Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2024.0429000

Pareto-Based Multi-Objective Optimization for Efficient UAV Target Selection and Engagement Operations

MUHYUN BYUN[1], EUNAE LEE[2], SEOK JOO DOO [3], and MIN YUN[4]
[1]Department of Mechanical Engineering, Korea Army Academy at Yeongcheon, Yeongcheon-si, Gyeongsangbuk-do 38900, Republic of Korea
[2]Department of Computer Science, Korea Army Academy at Yeongcheon, Yeongcheon-si, Gyeongsangbuk-do 38900, Republic of Korea
[3]Department of Electrical Engineering, Korea Army Academy at Yeongcheon, Yeongcheon-si, Gyeongsangbuk-do 38900, Republic of Korea
[4]Korea Institute for Defense Analyses, Seoul 02455, Republic of Korea

*Corresponding author: Muhyun Byun (e-mail: muhyuny83@gmail.com).

This work was supported by the Korea Institute for Defense Analyses (KIDA) under Contract No. R25TA00192271-00 (Project Code: KIDA2024-42).

ABSTRACT Recent advances in advanced science and technology have introduced various new weapon systems into modern warfare, among which unmanned aerial vehicles (UAVs) have emerged as one of the most influential systems. Despite their high lethality and potential, UAV mission engagement strategies in actual combat environments include conflicting factors that hinder efficient mission performance. In this study, the multi-objective assignment problem for UAVs is formalized as a multi-objective combinatorial optimization problem, addressing conflicting objectives such as maximizing attack effectiveness, minimizing detection time, and shortening mission duration. This problem incorporates realistic operational constraints, including single-attack (suicide-type) conditions, range limitations, and total mission counts. Experimental results demonstrated the ability to explore a wider range of solutions and achieve temporal efficiency in solution derivation. To solve this problem, we propose an extended non-dominated sorting genetic algorithm II (NSGA-II), referred to as DOPA (Dynamic Operationally-aware Pareto-based Assignment), which is tailored for military applications. The proposed algorithm introduces a Riemannian crowding distance-based selection mechanism, entropy-guided adaptive crossover and mutation control, and Wasserstein-1 distance tracking using the Sinkhorn approximation. Furthermore, a distance-based probabilistic initialization scheme is adopted to enhance the diversity of early-stage solutions. Four experimental scenarios (S1–S4) are designed to evaluate the effectiveness of various algorithm configurations. The results are quantitatively assessed using key performance metrics, including Generational Distance (GD), Diversity Spread (Δ), and Hypervolume (HV), along with Pareto front distribution analysis.

INDEX TERMS UAV mission planning, Multi-objective optimization, Pareto front, Wasserstein distance, Adaptive operator control.

I. INTRODUCTION

THE rapid advancement of cutting-edge science and technology is significantly transforming the nature of modern battlefields. At the core of this transformation are next-generation weapon systems equipped with autonomy and intelligence [1]. Among them, Unmanned Aerial Vehicles (UAVs) have emerged as versatile assets capable of performing a wide range of missions, including reconnaissance, surveillance, and precision strikes. Compared to traditional manned platforms, UAVs offer greater operational flexibility and survivability [2].

Despite these technological advances, the operational deployment of UAVs in real-world military environments remains a challenging task, primarily due to the inherent trade-offs among conflicting mission objectives [3]. For example, the goal of maximizing strike effectiveness may conflict with the objective of minimizing mission time. In UAV-based target engagement scenarios, decision makers are often required to simultaneously pursue dual goals, maximizing lethality while minimizing detection and mission completion time. These objectives inherently conflict, making the optimization problem more complex when considering realistic constraints such as single-use (suicide) mission conditions, total mission allocation limits, and range constraints between UAVs and targets. To address such complex problems, single-objective optimization approaches are insufficient. Instead, multi-objective optimization (MOO) frameworks are essential, as the UAV-based multi-target assignment problem is fundamentally a combinatorial problem with multiple competing objectives [4].

Although various heuristic and combinatorial approaches have been proposed in prior research on the weapon-target assignment (WTA) problem and UAV mission planning [5], [6], relatively few studies have developed MOO models that incorporate realistic military constraints [7]. In particular, there has been a notable lack of evolutionary optimization frameworks that simultaneously consider convergence and diversity of solutions in such constrained scenarios.

In response, this study formulates the UAV-based multi-target assignment problem as a multi-objective combinatorial optimization problem incorporating three conflicting objectives: (1) maximizing strike effectiveness, (2) minimizing detection time, and (3) minimizing total mission time. We propose a novel evolutionary optimization framework named *Dynamic Operationally-aware Pareto-based Assignment* (DOPA), which extends the classic NSGA-II algorithm with domain-specific enhancements tailored for military operations.

However, it is crucial to consider how this framework supports real-world decision making under operational constraints. In this regard, we explore the extent to which our method aligns with two essential requirements of military decision-support systems: speed and diversity of solutions. In military operations, decision-makers face high stakes, time-critical environments where delayed responses can lead to mission failure. Endsley [8] argues that timely and accurate situation awareness is fundamental to effective decision making, especially under dynamic operational conditions. At the same time, offering a diverse set of viable solutions is critical to cope with uncertainty and rapidly changing mission contexts. As highlighted by Klein [9], adaptive decision-making frameworks benefit from presenting multiple feasible options, enabling commanders to flexibly adjust strategies in response to evolving scenarios. In this study, we examine whether our proposed method satisfies these two essential criteria: the ability to generate rapid solutions and to present diverse operational alternatives.

