Research on Multi-Launch Strategies for Smoke-Generating Decoy Bombs Based on Spatio-Temporal Collaborative Optimization Models

Yunfei Cheng
Massey Institute, Nanjing University of Finance and Economics, Nanjing 210023, Jiangsu, China
E-mail: 3372936051@qq.com

Abstract: Precision-guided weapons pose a severe threat to critical ground targets, making smoke screening a key technology for enhancing target survivability. Traditional smoke deployment methods suffer from limited flexibility and restricted coverage. Unmanned aerial vehicles (UAVs), with their high maneuverability, offer an ideal platform for precise smoke screening execution. This paper focuses on the spatio-temporal coordinated optimization problem for multi-deployment of smoke-generating decoys by UAVs. By establishing a unified spatio-temporal coordinate system, precise kinematic models are developed for the UAV, smoke-generating decoys, smoke clouds, and missiles. In a single-deployment scenario, an optimization model incorporating UAV flight parameters and decoy deployment timing parameters is formulated to maximize effective concealment duration. The particle swarm optimization algorithm is employed to derive the optimal deployment strategy through spatio-temporal coordination. To address multi-directional, multi-batch threats in combat scenarios, a multi-objective optimization model is extended. This model balances objectives including maximizing total effective concealment time, minimizing initial concealment time, and minimizing resource consumption. The NSGA-II algorithm is employed to obtain a set of Pareto optimal solutions. This research establishes a comprehensive technical approach from theoretical modeling to algorithmic solution. Simulation validation confirms the model's validity and the algorithm's effectiveness, providing theoretical foundations and algorithmic support for the practical application of UAV-mounted smoke decoy systems.

Keywords: unmanned aerial vehicle; smoke-generating countermeasure; spatiotemporal coordinated optimization; deployment strategy; intelligent optimization algorithm

1. Introduction

The rapid advancement of precision-guided weapons has significantly increased the vulnerability of critical ground targets, creating a pressing need for effective countermeasure strategies. Among these, smoke countermeasures serve as a crucial defense mechanism by producing aerosol clouds that obscure optical and infrared signatures of targets. By generating clouds with specific density, dispersion, and coverage characteristics, smoke countermeasures can effectively disrupt the tracking systems of incoming threats, thereby enhancing the survivability of assets in complex operational environments. Traditional fixed smoke launchers, while widely used, are limited by constrained deployment flexibility, fixed coverage areas, and the inability to adapt dynamically to changing threat trajectories. These limitations often result in suboptimal protection and leave critical targets exposed to adversarial detection and targeting.

In contrast, unmanned aerial vehicles (UAVs) offer exceptional maneuverability and operational flexibility, making them highly suitable platforms for dynamic smoke interference deployment. UAVs can navigate complex environments, approach specific vantage points, and release countermeasure payloads with high temporal and spatial precision. However, leveraging UAVs for smoke deployment introduces a series of interdependent optimization challenges. These include planning the UAV flight path, selecting optimal timing for smoke release, determining detonation parameters, and ensuring that the resulting smoke clouds effectively block the line of sight between incoming munitions and protected targets at critical moments. This problem is inherently spatiotemporal and requires coordinated consideration of UAV kinematics, smoke grenade dynamics, smoke cloud behavior, and missile trajectories. The overall effectiveness of the countermeasure is highly sensitive to these deployment parameters, and minor deviations can significantly reduce masking performance.

This research addresses the aforementioned challenges by establishing a comprehensive spatiotemporal optimization framework for UAV-based smoke countermeasure deployment. The approach integrates models for UAV motion, grenade release mechanics, smoke dispersion, and incoming threat trajectories within a unified coordinate system. Through rigorous kinematic and dynamic modeling, the framework allows for quantitative evaluation of masking effectiveness under any given deployment scenario. On this basis, operational and tactical requirements are translated into formal optimization objectives and constraints, enabling the systematic application of advanced intelligent optimization algorithms to identify near-optimal deployment strategies. The proposed methodology not only bridges the gap between theoretical modeling and practical implementation but also provides a structured foundation for the design, evaluation, and real-time application of UAV-based smoke interference systems. By incorporating both the physical behavior of deployed countermeasures and the spatiotemporal characteristics of threats, this work establishes a technically robust and scalable solution for enhancing target survivability in modern threat environments.

