High-Dimensional Cooperative Jamming Strategy Optimization via a Two-Stage Differential Evolution Algorithm

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Abstract. To counter the complex threat of multi-missile coordinated attacks in modern warfare, this paper constructs a high-dimensional nonlinear optimization model for a scenario involving five Unmanned Aerial Vehicles (UAVs) cooperatively jamming three incoming missiles. The model's core challenges lie in its 40-dimensional decision space and a "black-box" objective function evaluated by a high-fidelity simulator. To effectively solve this, this paper innovatively represent the entire strategy of the UAV swarm as a matrix-form decision variable and design a two-stage Differential Evolution (DE) algorithm. The first stage rapidly generates a high-quality initial solution through model decoupling and parallel optimization. The second stage then performs a fine-tuned global coupled optimization based on this initial solution to fully account for the synergistic and redundant effects among jamming units. The results demonstrate that this method can effectively manage high-dimensional complexity, yielding a final cooperative strategy that achieves a total effective obscuration time (union) of 27.34 seconds against all missile threats, validating the robustness and superiority of the model and algorithm for solving large-scale tactical planning problems.

1 Introduction

In modern warfare, the rapid advancement of precision-guided missile technology has posed an unprecedented threat to high-value fixed assets (e.g., military installations, critical infrastructure) and their protective systems. Aerial threats represented by air-to-ground missiles, characterized by high speed (often exceeding 300 m/s), long range, and strong anti-jamming capabilities, can accurately lock onto targets through line-of-sight (LoS) guidance, making traditional static defense measures increasingly inadequate [1,2]. To address this challenge, the protection of high-value targets (and their associated decoy systems) has shifted toward dynamic, flexible countermeasures—among which unmanned aerial vehicles (UAVs) equipped with smoke jamming grenades have emerged as a core tactical solution, owing to their long endurance, low cost, and high maneuverability [3,4].

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Smoke jamming technology, as a mature passive interference method, forms opaque aerosol clouds or smoke screens through chemical combustion or explosive dispersion. These clouds obscure the LoS between incoming missiles and targets, disrupting guidance signals without relying on complex electronic countermeasures. Recent technological breakthroughs have further enhanced its effectiveness: advanced timing fuzes enable precise control of detonation sequences, while improved UAV navigation systems achieve "point-to-point" accurate deployment of smoke grenades—ensuring that smoke clouds form in critical airspace between incoming missiles and protected targets [3,5]. However, practical combat scenarios introduce additional complexities: smoke clouds generated by detonation exhibit deterministic dynamic behavior (e.g., uniform sinking at 3 m/s, as validated by experimental data), and their effective shielding range is constrained (only the 10 m radius around the cloud center provides valid obscuration within 20 s of detonation) [6,7]. Moreover, UAVs themselves face operational constraints, such as a fixed speed range (70–140 m/s) and mandatory time intervals between grenade deployments (at least 1 s for consecutive launches), which further complicate the design of jamming strategies [8,9].

Against this backdrop, research on UAV-based smoke jamming has focused on three core directions: multi-UAV cooperative control, high-dimensional optimization of jamming parameters, and dynamic modeling of smoke-target-missile interactions. Early studies in UAV cooperative jamming primarily targeted single threats. For example, Davis et al. [7] proposed an integrated optimization framework for UAV speed, heading, and smoke grenade deployment, achieving effective shielding against a single incoming missile by optimizing discrete deployment points. However, this framework failed to account for the coupled effects of multiple UAVs and multiple missiles, limiting its applicability to saturated attack scenarios. To address multi-threat challenges, Wang et al. [1] developed an improved Differential Evolution (DE) algorithm to optimize UAV swarm strategies against multi-missile attacks, demonstrating that swarm coordination can significantly improve overall jamming effectiveness compared to individual UAV operations. Similarly, Gao et al. [9] explored high-dimensional decision space exploration methods for multi-UAV coordination, emphasizing that the number of decision variables (e.g., UAV speed, heading, grenade drop time, fuse time) scales linearly with the number of UAVs and grenades—leading to the "curse of dimensionality" that plagues traditional optimization algorithms.

