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Review

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Examining application-specific resiliency implementations in UAV swarm scenarios

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Abstract

The number of real-world scenarios where the use of an unmanned aerial vehicle (UAV) swarm is beneficial has greatly increased in recent years. From precision agriculture to forest fire monitoring, post-disaster search and rescue applications, to military use, the applications are widespread. While it is a perceived requirement that all UAV swarms be inherently resilient, in reality, it is often not so. The incorporation of resilient mechanisms depends on an application usage scenario. This study examines a comprehensive range of application scenarios for UAV swarms to bring forward the multitude of components that work together to provide a measure of resilience to the overall swarm. A three-category scheme is used to classify swarm applications. While systemic resilience is an interconnected concept, most real-world applications of UAV swarm research focus on making certain components resilient to disturbances. A broad categorization of UAV swarm applications, categorized by recognized components and modules, is presented, and prevalent approaches for novel resilience mechanisms in each category are discussed.

Keywords: UAV, UAS, drone, resilience, disruptions

1. INTRODUCTION

UAV swarms, representing coordinated groups of drones operating through decentralized control algorithms, have recently emerged at the forefront of aerial robotics research. These swarms leverage collective behaviors to achieve complex tasks with minimal human oversight, epitomizing the confluence of advancements in electronics, communication technology, and algorithmic design.

The miniaturization of electronics has been instrumental in the evolution of UAV swarms. With the advent of compact microcontrollers, powerful computation can be integrated into relatively small drone chassis. Concurrently, the incorporation of Micro-Electro-Mechanical Systems (MEMS) sensors[1], including accelerometers, gyroscopes, and magnetometers, ensures robust Attitude and Heading Reference systems (AHRS) for individual UAVs. Communication remains central to the efficacy of UAV swarms, necessitating low latency and high reliability. Modern swarms predominantly employ protocols such as Zigbee, LoRa[2,3], or customized 2.4 GHz RF modules, with a distinct bias toward mesh network topologies, ensuring redundancy and robustness in intra-swarm communications. These communication frameworks, when coupled with decentralized control algorithms, such as consensus algorithms, distributed task allocation, and flocking behaviors, enable UAVs to exhibit collective intelligence.

At the core of each UAV in the swarm is a combination of onboard processors, sensor suites comprising Inertial Measurement Units (IMUs)[4], Global Navigation Satellite System (GNSS) receivers and transponders, and vision systems using cameras or Light Detection and Ranging (LiDAR)[5] for Simultaneous Localization And Mapping (SLAM) applications[6] and communication modules that sustain the necessary connectivity within the swarm and potentially with human operators.

With advancements in battery technology, particularly the ubiquity of high-energy-density Li-Po and Li-ion batteries, along with the efficiency of brushless DC motors, UAVs are now more enduring and agile than ever. Collectively, these innovations underpin the burgeoning potential of UAV swarms, positioning them as a transformative force in a diverse array of sectors, ranging from agriculture and defense to urban planning and entertainment.

Resiliency is a broad term that encompasses the ability of a system to continue working at acceptable performance levels despite disruptions. While conceptually, it can be defined as system rebound, inherent robustness, graceful extensibility, and unconstrained adaptability[7], these are a literary representation of ideal system characteristics to unwanted stimuli, external or internal. The study of resilience as applied to Unmanned Aerial Systems (UAS) has been widespread in the literature, and the problem is approached from various directions. Sometimes, addressing key components of the systemic makeup, such as trying to solve networking or area coverage issues, or sometimes, addressing the system as a whole[8,9]. This study performs a categorization of application-specific UAV swarms and their resilience mechanisms and condenses it into a structural representation. The review structure is summarized in Figure 1.

To curate the literature required for the review and updated insight into current trends, articles on UAV swarms published in the last five years (2019 to June 2023) were examined. The search was conducted using popular scientific databases, including Scopus, Science Direct, Web of Science, and Google Scholar. Out of the total 572 articles that were examined, 67 were survey articles that were removed. Figure 2 outlines the basic outline for the literature collection[10]. Articles that explicitly do not make use of UAV swarms for an application were removed. These include dataset descriptors[11] and machine learning and image processing methodologies using UAV imagery and sensor data.

The remaining articles were then classified into one of the three categories that were established. Figure 3 visualizes the literature divided into these three categories.

Figure 1. Review structure.

Additionally, a preliminary bibliometric analysis was conducted on the created literature dataset using VOSviewer[12], a popular tool useful for visualizing scientific networks. Topic mapping is a crucial step in literature analysis. This technique has been implemented in several relevant research studies for bibliometric analysis[13,14], citation, and co-authorship visualizations. Obtained outputs such as density visualization and keyword co-occurrence give relevant information such as the spread of literature, relevant research areas, and gaps.

Density visualization offers the advantage of visually rendering data point concentration and dispersion across datasets, facilitating the identification of inherent clusters, trends, and deviations. Conversely, network visualization provides a structured depiction of interconnections between discrete entities. By employing node-link diagrams or matrix representations, network visualization offers insights into intricate

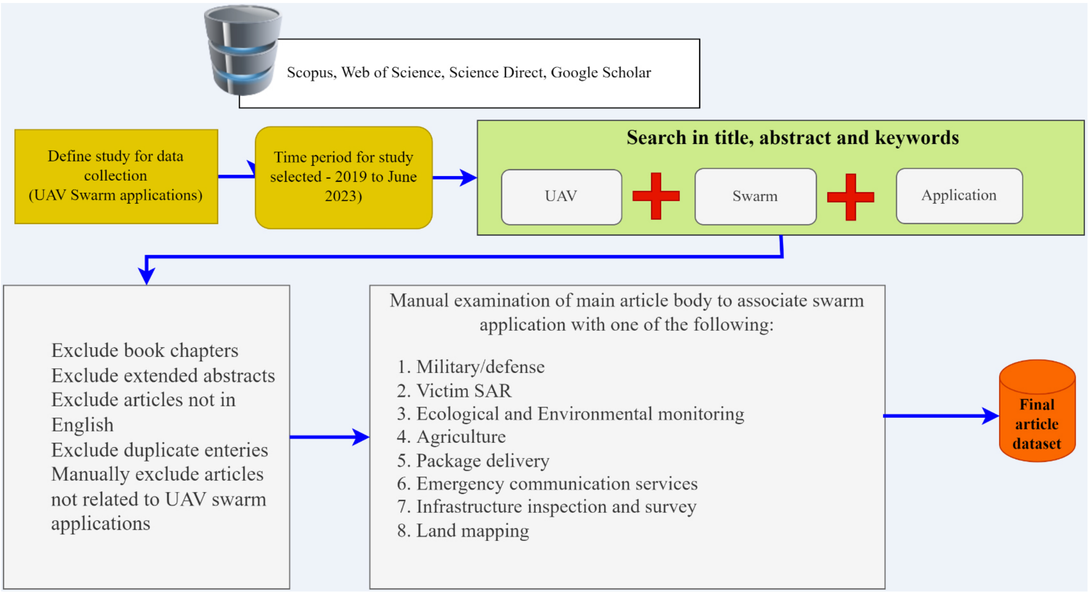

Figure 2. Article curation process for conducting the literature review.

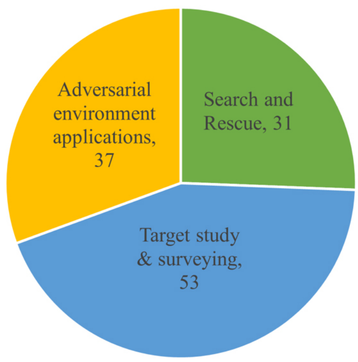

Figure 3. Distribution of selected articles into three established categories.

relationships present within systems, such as relevant keywords or co-authorship networks. Its ability to reveal node centrality, network modularity, and connectivity patterns proves invaluable in disciplines such as social network analysis, epidemiology, and information retrieval, where a grasp of relational dynamics informs strategic planning and system optimization. Figures 4 and 5 show network and density visualizations of the extracted literature dataset, respectively.