The remainder of this paper is organized as follows. Section II provides a formal mathematical definition of the problem and constraint modeling. Section III describes the structure and core components of the proposed algorithm. Section IV outlines the experimental settings and benchmark scenarios, and Section V presents the results and analysis of the quantitative performance evaluation. Finally, Section VI concludes the study and discusses future research directions.

A. RELATED WORK

Recent advances in UAV mission planning have led to a variety of approaches to address the target assignment problem. However, many of these approaches are based on static assumptions or oversimplified operational models, which limit their applicability in dynamic environment. For example, [10] proposed a cooperative task assignment framework using genetic algorithms to improve allocation efficiency; however, its applicability is limited in dynamic environments due to static task definitions. Real-time solutions such as greedy auction algorithms have been explored for adaptive tasking [11], but these methods may not provide globally optimal assignments. Reinforcement learning-based models like [12] have introduced joint optimization of path planning and target selection, yet such frameworks often suffer from training instability and lack robustness when applied to real-world mission variations. Furthermore, integration of trajectory and task assignment has been addressed from an information freshness perspective in [13], although the focus on Age of Information (AoI) narrows its generalizability. Early works such as [14] provided valuable insights into decentralized UAV coordination and intercept strategies, but their modeling assumptions were overly simplified. Meanwhile, networked UAV systems have been studied in [15], addressing communication and energy constraints, although their path assignment mechanisms remain decoupled from target dynamics. In contrast to these approaches, our work presents a dynamic, multi-objective model that accounts for evolving mission conditions, integrated constraints, and adaptable UAV-target relationships, offering broader flexibility and operational realism.

Several methods have been developed to address multi-objective optimization (MOO) problems, many of which apply genetic or evolutionary approaches. Among these, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) remains one of the most widely used algorithms for MOO due to its fast elitist strategy and effective diversity preservation mechanisms [16]. However, NSGA-II and similar population-based methods often suffer from scalability issues and limited adaptability to new problems, especially when applied without reinitialization or parameter turning. To overcome such limitations, recent studies have introduced neural evolutionary algorithms. For instance, Shao et al. proposed MONEADD, a neural evolutionary framework that integrates deep reinforcement learning (DRL) with decomposition-based multi-objective learning, showing its efficiency in solving TSP and Knapsack problems [17]. Similarly, Chen et al. designed NHDE, a neural heuristic method that enhances diversity by leveraging indicator-guided DRL and multiple Pareto optima strategies, achieving superior performance in generating diverse Pareto fronts [18]. Other approaches also explore interactive heuristics [19] and hybrid reinforcement learning techniques [20] to improve convergence and generalization. Despite these advancements, most methods assume fixed environments or rely on static representations of the optimization space, limiting their applicability in real-world scenarios where conditions may change rapidly. Our study extends this line of work by proposing a dynamic MOO framework that adapts to changing mission contexts in UAV-based target assignments, thus addressing a critical gap in existing methodologies.

B. CONTRIBUTIONS OF THIS WORK

Motivated by the limitations of existing approaches, this study proposes a multi-objective combinatorial optimization framework tailored for UAV-based multi-target assignment under realistic battlefield constraints. The primary contributions of this paper are as follows:

- We extend the classical NSGA-II framework by designing a Dynamic Operationally-aware Pareto-based Assignment (DOPA) algorithm that integrates operational constraints directly into the evolutionary search process.
- A Riemannian crowding distance-based selection operator and entropy-adaptive crossover and mutation operators are introduced to improve both convergence and diversity of the solution set.
- A Wasserstein-1 distance trace, computed via Sinkhorn approximation, is incorporated to quantitatively monitor the evolutionary dynamics of the population over generations.
- A distance-aware initialization mechanism is proposed to promote early-stage exploration by diversifying the initial population based on probabilistic modeling of spatial proximity.

II. PROBLEM FORMULATION AND MATHEMATICAL MODELING

In this study, the multi-target assignment problem using unmanned aerial vehicles (UAVs) is formulated as a multi-objective combinatorial optimization problem. Given a set of UAVs and a set of targets, each UAV is assigned to attack only one target under a one-time suicide strike constraint. The primary objective of this problem is to maximize the overall effectiveness and time efficiency of the mission. To this end, we define three conflicting objective functions:

1) Maximization of strike effectiveness: The total effectiveness is calculated by considering the strategic value of each target and the distance attenuation between UAVs and targets.
2) Minimization of detection time: The total time required for all UAVs to detect their assigned targets is minimized.
3) Minimization of the maximum mission duration: The maximum time among all UAVs, including detection and fixed mission preparation time, is minimized.

In addition, the following realistic operational constraints are incorporated to reflect military operational environments:

- Suicide constraint: Each UAV is allowed to perform exactly one mission.
- Distance constraint: A UAV cannot engage a target if the distance exceeds the maximum operational range $D_{\max}$.
- Total mission constraint: The total number of assigned missions must not exceed the allowable capacity C_{total}.

