^3 w_k \cdot \vec{d}_k\|} \quad (4.3)$$

with  $\vec{d}_1$  target direction,  $\vec{d}_2$  avoidance direction,  $\vec{d}_3$  exploration direction.

Sensor agents implement a hybrid decision-making logic that combines the execution of the overall plan with local adaptation to dynamic conditions. The decision-making architecture of a sensor agent follows a sequential process illustrated in Figure 3:

The intelligent behavior of the sensor agent follows the detailed algorithm 2:

Each sensor agent implements a proactive energy management strategy described by the following differential equation:

$$v_i(t + \Delta t) = v_i(t) - [\delta_{\text{active}} \cdot x_i(t) + \delta_{\text{sleep}} \cdot (1 - x_i(t))] \cdot \Delta t \quad (4.4)$$

where  $\delta_{\text{active}}$  and  $\delta_{\text{sleep}}$  represent the consumption rates in active and sleep modes, respectively, and  $x_i(t)$  is a binary variable indicating the activation state of the sensor.

The coordinating agent serves as the conductor of the system, ensuring coherence between global optimization and distributed execution. Its modular architecture includes several components illustrated in Figure 4:

The global coordination process follows the detailed algorithm 3:

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**Algorithm 1** Advanced Behavior of Target Agent  $j$ 


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**Require:** Nominal trajectory  $T_j$ , mission objectives, safety thresholds

**Ensure:** Adaptive behavior and movement decisions

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1: Initialization:  $state \leftarrow \text{NORMAL}$ ,  $P_j(t) \leftarrow P_j^0$ ,  $v_j \leftarrow v_j^0$ 
2: loop
3:   Observe local environment  $\mathcal{E}_j(t)$ 
4:   Estimate detection risk  $r_d(t) \leftarrow f_d(\mathcal{E}_j(t))$ 
5:   Evaluate mission objectives  $o_m(t) \leftarrow f_m(t)$ 
6:   Compute behavioral utility  $U_b \leftarrow w_1 \cdot r_d(t) + w_2 \cdot o_m(t)$ 
7:   Switch  $state$ 
8:     Case NORMAL:
9:       If  $r_d(t) > \tau_{\text{escape}}$  then  $state \leftarrow \text{EVASIVE}$ 
10:      Else If  $o_m(t) < \tau_{\text{coop}}$  then  $state \leftarrow \text{COOPERATIVE}$ 
11:     Case EVASIVE:
12:       Compute escape trajectory  $T_j^{\text{escape}}$ 
13:       Adjust speed  $v_j \leftarrow v_j \cdot (1 + \alpha_{\text{escape}})$ 
14:       If  $r_d(t) < \tau_{\text{safety}}$  then  $state \leftarrow \text{NORMAL}$ 
15:     Case COOPERATIVE:
16:       Optimize trajectory for network energy efficiency
17:       Communicate intentions to neighboring sensors
18:       If  $o_m(t) > \tau_{\text{mission}}$  then  $state \leftarrow \text{NORMAL}$ 
19:   Update position  $P_j(t + \Delta t)$ 
20:   Broadcast position information to sensor agents in  $\mathcal{N}_j$ 
21:   Update position history  $\mathcal{H}_j \leftarrow \mathcal{H}_j \cup \{P_j(t)\}$ 
22: end loop
    
```

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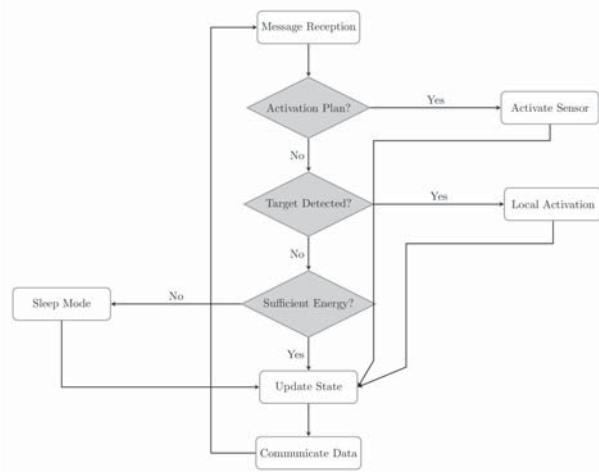


Figure 3: Decision-making architecture of a sensor agent showing the hybrid decision-making process

---

**Algorithm 2** Intelligent Behavior of Sensor Agent  $i$ 

---

**Require:** Initial lifetime  $V_i$ , neighborhood  $\mathcal{N}_i$ , energy thresholds**Ensure:** optimized activation decisions and energy management