Aerial swarm operations face a multitude of challenges both due to internal and external factors. The resilience of UAV swarms is an integral need due to the dynamic environment in which these swarms usually function. The authors have previously comprehensively examined UAV swarm systemic composition and categorized it into components and modules[15]. The major system operations are condensed into seven recognized components: Communication, Movement, search and rescue (SAR), Security, Resource and Task Handling, Agent Properties, and Resilience Evaluation. Each component has one or more modules, which are integral systemic connections that make up a corresponding component. These components are based on core elements of swarm systems and generalized swarm architectures such as those presented in[16] combined with bibliometric analysis of prevalent literature on UAV swarms[10]. As

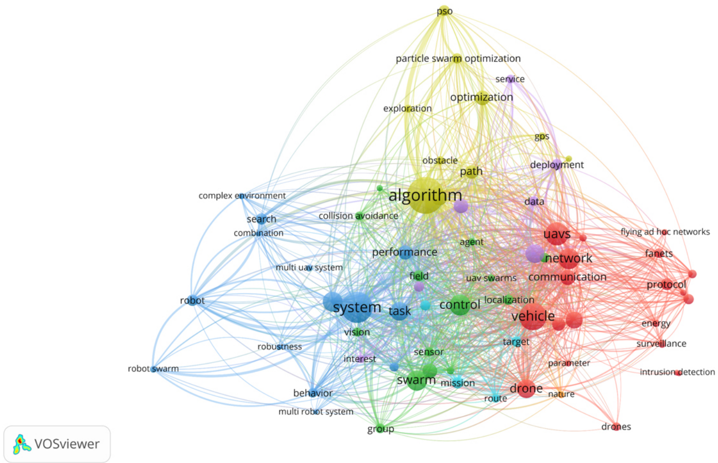

Figure 4. The network visualization of extracted keywords from the selected and compiled literature.

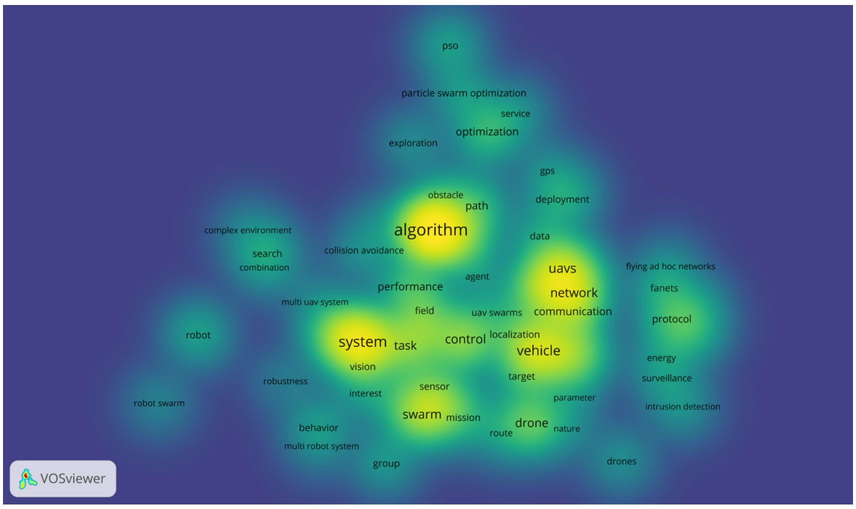

Figure 5. The density visualization of keywords from the selected and compiled literature.

mentioned earlier, the division into components and modules is based on previous work by the authors. This work is presented as a systematic component analysis[15] and summarized in Figure 6. The seven main components of UAV swarms are listed, and each component has its child modules. Good system design practice includes addressing each module for robustness to bring a measure of resilience to the parent component's function.

In general, the approach in the literature has always been to incorporate the most obvious and important resilience mechanisms in UAV swarm components. However, this is an idealistic approach that is worth closer examination. While specific use case scenarios may not require such a comprehensive integration of mechanisms to respond to disruptions that are not predicted to occur in their state space, this review considers a broad body of research on UAV and UAV swarms and their proposed usage. Often, the choice of the component to implement resilient mechanisms for was also based on the application the swarms will be used for.

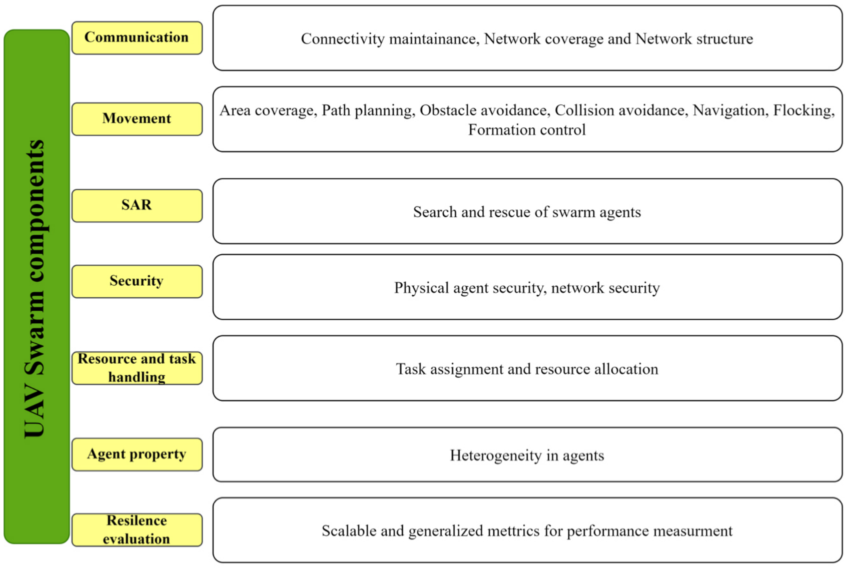

Figure 6. A condensation of unmanned aerial vehicle (UAV) swarm resiliency incorporation into its components and modules.

Designing specific experiment series for every application of UAV swarm technology is essential to ensure the optimal functioning and performance of both individual components and the system as a whole. Each application, whether it is environmental monitoring, disaster response, precision agriculture, or surveillance, poses unique challenges and requirements that can influence how UAVs interact and collaborate. By tailoring the experiment series to the specific application, researchers can comprehensively assess the capabilities of individual UAV components, such as sensors, communication systems, and autonomy algorithms, within the context in which they will operate[17]. Furthermore, testing the entire swarm system in scenarios relevant to the application allows for the identification of potential bottlenecks, vulnerabilities, or unexpected behaviors that may arise when UAVs work together. This approach not only enhances the reliability and efficiency of UAV swarm deployments but also enables iterative refinement of the technology to meet the specific demands of each real-world scenario. Figure 7 visualizes the major applications that UAV swarms are typically used for. Table 1 mentions relevant studies for each application outlined in Figure 7.