A. VARIABLE DEFINITIONS

- N: Total number of UAVs
- M: Total number of targets
- $x_{ij} \in \{0,1\}$: Binary assignment variable (1 if UAV i is assigned to target j; 0 otherwise)
- d_{ij}: Distance between UAV i and target j, which determines both the probability of successful strike and eligibility for assignment.
- $D_{\max}$: Maximum allowable strike distance. If $d_{ij} > D_{\max}$, the assignment is considered infeasible.
- C_{total}: Maximum number of total target assignments allowed across all UAVs.
- v_j: Strike value of target j
- T_{ij}^{detect}: Detection time of UAV i for target j
- T_i^{mission}: Fixed mission time for UAV i

B. OBJECTIVE FUNCTIONS

$$\max F_1 = \sum_{i=1}^{N}\sum_{j=1}^{M} x_{ij}\cdot v_j \cdot e^{-\lambda d_{ij}} \tag{1}$$

$$\min F_2 = \sum_{i=1}^{N}\sum_{j=1}^{M} x_{ij}\cdot T_{ij}^{\text{detect}} \tag{2}$$

$$\min F_3 = \max_i \left(\sum_{j=1}^{M} x_{ij}\cdot T_{ij}^{\text{detect}} + T_i^{\text{mission}}\right) \tag{3}$$

The first objective function F_1 quantifies the expected cumulative strike value by considering both the importance of each target (v_j) and the probabilistic success rate of engagement, modeled as an exponential decay $e^{-\lambda d_{ij}}$ with respect to the distance d_{ij}. The decay factor $\lambda > 0$ reflects that targets farther from UAVs are less likely to be successfully struck. The second objective F_2 aims to minimize the total detection time over all assignments, promoting efficient information gathering. The third objective F_3 minimizes the worst-case mission completion time across all UAVs, where each UAV's mission time is the sum of its detection durations and its fixed operation duration T_i^{mission}. This reflects the operational efficiency and robustness of the overall mission.

C. CONSTRAINTS

$$\sum_{j=1}^{M} x_{ij} = 1, \quad \forall i \in \{1,\ldots,N\} \tag{4}$$

$$x_{ij} = 0 \quad \text{if } d_{ij} > D_{\max} \tag{5}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{M} x_{ij} \le C_{\text{total}} \tag{6}$$

The first constraint enforces a one-to-one assignment structure, where each UAV must be assigned to exactly one target, reflecting a suicide-type mission profile. The second constraint limits the feasible assignment set by enforcing a maximum strike range $D_{\max}$. If the distance d_{ij} exceeds this value, the assignment becomes infeasible ($x_{ij} = 0$). The third constraint ensures that the total number of assignments across all UAVs does not exceed a global capacity threshold C_{total}, representing a mission-level resource constraint such as total allowable sorties, munitions, or command bandwidth.

III. ALGORITHM DESCRIPTION

To solve the multi-objective combinatorial optimization problem formulated by multi-target assignments for UAVs under military constraints, this study proposes an extended version of the NSGA-II algorithm, tailored to the operational characteristics of UAVs deployment. We refer to this framework as DOPA. DOPA introduces four major improvements over the standard NSGA-II [16]: (1) *diversity-enhanced initialization*, which promotes broader exploration of the solution space from the outset; (2) *Riemannian crowding distance-based selection*, which preserves solution diversity more effectively by accounting for the geometry of the objective space; (3) *entropy-based adaptive operator control*, which dynamically balances exploration and exploitation based on population entropy; and (4) *Wasserstein distance-based convergence analysis*, which provides a robust and interpretable indicator of structural change in the population distribution over generations.

A. DIVERSITY-AWARE INITIAL POPULATION GENERATION

In conventional NSGA-II, the initial population is typically generated randomly, which may lead to poor coverage of the decision space [16]. In contrast, DOPA generates initial individuals based on a probability distribution that decays with distance between UAVs and targets. For each UAV i, target j is selected according to the sigmoid probability:

$$P_{ij} = \frac{1}{1 + \exp\left(\frac{d_{ij} - D_{\max}}{\sigma}\right)} \tag{7}$$

where d_{ij} is the distance between UAV i and target j, and σ is a scale parameter controlling the decay sharpness. The probability is normalized before sampling.

B. RIEMANNIAN CROWDING DISTANCE FOR SELECTION

To improve selection diversity, we adopt a crowding distance metric based on variance-normalized objective space. The normalized objective value $\tilde{f}_{ik}$ of individual i for objective k is defined as:

$$\tilde{f}_{ik} = \frac{f_{ik}}{\mathrm{Var}(f_k) + \epsilon} \tag{8}$$

where ϵ is a small constant to avoid division by zero. The Riemannian crowding distance is computed as the sum of distances to neighbors in each normalized objective dimension.