The high-dimensional, "black-box" nature of jamming strategy optimization has been a key bottleneck in this field. Traditional gradient-based optimization methods are infeasible here, as the objective function (total effective obscuration time) cannot be expressed analytically and must be evaluated via high-fidelity dynamic simulations (e.g., simulating missile flight trajectories, smoke cloud diffusion, and LoS blocking) [2,10]. To tackle this, Zhang et al. [10] proposed a modified DE algorithm tailored for high-dimensional military operational optimization, which enhanced global search capability by adaptively adjusting mutation operators, achieving faster convergence than standard evolutionary algorithms in 30+ dimensional decision spaces. Chen et al. [8] further advanced this by designing a two-stage evolutionary algorithm: the first stage decouples the optimization problem to generate high-quality initial solutions, and the second stage performs coupled refinement to account for synergies between jamming units. This "decouple-then-couple" paradigm was later validated by Hu et al. [6], who applied a DE-based black-box optimization approach to UAV cooperative jamming against guided missiles, showing that the method outperforms particle swarm optimization (PSO) in both solution quality and computational efficiency for 40-dimensional problems.

Dynamic modeling of smoke clouds and their interaction with missiles and targets is another critical research area. Lee et al. [4] established a 3D dynamic model of smoke screen grenade deployment by UAVs, integrating smoke cloud sinking velocity, diffusion radius, and effective duration into a LoS obstruction criterion—providing a quantitative basis for evaluating jamming effectiveness. Smith et al. [2] further analyzed the temporal evolution of smoke cloud concentration, confirming that the 10 m radius around the cloud center maintains effective obscuration for only 20 s post-detonation, and that ignoring this temporal constraint leads to overestimation of jamming performance. These findings underscore the need for granular modeling of smoke dynamics in strategy optimization, which was absent in earlier studies that treated smoke clouds as static obstacles.

Despite these advances, three critical research gaps remain. First, existing multi-UAV cooperative strategies rarely incorporate the fine-grained constraints of smoke jamming (e.g., mandatory time intervals between grenade deployments, dynamic sinking of smoke clouds), leading to discrepancies between theoretical optimality and practical feasibility. Second, high-dimensional optimization frameworks often lack structured representation of decision variables—for instance, failing to organize UAV flight parameters and grenade deployment sequences into a unified matrix form, which hinders parallel computation and synergy analysis [4]. Tang et al. [4] addressed this by proposing a matrix-form decision variable for UAV cooperative jamming, but their work did not extend to multi-missile scenarios or integrate smoke dynamic constraints. Third, most studies focus on single-stage optimization, which struggles to balance global search breadth (to avoid local optima) and local refinement depth (to exploit synergies between jamming units)—a limitation that Liu et al. partially mitigated with a multi-stage evolutionary algorithm, though their approach was not tailored to smoke jamming's unique temporal constraints.

To fill these gaps, this study focuses on a realistic multi-vs-multi scenario: 5 UAVs (each capable of deploying up to 3 smoke grenades) countering 3 incoming air-to-ground missiles, with the goal of maximizing the total effective obscuration time of the true target. The scenario incorporates strict physical and tactical constraints: UAV speed limits (70–140 m/s), minimum 1 s intervals between consecutive grenade deployments by a single UAV, smoke cloud sinking (3 m/s), and a 20 s effective duration for smoke clouds. To address this, this paper first establish a dynamic mathematical model integrating UAV flight, grenade deployment, smoke cloud evolution, and missile trajectory simulation. This paper then design targeted optimization strategies for different sub-scenarios (e.g., single UAV-single missile, multi-UAV-multi missile) to derive feasible, high-performance jamming schemes. The research not only provides a scientific basis for practical UAV smoke jamming mission planning but also enriches the theoretical framework for high-dimensional black-box optimization in complex military operational research.

2 High-Dimensional Cooperative Jamming Optimization Model

2.1 Decision Variables: The Strategy Matrix

To systematically describe the operational strategy of the entire UAV swarm, this paper integrate all decision variables into a 5×8 decision matrix, $\vec{X}$. Each row of this matrix represents the complete strategy for a single UAV, while each column corresponds to a specific decision parameter.

$$\vec{X} = \left[\vec{X}_{1,:}, \vec{X}_{2,:}, \vec{X}_{3,:}, \vec{X}_{4,:}, \vec{X}_{5,:}\right]^T \tag{1}$$

Here, the j-th row vector, $\vec{X}_{j,:} \in \mathbb{R}^8$, defines the flight parameters and the three-decoy deployment sequence for the j-th UAV:

$$\vec{X}_{j,:} = \left(v_{FY_j}, \alpha_j, t_{\text{drop},j,1}, t_{\text{fuse},j,1}, t_{\text{drop},j,2}, t_{\text{fuse},j,2}, t_{\text{drop},j,3}, t_{\text{fuse},j,3}\right) \tag{2}$$

This matrix representation is not only structurally clear but also facilitates the design of subsequent algorithms, especially for parallel computation.