Table 1. Major applications of unmanned aerial vehicle (UAV) swarms with relevant studies examined

Application area	Relevant work in the application area
Precision agriculture	[18-22]
Ecological and environmental monitoring	[23-25]
Victim search and rescue	[26,27]
Military defense applications	[28-30]
Land mapping	[13]
Infrastructure inspection and survey	[31-34]
Emergency communication services	[35,36]
Package delivery	[37,38]

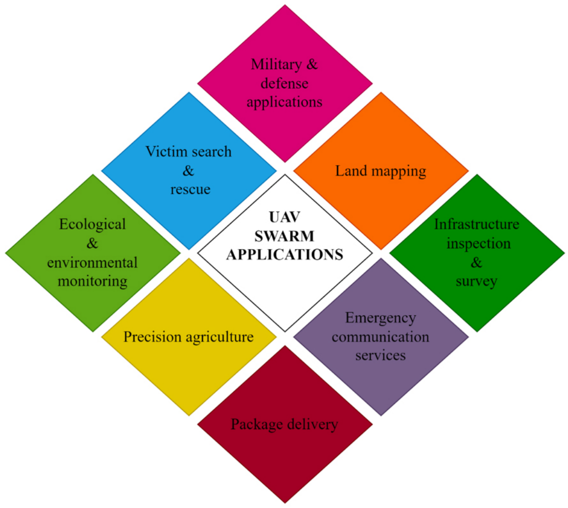

Figure 7. An overview of unmanned aerial vehicle (UAV) swarm applications.

The application scenarios were categorized into three major categories. Each category is then discussed for its unique implementations and contributions to making a specific parent component more resilient. The major contributions of this study are as follows.

1. Establishing a categorization system that uniquely classifies UAV swarm applications into one of the three established divisions, namely, adversarial environment applications, SAR applications, or target study and surveying.

2. Category 2, i.e., SAR, is a broad domain. This article uniquely recognizes two subcategories. An application-focused SAR methodology that uses UAV swarms to search for targets, such as victims, after a disaster, swarm-specific SAR (SS-SAR) methodologies are focused on the UAV swarm agents themselves. While the former is a use-case scenario of UAV swarms that provides a beneficial service, the latter focuses on creating robust swarm deployments by taking care of swarm agents during an operation.

3. For each category, current literature is examined, and the resilience component/module that they target is discussed.

2. CATEGORIZATION OF UAV SWARM RESEARCH

Based on the way UAV swarm usage is targeted, there are three major categories into which an application can be condensed: Adversarial environment, SAR, and Target study and surveying. Any use case scenario can be reasonably categorized into one of the application categories. Table 2 organizes swarm applications into these major categories and their broad description. In the following sections, we approach each category and examine multiple research approaches that have been indexed under each study for their novel approach toward resilient UAV swarms.

Table 2. Three major categories for unmanned aerial vehicle (UAV) swarm applications

Major application category	General description of the method of resilient operation
Adversarial environment applications (military, security)	Demonstrate robust network, formation control, and tracking of targets in adversarial environments, avoid hostile network takeover attempts, jamming resistance, and external agent attacks
Search and rescue applications	Maximize search area coverage, ad hoc network coverage robustness
Target study, surveying, long-term area commitment applications	Efficient information recording, accurate target detection, long-term energy-efficient operations for mapping, analysis, or DaaS (Drones as a Service) provisions

2.1. Adversarial environment applications

An adversarial environment is broadly defined as an environment where an agent may encounter any kind of resistance to its activity or danger to its well-being. In such an environment, UAV swarms are expected to face disruptions. However, an adversarial environment in military-specific applications is further constructively defined as an environment where the swarm may be attacked by physical agents, such as ground-based vehicles, projectiles, or other UAVs, in an attempt to impede its progress. Network attacks, such as takeover and hacking attempts, or attempted swarm attacks by network jamming are also included. Figure 8 shows a heterogeneous UAV swarm that consists of a high-altitude fixed-wing aircraft that acts as a relay node for a swarm of low-altitude recon quadcopters. The fixed-wing provides a connection relay service to base stations beyond the line of sight of the low-altitude swarm. Adversarial environment functions include signal jammers, enemy UAVs, and surface-to-air anti-aircraft defense systems.

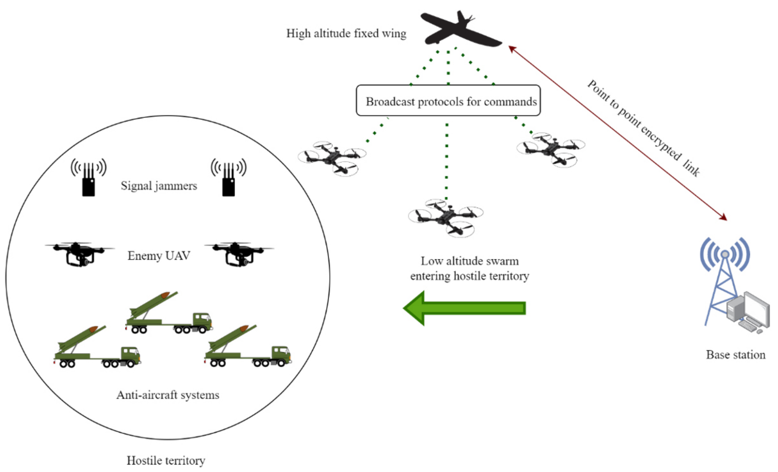

Figure 8. Examples of adversarial environments an unmanned aerial vehicle (UAV) swarm might encounter.

Table 3 organizes the referenced works by the primary resiliency module they focus on. Swarms working in adversarial environments, in general, require thorough provisioning for intrusion detection in both physical and cyberspace, along with the implementation of secure encrypted network protocols for data transmission. Resilient networking protocols for UAV swarms are important links to other agents and ground control. Once a UAV swarm enters hostile territory, the enemy will try both physical and cyberattack approaches to deter the swarm from accomplishing its goal. Network security, such as an IDS (Intrusion Detection System), should be incorporated into the development of network topology and routing protocols. There is a complete taxonomy of network IDS[39] that can be incorporated based on the capability of the swarm and mission scenarios.

The other form of swarm security, physical agent security, is necessary for environments where adversarial activity is expected. Commonly explored approaches use onboard sensors, such as vision and LiDAR, to effectively detect physical space intrusions by external non-swarm entities. Article[40] proposes the use of LiDAR as a means for obstacle recognition and physical space intrusion detection. A model proposed by authors in[41] takes inspiration from shoal formations in the real world, such as bees and fish, to demonstrate a cooperative hunting strategy for a swarm. Such techniques can be used to both hunt targets, evade enemy agents, and address multiple swarm components and modules. Bio-inspired algorithms are proving to provide solutions to multiple challenges faced by UAV swarms. Based on group hunting behavior in nature[42], provides a reinforcement learning-based decision scheme for attack and defense maneuvers for the swarm.

Table 3. Categorization of referenced studies by the major resilience module/component that they consider (adversarial environment)

Resilience component/module highlighted	Referenced study
Area coverage	[45]
Agent security (physical)	[40,42,44]
Path planning, collision avoidance	[40,43]
Agent property (heterogeneity)	[44,45,47]
Resource allocation/task reassignment	[44,45]
Formation control	[41,46]
Network security	[50]

This technique can also be scaled and applied to swarm systems to track cooperative swarm agents for collision avoidance and external dynamic and static obstacle avoidance. A similar technique using visual sensing has been used in[43] to detect cooperative UAVs in swarms. This is an effective method for inter-agent collision avoidance, and the technique can also be expanded to track any external UAV entering the proximity of the swarm. This is especially useful in perimeter protection and defense strategy, where a swarm of UAVs can effectively form a perimeter around an area to be protected. Any external UAV attempting entry can be detected and actively tracked for other defensive establishments to destroy. Pursue-evader applications using UAV agents are also a possibility in the military domain. Applications involve the use of UAV swarms to collectively pursue other UAV targets to jam their communications, impede progress, or intentionally collide with them to bring them down. Development in this field is ongoing, but innovative work was done in[44] that combines evader-pursuer algorithms with the possibility that the two parties being tracked may be heterogeneous in terms of their flight capabilities and accounts for it by proposing Apollonius algorithms to efficiently detect evaders by resource allocation.