2. Theoretical Foundations and Fundamental Assumptions

To ensure the validity, tractability, and solvability of the modeled system, this study establishes a set of fundamental assumptions prior to constructing mathematical and computational models. These assumptions are designed to capture the essential characteristics and primary contradictions inherent in the problem, while simplifying secondary or less influential factors. This approach facilitates the development of a theoretical framework that accurately reflects the underlying physical phenomena and allows for precise mathematical treatment, ensuring that subsequent analyses and optimizations remain computationally feasible and conceptually clear.

First, the motion of the incoming missile is idealized. It is assumed that the missile maintains uniform linear motion throughout the penetration process, with its trajectory precisely aimed at the center of the protected target. This assumption intentionally disregards terminal maneuvering, trajectory adjustments, or any aerodynamic perturbations, allowing the analysis to focus exclusively on the optimization of countermeasure deployment under a predetermined flight path.

By reducing the complexity associated with adaptive missile behavior, the study can concentrate on evaluating the timing, positioning, and effectiveness of smoke interference strategies in a controlled scenario.

Second, the deployment and behavior of the smoke countermeasures are idealized for modeling purposes. The ballistic trajectory of each smoke grenade is assumed to follow ideal free-fall motion after release, ignoring the influence of air resistance or minor environmental perturbations. Upon detonation, the smoke is assumed to form an instantaneous, regular spherical cloud of uniform density, descending at a constant vertical speed. Such simplifications transform the inherently complex physicochemical processes of smoke diffusion and aerosol dispersion into mathematically tractable models with clearly defined geometric boundaries and predictable motion laws. This idealization allows the optimization framework to focus on the spatial and temporal placement of the smoke cloud relative to incoming threats.

Regarding the UAV platform, it is assumed to possess idealized maneuverability, capable of instantaneous adjustments to speed, heading, and altitude in response to command inputs. This assumption isolates the optimization problem from platform-specific dynamic constraints, such as rotor inertia, acceleration limits, or energy consumption, and instead emphasizes the strategic deployment of countermeasures. Furthermore, it is assumed that all actions among combat units-including missiles, UAVs, and decoys-occur independently, without interference from coordination delays, communication latency, or operational conflicts.

Environmental factors, such as wind speed, humidity, and temperature variations, which could affect smoke cloud dispersion and density, are temporarily disregarded in the current model. Additionally, it is assumed that the initial target information provided by detection systems is accurate and reliable, ensuring that the UAV can plan deployment strategies based on correct positional data.

Collectively, these assumptions establish a controlled, simplified, and analytically manageable research environment. By reducing the problem to its most critical components while preserving the essential interactions between incoming threats, UAV platforms, and smoke countermeasures, the study lays a rigorous foundation for precise kinematic modeling, quantitative evaluation, and subsequent optimization of countermeasure strategies. This systematic approach ensures that the developed theoretical models remain both scientifically valid and practically applicable, forming the groundwork for advanced solution methods in UAV-based dynamic smoke interference systems.

3. Construction and Solution of the Spatio-Temporal Coordination Optimization Model for Single-Dispenser Deployment

The single-deployment scenario serves as the foundation for studying multi-deployment coordination. Its core objective is to optimize the deployment strategy for a single drone carrying one decoy to maximize the effective concealment time of the smoke screen against incoming missiles.