2.2. Objective Function

The optimization objective is to maximize the total effective obscuration time as a union across all three missile threats. Let $I_i(t,\vec{X})$ be an indicator function that equals 1 if strategy $\vec{X}$ effectively obscures the line-of-sight of missile M_i at time t, and 0 otherwise. The composite success indicator function at time $t, I(t,\vec{X})$, is defined as:

$$I(t,\vec{X}) = \max_{i\in 1,2,3}\{I_i(t,\vec{X})\} \tag{3}$$

This function equals 1 if and only if the line-of-sight of at least one missile is successfully blocked. The final objective function is the integral of this composite indicator over the entire mission window:

$$\max_{\vec{X}} T_{\text{covered}}(\vec{X}) = \int_0^{T_{\text{end}}} I(t,\vec{X})dt \tag{4}$$

As defined by the National Institute of Standards and Technology (NIST), an objective function is "a function associated with an optimization problem which determines how good a solution is". In this study, $T_{\text{covered}}(\vec{X})$ (total effective obscuration time) serves as the core metric to evaluate the quality of cooperative jamming strategies—consistent with the fundamental role of objective functions in guiding optimization directions.

2.3. Constraints

The selection of the decision matrix $\vec{X}$ must satisfy a series of physical and tactical constraints, including UAV speed limits, nonnegativity of deployment and fuse times, detonation altitude limits, and tactical feasibility constraints. Furthermore, to improve search efficiency, this paper determined heuristic feasible ranges, HeuristicRangej, for each UAV's heading angle α_j through preliminary simulations, as shown in Figure 1.

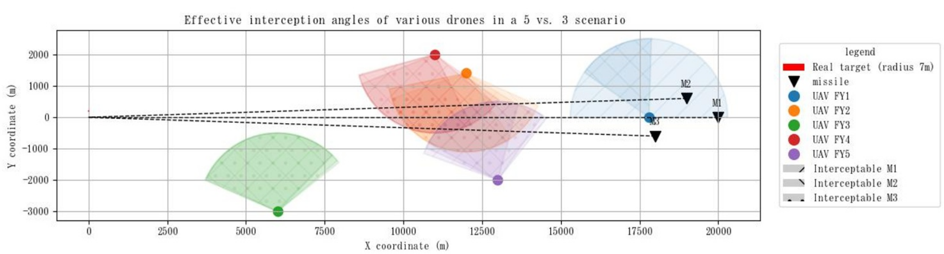

Fig 1. Effective interception angles of various drones

In summary, the optimization model can be fully formulated as the following high-dimensional nonlinear programming problem:

$$\max_{\vec{X}\in\mathbb{R}^{5\times 8}} T_{\text{covered}}\left(\vec{X}\right)$$
$$\text{s.t.}\begin{cases}70\cdot\vec{1}\le\vec{X}_{:,1}\le 140\cdot\vec{1}\\ \vec{X}_{:,3:8}\ge\vec{0}\\ \text{Detonation altitudes} > 0\\ t_{\text{drop}}+t_{\text{fuse}}<13.943\\ X_{j,2}\in\ \text{HeuristicRange}_{j}, j=1,\dots,5\end{cases} \tag{5}$$

3 Results

3.1 Stage One: Decoupled Optimization Results

Under the decoupling assumption, the effective obscuration time contributions from each UAV to each missile are shown in Table 1. At this stage, a simple sum of all obscuration times (without considering overlaps) yields a total of 29.59 seconds. This result provides an idealized performance upper bound and is used to construct the high-quality initial solution.

