

Clustering-based Adaptive UAV Formation Shape for Cooperative Defense

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ABSTRACT

Unmanned Aerial Vehicles (UAVs) operating in formation can leverage the capability and efficiency of UAV systems. This paper analyses the impact of UAV formation shape selection in a simulated defense scenario with a manned and unmanned team against threatening drone swarm attacks and proposes an adaptive formation shape strategy method based on spatial threat clustering and artificial potential fields to defend a high-value target. We evaluate the effectiveness of defensive fixed and adaptive formation shapes via simulations of hypothetical different threat drone swarm formations using a realistic 3D UAV simulator. The research shows that it is possible to gain an advantage over an enemy swarm, even when outnumbered, using an adaptive defensive formation shape strategy.

KEYWORDS. Decision-Making, Formation Shape, Defensive Strategies, Multi-Agent System, UAV Swarm

Paper topics: SE-PODMAR, Simulation

1. Introduction

In recent years, unmanned aerial vehicles (UAVs) have been widely used in both military and civilian fields for a variety of applications. For instance, UAVs are being used in public safety to support the monitoring of large-scale events such as stadiums, public concerts, and protests, in search and rescue in response to natural disasters, and have also been used to combat environmental crimes and drug trafficking. In the military field, UAVs have become required assets in modern warfare, revolutionizing attack and defense strategies, surveillance methods, reconnaissance, and logistics due to their capability to fly over dangerous environments without putting the lives of pilots at risk during the mission in addition to the ability to operate for long hours and provide data in real-time. In future operational scenarios with Cooperative Engagement Capability (CEC) [APL-Team, 1995], manned-unmanned teaming (MUM-T) allows unmanned platforms to cooperate with manned aircraft in missions with a shared objective. In this context, we have the concept of loyal wingman (LW) [Ricardo et al., 2023], where intelligent and connected UAVs can act as force and capability multipliers operating under the tactical guidance and control of the manned aircraft, as well as a higher-level remotely controlled UAV in the future.

Due to recent UAV attacks [BBC, 2024], deployment of an efficient counter-UAV (C-UAV) system has become an essential requirement to protect high-value assets and areas against threats. C-UAV systems have the ability to detect and identify hostile UAVs and produce specific responses to mitigate threat. Several approaches [Castrillo et al., 2022] have been considered to neutralize UAV threats, including non-physical responses such as laser weapons, radio wave jamming, signal spoofing and cyberattacks, as well as physical responses such as projectiles, loitering munitions, drones with capture nets [DroneCatcher, 2024] as payloads, or even trained eagles [Aviationfiles, 2023]. Research and new products using Multi-rotor Aerial Vehicles (MAVs) have gained focus in recent years due to their flexible capabilities and low cost, facilitating innovation and making them viable for various applications, including the creation of C-UAV systems.

Our work addresses and analyzes the influence of strategic defensive formations in a future MUM-T air defense scenario against swarm attacks extended from [Ricardo et al., 2023], through the proposal of a new adaptive formation shape based on threat clustering. We compare the effectiveness of the proposal against two well-known fixed defense formations using different hypothetical attack formations.

The rest of this paper is organized as follows. First, the literature related to UAV formation control for defense is discussed. We describe the methodology in Section 2 and the experiments and results in Section 3. Final considerations and future work are discussed in Section 4.

1.1. Related Work

Despite growing interest in UAV swarm systems in military applications, the literature remains scarce regarding specific studies focused on defensive scenarios, most likely because it contains classified data. Few studies address defensive formation strategies to protect high-value units against threats such as kamikaze drone swarms. Most research focuses on aspects of task allocation, decision-making, and formation control during flight, leaving a significant gap in the understanding and development of defense formation tactics. This highlights the need for more focused studies on effective defensive formations and their impacts in operational scenarios.