```

1: Initialization:  $state \leftarrow \text{INACTIVE}$ ,  $v_i \leftarrow V_i$ ,  $\mathcal{P} \leftarrow \emptyset$ 
2: Subscribe to channels: Target Positions, Neighbor Coordination, Central Plans
3: loop
4:   Asynchronous reception of incoming messages
5:   For each message  $m$  do
6:     If  $m.type = \text{ACTIVATION\_PLAN}$  then
7:        $\mathcal{P} \leftarrow m.plan$ 
8:       Schedule activation according to  $\mathcal{P}$ 
9:     If  $m.type = \text{TARGET\_POSITION}$  then
10:      Update  $\mathcal{L}_i$  (local target list)
11:      Evaluate need for local activation
12:     If  $m.type = \text{NEIGHBOR\_REQUEST}$  then
13:      Negotiate coordination with neighboring sensors
14:   End For
15:   Evaluate local activation conditions:
16:    $A_{\text{local}} \leftarrow (\mathcal{L}_i \neq \emptyset) \wedge (v_i > \tau_{\min})$ 
17:    $A_{\text{plan}} \leftarrow \text{is Activation Period}(\mathcal{P}, t)$ 
18:   If  $A_{\text{plan}} \vee A_{\text{local}}$  then
19:     If  $\neg A_{\text{plan}} \wedge A_{\text{local}}$  then
20:       Initiate coordination protocol with  $\mathcal{N}_i$ 
21:     End If
22:     Activate sensor and begin monitoring
23:     Collect environmental data  $\mathcal{D}_i$ 
24:     Update energy:  $v_i \leftarrow v_i - \Delta t \cdot P_{\text{active}}$ 
25:     If anomaly detected then
26:       Notify coordinator and neighboring sensors
27:     End If
28:   Else
29:     Maintain sleep mode
30:      $v_i \leftarrow v_i - \Delta t \cdot P_{\text{sleep}}$ 
31:   End If
32:   If  $t \bmod T_{\text{report}} = 0$  then
33:     Send status report to coordinator
34:   End If
35:   If  $v_i < \tau_{\text{critical}}$  then
36:     Notify critical state and disable non-essential functions
37:   End If
38: end loop

```

---

---

**Algorithm 3** Global Coordination Process

---

**Require:** Sensor network  $\mathcal{I}$ , targets  $\mathcal{J}$ , missions  $\mathcal{M}$ **Ensure:** optimized activation plans and continuous monitoring1: **Initialization:**

Load topology, models, and operational constraints

Establish connections with all sensor and target agents

2: **loop**3:   **Phase 1: Data Collection**4:   Receive status reports from sensor agents  $\rightarrow \mathcal{E}$ 5:   Receive target position updates  $\rightarrow \mathcal{P}$ 6:   Update the global database  $\mathcal{G}$ 7:   **Phase 2: Evaluation and Triggering**8:   Compute performance indicators  $KPI \leftarrow f(\mathcal{G})$ 9:   **if**  $t \bmod T_{\text{optim}} = 0$  **or** anomaly detected **or**  $KPI < \tau$  **then**10:     **Phase 3: Optimization**11:     Build the MILP model instance from  $\mathcal{G}$ 12:     Solve the optimization problem:  $\mathcal{P}^* \leftarrow \text{MILP}(\mathcal{G})$ 13:     Validate the feasibility of the optimized plan  $\mathcal{P}^*$ 14:     **if** plan is feasible **then**15:       **Phase 4: Dissemination**