C. ENTROPY-BASED ADAPTIVE CROSSOVER AND MUTATION RATES

To dynamically control exploration and exploitation, population entropy is computed at each generation:

$$H = \frac{1}{m} \sum_{k=1}^{m} \left(- \sum_{b=1}^{K} p_{kb} \log p_{kb} \right) \tag{9}$$

$$p_c = \lambda_{c1} + \lambda_{c2} \cdot H_{\text{norm}} \tag{10}$$

$$p_m = \lambda_{m1} + \lambda_{m2} \cdot H_{\text{norm}} \tag{11}$$

where m denotes the number of objectives, K is the number of histogram bins used for discretization, and p_{kb} represents the proportion of solutions falling into bin b for the k-th objective. The entropy H reflects the diversity of solutions across the objective space. The normalized entropy H_{norm} is computed by scaling H within an empirically defined range, and is then used to adaptively adjust the crossover probability p_c and mutation probability p_m. The coefficients $\lambda_{c1}, \lambda_{c2}, \lambda_{m1}, \lambda_{m2}$ are hyperparameters controlling the sensitivity of these probabilities to entropy dynamics.

D. WASSERSTEIN-1 DISTANCE TRACKING

Convergence is monitored using Sinkhorn-approximated Wasserstein-1 distance between generations. Given two distributions P_t and P_{t+1} in objective space, the distance is approximated as:

$$W_1(P_t, P_{t+1}) \approx \min_{\gamma \in \Pi(a,b)} \sum_{i,j} \gamma_{ij} c_{ij} \tag{12}$$

where c_{ij} denotes the cost matrix (Euclidean distance), and γ is the optimal transport plan approximated via Sinkhorn projection.

E. ALGORITHM: DOPA-NSGA-II

The proposed algorithm is summarized in Algorithm 1. It extends NSGA-II by introducing domain-aware initialization, adaptive operator control, and Riemannian diversity-preserving selection.

IV. EXPERIMENTAL SETTINGS AND BENCHMARK SCENARIOS

This section presents the experimental setup and benchmark scenarios used to quantitatively evaluate the performance of the proposed DOPA algorithm. All experiments were conducted in a simulation environment that emulates a multi-UAV loitering munition mission scenario. To ensure reliability, each experiment was repeated under identical conditions using multiple random seeds. The number of UAVs and targets was fixed at $N = 50$ and $M = 20$, respectively. Parameters such as UAV-target distance d_{ij}, target value v_j, detection time T_{ij}^{detect}, and mission preparation time T_i^{mission} were randomly generated to reflect operational uncertainty in realistic mission environments.

Algorithm 1 DOPA-NSGA-II Framework

1: **Input:** Number of generations G, population size N
2: **Input:** Distance matrix d_{ij}, detection time T_{ij}^{detect}, mission time T_i^{mission}, target value v_j
3: Initialize population P_0 using distance-aware sigmoid sampling
4: Evaluate fitness of individuals in P_0
5: **for** $t = 1$ to G **do**
6: Compute normalized entropy H_t^{norm}
7: Update crossover rate p_c and mutation rate p_m using H_t^{norm}
8: Select parents using Pareto ranking and Riemannian crowding distance
9: Apply crossover (probability p_c) and mutation (probability p_m)
10: Evaluate fitness of offspring
11: Merge parent and offspring populations
12: Perform non-dominated sorting and selection
13: Track Wasserstein-1 distance between P_{t-1} and P_t
14: **end for**
15: **Output:** Final Pareto front P_G

Each experiment was repeated across five different random seeds. The number of generations was set to 400, and the population size was set to 200 individuals. The initial population was generated using a probabilistic distribution based on UAV-target distances to ensure diversity, thereby improving the chance of approaching a global optimum early in the search process.

A. COMPARATIVE EXPERIMENT SCENARIOS

To analyze the effect of each component of the proposed algorithm, particularly the adaptive operator adjustment and Riemannian-based selection mechanism, four benchmark scenarios (S) were designed as follows:

- S1 (Baseline): The standard NSGA-II configuration using fixed crossover and mutation probabilities.
- S2 (Adaptive Mutation Only): Mutation probability is adjusted adaptively using population entropy, while crossover probability remains fixed.
- S3 (Adaptive Crossover Only): Crossover probability is adaptively adjusted, while mutation probability is fixed.
- S4 (DOPA-Full): Both crossover and mutation operators are adaptively adjusted, and Riemannian-based crowding distance is applied during selection.

All scenarios are evaluated under identical constraints and initial conditions to investigate the effect of adaptive behavior and selection strategy on solution quality and distribution.

B. EVALUATION METRICS AND CONVERGENCE ANALYSIS

The quality of solutions produced by each scenario can be evaluated using well-established multi-objective optimization metrics:

- Generational Distance (GD): Measures how close the obtained solutions are to the ideal Pareto front.
- Diversity Spread (Δ): Assesses the distribution and uniformity of the solutions along the Pareto front.
- Hypervolume (HV): Quantifies the volume of the objective space dominated by the Pareto front, relative to a reference point.

In addition to these metrics, the generation-wise Wasserstein-1 distance was also tracked to analyze the convergence speed and structural change in the solution distribution over time. This allowed us to visualize and assess how the algorithm explores and exploits the solution space.