We can highlight the following works on the defense theme. [Strickland et al., 2019] conducted a study exploring the use of heterogeneous UAV swarms to defend a high-value unit (HVV), inspired by the *Tetragonisca Angustula* honeybee defense of the hive. These bees use hovering and stationary guards to distinguish between different types of intruders. The hovering UAVs, despite their higher cost, serve as a crucial first line of defense. [Wang et al., 2023] proposed an optimal deployment model for multiple UAV swarms along an interception line to minimize the

penetration zone area. Comparative analysis against uniform and random deployments confirmed that the proposed model was effective in reducing penetration areas. [Chi et al., 2023] proposed a bio-inspired Wolf pack decision-making method for UAV swarm attack-defense confrontations using a multi-agent reinforcement learning (MARL) approach. The defense was organized into three swarms of four UAVs, where each one was assigned to different zones using a line formation shape, creating a three-layered defense line against only one threat to protect the base. [De Lima Filho et al., 2022] developed six metaheuristics to optimize UAV swarm formations for beyond visual range (BVR) combat in a high-fidelity simulator against a swarm in line-abreast formation. The optimized defense swarm formations consistently defeated the enemy swarm in the simulations, even under enemy position uncertainties.

In [Brust et al., 2021], an autonomous defense system against malicious UAVs that utilizes a self-organized swarm of UAVs to intercept, capture, and escort the single UAV intruders outside a defended zone was analyzed. The defense swarm creates a three-dimensional cluster intercept-and-capture formation around the UAV intruder, ensuring spatial enclosure to the threat. Using a similar approach but considering a multiple UAV swarm scenario, [Chipade et al., 2021] proposed the *StringNet* herding approach in two-dimensional, and later also in a three-dimensional approach [Zhang et al., 2021], which confines the adversarial swarms by dynamically reallocating defenders based on the spatial distribution of attackers, ensuring effective engagement and control over multiple threats. [Stolfi and Danoy, 2025] also presented a drone swarm system designed to encircle and escort various types of targets, such as unidentified drones or ground vehicles, utilizing swarm intelligence and evolutionary optimization to achieve self-organization. In both works, it is assumed that the intruders always try to avoid collisions with the defenders, making it possible to gather or escort the intruders to determined safe areas, which is not realistic in conflict scenarios but introduces essential relevant concepts to defense scenarios.

[Guinaldo et al., 2024] proposed a method for deploying UAVs as a protective shield over infrastructure, ensuring the agents are almost uniformly distributed using the Delaunay triangulation topology in the three-dimensional space. The coordination was performed using a central formation controller, which distributes the desired position to each UAV. In [Kim and Kim, 2023], a MUM-T Integrated Simulation Platform was constructed to enable realistic 3D simulation scenarios. The platform integrates a full-scale manned vehicle simulator with multiple UAVs using the PX4 autopilot, along with custom Human Interface devices. It supports missions such as formation flying using dynamic circular or semi-circular formation, where relative positioning data is shared with the UAVs without adding pilot workload. The system has been tested with real pilots and mission managers and is positioned as a training and research tool for MUM-T operations.

Regarding adaptive formation control, it is possible to highlight some studies for multi-agents in various application contexts. Shape generation from predefined patterns is addressed by [Wang and Rubenstein, 2020], that proposed a distributed algorithm that converts an image into a rectangular grid to assign positions to ground robots. V-shaped formation was explored in [Quang et al., 2022] by optimizing UAV coverage for patrol and surveillance using a leader-follower configuration, and [Bui et al., 2024] enhanced this formation's flexibility by enabling navigation through narrow passages via dynamic position adjustment. Adaptive formation scaling is proposed by [Li et al., 2024], whose distributed method adjusts formation size based on local density, allowing robot swarms to accommodate changes in swarm size dynamically.

Our work proposes a new mixed adaptive formation definition shape approach for MUM-T, dynamically creating a multi-layered defense based on the concentration of swarm threats for a future scenario.

2. Methodology

2.1. Scenario description

The defense conceptual scenario of interest, based on the previous research by [Ricardo et al., 2023] and the mentioned occurred real cases over the world, assumes that hostile MAVs have been detected approaching a protected area with a HVU, as shown in Fig. 1. In response, a fleet of defense MAVs has been deployed to initiate a defense mission. This fleet uses the Manned-Unmanned Teaming (MUM-T) concept, and it is formed by a remote-controlled MAV, identified as leader, and other autonomous MAVs as loyal wingmen (LW) under the tactical command of the leader. A human remotely controls the leader MAV and is in charge of authorizing or overriding the behaviors of each LW MAV. The scenario could also be applied to naval operations by considering the HVU as a ship under attack.