16:       Segment the plan by geographic zones

17:       Distribute plans to the corresponding sensor agents

18:       Receive acknowledgments and handle exceptions

19:     **else**

20:       Apply a degraded fallback strategy

21:     **end if**22:   **end if**23:   **Phase 5: Continuous Monitoring**

24:   Monitor network health indicators

25:   Detect drifts and abnormal behaviors

26:   Adjust system parameters if necessary

27:   Wait for the next coordination cycle

28: **end loop**

---

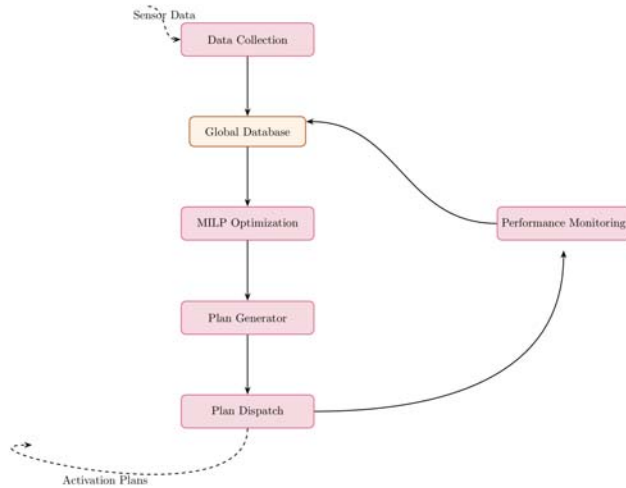


Figure 4: Modular architecture of the coordinating agent

Our system uses an asynchronous communication model with four main types of messages described in the Table 1:

Table 1: Types of Messages in the Multi-Agent System

| Type             | Sender      | Receiver            | Content                       |
|------------------|-------------|---------------------|-------------------------------|
| POSITION_UPDATE  | Target      | Neighboring sensors | Position, velocity, intention |
| ACTIVATION_PLAN  | Coordinator | Sensors             | Optimized activation plan     |
| ENERGY_ALERT     | Sensor      | Coordinator         | Critical energy level         |
| COORDINATION_REQ | Sensor      | Neighbors           | Local coordination request    |

The coordination protocol between neighboring sensors allows for distributed management of unplanned activations according to the algorithm 4:

The system integrates several mechanisms to ensure robustness in the face of unforeseen events, including a failure management process illustrated in the Figure5:

The system implements several levels of fallback strategies according to the algorithm 5:

This comprehensive multi-agent architecture allows for an optimal balance between overall efficiency and local adaptability, while maintaining robustness in the face of uncertainties and failures. The combination of the intelligent behaviors of target agents, the hybrid decision-making logic of sensor agents, and the global coordination of the coordinator agent constitutes an innovative approach to monitoring mobile targets in wireless sensor networks.

## 5 Integration of the two approaches

The integration of the linear optimization model and the multi-agent system constitutes the main innovation of our work. This hybrid architecture combines the advantages of both paradigms:

**Algorithm 4** Coordination Protocol Between Neighboring Sensors**Require:** Sensor  $i$  detecting an unplanned activation need**Ensure:** coordinated activation decision, minimizing energy consumption