V. EXPERIMENTAL RESULTS

This section presents and analyzes the simulation results for the proposed DOPA-NSGA-II framework. A total of four algorithmic scenarios (S1–S4) were evaluated to compare the impact of adaptive operator control and Riemannian-based selection on multi-objective performance. Each scenario was executed five times with different random seeds under identical environmental and parameter settings, and the results were analyzed using statistical measures such as mean and standard deviation.

A. DISTRIBUTION CHARACTERISTICS OF PARETO FRONTS

Figures 1 illustrate the distribution of the final Pareto fronts in two-dimensional (F1 vs. F2, F1 vs. F3) and three-dimensional (F1, F2, and F3) objective spaces. The three objectives are inherently in conflict:

- F1 (Strike Effectiveness, unitless): Maximized by prioritizing high-value targets with higher probability of successful strike. This value is a dimensionless score based on weighted impact and engagement likelihood.
- F2 (Total Detection Time, seconds): Minimized by assigning UAVs to closer targets that can be detected more quickly. This is the cumulative sum of detection times across all UAV-target pairs.
- F3 (Maximum Mission Time per UAV, seconds): Minimized to ensure no UAV is overloaded with long missions. It captures the worst-case (maximum) sum of detection and mission time across all UAVs.

This trade-off emerges because high-value targets are often farther from UAVs or require longer detection durations. Consequently, improving F1 often results in deterioration of F2 and F3. Conversely, minimizing F2 and F3 may reduce the cumulative mission effectiveness due to selection of low-value targets. As a result, the Pareto fronts inherently form a non-convex, curved structure that reflects this spectrum of trade-offs.

In the three-dimensional Pareto front (bottom in Figure 1), Scenario S4 (DOPA-Full) exhibits:

- Lower curvature and wider coverage, suggesting that the algorithm maintained a balanced trade-off across all objectives.

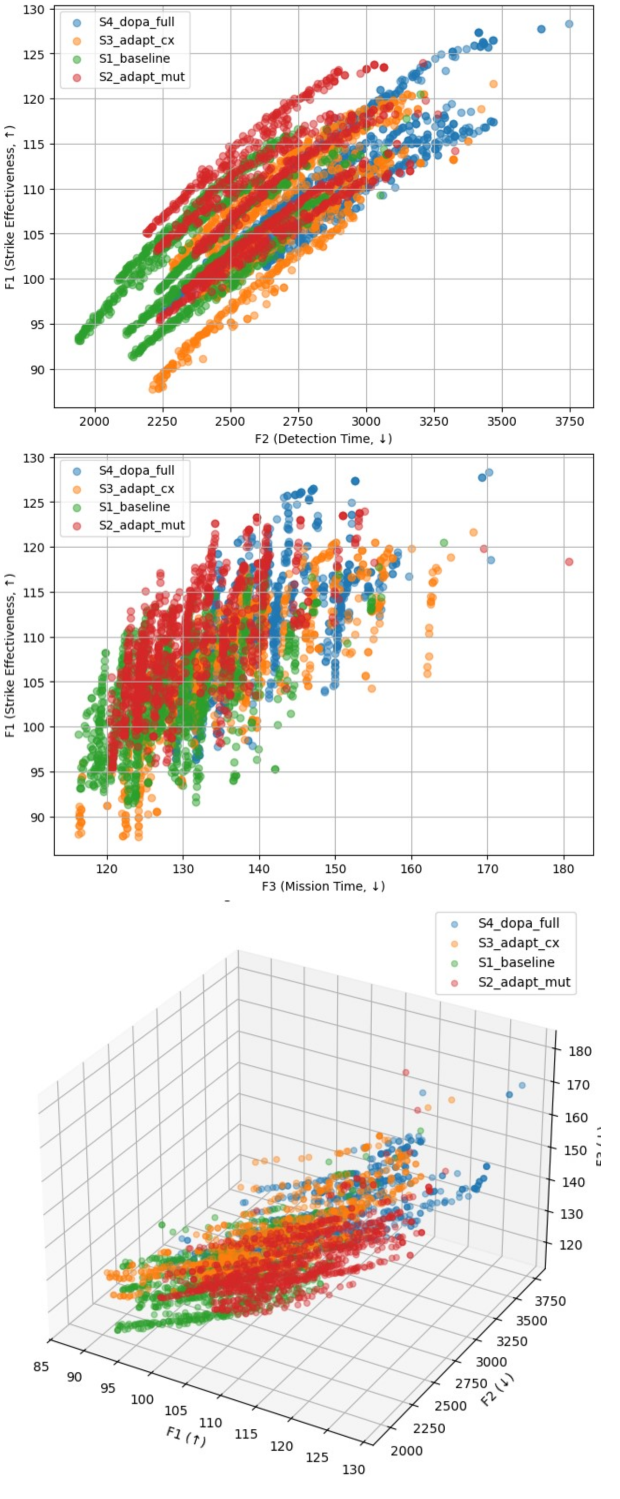

FIGURE 1. **Pareto front distribution across objectives: (top) F2 (Detection Time, ↓) vs. F1 (Strike Effectiveness, ↑), (middle) F3 (Mission Time, ↓) vs. F1 (Strike Effectiveness, ↑), and (bottom) 3D Pareto front in (F1, F2, F3) space**

- These characteristics arise from the synergy between the Riemannian-based selection mechanism and the distance-aware probabilistic initialization.