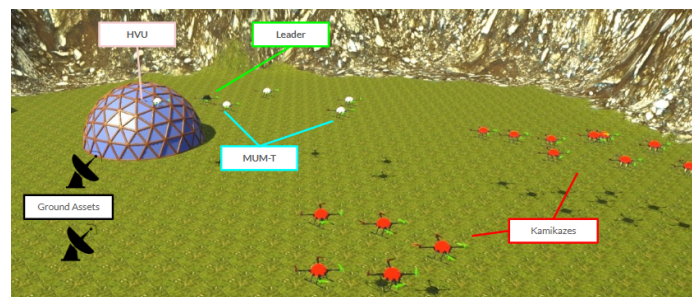


Figure 1: Defense scenario of interest

The objective is to intercept and neutralize all incoming threats and protect the HVU and the leader. The goal of the threats is to destroy the HVU using a technique known as a kamikaze attack, where each threat self-destructs by colliding with the target. The kamikaze are identified as KM MAVs. Each LW MAV is autonomous and capable of making decisions based on situational awareness information of the KM MAVs provided by ground sensors [Giacomossi Jr et al., 2023]. The LW MAVs are equipped with a single hypothetical weapon inspired by [DroneCatcher, 2024], with limited rounds. The KM MAVs, which are modeled with a simplified AI, fly together, aiming the HVU at the same altitude with a maximum speed of 2.4 m/s, making them 20% faster than the LW MAVs, which operated at a capped speed of 2.0 m/s. This speed advantage makes defensive positioning an important factor in the success of neutralizing the threats. Each KM MAV explodes when it collides with the HVU or any other MAV in the scenario. We improved the 3D simulation scenario developed and used in [Ricardo et al., 2023] by adding swarm formations attacks. Similar to their work, we also made certain assumptions to focus on analyzing the impact of using a defensive formation strategy. The defense team has perfect transmission capability, an infinite battery, and the hypothetical weapon is capable of completely neutralizing the threat. The HVU has a high-quality MAV monitoring system in place that is capable of detecting and identifying malicious MAVs and the LW MAVs access distances and relative positioning of all MAVs of the scenario. Environmental factors such as weather, wind, and other forces are not considered. The KM MAVs have simple behavior and use a straight-line trajectory to attack the HVU.

2.2. Problem breakdown

In this work, we consider the system architecture proposed by [Ricardo et al., 2023] as a use case in our research, where the MUM-T defense system is composed of a high-level (HL) decision-making component and a low-level (LL) control component. The LL control is responsible for the robust MAV flight control and implements a joint geometric position-attitude control law using a multi-input first-order sliding mode strategy and the reciprocal acceleration velocity obstacle

(AVO) method to predict and avoid collisions. The autonomous behavior of the MAVs is designed using behavior trees (BTs) and decision-making algorithms to select and execute modular behaviors for the LW [Giacomossi Jr et al., 2023]. These autonomous behaviors are *ApproachFormation*, *GoFormation*, *GunFire*, and *Sacrifice*. [Ricardo et al., 2023] implemented the uniform-circular formation as a defensive strategy against the KM MAVs. This formation, with place rotation upon MAVs rejoining the formation, works effectively in scenarios where kamikazes attack in sparse and isolated timing. However, when they strike as a swarm or in scattered small fleets, the defense becomes ineffective in some scenarios, resulting in the HVU being destroyed by the threats. Since kinematic interception is one of the ways to neutralize the threats, in other words, it must physically collide with the kamikaze, planning the positioning of LW MAV in the formation is critical.

Swarm flight formations refer to patterns or configurations in which a group of birds, insects, or UAVs fly together in a coordinated and decentralized manner. These formations are designed to take advantage of the collective capabilities of the swarm and achieve specific mission objectives. Common UAV formation patterns found in the literature [Liu and Bucknall, 2018] [Javed et al., 2024][Li et al., 2024] include fixed-shape formations, such as the V formation, observed in migratory birds like geese and ducks, and the Echelon formation, both of which have the advantage of reducing aerodynamic drag, and the latter also improves visibility. Other frequently used shapes include the Circular, Line variations, the V-shape, and Diamond formations. Distributed formations disperse UAVs across an area, maintaining predefined inter-vehicle distances, increasing swarm resilience and enabling broader coverage for missions such as surveillance, reconnaissance, and environmental monitoring. Adaptive formations dynamically adjust the formation shape in response to mission objectives, environmental changes, or evolving threat conditions, allowing the swarm to optimize positioning for greater efficiency, survivability, or task performance.