```

1:  $i$  broadcasts COORDINATION_REQ to its neighborhood  $\mathcal{N}_i$ 
2: for all  $k \in \mathcal{N}_i$  in parallel do
3:    $k$  evaluates its ability to cover the target area
4:    $k$  computes its activation cost  $c_k \leftarrow f(v_k, position)$ 
5:    $k$  sends COORDINATION_RESP back to  $i$ 
6: end for
7:  $i$  collects all responses during the timeout period  $T_{timeout}$ 
8:  $i$  selects the optimal sensor  $k^* \leftarrow \arg \min_k c_k$ 
9: if  $k^* = i$  then
10:   $i$  activates itself and notifies others
11: else
12:   $i$  requests activation from  $k^*$ 
13:   $k^*$  confirms and activates
14: end if

```

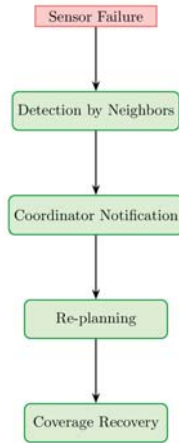


Figure 5: Failure management process in the multi-agent system

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**Algorithm 5** Multi-Level Fallback Strategies

---

**Require:** Type of unforeseen event, network state, mission priorities

**Ensure:** Appropriate fallback actions

- 1: Assess the severity of the incident and available resources
  - 2: **if** the issue is localized and resources are sufficient **then**
  - 3:     **Level 1:** Local adaptation through neighbor coordination
  - 4:     Execute the local coordination protocol (Algorithm 4)
  - 5:     **if** failure after  $T_{\text{timeout}}$  **then**
  - 6:         Escalate to Level 2
  - 7:     **end if**
  - 8: **else if** the issue is widespread or Level 1 fails **then**
  - 9:     **Level 2:** Partial re-planning by the coordinating agent
  - 10:     Notify the coordinator about the incident
  - 11:     The coordinator performs partial re-planning (Algorithm 3, Phase 3)
  - 12:     **if** partial re-planning fails **then**
  - 13:         Escalate to Level 3
  - 14:     **end if**
  - 15: **else**
  - 16:     **Level 3:** Degraded mode with prioritized coverage
  - 17:     Deactivate non-critical missions
  - 18:     Activate all sensors in critical zones
  - 19:     Apply strict energy-saving policy
  - 20: **end if**
  - 21: **Output:** The system maintains operation with graceful degradation
-

the global optimality of mathematical optimization and the local adaptability of multi-agent systems. This section presents the detailed architecture, coupling mechanisms, and synchronization protocols that ensure effective coordination among the system's components.

Our hybrid architecture operates on three interdependent levels, illustrated in the Figure 6 :

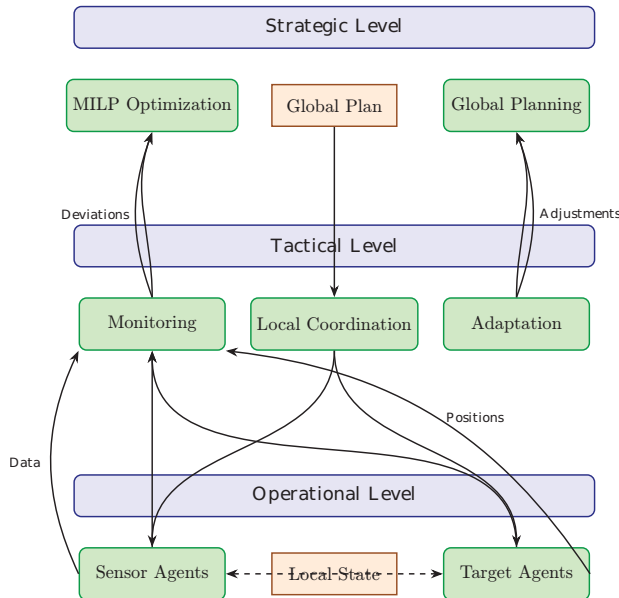


Figure 6: Hybrid three-level architecture integrating central optimization and distributed execution

The strategic level is responsible for long-term overall optimization, in which the coordinating agent periodically solves the MILP model to generate optimal activation plans over an extended planning horizon. This level includes MILP optimization to solve the complete mathematical model, considering all missions, energy constraints, and strategic objectives; global planning to develop detailed activation plans by mission, time window, and coverage face; and resource allocation to optimize workload distribution among sensors to maximize the network's lifespan. The tactical level ensures coordination and adaptation between global planning and local execution. It includes local coordination to manage interactions between neighboring agents to resolve conflicts and optimize local decisions; continuous monitoring for real-time surveillance of discrepancies between the plan and execution, with anomaly detection; and proactive adaptation to adjust operational parameters in response to changing environmental conditions.