3.1 Kinematic and Obstruction Detection Model

The model operates within a three-dimensional Cartesian coordinate system. The UAV's flight trajectory is determined by its initial position, velocity magnitude, and direction vector. The direction vector is parameterized by heading angle and pitch angle, ensuring directional uniqueness. After deployment, the decoy follows a parabolic trajectory driven by the initial velocity imparted by the UAV and gravitational acceleration. The smoke cloud forms at the detonation point after a preset delay and subsequently moves downward at a constant rate. The incoming missile's trajectory is directly determined by its initial position and constant velocity vector. The critical step is assessing the effectiveness of the shielding: this is determined by calculating the vertical distance between the center of the smoke cloud and the line connecting the missile and the true target at any given moment. Effective concealment is achieved when this distance is less than the smoke cloud's effective concealment radius and occurs within the effective duration window of the smoke. The total effective concealment time is the cumulative sum of all such qualifying moments.

3.2 Optimization Model and Algorithm Solution

The optimization objective function in this scenario is defined as maximizing the effective masking duration calculated above. The decision variables requiring optimization include the UAV's flight speed, heading angle, pitch angle, countermeasure deployment time, and detonation delay time. These variables are mutually coupled and collectively influence the quality of masking effectiveness. Model constraints primarily reflect the performance limitations of the drone platform (e.g., speed range) and the non-negativity requirement for time. Due to the highly nonlinear nature of the model, traditional gradient-based optimization methods are difficult to apply. This study employs the Particle Swarm Optimization (PSO) algorithm, an efficient swarm intelligence optimization technique, for solution. The PSO algorithm simulates the social behavior of bird flocks, enabling particles to search the solution space by following the current optimal particle. It offers advantages such as fewer parameters and fast convergence. Each particle represents a set of potential deployment strategy parameters (velocity, angle, time). The algorithm iteratively updates particle velocity and position to progressively approach the optimal solution. During implementation, grid search optimization was applied to the PSO algorithm's internal parameters (inertia weight, learning rate) to enhance performance. The solution process demonstrated excellent convergence characteristics.

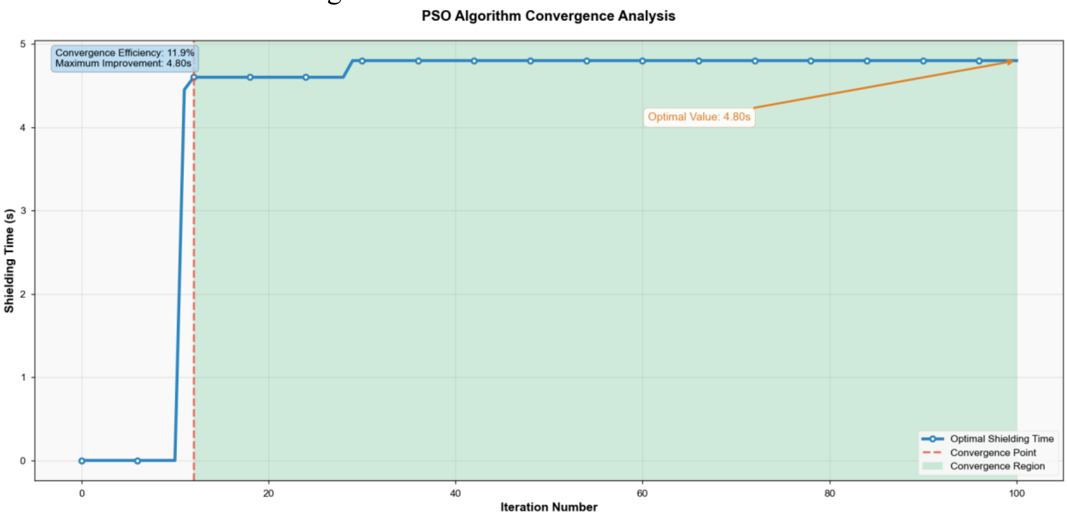

Figure 1. Convergence Curve

The convergence curve reveals that the PSO algorithm exhibits extremely rapid convergence in the initial phase, with the fitness value rising sharply and covering most of the optimization range, demonstrating the algorithm's powerful global search capability. Subsequently, the algorithm enters a stable convergence phase, performing fine-tuning adjustments to ultimately find the optimal solution.