A sophisticated adaptive formation strategy is indispensable to ensure the safeguarding of the HVU across countless diverse situations in which the geometric configuration of the formation may be either autonomously optimized through advanced algorithms or explicitly delineated by a leader MAV that is operated remotely. [Liu and Bucknall, 2018] provided an interesting comparison of the foremost used approaches and key concepts in formation control and cooperative motion planning by unmanned vehicles over the recent decade, where the formation shape definition and its variation key concepts are missing in the previous proposed system architecture. In our work, we investigate the effectiveness of UAV formation defense strategies against aerial attacks, relying on the latest and sophisticated approaches to improve the adaptability of the defense.

2.3. System Architecture

Based on the similar system hierarchical layer structure approach for formation control of Unmanned Surface Vehicles described by [Liu and Bucknall, 2015], we extended the concept of the previous research of [Ricardo et al., 2023], adding a Formation Design Layer into the High-Level Decision-Making component of the system, as presented in Fig.2. This new decision-making layer in the current system establishes a formation shape for the MUM-T defense agents and its variations to enhance the defensive strategy against potential threats. The current system approach uses the Leader-Follower Approach (LFA), where the Leader MAV has the anchor role in controlling the overall formation, and the LW MAV are followers. As we use a hierarchical decision-making approach where each LW MAV can act autonomously under the supervision and authorization of the Leader MAV, each LW receives the positioning command from the leader and goes to the position in the formation upon entering the *GoToFormation* behavior. All positioning commands between the High-Level Decision-Making and Low-Level Control layers use relative positioning concerning the absolute Leader MAV position. The Task Allocation layer employs the Hungarian algorithm to leverage the Assign-Nearest policy as identified as the best swarm tactic approach for engagements

in [Gergal, 2021]. The Low-Level Control Layer developed by [Ricardo et al., 2023] is responsible for the stability, robustness, vehicle dynamics, and the current selected formation shape maintenance using a first-order sliding mode control (SMC) approach.

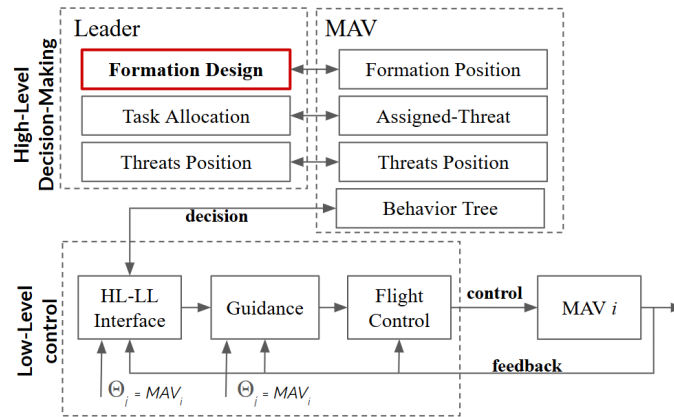


Figure 2: System Architecture overview with Formation Design layer highlighted

The new Formation Design layer creates formation shapes for the defense swarm, discovering each LW MAV's best strategic defense position and ensuring a free collision formation position. Our approach uses a Dynamic Artificial Potential Field to adapt the formation shape of the MUM-T defense system, treating the threat swarms (KM MAVs) as attractive forces and our MUM-T agents as repulsive forces. Instead of statically assigning target positions, this approach guarantees adaptability where the formation emerges using different forces from the scenario elements, building concave or protective shapes automatically. To balance and create shapes that fit possible distinct attack vectors, a clustering algorithm was chosen to dynamically recognize threat formations based on their position and weigh the force proportionally with the number of kamikazes in each threat cluster. Then, based on the Bio-inspired Role Allocation study in [Strickland et al., 2019], we divided the LW MAV swarm into two defense layers: hovering and standing, where the first layer of MAVs goes further away using the resultant force of the potential field, and the second layer standing along the Leader MAV, using the Semi-Circular fixed formation shape, to protect the leader and consequently the HVU. This adaptive formation shape approach was named MixAPF.