Combination studies such as this comprehensively address agent heterogeneity, resource allocation, and swarm security components under one application scenario. A similar study conducted in[45] proposes autonomous unmanned heterogeneous vehicles for persistent monitoring in defense and monitoring high-value targets such as military installation camps. Using a variety of quadcopters and fixed-wing agents, the proposed framework can also track static and dynamic ground targets. When entering adversarial environments, it can be expected that UAV swarms may lose connection with ground control or space segments, resulting in temporary or permanent control or navigation signal loss. The key focus was the development of enabling technology to address task assignment, coverage, and swarm management policies in such scenarios. Bearing-based formation control methods, such as[46,47], may use neighboring agents, ground control planes, and tertiary data to align themselves and prevent immediate mission failure. This allows both ground control and the swarm additional time to attempt signal reconnection. While some methods study single-space operational swarms only, certain approaches expand the formation control and management policies to multi-operational space heterogeneous agents[47]. However, it cannot be assumed that all heterogeneous agents are for support purposes. In problems such as these, the heterogeneous agents are the advertisers of the UAV swarm. With the rapid development of surface-to-air missiles, swarms also have to consider the occurrence of land-based malicious entities such as missiles and jammers that are focused on damaging aerial swarms. A consensus algorithm is proposed in[48] for a swarm of herding UAVs that have to deal with land-based anti-aircraft vehicles. Continuous tracking of heterogeneous targets is such a broad domain that it requires additional development, as demonstrated in[49].

While secure network communication is a basic requirement of all swarms, both energy-efficient and secure UAV communications are a primary concern during warfare. Working in conjunction with anomaly detection IDS, a joint resource allocation and secure protocol can work despite experiencing downlinks and in the presence of eavesdroppers yet still provide efficient communication support to ground users[50].

2.2. Search and rescue of targets

While resiliency components highlight the SS-SAR features needed, this section refers to application-specific SAR (AS-SAR) uses. It is first necessary to establish a differentiation between the two methods. AS-SAR deals with the process of using a UAV swarm to effectively search an area for a specific target. Such target search examples include searching for lost or trapped miners in underground mines[51], detecting forest fires[52-59], and marine rescue scenarios[60-63]. The segregation of the two approaches is summarized in Figure 9.

SS-SAR is a different research area from AS-SAR. While both are exploratory problems, the former is concerned with internal agents while the latter has the search for an external target as its end goal. SS-SAR frameworks have the sole purpose of keeping track of the individual agents that make up the swarm. If an agent of the swarm is lost, the other agents attempt to locate and rescue the fallen agent. It can, thus, be comprehended that while AS-SAR is a use-case scenario of UAV swarms, SS-SAR is a resiliency component within itself. The availability and efficacy of SS-SAR frameworks contribute to the overall increase or decrease in swarm resilience.

AS-SAR varies widely in terms of methodology. Researchers often employ a wide range of approaches, including game theory, deep learning, and probabilistic approaches, such that it is impossible to condense them under a single framework. SS-SAR approaches, on the other hand, being a relatively novel field, have a generalized workflow that has been proposed.

Figure 10 shows an AS-SAR scenario where a UAV swarm coordinates to search a region for a missing person. Figure 11 depicts an SS-SAR scenario where any swarm agents that fall into distress themselves while conducting an AS-SAR mission may be rescued. This is done using pose checks, agent well-being checks, and reconnection protocols. If immediate rescue is not possible, SS-SAR opens up avenues such as marking the location of the fallen agent for possible retrieval later on. Comparing Figures 10 and 11, a difference between the two scenarios is realized. Current work by the author focuses on developing the aforementioned SS-SAR protocols to realize the proposed SS-SAR scenario as a novel area of research. Figure 12 shows a part of the experiments that the authors are conducting to test distressed agent recovery in simulated environments[64].

Figure 13 presents an SS-SAR framework for rescuing distressed UAV swarm agents[64]. It comprises several stages for agent tracking and initiating rescue protocols. The advantage of such frameworks is their modular nature. Modules can be swapped or upgraded as per factors such as mission requirements and agent capability. Section 1 uses periodic "*hello messages*" from agents labeled as HBS (Heartbeat Signals) to track agent well-being. Further modules perform static and dynamic obstacle checks near distressed agents to determine causes of failure, followed by higher-level system checks for battery, network connection, and hardware integrity. The last stages involve agent recovery procedures or loss procedures and task reassignment.

While it was important to highlight the difference between SS-SAR and AS-SAR, this study focuses on reviewing AS-SAR research and the various methodologies that have been implemented to make such scenarios more robust and effective. Table 4 organizes referred works by their major resiliency module focus. Victim SAR scenarios have often relied on large teams of people searching for the victim through

Table 4. Categorization of referenced study by the major resilience module/component they consider (SAR)

Resilience component/module highlighted	Referenced study
Network coverage	[69,76]
Area coverage	[68,69,76]
Path planning, collision avoidance	[62,79]
Agent property (heterogeneity)	[68,79]
Resource allocation/task reassignment	[80]
Formation control	[68,76]

SAR: search and rescue.

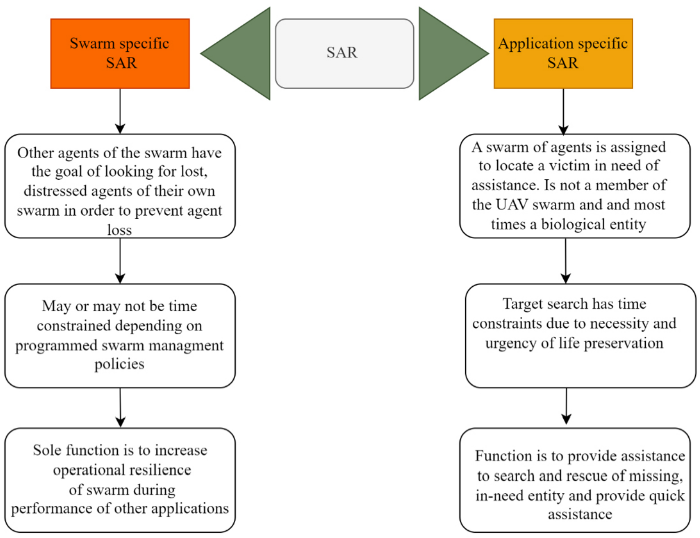

Figure 9. A differentiation between swarm-specific and application-specific search and rescue (SAR).

building rubble, forests, and water. The last known location of the missing person is often triangulated and searched manually. Post-disaster locations are typically manually and meticulously gone through for days to look for live victims trapped or injured. Due to the nature of such scenarios, time constraints are of the utmost importance. The advent of remotely operated robots on land, water, and air has rapidly seen their inclusion in SAR missions. Often, a swarm of such robots can effectively cover a larger area in less time. Additionally, multiple passes over a single area are possible as an added advantage. Target detection using sensors is the most prevalent choice for this methodology, with vision sensors being the primary choice for victim detection[65,66]. Speed and efficiency factors of a SAR operation can depend on the extent of the environmental knowledge of the search area.