The operational level executes concrete monitoring actions and manages direct interactions with the environment. This level includes sensor agents for implementing activation/deactivation decisions, data collection, and local energy management; target agents for adaptive navigation, position communication, and strategic behaviors; and the local state for maintaining contextual information necessary for operational decisions.

The heart of our integrated approach lies in the adaptive optimization loop, which ensures close coordination across levels. This loop collects and combines data from sensors, targets, and the environment in a series of steps. Next comes performance evaluation, including cal-

culating discrepancies between the plan and execution, assessing key performance indicators, and detecting anomalies. The optimization decision phase determines whether a global re-optimization is necessary based on temporal criteria, deviation thresholds, or the presence of anomalies. When a reoptimization is triggered, the system solves the updated MILP model, adjusts the safety margins, and disseminates the new plan. Otherwise, local incremental adaptations are applied. The distributed execution phase allows each sensor agent to execute the plan while managing local contingencies. Finally, the learning and adaptation phase updates the models and adjusts the system parameters to improve future performance.

In Figure 7, the coupling mechanisms ensure a harmonious integration between the centralized and distributed components. The strong coupling at the strategic level ensures that local decisions respect global constraints, with the local plan contained within a controlled dilation of the global plan. At the tactical level, weaker coupling allows for flexible adaptation, with local actions minimizing both deviation from the global plan and the cost of adapting to local conditions.

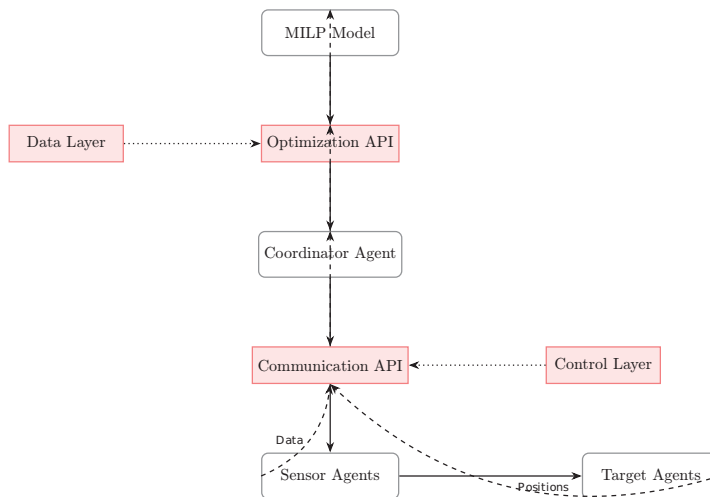


Figure 7: Detailed architecture of the coupling mechanisms between optimization and multi-agents

The management of uncertainties and robustness is ensured by several sophisticated mechanisms. An adaptive safety margin is introduced into the coverage constraints to account for uncertainties in target positions. This margin is a parameter dynamically adjusted based on the historical variability of positions and the current sensor-estimated uncertainty. The uncertainty about the targets' positions is modeled as Gaussian distributions, with the covariance matrix estimated in real time from sensor data. An adaptive uncertainty management algorithm continuously adjusts safety margins based on historical data and current observations, with adjustment coefficients learned online through gradient descent to minimize coverage disruptions.

This successful integration enables an optimal balance between strategic planning and tactical execution while maintaining exceptional robustness in the face of uncertainties and unforeseen

events. The hybrid architecture thus offers a comprehensive solution that overcomes the limitations of traditional approaches by effectively combining global optimization and distributed intelligence.

## 6 Experimental results

This section presents the experimental results obtained to validate our hybrid approach. The experimental setup was designed to evaluate the robustness, energy efficiency, and adaptability of our solution under conditions close to those of real-world deployment.

To conduct these experiments, we developed a comprehensive simulation platform that replicates the real-world conditions of a sensor network deployment. Table 2 summarizes the main parameters of our experimental setup:

Table 2: Experimental Configuration Parameters

| Parameter                 | Value            | Description                                          |
|---------------------------|------------------|------------------------------------------------------|
| Monitoring area           | 100m x 100m      | Square area with coordinates from (0,0) to (100,100) |
| Number of sensors         | 15               | Randomly deployed following a uniform distribution   |
| Detection radius          | 20m              | Circular sensing coverage per sensor                 |
| Initial lifetime          | 300h             | Total available energy per sensor                    |
| Active power              | 100mW            | Power consumption in monitoring mode                 |
| Sleep power               | 1mW              | Power consumption in idle mode                       |
| Number of targets         | 5                | Mobile agents with various behaviors                 |
| Trajectory types          | 3                | Linear, sinusoidal, and random                       |
| Target speed              | 1–3 m/s          | Varies according to behavior                         |
| Missions                  | 3                | Each lasting 24h with distinct objectives            |
| Time windows              | 7                | Per mission, variable duration                       |
| Optimization period       | 30 min           | Interval between MILP re-executions                  |
| Re-optimization threshold | 15%              | Maximum tolerated deviation before re-optimization   |
| Initial safety margin     | $\delta_0 = 0.2$ | Initial robustness parameter                         |

Three main scenarios were defined to evaluate our approach:

1. the nominal conditions scenario with predictable trajectories and minor disturbances;
2. the adaptive behavior scenario, where targets dynamically adjust their trajectories to avoid detection;
3. the extreme conditions scenario, including sensor failures and erratic target behavior.

Our study integrates multiple applications of the same sensor network, unlike recent work such as (Farsi et al., 2019; ?).

Several metrics have been defined to quantify the performance of our approach: network lifetime, coverage rate, energy efficiency, and reaction latency as primary metrics, supplemented by secondary metrics such as load balancing, communication overload, and robustness.

Our hybrid approach is compared to two reference approaches: a purely centralized approach (MILP alone) and a purely distributed approach (SMA alone). The detailed results of this comparison are presented in Table 3:

Table 3: Detailed Performance Comparison Across the Three Missions

| Approach        | Lifetime (h) | Coverage (%) | Energy (J) | Load Balancing | Latency (s) | Robustness |
|-----------------|--------------|--------------|------------|----------------|-------------|------------|
| MILP only       | 215          | 98.5         | 1250       | 0.85           | 45          | 0.72       |
| MAS only        | 185          | 99.2         | 1450       | 0.92           | 12          | 0.65       |
| Hybrid approach | 245          | 99.0         | 950        | 0.88           | 18          | 0.89       |
| Improvement     | +14%         | +0.5%        | -24%       | +3.5%          | -60%        | +23.6%     |

Figure 8 presents a radar comparison of the performance of the three approaches (normalized values):

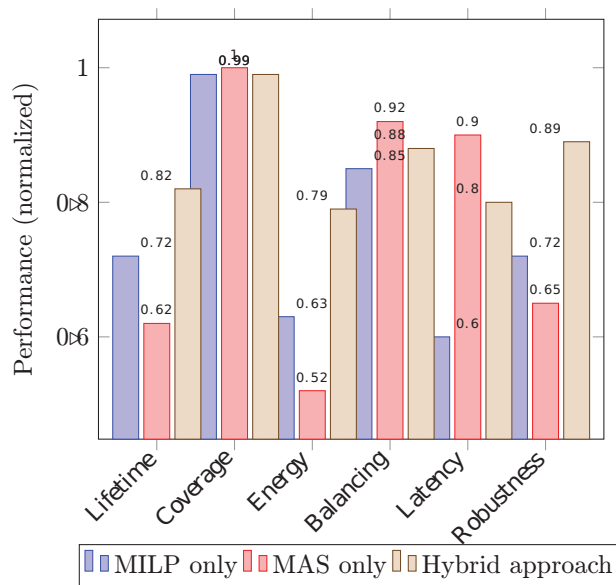