2.3.1. Clustering Algorithm

Identification of kamikaze swarm formations is performed using the density-based spatial clustering of applications with noise (DBSCAN) [Ester et al., 1996]. It determines the number of clusters based on the density of data points, which, in our case, is the position of each kamikaze, and each cluster represents a swarm. It has the advantage of detecting noise or outliers that do not belong to any cluster for possible single attacks. This algorithm was chosen due to the low overall runtime complexity $O(n \log n)$, and its ability to dynamically determine the number of swarms. It is worth mentioning that the estimated position of the threats does not need to be highly precise (as long as the estimation is not biased), as our algorithm considers the centroid of the clusters to compute the formation shape. DBSCAN starts by picking an arbitrary point and checking if it has enough neighboring points within a given distance ε to qualify itself as a core point. If the minimum number of points required to form a dense region is satisfied (*MinPts* parameter), a cluster is formed, and DBSCAN expands it by adding all density-reachable points. Points that do not meet the core point criteria but are within ε of a core point are considered border points. Any points not part of a cluster are labeled as noise. The process repeats for all unvisited points, automatically determining the number of clusters based on data density.

2.3.2. Artificial Potential Fields

The Artificial Potential Fields method (APF) [Khatib, 1985] is used in robotics, autonomous navigation and control systems [Zhang et al., 2024]. It involves simulating the environment as a potential field where agents can navigate by following the gradients of the field to achieve goals such as reaching a target or avoiding obstacles. The potential field U results from the sum of all attractive and repulsive forces, and q represents a set of coordinates (x, y) in this field. The resultant forces representation is exemplified in Fig. 3. The field parameters are computed using the following Euclidean distances from position q : distance to Leader MAV (ϕ_q), distance to the HVU (γ_q), distance to the i th LW MAV ($\zeta_{q,i}$), and distance to the j th threat cluster centroid ($v_{q,j}$). Positive constants k_{ld} , k_{lw} , k_{hvu} , and k_{km} determine the strength factor for each force.

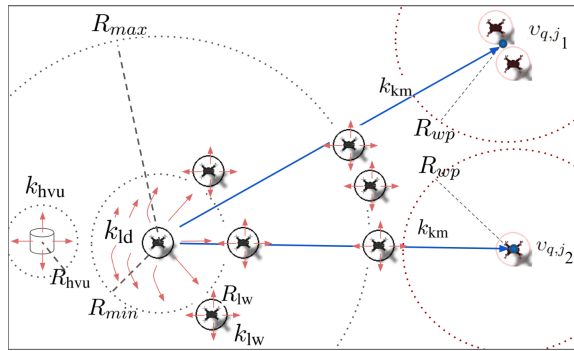


Figure 3: Force decomposition for the Artificial Potential Field method

The attractive force $U_a(q)$ is the sum of the distances from the centroid of each threat cluster $v_{q,j}$, weighted by the magnitude of the force of each cluster using the ratio G_k of the number of threats G_{km} by the total amount of threats C_{km} in the scenario, and zero within the weapon range (R_{wp}) of the LW MAV (Eq. 1). The repulsive force of the Leader MAV $U_r(q)$, given in Eq. 2, is a biased proportional angular force within radius distance R_{min} of the Leader MAV position (x_{ld}, y_{ld}), providing a minimum distance to avoid collision and the local minima problem between the HVU and the Leader MAV, where $\beta_q(\theta) = \phi_q * [\frac{x-x_{ld}}{\phi_q} + \cos(\theta), \frac{y-y_{ld}}{\phi_q} + \sin(\theta)]$. Angle θ controls the force direction. The repulsive forces for the HVU ($U_{rep,hvu}(q)$) and for each LW MAV ($U_{rep,lw}(q)$) are defined as a proportional force within a radius distance R_{hvu} and R_{lw} , respectively.

$$U_a(q) = \sum_{j=0}^W \begin{cases} G_k \frac{1}{2} k_{km} v_{q,j}^2, & v_{q,j} \geq R_{wp} \\ 0, & v_{q,j} < R_{wp} \end{cases} \quad U_{r,ld}(q) = \begin{cases} \frac{1}{2} k_{ld} \left(\frac{1}{\beta_q(\theta)} - \frac{1}{R_m} \right)^2, & \text{if } \phi_q \leq R_{min}, \\ 0, & \text{if } \phi_q > R_{min}. \end{cases} \quad (1) \quad (2)$$