Swarm agent heterogeneity can be implemented in many ways via the choice of swarm hardware, area of operation, and agent characteristics. A UGV (Unmanned Ground Vehicle) can provide efficient and low-error information such as terrain, surface, and elevation, including the presence of obstacles and their dimensions[67]. Multiple quadcopters performing post-tsunami swarming maneuvers to assist in SAR use control systems that defined simple behaviors based on UAV personality type. This addresses the heterogeneity by agent nature of swarms[68]. The speed of victim detection is also an indirect function of the maximum area coverage. The faster the swarm of drones covers the target area, the higher the probability of the target being detected. As such, maximum area coverage optimization problems using mobile nodes and the associated network coverage problem need to be addressed. Adjacent agents need to ensure that they

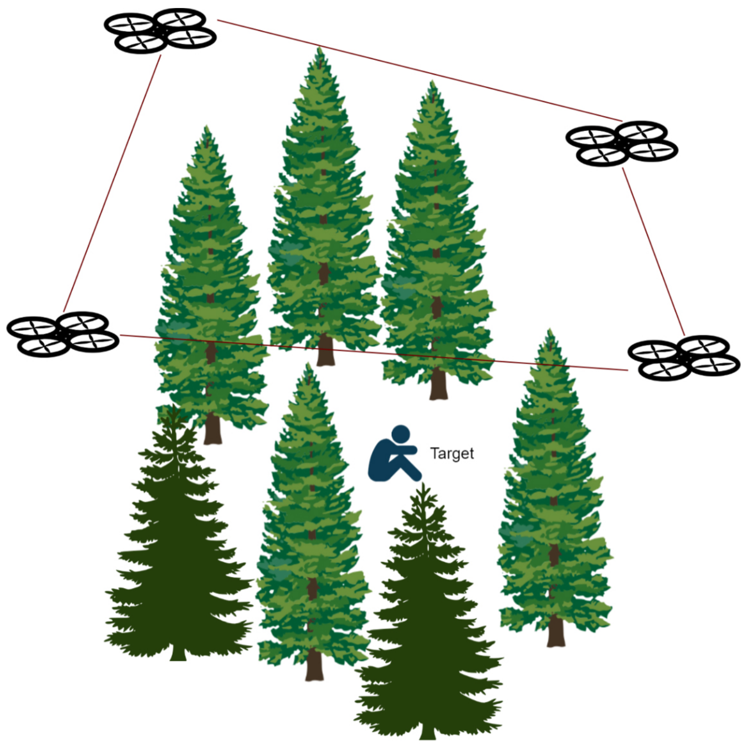

Figure 10. A swarm of UAVs searching for a person lost in a forest. UAV: unmanned aerial vehicle.

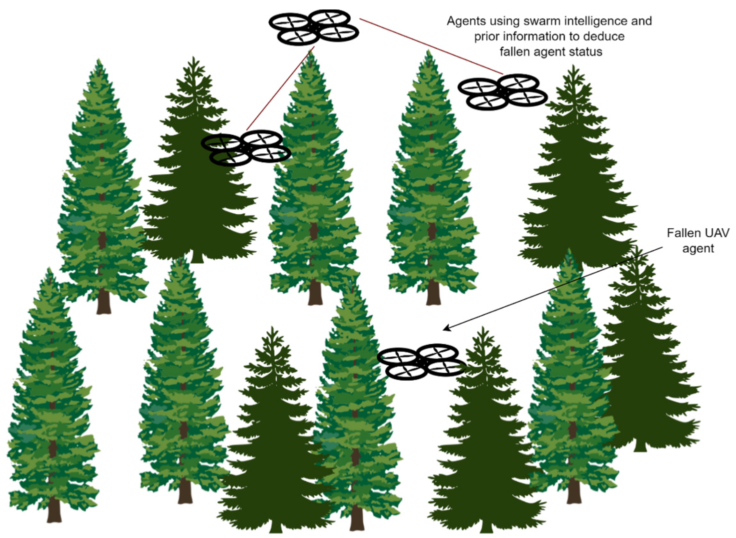

Figure 11. A representation of a swarm-specific SAR (SS-SAR) scenario. SAR: search and rescue.

cover the maximum area but also ensure that they are within range to maintain a network connection to the swarm as well. How they stay connected depends on the underlying network topology. One approach is to maintain a mesh-based data hop connection where every agent is connected to at least two other agents. Additional constraints are required so that the connections do not result in closed-loop scenarios.

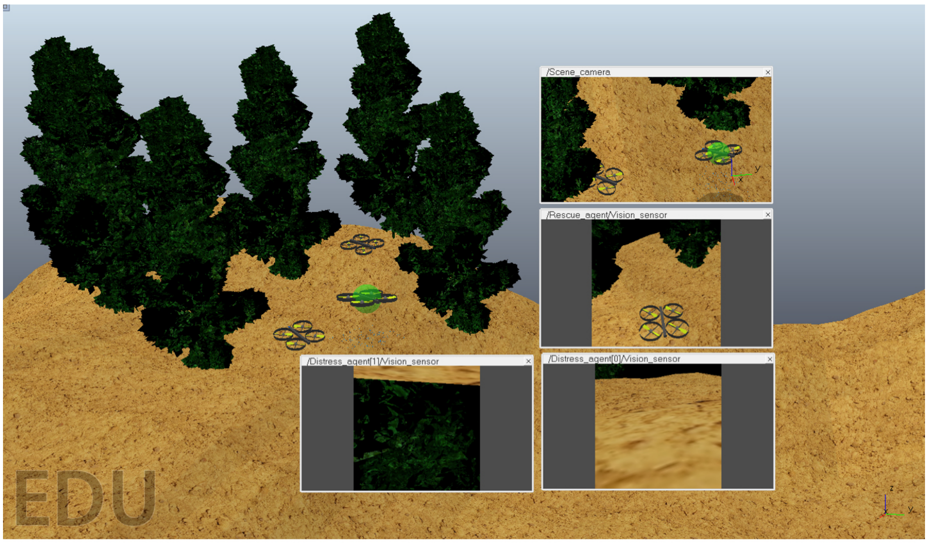

Figure 12. An execution of a swarm-specific SAR (SS-SAR) scenario in a CoppeliaSim simulated environment.

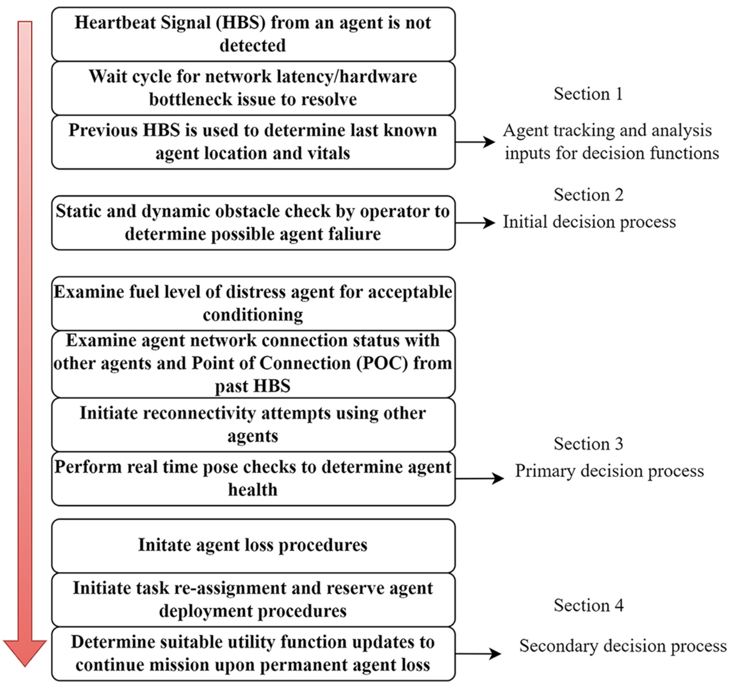

Figure 13. A swarm-specific SAR (SS-SAR) workflow for agent tracking and distressed agent rescue. SAR: search and rescue.