This enables Scenario S4 to offer decision-makers a broader range of strategic alternatives based on differing operational preferences.

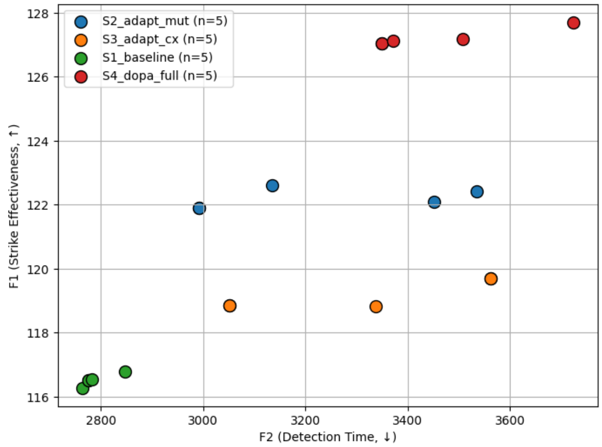

FIGURE 2. **Top k(=4) solutions from each scenario by F1 ranking, plotted with corresponding F2 values.**

B. COMPARISON OF TOP-PERFORMING SOLUTIONS

Figure 2 visualizes the top k non-dominated solutions with the highest F_1 (Strike Effectiveness) from each scenario. In this experiment, $k = 4$. As expected, Scenario S4 (*DOPA-Full*) achieves the highest F_1 values, demonstrating the effectiveness of the proposed hybrid strategy in identifying high-value targets. However, these gains in F_1 are accompanied by an increase in F_2 (Detection Time), indicating a trade-off between maximizing mission impact and minimizing operational latency.

In contrast, Scenario S1 (*Baseline*) exhibits the lowest F_2 values, suggesting that the baseline NSGA-II algorithm tends to prioritize targets with shorter distances and faster detection times. However, the corresponding F_1 values remain relatively low, implying that the algorithm mostly selects lower-value or suboptimal targets to reduce detection time.

The divergent results between S1 and S4 stem from their fundamentally different search strategies. S1 focuses on minimizing F_2 by quickly assigning UAVs to nearby and easily detectable targets. This results in lower strike effectiveness (F_1) due to suboptimal target selection. The absence of adaptive mechanisms and diversity-aware selection limits its exploration capacity. On the other hand, S4 employs a distance-aware initialization, Riemannian-based selection, and adaptive crossover/mutation driven by entropy. This strategy enables exploration of high-value targets, even if they are farther away. Consequently, F_1 is maximized at the cost of increased F_2.

These findings demonstrate that DOPA enables more strategic trade-offs between mission value and timeliness, adapting its search behavior based on feedback from population diversity and convergence signals. As such, the framework supports more deliberate decision-making under complex operational constraints.

TABLE 1. Performance Metrics for Multi-objective Optimization

S	GD (↓)	Δ (↑)	HV (↑)
S1	1300.26 ± 50.75	0.82 ± 0.03	3.74e+06 ± 2.67e+06
S2	1136.31 ± 91.26	0.80 ± 0.02	3.90e+06 ± 5.81e+06
S3	995.58 ± 74.62	**0.93 ± 0.05**	**4.41e+06 ± 5.34e+06**
S4	**916.99 ± 110.47**	0.89 ± 0.04	4.25e+06 ± 5.08e+06

C. QUANTITATIVE METRICS: GD, DS, AND HV

As shown in Table 1, Scenario S4 achieved the lowest Generational Distance (GD), indicating the strongest convergence toward the ideal Pareto front among all configurations. While Scenario S3 recorded the highest Diversity Spread (Δ) and Hypervolume (HV), suggesting wider and more uniform exploration of the objective space, Scenario S4 demonstrated a highly competitive HV and strong diversity while clearly outperforming other configurations in convergence. These results confirm that S4 provides a well-balanced trade-off between convergence accuracy and solution diversity, validating the robustness of the proposed DOPA-NSGA-II framework under operational constraints.

D. SEARCH EFFICIENCY AND RUNTIME COMPARISON

Figure 3 shows the total execution time (in seconds) for each scenario. Scenarios S1 and S2 took over 85 seconds on average, whereas S3 and S4 completed in approximately 61–62 seconds.

This result highlights that DOPA-Full (S4) is not only effective in generating high-quality solutions but also computationally efficient. The adaptive operator control mechanism reduces unnecessary exploration and helps stabilize the search by adjusting the crossover and mutation rates based on entropy feedback. This enables the algorithm to allocate computation more intelligently, which is particularly advantageous in real-time military planning environments.

E. CONVERGENCE AND EXPLORATION DYNAMICS ANALYSIS

To evaluate the convergence stability and exploration behavior of the proposed DOPA-NSGA-II framework, we analyzed the generation-wise Wasserstein-1 distance and population entropy across scenarios. The Wasserstein-1 distance, shown in Fig. 4, captures the distributional change in the Pareto front between successive generations. Scenario S4 (DOPA-Full) maintains near-zero values throughout the optimization process, indicating highly stable convergence with minimal structural fluctuation. In contrast, Scenario S1 (Baseline) exhibits persistent spikes and oscillations, reflecting inconsistent search behavior and potential stagnation.