Unlike other research in motion planning that uses APF, our objective is to create an adapted polygon for defining the formation shape of the MUM-T as a strategy to improve defense capability. The non-regular formation shape will be formed by fixing positions using a semi-circular distribution along the Leader MAV for the standing LW. Then, a gradient descent using the potential field U is applied on each hovering LW position until a maximum distance R_{max} from the Leader MAV is reached. The formation shape output for a sample scenario is represented in Fig. 4, where the dynamic potential field is displayed using gray arrows to show the direction and the resultant force on each mapped point of the scenario. This field is used to determine the position of four hovering LW MAVs, and the position of the three standing ones uses a fixed semi-circular distribution from the Leader MAV. The resultant force is zero when the hovering LWs create a line barrier,

increasing concentrated layers of defense. Our focus is the strategic defense of the HVU, as the Leader MAV stands close to ensuring its protection using our adaptive formation shape.

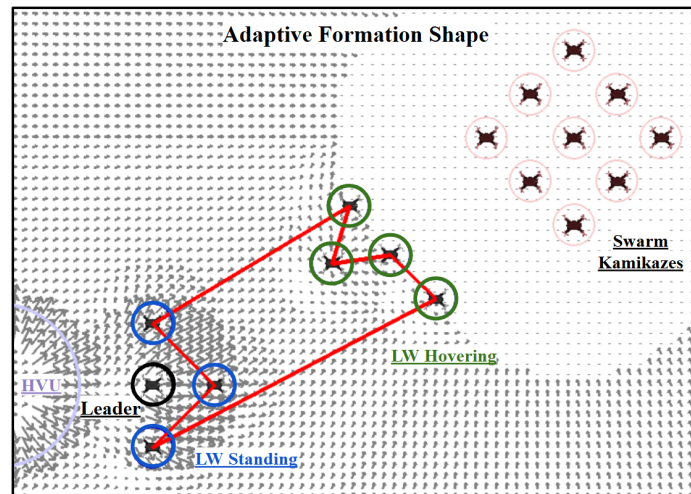


Figure 4: Sample case of our adaptive formation shape method

3. Experiments and Results

In this section, we describe a series of simulations to evaluate the overall impact of the formation strategy in our defense scenario and check how effective a determined formation was. The following metrics were evaluated: (a) number of received kamikaze hits by the HVU, and (b) number of times the HVU has been destroyed. In our scenario, the HVU is destroyed upon receiving five hits from the kamikazes. Each LW MAV is equipped with a fictitious non-lethal weapon with a single round capable of shooting down one kamikaze. Therefore, when we have five LW MAV, we can shoot down a maximum of five threats and, as a last resort, perform a sacrificial maneuver (*SacrificeBehavior*), adding five more neutralizations, summing a maximum total number of ten. The Leader MAV has no weapon and acts as an anchor in front of the HVU to protect it. The number of received hits by the HVU was measured even though all defense agents (LW and Leader) had been destroyed before.

The simulations were conducted with three types of defense formations: two fixed-shape formations, Circular and Semi-Circular, and our new adaptive formation shape approach, identified as MixAPF.¹ The experiments were conducted using two different cases of attack-defense MAV ratios: a balanced defense force first case, which involves a defensive capacity equivalent to the attack that is capable of destroying all attackers by shooting or sacrifice, and second, an outnumbered defense force case of 5 LW MAV against 14 KM MAV, where the defensive capacity is lower than the number of attackers, making it impossible to neutralize all kamikaze attackers. Five attack scenarios with distinct formations were created to check each experiment case, as shown in Fig. 5. The attack scenario descriptions are: (1) Concentrated Arrow Formation; (2) Concentrated Diamond Formation; (3) Three scattered small groups; (4) Two balanced distinct groups; and (5) Two non-balanced distinct groups. For each experiment, 50 instances were executed, and the results were categorized by formation shape definition approach and scenario.

To evaluate the final performance of the defense strategy, the average number of collisions in the HVU was converted into the probability of destruction, where values closer to 1 indicate a greater probability of the HVU being destroyed. In the experiments, the MUM-T is composed of

¹ A video demonstration of MixAPF is available at <https://youtu.be/D3SjKShk2Hc>.