3.3 Results Analysis and Discussion

Through PSO algorithm optimization, a set of optimal deployment strategy parameters was obtained. Analysis of these parameters reveals that the optimal drone speed approaches its performance ceiling, providing greater initial kinetic energy to the decoy and facilitating trajectory adjustment. The specific combination of heading and pitch angles ensures the drone occupies the spatial position most effective for intercepting the missile's line of sight. The optimized deployment timing and detonation delay precisely control the spatial positioning of the smoke cloud at critical moments. The following table presents key parameter configurations under the optimal strategy along with brief analysis:

Table 1. Optimal Parameter Configuration and Analysis for Single-Missile Deployment

Optimized Parameter	Symbol	Optimal Value	Physical Meaning and Analysis
Drone Speed	v^u	133.64 m/s	Approaching the drone's maximum speed limit, leveraging high speed to achieve a more advantageous tactical position.
Heading Angle	θ	84.5 °	Indicates the drone's flight direction is close to true north, forming a favorable angle with the incoming missile's trajectory.
Pitch Angle	ϕ	-39.7 °	A negative value indicates the drone is diving, aiding in adjusting the bomb's trajectory.
Release Time	t^d	0.00 s	Indicates that immediate release upon decision is optimal, emphasizing timeliness.
Detonation Delay	Δt	0.14 s	An extremely short delay ensures rapid formation of the smoke cloud to counter high-speed targets.

The synergistic relationship among parameters is reflected through their normalized distribution. The velocity parameter plays a dominant role, while the angle and time parameters serve as auxiliary regulators, collectively forming a highly coordinated optimal solution at the spatiotemporal level.

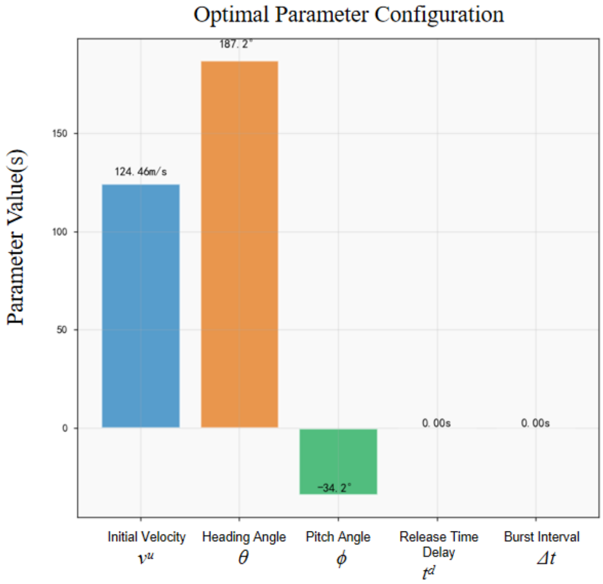

Figure 2. Parameter Configuration

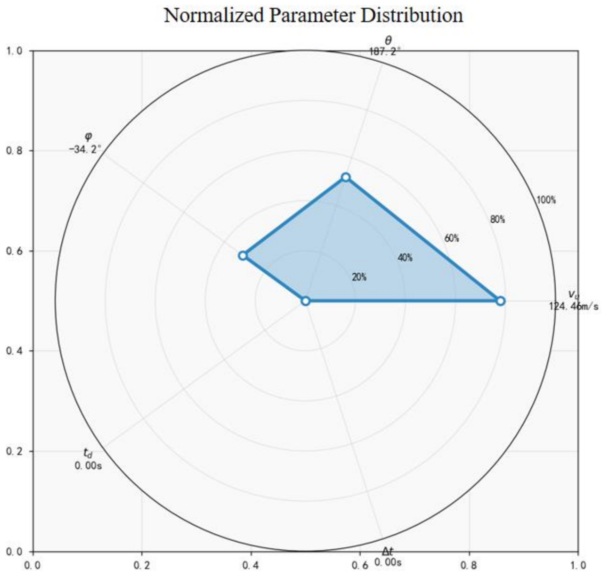

Figure 3. Normalized Distribution

This radar chart visually displays the normalized distribution patterns of the five optimization parameters. The velocity parameter exhibits the largest radial distance, highlighting its central role in the optimization process. The heading angle parameter follows, while the pitch angle, deployment time, and detonation delay parameters exhibit relatively smaller normalized values. Together, they form a fine-tuning mechanism for the dominant parameter. This irregular geometric shape reveals the complex coupling relationships among the decision variables, with the successful optimization strategy resulting from effectively balancing these interactions.