Meanwhile, the entropy trajectory in Fig. 5 reflects how solution diversity evolves over generations. While both scenarios start with similar entropy, S4 shows a more controlled and gradual increase, suggesting that the adaptive operator mechanism effectively stabilizes the search and avoids premature over-exploration. On the other hand, S1 displays a more erratic entropy growth, implying that it maintains unnecessarily high diversity without consistent refinement of solutions.

FIGURE 3. Execution time comparison across scenarios

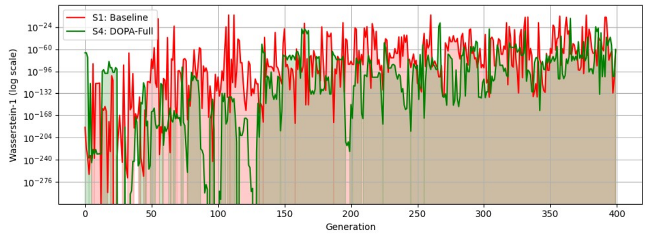

FIGURE 4. Generation-wise Wasserstein-1 distance (log scale) for S1 (Baseline) vs. S4 (DOPA-Full)

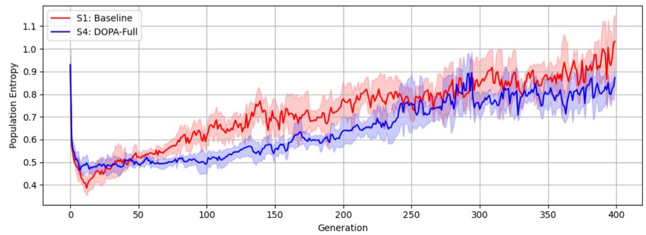

FIGURE 5. Population entropy over generations for S1 and S4

These findings confirm that the proposed DOPA-NSGA-II algorithm not only ensures faster and more stable convergence but also fosters more disciplined exploration dynamics. The integration of entropy-aware adaptation and Wasserstein-based monitoring contributes to a balanced optimization process, particularly suitable for real-time UAV target selection and engagement operations under multi-objective constraints.

VI. CONCLUSION

This study formulated the multi-target assignment problem using Unmanned Aerial Vehicles (UAVs) as a multi-objective combinatorial optimization problem and proposed a novel evolutionary search-based framework, called DOPA (Dynamic Operationally-aware Pareto-based Assignment), to effectively solve it. The proposed framework extends the conventional NSGA-II algorithm by incorporating realistic operational constraints and integrating several key techniques, including a Riemannian distance-based selection operator, entropy-driven adaptive crossover and mutation mechanisms, and a Wasserstein-1 distance trace module to balance convergence and diversity simultaneously.

Experimental results demonstrated that the proposed DOPA framework outperformed the baseline configurations in terms of Pareto front distribution characteristics, Generational Distance (GD), and Diversity Spread (Δ). In particular, the S4 scenario with both adaptive operators enabled showed a broad and low-curvature Pareto front in 3D space, indicating that the proposed strategy achieves both high convergence and diversity. These findings imply that the designed evolutionary mechanism is capable of effectively exploring complex trade-offs among 3 conflicting factors commonly found in military operational contexts. Overall, this work contributes to the field by providing a robust and adaptable optimization framework that not only addresses current multi-objective mission planning needs but also lays the groundwork for future integration with real-time decision-making systems and adaptive operations in dynamic and uncertain environments.

ACKNOWLEDGMENT

This work was supported by the Korea Institute for Defense Analyses (KIDA) under Contract No. R25TA00192271-00 (Project Code: KIDA2024-42). The authors express their sincere gratitude to the project sponsors for their support and guidance throughout the research.