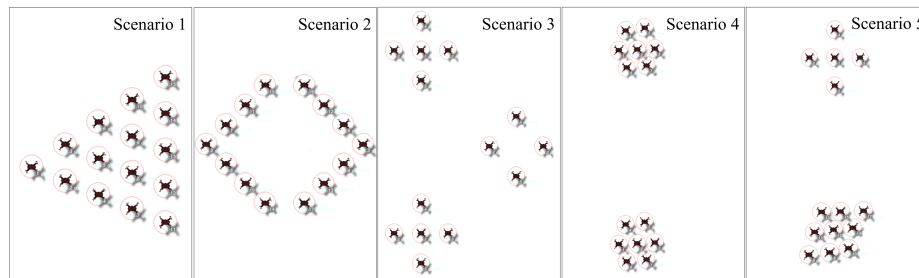


Figure 5: Different attack scenarios with different patterns approach

the Leader and 5 LW MAV, and the threats of the scenario were 10 kamikazes for the balanced case and 14 for the outnumbered case.

When analyzing the scenarios in the context of the balanced defense forces case (Fig. 6a), all formations managed to protect the HVU, preventing it from being destroyed; however, the Circular formation faced difficulties against aggressive attacks — the ones with a concentrated wave of kamikazes in Scenarios 1 and 2. In Scenario 1, the Circular formation exhibited a HVU destruction probability of 28%, indicating that it allowed more threats to penetrate and hit the HVU, while the other formations demonstrated probabilities lower than 10%. In scenarios 1 and 2, our MixAPF approach marginally outperformed other formations. In Scenario 3, the Leader MAV was incapacitated in all formation shapes, however the Semi-Circular formation produced the most favorable results. In Scenario 4, the Circular formation performed slightly better than the others, as the attack was spread out across a wider range, allowing this formation to cover the various attack angles more effectively. The Circular and Semi-Circular formations performed similarly for Scenario 5, outperforming the MixAPF approach. In scenarios characterized by an outnumbered context (Fig. 6b), as expected, the HVU has larger probabilities of being destroyed. Despite the elevated hit rates, MixAPF outperformed others, preventing destruction of the HVU in Scenarios 1 and 2 (Fig. 7), with the Circular formation shape having the poorest performance. For Scenario 3, the Leader was similarly compromised in all instances, and the MixAPF approach created more breaches in the Leader's defenses compared to the fixed formations. In Scenarios 4 and 5, the

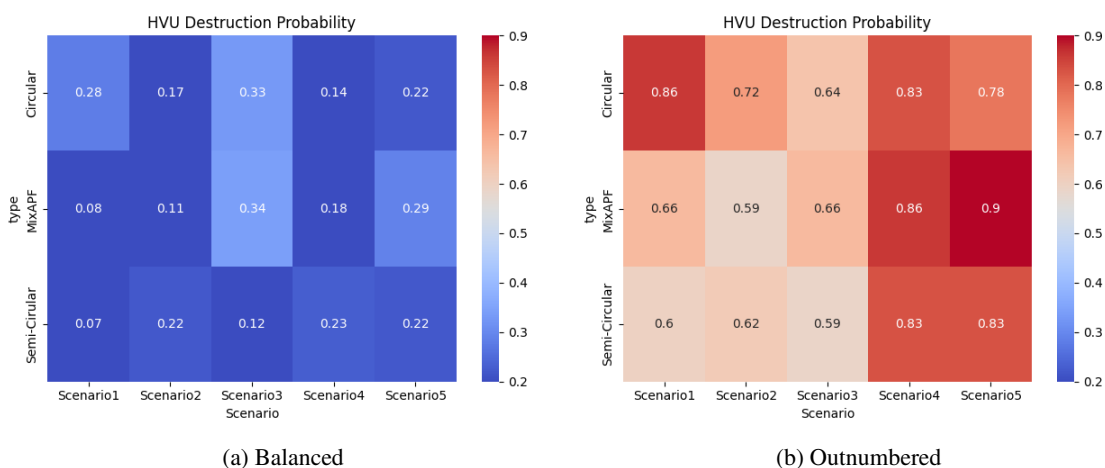


Figure 6: Defense Forces results

ineffective chases to intercept and self-collide, mainly due to the kamikazes being faster than the LW MAVs in our simulation, resulted in decreasing effectiveness of the MixAPF approach. The MixAPF formation exhibited similar or superior performance in the majority of cases, yet it does not fit all problems in our simulated scenario; conversely, the Circular formation was markedly ineffective in Scenarios 1 and 2, although it performed adequately in Scenario 5.