4. Multi-Droned Cooperative Deployment Multi-Objective Optimization Model Extension

While the single-deploy model addresses fundamental deployment challenges for UAV-based smoke countermeasures, real-world operational scenarios frequently require multiple UAVs to coordinate the release of multiple decoys simultaneously or sequentially. Such scenarios may involve threats originating from multiple directions, the need to extend the effective shielding duration, or the necessity to enlarge the coverage area of smoke interference. These practical considerations introduce a more intricate optimization problem, which involves determining optimal multi-UAV coordination strategies, deployment sequences, and temporal synchronization to achieve maximum operational effectiveness.

4.1 Necessity of the Target Optimization Model

In multi-deploy scenarios, the tactical objectives expand beyond a single metric, making optimization more complex. While maximizing total effective jamming duration remains important, additional objectives must be considered. These include: ensuring that initial jamming coverage is established as early as possible to address uncertainties in threat arrival; optimizing the transitions and overlaps of smoke clouds to eliminate potential coverage gaps; and enhancing overall operational reliability, such as maintaining at least two smoke clouds simultaneously active during critical time windows. Moreover, resource efficiency becomes a significant consideration, including the number of UAV sorties deployed, the quantity of chaff or flare dispensers used, and the total energy or operational cost of the UAVs. These objectives often conflict with one another-for example, pursuing maximum coverage may substantially increase resource consumption or operational complexity. Consequently, relying solely on a single objective, such as maximizing obscuration duration, fails to capture the multi-dimensional tactical requirements of realistic operational scenarios. A comprehensive multi-objective optimization framework is therefore necessary to balance competing performance metrics effectively.

4.2 Model Framework and Algorithm Selection

The multi-deploy coordination optimization model represents an extension of the single-deploy framework. Its decision variables encompass all relevant UAV flight parameters, including velocity, heading angle, and pitch angle, as well as deployment timing variables for each decoy, such as release time and detonation delay. The fundamental kinematic modeling principles and concealment assessment methods established for the single-UAV scenario are retained; however, the multi-UAV context requires calculation of the combined masking effect produced by all active smoke clouds on each missile's line of sight. This introduces additional computational complexity, as the model must account for overlapping clouds, temporal coverage continuity, and interactions among multiple deployment platforms.

The multi-objective optimization problem is formulated to simultaneously satisfy two or more operational goals. Typical objectives may include: 1) maximizing the total effective obscuration time across all threats; 2) minimizing the time between missile entry into the threat zone and the first effective obscuration, thereby reducing vulnerability during initial engagement; and 3) minimizing the number of decoys or UAV sorties deployed, thereby conserving operational resources. Constraints include UAV performance limitations, safe separation distances to prevent collisions, and deployment feasibility under operational conditions.

Solving this class of multi-objective problems aims to obtain a Pareto-optimal solution set, which consists of solutions where improvement in one objective necessarily results in trade-offs with others. In this study, the NSGA-II (Non-Dominated Sorting Genetic Algorithm II) is employed due to its proven efficiency in handling complex multi-objective evolutionary problems. NSGA-II operates by performing non-dominated sorting of candidate solutions and incorporates crowding distance calculations to preserve diversity across the solution set. Through iterative selection, crossover, and mutation, NSGA-II approximates the Pareto frontier, providing decision-makers with a spectrum of optimal deployment strategies that balance trade-offs between effectiveness, timeliness, and resource consumption. By applying this approach, multi-UAV smoke deployment strategies can be systematically designed to enhance both coverage reliability and operational efficiency in dynamic threat environments.