Figure 8: Radar comparison of the performance of the three approaches (normalized values)

A sensitivity analysis was performed to assess the impact of different parameters on performance. Sensor density significantly influences network lifetime, as illustrated in Figure 9:

The number of targets monitored also affects performance, with a gradual degradation in battery life as the number of targets increases, as shown in Figure 10:

The detection range of the sensors also influences performance, with a trade-off between coverage and energy consumption shown in Table 4:

Table 4: Impact of Detection Range on Performance

| Range (m) | Lifetime (h) | Coverage (%) | Active Sensors | Energy (J) |
|-----------|--------------|--------------|----------------|------------|
| 15        | 230          | 97.5         | 8.2            | 1050       |
| 20        | 245          | 99.0         | 6.5            | 950        |
| 25        | 255          | 99.3         | 5.1            | 890        |
| 30        | 260          | 99.5         | 4.3            | 850        |

Our approach demonstrates a remarkable ability to maintain high coverage even when faced

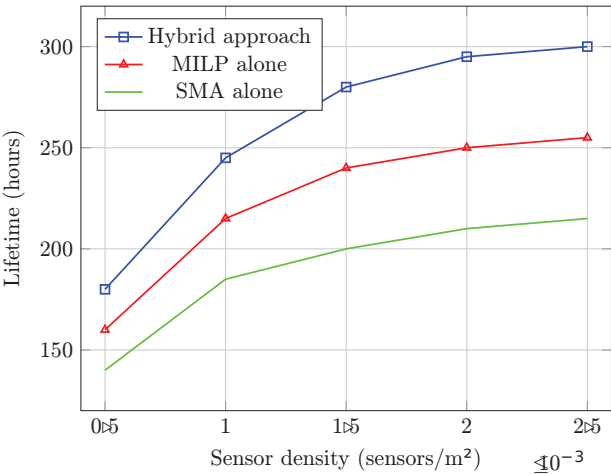


Figure 9: Impact of sensor density on network lifetime

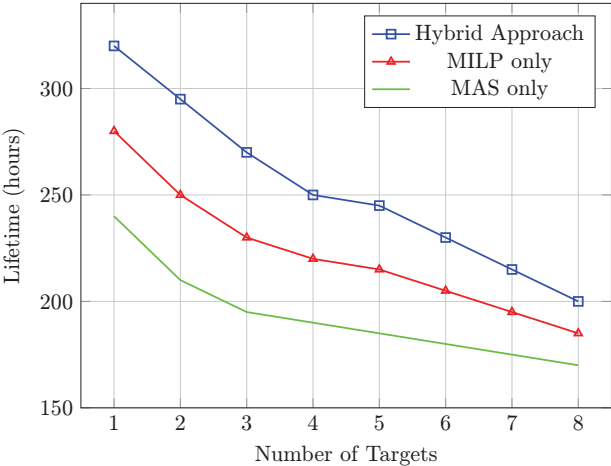


Figure 10: Impact of the number of targets on the network's lifespan

with targets that actively engage in evasive behavior, as shown in Figure 11:

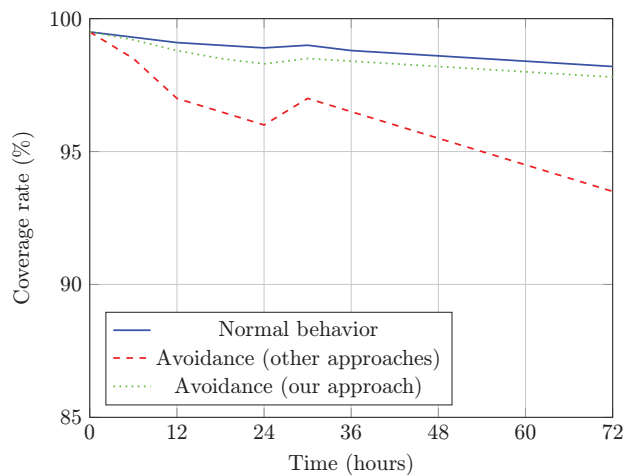


Figure 11: Change in coverage rate under different target behaviors

The robustness of our approach was evaluated by simulating random sensor failures, showing a gradual but controlled degradation in performance (Table 5):

Table 5: Robustness to Sensor Failures

| Failure (%) | Coverage (%) | Lifetime (h) | Reconfiguration Time (s) | Data Loss (%) |
|-------------|--------------|--------------|--------------------------|---------------|
| 0%          | 99.0         | 245          | -                        | 0.0           |
| 10%         | 98.2         | 240          | 12.5                     | 0.8           |
| 20%         | 96.5         | 230          | 18.3                     | 2.1           |
| 30%         | 93.8         | 215          | 25.7                     | 5.2           |
| 40%         | 89.5         | 195          | 35.2                     | 9.5           |

The energy efficiency analysis reveals a balanced distribution of consumption among the various activities in the network, as illustrated in Figure 12:

Figure 13 shows the comparative evolution of average residual energy, highlighting the superiority of our approach in terms of energy resource conservation:

A specific case study was conducted on a critical 24-hour intensive surveillance mission, with particular requirements including two high-priority targets requiring continuous coverage, periods of enhanced surveillance, and strict energy constraints. The results are presented in Table 6:

Table 6: Performance during the Critical Mission

| Metric                   | Our Approach | MILP Only | MAS Only |
|--------------------------|--------------|-----------|----------|
| Priority Target Coverage | 99.8%        | 98.5%     | 99.5%    |
| Energy Consumed          | 880 J        | 1100 J    | 1350 J   |
| Activation Peaks         | 4.2          | 6.8       | 3.1      |
| Maximum Latency          | 8 s          | 52 s      | 6 s      |
| Constraint Satisfaction  | 98%          | 85%       | 92%      |

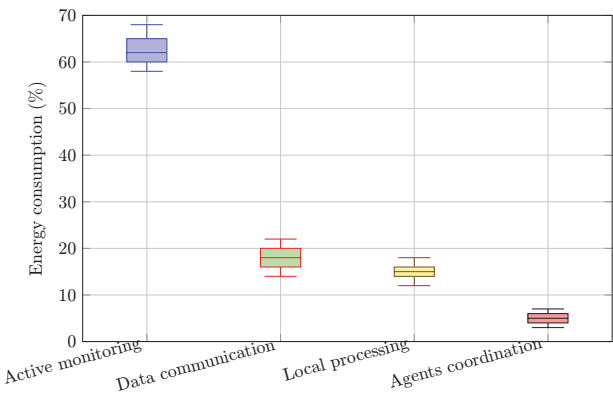


Figure 12: Breakdown of energy consumption in our approach

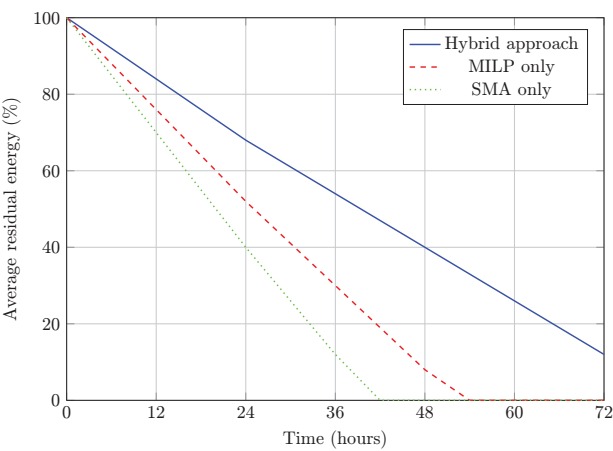