Area optimization during SAR approaches, such as in[69], aims to cover multiple such modules before the SAR exploratory problem can even be approached. Naturally occurring flocks of creatures have been observed to demonstrate some highly efficient maneuvers for member management, deployment, and exploratory behaviors. Inspired algorithms from such behaviors are categorized as bio-inspired algorithms. Each algorithm has popularly been associated with particular behaviors of a swarm, such as modifications of the wolf pack algorithm for task assignments[70-72] and the fruit fly algorithm for mission planning and consensus[73-75]. Article[76] covers an autonomous deployment of a UAV array in a tactical formation using a learning approach called self-organizing maps. This methodology condenses the area-network coverage problems into singular solutions that can output arrays of mobile agents over the target area. This broad study can be programmed to military scenarios as well, where such efficient formations can provide emergency communications to troops on the ground. The authors, however, have modeled this scenario with SAR as their primary scenario descriptor.

Such methodologies can be used to complement existing swarm deployments using information exchange policies for environmental awareness. Appearance-based tracking algorithms, such as[77], can detect victims on the ground in SAR scenarios. It is possible to employ such techniques on collaborative UAVs to effectively cover a larger area or track a single target from multiple frames to gain higher confidence levels on target detection probability. Additional approaches involve using bimodal information-based target recognition for victim detection[78]. A collaborative process in[79] uses a UAV-UGV to solve a SAR scene locally in the absence of GNSS information. While GNSS is an integral part of robot navigation, it is also prone to errors, signal sparsity, and jamming. Developing methodologies that can function without GNSS, even temporarily, is an important addition to the overall resilience factor of a swarm. The UGV here is a humanoid robot that localizes using a combination of local odometry and adaptive Monte Carlo localization. In this study, a camera sensor backed by a neural network is used for detecting humans. The aerial robot provides a 2.5-D map that is used as input by the path-planning process of ground robots. Such hardware and operational space heterogeneous agents also highlight developments in the agent property component. Decision independence in individual agents is a complex research task. It measures the availability of decision-making capability that each agent is capable of during tasks. Agents that are capable of making individual decisions have been shown to provide better results for SAR missions when compared with a swarm that has centralized control[80]. This is a problem that broadly falls under the resource allocation and reassignment scheme for swarms. Agents are capable of requesting, holding on to, or releasing common resources and reassignment tasks for accomplishing a common objective by making individual decisions. The limitations to executing tasks by agents are their limited fuel and computing capacity.

Path planning and obstacle avoidance fall under the control system area of swarm development using optimization problems and environmental information based on simultaneously occurring external incidents. Article[62] uses multiple UAVs to decompose search grids and create efficient paths along polygon edges in maritime SAR.

2.3. Target study and surveying

Target studying and surveying is a broad category that describes the use of UAV swarms for remote sensing and ecological and agricultural scenarios. It differs from the above SAR section by its primary factor of time constraints. While it is vital to accomplish victim detection and rescue in post-disaster scenarios, target study, and surveying may require a long-term commitment to the interaction between the UAV swarm and the target site. For example, following a herd of buffalos being hunted by lions to study pack hunting strategies or using UAV swarms to create agricultural field vegetation maps for plant disease detection[22,81]. Applications such as using fixed-wing aircraft to collect cumulus cloud data[82] also fall under this category. Table 5 highlights referred works that incorporate resilient mechanisms in target study applications.

Hence, there is an inherent shift in the way resiliency is perceived in such applications. A focus on sensor data quality, sensor fusion, efficient transmission of data through network protocols, and energy-aware routing protocols[83-88] is prevalent in resilient mechanisms. In persistent surveying applications such as crowd control and surveying[89], there is no need for SAR protocols. However, UAV swarms may be used to

Table 5. Categorization of referenced study by the major resilience module/component they consider (target study)

Resilience component/module highlighted	Referenced study
Area coverage	[32,85,93,98-100,104]
Path planning	[95]
Agent property (heterogeneity)	[94,102-104]
Testbed design and resilience measurement metrics	[97]
Resource allocation, optimization	[85,92,97,99,100,103,105]
Task assignment/reassignment	[84,98]
Network coverage, structure	[94]

analyze crowd movements or use vision sensors to detect and track certain people as they move through the crowd. Police drone swarms use vision sensors and onboard light displays as means of crowd control, evidence recording, and criminal activity deterrents[90,91]. These applications, in particular, require persistent presence. Energy-efficient resource allocations such as[85] are ideal. They may also achieve this by task-offloading algorithms using fast network protocols for data management. Joint modules such as area coverage and resource allocation are thus actively covered[85,92]. Topology control and routing protocols, such as in[93], recognize the tradeoff between area coverage and connectivity and provide solutions based on modules that balance mission completion and communication. Target surveying may also be classified by the size of the area being surveyed. Using UAV swarms to monitor traffic conditions and road bottlenecks is one such perceived application[34]. Current persistent schemes, as outlined in[94], are the replacement of agents, novel team formation approaches, and energy-efficient behaviors for path planning. Individual modules of swarm functioning, such as path planning, are ideal recipients of learning-based augmentation methods to improve efficiency. A reinforcement learning-based algorithm performs centralized training on all agents of a swarm[95]. Individual agents can then make optimal decisions, while the swarm as a whole can function with sparse information and historical map data.

Hierarchical structures are possible, which bring cohesion between swarm heterogeneity and control schemes to produce better results. A high-altitude fixed-wing aircraft provides critical management support to a swarm of lower-level quadcopters. Here, multiple approaches, such as task offloading, agent heterogeneity, and robust communication links between swarm and ground controls, are explored.

Additional collaboration techniques exist between mobile sensors on aerial UAV agents and ground-based static sensors to create a hybrid strategy for target search. This technique is more viable in Category 3: Target search rather than in Category 2: SAR. This is because hybrid strategies require the pre-placement of hybrid sensors such as ground-based mission pads, time-of-flight cameras, environment-sensing vision cameras, or terrestrial LiDAR. This approach is more viable when it is possible to set up these static sensors beforehand, such as agricultural fields, roads, or urban buildings. SAR operation scenarios are usually more unpredictable, with no pre-planning. A study in[96] uses such static sensors for target search of SAR of a lost person but makes wide-ranging assumptions about each sensor and agent having global access to a central controller. Additionally, the sensors are non-retrievable and non-relocatable. While the approach is sound, it makes more economic sense to deploy sensors at locations where their benefit can be realized in typical operational scenarios. Potential applications include tracking cars at signal junctions or the number of animals entering fields to consume crops.

Distributed sensing using multiple drones is one of the techniques implemented for such scenarios. One single drone fitted with varied sensor payload is expensive and, if damaged, can put a stop to mission progress; multiple smaller drones spread over an area is a more flexible approach. Testbeds and the design of relevant resilient metrics to measure incorporated resilience are important steps of such swarm development. Distributed sensing using multiple sensors in a target area has been examined in[97]. Optimal area coverage, as discussed above, recognizes a tradeoff between the area to be covered and inter-agent network strengths. Additionally, approaches may address the issue of preventing multiple UAVs from covering the same area as a way of addressing the maximum area coverage problem. By reducing repeat passes, one can decrease the time it takes for a swarm to completely survey an area, particularly in scenarios where a single pass data collection flight is perceived to be enough. Addressing task assignment with optimal coverage, a study[98] proposed a unique optimized waypoint-defining technique.