REFERENCES

[1] E. Schwarz, "Autonomous weapons systems, artificial intelligence, and the problem of meaningful human control," *Philosophical Journal of Conflict and Violence*, 2021.
[2] J. M. Burgett, D. Bausman, G. Comert *et al.*, "Unmanned aircraft systems (uas) impact on operational efficiency and connectivity," 2019.
[3] R. Shakeri, M. A. Al-Garadi, A. Badawy, A. Mohamed, T. Khattab, A. K. Al-Ali, K. A. Harras, and M. Guizani, "Design challenges of multi-uav systems in cyber-physical applications: A comprehensive survey and future directions," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 4, pp. 3340–3385, 2019.
[4] Y. Yu, J. Tang, J. Huang, X. Zhang, D. K. C. So, and K.-K. Wong, "Multi-objective optimization for uav-assisted wireless powered iot networks based on extended ddpg algorithm," *IEEE Transactions on Communications*, vol. 69, no. 9, pp. 6361–6374, 2021.
[5] A. S. Manne, "A target-assignment problem," *Operations research*, vol. 6, no. 3, pp. 346–351, 1958.
[6] A. Kline, D. Ahner, and R. Hill, "The weapon-target assignment problem," *Computers & Operations Research*, vol. 105, pp. 226–236, 2019.
[7] N. Ahn and S. Kim, "Optimal and heuristic algorithms for the multi-objective vehicle routing problem with drones for military surveillance operations." *Journal of Industrial & Management Optimization*, vol. 18, no. 3, 2022.
[8] M. R. Endsley, "Design and evaluation for situation awareness enhancement," in *Proceedings of the Human Factors Society annual meeting*, vol. 32, no. 2. Sage Publications Sage CA: Los Angeles, CA, 1988, pp. 97–101.
[9] G. A. Klein, *Sources of power: How people make decisions*. MIT press, 2017.
[10] T. Shima, S. J. Rasmussen, and A. G. Sparks, "Uav cooperative multiple task assignments using genetic algorithms," in *Proceedings of the 2005, American Control Conference, 2005.* IEEE, 2005, pp. 2989–2994.
[11] G. Wang, F. Wang, J. Wang, M. Li, L. Gai, and D. Xu, "Collaborative target assignment problem for large-scale uav swarm based on two-stage greedy auction algorithm," *Aerospace Science and Technology*, vol. 149, p. 109146, 2024.
[12] H. Qie, D. Shi, T. Shen, X. Xu, Y. Li, and L. Wang, "Joint optimization of multi-uav target assignment and path planning based on multi-agent reinforcement learning," *IEEE access*, vol. 7, pp. 146 264–146 272, 2019.
[13] C. Liu, Y. Guo, N. Li, and X. Song, "Aoi-minimal task assignment and trajectory optimization in multi-uav-assisted iot networks," *IEEE Internet of Things Journal*, vol. 9, no. 21, pp. 21 777–21 791, 2022.
[14] R. W. Beard, T. W. McLain, M. A. Goodrich, and E. P. Anderson, "Coordinated target assignment and intercept for unmanned air vehicles," *IEEE transactions on robotics and automation*, vol. 18, no. 6, pp. 911–922, 2003.
[15] M. Li, N. Cheng, J. Gao, Y. Wang, L. Zhao, and X. Shen, "Energy-efficient uav-assisted mobile edge computing: Resource allocation and trajectory optimization," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 3, pp. 3424–3438, 2020.
[16] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multi-objective genetic algorithm: Nsga-ii," *IEEE transactions on evolutionary computation*, vol. 6, no. 2, pp. 182–197, 2002.
[17] Y. Shao, J. C.-W. Lin, G. Srivastava, D. Guo, H. Zhang, H. Yi, and A. Jolfaei, "Multi-objective neural evolutionary algorithm for combinatorial optimization problems," *IEEE transactions on neural networks and learning systems*, vol. 34, no. 4, pp. 2133–2143, 2021.
[18] J. Chen, Z. Zhang, Z. Cao, Y. Wu, Y. Ma, T. Ye, and J. Wang, "Neural multi-objective combinatorial optimization with diversity enhancement," *Advances in Neural Information Processing Systems*, vol. 36, pp. 39 176–39 188, 2023.
[19] J. Teghem, D. Tuyttens, and E. L. Ulungu, "An interactive heuristic method for multi-objective combinatorial optimization," *Computers & Operations Research*, vol. 27, no. 7-8, pp. 621–634, 2000.
[20] W. Liu, R. Wang, T. Zhang, K. Li, W. Li, H. Ishibuchi, and X. Liao, "Hybridization of evolutionary algorithm and deep reinforcement learning for multiobjective orienteering optimization," *IEEE Transactions on Evolutionary Computation*, vol. 27, no. 5, pp. 1260–1274, 2022.

MUHYUN BYUN received the B.S. degree in mathematics from the Korea Military Academy, Seoul, South Korea, the M.S. degree in operations research from the Korea National Defense University, and the Ph.D. degree in industrial and systems engineering from KAIST (Korea Advanced Institute of Science and Technology), Daejeon, South Korea. He is currently an Assistant Professor with the Korea Army Academy at Yeongcheon (KAAY). His research interests include reinforcement learning, combinatorial optimization, and simulation-based decision support systems.

author122.jpeg

EUNAE LEE received the B.S. degree in mathematics from the Korea Military Academy, Seoul, South Korea, in 2017, and the M.S. degree in electrical engineering from the University of California, Los Angeles, CA, USA, in 2022. She is currently a Lecturer with the Department of Computer Science, Korea Army Academy at Yeongcheon, South Korea. Her research interests include optimization, machine learning, and sensor-based control.

doos.jpg

SEOK JOO DOO received the B.S. degree from the Korea Military Academy, Seoul, Korea, in 1995, the M.S. degree in electronic engineering from Yonsei University, Seoul, in 1999, and the Ph.D. degree in electrical and computer engineering from The Ohio State University, Columbus, in 2008. In 1999, he joined the Department of Electronic Engineering, Korea Army Academy at Yeongcheon, where he is currently a Professor. His research interests include electromagnetic warfare, RADAR, unmanned aerial vehicles, and non-linear RF devices.

yun.png

MIN YUN received the M.A. degree in economics from Sungkyunkwan University, Seoul, South Korea, and completed the Ph.D. coursework in public administration at the same university. Since 2011, he has been with the Korea Institute for Defense Analyses (KIDA), where he is currently a Senior Research Fellow with the Center for Force Investment Analysis. His research interests include defense investment evaluation, operational effectiveness of weapon systems, and defense resource optimization.