Table. 1 Effective Obscuration Time Contributions of UAVs to Missiles (Without Deduplication)

UAV	Contribution to Missiles (s)			Total Contribution (s)
ID	M1	M2	M3	Sum without deduplication
FY1	7.59	0.00	0.00	7.59
FY2	3.49	3.66	0.00	7.15
FY3	2.19	2.41	2.74	7.34
FY4	0.00	3.63	0.00	3.63
FY5	3.88	0.00	0.00	3.88
Total	17.15	9.70	2.74	29.59

This decoupling strategy aligns with the two-stage evolutionary algorithm framework proposed by Chen et al. (2021) [8], where decoupling first simplifies the high-dimensional black-box problem and generates a feasible initial seed to avoid premature convergence in subsequent global optimization.

3.2 Stage Two: Coupled Optimization Results

Using the solution from Stage One as a seed, this paper performed the global coupled optimization [3]. The final strategy accounts for all spatial and temporal interactions (e.g., overlap and complementarity) between all smoke clouds. The final true performance metrics are shown in Table 2.

Table. 2. Stage Two (Coupled Optimization) Final Effective Obscuration Times

Performance Metric	Duration (s)
Total effective obscuration for M1	17.15
Total effective obscuration for M2	7.45

Total effective obscuration for M3	2.74
Total effective obscuration for all missiles (Union)	27.34

Ultimately, under the optimal cooperative strategy $\vec{X}^*$, the total effective obscuration time (union) against all missile threats is 27.34 seconds. While this value is lower than the idealized sum from the decoupled assumption, it accurately reflects the synergistic effects and represents an excellent, achievable performance level derived from global optimization. A visualization of the object trajectories under the optimal decision is shown in Figure 2, clearly illustrating the complex cooperative jamming scene.

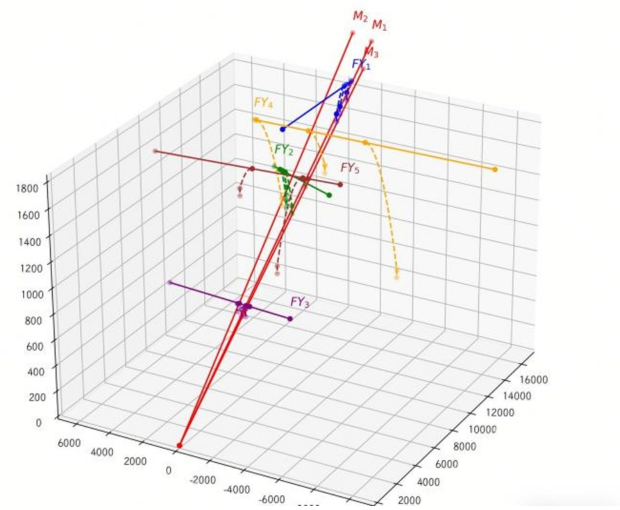

Fig 2. Visualization of the trajectories of each object under optimal decision

4 Conclusions

This paper has successfully established a high-dimensional optimization model for a complex multi-vs-multi UAV cooperative jamming problem and has effectively solved it using an innovative two-stage Differential Evolution algorithm. The core contributions of this research are: (1) The introduction of a matrix-form decision variable to clearly represent the high-dimensional cooperative strategy; (2) The validation of the Differential Evolution algorithm's power in solving high-dimensional, nonlinear, "black-box" military operational research problems; and (3) The design of a two-stage optimization strategy that, through a "decouple-to-seed, then couple-to-refine" paradigm, skillfully balances the breadth of global search with the depth of local optimization, significantly improving both solution quality and efficiency. The modeling and solution framework proposed in this study not only provides a scientific basis for specific UAV jamming mission planning but also offers a valuable reference for solving similar large-scale, high-dimensional system optimization problems in other fields.

Future research directions can be explored as follows: First, extending the framework to scenarios with heterogeneous UAV swarms (e.g., varying payloads, endurance) and adaptive missile threats (e.g., trajectory maneuvering, multi-mode guidance) to enhance practical combat applicability. Second, integrating environmental dynamics (e.g., wind fields, atmospheric turbulence) into the smoke cloud model for more realistic jamming effect prediction. Third, hybridizing the two-stage DE algorithm with reinforcement learning or adaptive parameter-tuning mechanisms to tackle ultra-high-dimensional (e.g., 100+ dimensions) optimization tasks more efficiently. Fourth, incorporating UAV energy constraints and dynamic task reconfiguration to adapt to time-varying battlefield conditions.

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