Area considerations are not only limited to maximum area coverage problems. Persistent interactions with the environment are also required for extremely specific applications such as in[99], which uses LiDAR data collected during the survey to also calculate emergency landing spots for the UAV to land in case of any occurrence where the UAV needs to land but is unable to return to base. A combination of onboard data processing in real-time using resource allocation and area coverage is addressed here. Such implementations, when scaled to larger swarms, can help assist swarm agents facing issues to land in optimal zones rather than losing control altogether. Another issue that comes with long-term persistent interactions with the environment is energy efficiency. A swarm that performs quick operations over a small region requires significantly less power than one that operates over a considerable time or area. The power management and fuel source systems on such deployments may be adjusted proportionally. Long-term surveillance, reconnaissance, and mapping functionality may require advanced energy and fuel optimization techniques. This can be accomplished by either designing fuel stations or recharging locations at strategic locations that enable agents to land and refuel[100]. This involves the collaboration of optimization techniques for maximum area coverage by minimum fuel stations, plus the design of appropriate energy-aware protocols[101].

Surveying using remote sensing and photogrammetry principles often involves the usage of sensors to create extensive point clouds of the surveyed area for analysis and further processing. A study by[102] used heterogeneous unmanned robotic systems to propose a framework for the registration and segmentation of point clouds of complex terrain. They use a multi-module system where a combination of UAV-UGV each produces point clouds. The UGV uses a laser range finder, and the UAV produces a point cloud from images using SfM (Structure from Motion) photogrammetry. A collaborative mapping scenario between Micro UAV-UGV[103,104] is another such example where different operational space vehicles collect and augment data for richer mapping outputs. Such implementations require robust formation control and data exchange and fusion policies to be in place. In this study, key areas of resilience incorporation are communication, navigation, and resource allocation. Observations to support the claims of this study are validated when such novel methodologies implement robust algorithms for processing sensor fusion and communication, whereas omitting developments to the physical or cyber security of swarms. Survey missions may use behavior-based control for network optimization, positioning, and even for the loss of a portion of the swarm, creating robust packages of disruption handling mechanisms. This can improve the efficiency of surveys in terms of time taken and data quality. It is interesting to note that by the classification set by this study, while victim detection in a post-earthquake scenario would be classified as a SAR target problem and be placed in the previous section, detection, and survey of damage done to structures and infrastructure would be classified in this section. Figure 14 shows a UAV swarm conducting an infrastructure examination operation.

This again highlights the variety of UAV applications and their specific resiliency requirements. While SAR problems are exploratory and time-constrained, problems such as[32] for building damage assessment need

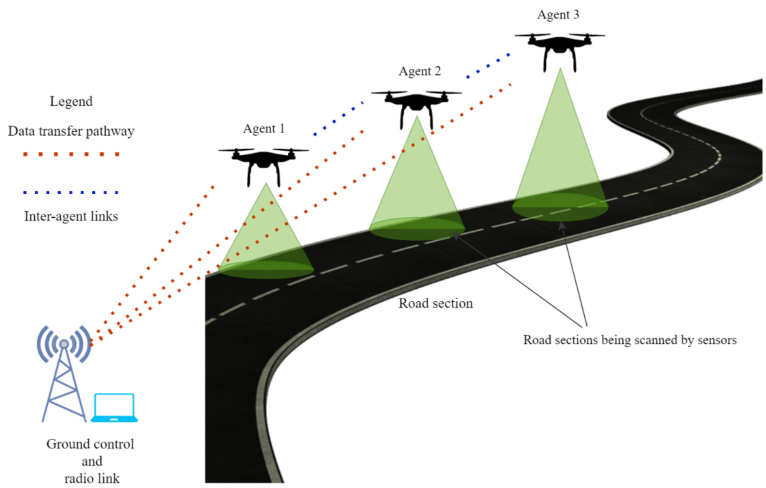

Figure 14. An unmanned aerial vehicle (UAV) swarm examining a road for cracks and potholes.

high-quality and accurate sensor data for real-time and post-processing analysis. As such, their resilience requirements may entirely vary. Area coverage problems are addressed in this study, where efficient data extraction is required from oblique photos. As survey timelines go, it might not be possible to accurately cover damaged areas without the effect of sensor tilt, whereas efficient area coverage might require gathering data for larger areas using predefined points only, resulting in oblique sensor readings. It is then necessary to post-process the data to extract the maximum accuracy information from the sensor measurements.

3. NON-APPLICATION SPECIFIC AND FLEXIBLE DEVELOPMENTS

This section highlights methodologies that are not specifically focused on UAV swarms or for specific application scenarios. However, they do propose unique methodologies for dealing with the many challenges that UAVs face during operation. These could be applied to any of the scenarios discussed above as needed to create more efficient outputs. The advantage of examining such research is that they have been developed with a generalized outlook on the problem statement. Thus, they can effectively be scaled and applied to any application-specific scenario to effectively increase overall resiliency. Table 6 categorizes generalized work on UAV implementation that increases operational resilience.

This section covers all the modules that were recognized in UAV swarm operations above. Formation control of swarm agents, as they move in the operational space, is a vital area for resilience integration. Inter-agent collisions can lead to a cascaded failure of the entire swarm. An increase in the distance between agents as they navigate obstacles can also impact connectivity between them. Implementations such as those in article[106] introduce formation control appr Self-organization is an important characteristic of UAV swarms and involves the ability of agents to recognize other agents as those of the swarm itself or outsiders. This awareness leads to the development of better formation policies and inherent security against external agents. Evolutionary hybrid algorithms[107] have seen a high rate of success for such ideas.

Task planning for agents with distinctive characteristics and goals involves interfacing multiple protocols with each other. One such example is article[108], which addresses task planning problems for a swarm of heterogeneous UAVs, where the swarm agents are defined as having different operational capabilities. A multi-type-task allocation algorithm is introduced that considers different mission requirements and the individual ability of each agent of the swarm, thus addressing the task planning module along with the agent

Table 6. Categorization of referenced study by the major resilience module/component they consider (general)

Resilience component/module highlighted	Referenced study
Path planning	[115]
Obstacle avoidance and detection	[115]
Task assignment/reassignment	[108,118]
Flocking	[116,117]
Network connectivity and structure	[116,119]
Swarm size scalability	[116]
Agent property (heterogeneity)	[108]
Scalable resilience evaluation metrics	[120]
Navigation	[110,112-114,121]
Area coverage	[98]
Formation control	[106,107]

property component. An application where budget constraints apply is for efficient sensing of the environment using low-cost sensors onboard toy drones. The study in[109] uses a divided framework to map its surrounding terrain with a fast 3D model in the frontend and an offline backend that uses an MVS (Multi-View Stereo) to create a higher resolution 3D model. Such models aim to combine fast sensing and data acquisition platforms with post-processing methodology for high-resolution data acquisition. This provides a good example of using fast MVS methodologies to create an automated low-cost 3D map from inexpensive UAVs, with potential applications in surveying and mapping. For accurate comprehensive mapping ability, an optimized area coverage approach is vital. Most Flying Ad Hoc Network (FANET) applications require the ROI (Region of Interest) to be maximally covered, with additional constraints such as time and resource limitations. Setting optimized waypoints is often the first step in semi-autonomous flight planning systems[98]. This, combined with dynamic grid decomposition and selection schemes, provides better results than planner-only approaches.

Autonomous swarm navigation with multi-target sensing and tracking in the presence of dynamic obstacles is another such generalized development that can be applied to military, SAR, and general surveying applications discussed above. Navigation methods need to be fault-tolerant and capable of functioning in sparse and GNSS-deprived environments[110,111]. Indoor localization[112,113] is an additional challenge where GNSS signals might be weaker, hence relying on other sensor readings, passive beacons, fiducial markers[114], or cooperative localization techniques.