5. Conclusion

This paper presents a systematic investigation into the spatiotemporal coordination and optimization of UAV-based deployment of multiple smoke-generating decoys, providing a comprehensive framework for enhancing target concealment in dynamic operational environments. The study developed both single-deployment and multi-deployment models, integrating UAV kinematics, smoke dispersion behavior, and missile trajectories within a unified spatiotemporal framework to quantitatively evaluate the effectiveness of masking strategies.

For the single-deployment scenario, the optimization model was successfully solved using the particle swarm optimization (PSO) algorithm. The results demonstrated that the UAV's velocity approached its performance ceiling, while the heading and pitch angles were optimized to form an advantageous interception posture, effectively positioning the UAV for precise decoy release. The timing parameters, including deployment and detonation delays, were found to be critical in ensuring that the generated smoke cloud reached the optimal position at the right moment, thereby maximizing the masking effect. These findings validate the scientific rigor and practical applicability of the single-deployment model, confirming that precise spatiotemporal coordination can significantly improve countermeasure efficiency under controlled assumptions.

In multi-deployment and multi-target scenarios, where multiple UAVs and decoys are required to simultaneously address threats from different directions or extend coverage duration, the study developed a multi-objective optimization model. This model successfully captures the trade-offs between conflicting objectives, such as maximizing total effective obscuration, minimizing initial exposure time, and reducing resource consumption. The NSGA-II algorithm was employed to solve this multi-objective problem, generating a Pareto-optimal solution set that provides a spectrum of flexible operational options. This approach overcomes the limitations of single-objective models, offering commanders a decision-support tool to balance competing tactical priorities under varying conditions.

Analysis of the computational performance indicated that particle swarm optimization exhibits rapid convergence and strong capability in single-objective optimization problems, while NSGA-II effectively maintains diversity within the solution set and ensures proximity to the true Pareto frontier in multi-objective contexts. Together, these models and algorithms provide a robust technical foundation for UAV-based smoke interference systems, supporting both strategic planning and real-time deployment decisions.

Future research directions include incorporating additional environmental factors such as wind speed, humidity, and temperature variations, which may influence smoke dispersion dynamics. Further refinement could involve modeling potential missile maneuvering and trajectory deviations to improve the adaptability of UAV deployment strategies in more complex operational conditions. Moreover, extending the framework to account for multiple UAV platforms operating in coordination under stochastic threat patterns could enhance the overall robustness and resilience of countermeasure operations. By addressing these factors, the models can be progressively refined to support more realistic scenarios and higher levels of operational effectiveness, ultimately contributing to the development of advanced UAV-based concealment and survivability solutions.

References

A. Stanley, Q. H. Liu, and Q. Wu, "Particle swarm optimisation of a PID-based virtual coupling controller for metro railway trains," ***Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*****, 2025.**

M. A. Al-Betar, M. S. Braik, Q. Y. Shambour, G. Al-Naymat, and T. Porntaveetus, "Ameliorated elk herd optimizer for global optimization and engineering problems," ***Artificial Intelligence Review*****, vol. 58, no. 11, p. 360, 2025. doi: 10.1007/s10462-025-11360-1**

X. Liu, M. Tian, and X. Wang, "Enhanced particle swarm algorithm with diversity-based adaptive predicted learning strategy for numerical optimization," ***Cluster Computing*****, vol. 28, no. 9, p. 611, 2025. doi: 10.1007/s10586-025-05238-8**

H. Su, H. Yu, X. Chen, and L. Han, "A Computational Framework for Smoke Screen Scheduling in Multi-Agent UAV Systems Using Differential Evolution," ***Journal of Technology Innovation and Engineering*****, vol. 1, no. 5, 2025.**

C. JIA, C. MA, Y. ZHANG, B. YI, and H. WANG, "Research on optimization method of intelligent trackless auxiliary dispatching path in coal mine underground based on improved NSGA-II," ***CHINA MINING MAGAZINE*****, vol. 34, no. 5, pp. 137-143, 2025.**