Overall, the proposed adaptive MixAPF formation achieved the main objective of improving the defense performance against swarm attacks, demonstrating clear superiority in concentrated attack conditions (Scenarios 1 and 2). The primary advantage of the approach lies in its layered defense strategy, which distributes and sequences engagements against short and successive kamikaze waves in a single attack vector, reducing the risk of overcommitment where the defense engages simultaneously or prematurely. This adaptability enhances responsiveness to concentrated directional attacks, providing greater resilience even when outnumbered, a feature that was not observed in fixed-shape formations. The model, however, has limitations that restrict its general applicability. The fixed-shape Semi-Circular or Circular formations outperformed the MixAPF in scenarios with multiple dispersed swarm attacks, demonstrating that it cannot guarantee superior performance in all cases. Furthermore, the central architectural dependency of the leader remains critical, leaving the defense system incapacitated when it is destroyed, regardless of the chosen formation.

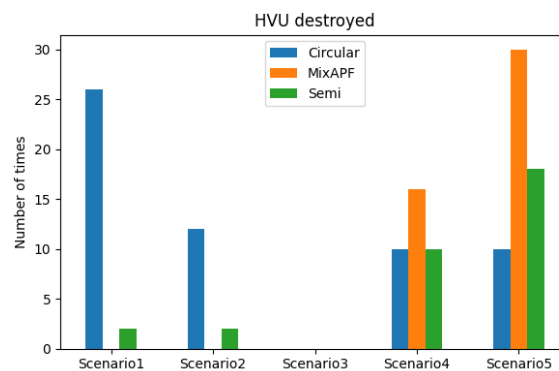


Figure 7: Outnumbered Defense Forces HVU destroyed

4. Final Considerations

With the increasing use of UAVs in modern warfare, coordinated swarm attacks against high-value units (HVUs) pose a new emerging threat, requiring new defensive strategies. Conventional fixed-shape formations lack the adaptability needed to respond effectively to different types of attacks, especially in the dynamic context of UAV swarms. This research aimed to develop and evaluate the effectiveness of an adaptive formation shape compared to fixed-shape formations in a future MUM-T air defense scenario against different hypothetical kamikaze swarm attacks, using a high-fidelity three-dimensional simulated environment.

A new adaptive formation shape capable of dynamically reconfiguring the formation based on clusters of threats has been formulated to improve the defensive capability. The proposed approach differs from conventional fixed-shape formations by generating a non-regular formation shape based on threat positions. In the simulated experiments, the proposed adaptive formation strategy demonstrated superior effectiveness compared to fixed-shaped formations in scenarios with a concentrated number of threats, even when the defense force is outnumbered, thereby decreasing the incidence of hits in the HVU. However, the approach did not perform well in scenarios with distributed multi-vector attacks due to the loyal wingmen position distribution and reaction time to pursue faster kamikazes, which prevented interception using the self-collision.

The main objective of increasing defensive resilience against swarm attacks was achieved by creating a layered defense formation strategy, which distributes and sequences engagements against short and successive kamikaze waves in a single attack vector. However, additional defense balance improvements are needed to handle multi-directional attacks. Several research areas remain for future exploration to enhance performance, scalability, and applicability. Timing to adapt the formation to the desired computed shape is a big challenge in this very dynamic scenario. A trajectory prediction algorithm needs to be introduced into the system to correct inaccurate pursuits during sacrificial maneuvers. Another important point for future work is the inclusion of LW engagement restrictions in high-density environments, since layered defense increases the risk of friendly fire. Moreover, adversary swarms can use different attack strategies to evaluate the effectiveness of the defensive strategy, and the use of real drones in a controlled environment to evaluate the complexities of real-world conditions, such as sensor noise, communication delays, and environmental conditions, can also be the subject of future work.

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