Article[115] discusses a multi-view approach to swarm management, path planning, and obstacle detection and tracking using trust region policy and proximal policy optimization algorithms. An interesting assumption by the study is that the agents are homogeneous; heterogeneous agent additions have been omitted. The authors in[116] present a distributed flocking protocol for mid-sized UAV swarms (< 100 agents) where they define swarm size, communication radius, and collision parameters to create resilient implementations and a research methodology for future development in control theories and statistical analysis of the results. This requires the design of relevant scalable metrics for performance evaluation.

Data transfer policies between swarm agents and non-connected swarm entities are a network issue for swarm devices. Article[117] proposes an adaptive data transfer method for separated non-swarm devices using offline evolving swarms to enable the connection between disconnected network nodes. The resultant swarm was able to adapt emergent behavior and achieve effective transmission between the desired nodes. Resource allocation and task assignment problems are also prevalent issues in all scenarios, application-specific or generalized. Multi-UAV cooperative task assignment problems by considering different UAV nature types are considered in[118]. Routing protocols strengthen data transmission and optimize networks for FANETs. Biologically inspired algorithms often work on natural swarming and exchanges observed in real-world animal gatherings such as for ants, bees, and wolves. Article[119] uses a novel ant colony optimization algorithm with fuzzy logic for improving UAV swarm routing performance. Fuzzy models can make decisions in uncertain environments commonly found in swarm operations. The predicted advantage of fuzzy models is their efficiency in performance when achieving high throughput in large network loads for mobile agents. Efficient routing protocols form the basis of any resilient communication component. Although every study usually has its own set of proposed or existing methods that it uses to validate performance, perhaps via Monte Carlo methods or comparisons with existing state-of-art, there is a necessity for universal scalable metrics for the assessment of UAV swarm resilience. The very nature of such proposals is not to fit into a single application domain but rather to promote widespread usage of common metrics. Using common assessment methods and metrics makes it easier to compare the multitude of novel techniques with each other. Although such literature is sparse, methodologies such as those in[120] introduce baseline assessment methods for swarm resilience based on complex networks.

4. DISCUSSION

Our investigation has uncovered a multifaceted landscape of UAV swarm resilience that underscores the complexity inherent in diverse application scenarios. The tailoring of resilience mechanisms to match specific challenges within each scenario is evident, reinforcing the importance of a context-driven approach. By examining the responses of individual components and their collective behavior, we have unraveled emergent properties that enhance the overall resilience of the swarm. Using keyword analysis and network visualization allows the researcher to access the range and spread of the research topic in question and identify key points of entry for further research directions.

The significance of this study extends to the broader realm of research on UAV swarm applications and resilience. Our findings emphasize the need for a holistic understanding of the interplay between components, recognizing the potential for emergent behavior. This insight extends beyond the immediate scope of resilience, highlighting the importance of considering system-level behavior when designing and deploying UAV swarm systems.

While our study aims to contribute valuable insights, it is essential to acknowledge the limitations we encountered in crafting resilient case studies for UAV swarm scenarios. Literature dataset curation for surveys is often influenced by the authors' perspectives on trends and how they are interpreted. This can be remedied by creating up-to-date surveys on the research topic that offers multifaceted viewpoints. This allows the reader to explore a wide range of possibilities and prevents biased outlooks. Additionally, it is impossible for a single survey to accurately cover every single research article and methodology. Multiple surveys offer a broader coverage of the topic, ensuring that all key literature is included.

The inherent complexity of real-world applications often defies complete emulation in controlled environments. Overcoming this challenge calls for collaborative efforts between researchers, industry partners, and regulators to create realistic and representative testbeds for comprehensive resilience evaluations. When it comes to the individual agents that make up the swarm, they are often influenced by ongoing changes in regulations that require certain changes to them. For example, the FAA[122] has enforced the RID (Remote Identification) rule that requires certain classes of UAV agents to have an open broadcast module that will transmit the location and certain identifying information of the agent and operator at all times. Regulations such as this are certain to influence the way this information is processed by swarms and their applications[123].

There are several directions that justify further exploration. A multi-objective optimization approach would hold promise for balancing diverse objectives while enhancing resilience. Dynamic adaptation mechanisms, powered by machine learning and AI, can facilitate real-time adjustments based on evolving conditions. Additionally, fostering effective human-swarm interaction techniques and exploring innovative sensor configurations can amplify the resilience of UAV swarms.

The significance of our findings resonates in the advancement of resilient UAV swarm applications across various domains. From disaster response to agriculture[124], the potential impact on societal well-being is substantial. This survey is designed to motivate readers to contemplate the intricate dynamics of UAV swarm resilience, to critically assess their applicability within their fields, and to contribute to the ongoing discourse in this area of research.

5. FUTURE RESEARCH DIRECTIONS

Few researchers have addressed the problem of swarm agent resilience and well-being as they perform their assigned tasks. Depending on the resilience thresholds designed, the loss of several agents during mission progress can affect the ability of the swarm to complete its mission. Even with tight constraints, some agents can exhibit degraded performance and fail. As such, the swarm must have the capability for self-awareness of the location and well-being of its agents. Previous studies have not addressed methodologies to track and rescue their agents in the case that a loss occurs. SAR of swarm agents has been recognized as component three[15] by the authors of this study, where we found that there was almost no current research to reference its implementation. One of the closest approaches to awareness policy by swarms to replace lost UAVs is described in[125], which uses a replacement policy to replace lost UAVs. Recovery policies are almost absent in current deployments where UAV swarm actively tries to recover lost agents. A different approach that the authors of[126] took was to design rescue depots and dynamic mission abort policies for swarm agent well-being. These are perfect examples of preliminary work on SS-SAR procedures.

The presence of heterogeneity in swarms can be categorized by a variety of factors, such as their hardware buildup, operational space, and agent property. Operational space heterogeneity occurs when a swarm comprises of agents working across a diverse target space, such as quadcopters and water surface vehicles or ground-based rovers. Heterogeneity by nature is introduced when heterogeneity is induced by the assigned operational characteristics in homogeneous hardware agents, such as a fast and slow agent or exploratory and cautious agent combination swarms. Although challenging to address, heterogeneous swarms have been observed to produce better performance, including co-evolution and the natural emergence of agent capabilities[127,128]. This occurs due to complementary abilities brought about by heterogeneous agents and extended thresholds on agent ability. Multiple demonstrations of operational space combinations have been trialed, such as air-underwater vehicles[129], air-water surface[130], and air-ground vehicles[25]. A selection of research exists that specifically targets heterogeneous agent issues in swarms as discussed above in each category; however, prevalent issues with implementation along with wide-ranging assumptions during experimental designs warrant further research.

6. CONCLUSION

This study conducts a general review of different application scenarios and the various novel resiliency mechanisms that have been proposed to make swarms more efficient in accomplishing assigned goals. The end goal of systemic resiliency research is the complete integration of such mechanisms in every facet of system operation. This is an ambitious goal by itself, which requires ground-up development for all system components.

Researchers have broken down the swarm resiliency problem into smaller parts and aim to address each component individually. As these are part of an integrated system design, the performance of individual components often cannot be accurately validated beyond certain thresholds. This results in the linking of disjoint components during development without incorporating them into a holistic system. The issue of the lack of a comprehensive resilient swarm mechanism still exists. This study recognizes this research gap and presents a systematic review of the various novel implementations of resilience in application-specific scenarios.

DECLARATIONS

Authors' contributions

Conceptualization, Methodology, Validation, Investigation, original draft writing: Phadke A
Conceptualization, Validation, draft review & editing, supervision: Medrano FA

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Ethical approval and consent to participate

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