Figure 13: Comparative evolution of average residual energy

Statistical tests were performed to validate the significance of the improvements observed, confirming the statistical superiority of our approach (Table 7):

Table 7: Student's t-test for Lifetime (n=30 simulations)

| Comparison     | t-value | p-value       | Significant           |
|----------------|---------|---------------|-----------------------|
| Hybrid vs MILP | 4.32    | 0.0001        | Yes ( $p \leq 0.01$ ) |
| Hybrid vs MAS  | 5.87    | $\leq 0.0001$ | Yes ( $p \leq 0.01$ ) |
| MILP vs MAS    | 2.45    | 0.021         | Yes ( $p \leq 0.05$ ) |

A one-way analysis of variance (ANOVA) confirms significant differences between approaches with  $F(2, 87) = 28.64$ ,  $p \leq 0.0001$ ,  $\eta^2 = 0.62$ , indicating a large effect, and a statistical power of 0.99.

The experimental results clearly demonstrate the superiority of our hybrid approach: a 14% longer lifetime compared to MILP alone and 32% longer compared to SMA alone, a 24% reduction in energy consumption, exceptional robustness allowing continuous coverage even in adverse conditions, and adaptability with a 60% reduction in response latency compared to purely centralized approaches.

Some limitations have been identified, including computational overload during frequent re-optimizations, increased deployment complexity, and a learning curve for parameter tuning. These results suggest several avenues for future improvement, such as the implementation of more efficient optimization algorithms, the introduction of machine learning techniques for trajectory prediction, and the development of parameter self-tuning mechanisms.

Taken together, these experimental results validate the effectiveness of our hybrid approach and pave the way for practical applications in real-world surveillance scenarios.

## 7 Conclusion and Perspectives

This work presented an innovative approach combining centralized mathematical optimization and a distributed multi-agent system to maximize the lifespan of sensor networks monitoring mobile targets. The hybrid approach developed demonstrates significant superiority over conventional methods, with improvements of 14% to 32% in network lifespan across scenarios.

The proposed MILP model enables optimal strategic planning that integrates all energy, temporal, and coverage constraints, whereas the multi-agent system introduces a conceptual shift by modeling targets as active, intelligent entities. This duality reconciles global optimality and local adaptability, with coordination mechanisms ensuring a harmonious transition between planning and execution.

The experimental results empirically validate the approach's effectiveness: a 24% reduction in energy consumption, a 60% decrease in reaction latency, and maintenance of a coverage rate above 99% even in the face of evasive behaviors. The robustness to failures is particularly remarkable, with 96.5% coverage preserved after the loss of 20% of the sensors.

The practical implications span critical areas requiring reliable, sustainable monitoring: military applications, protection of vital infrastructure, and environmental monitoring. The proposed

architecture offers operators a comprehensive solution combining energy longevity and high service quality.

Research perspectives include integrating machine learning techniques to improve trajectory predictions, developing stochastic models to better manage uncertainty, and adapting to specific scenarios, such as autonomous vehicle monitoring or wildlife tracking.

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