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# DECIPHERING MILITARY MULTI-UAV SYSTEMS RESILIENCE: A FMECA-BASED FRAMEWORK FOR RAPID TACTICAL DECISIONS

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***Abstract:*** *Given that in modern conflicts drone-type technological systems are increasingly used, evolving from their singular use to that represented by multi-UAV systems and swarms and implementing artificial intelligence at their level through machine learning capabilities, it is necessary to lean towards their management at the decision-making level, but through the possibility of performing an automatic risk analysis in order to guide a drone system. This paper aims to deepen the understanding of the implementation and maintenance of the resilience of multi-UAV systems. Starting from the FMECA risk management method, a unique decision-making framework is offered for the development of decisions specific to the tactical use of intelligent aerial robot systems to support armed forces in military operations.*

***Keywords:*** *multi-UAV systems (mUAV-S), Machine Learning, Swarm, FMECA, Artificial Intelligence, Military Operations; Tactical decisions*

## 1. INTRODUCTION

With the introduction and expansion of robotic technology related to Industry 4.0, unmanned aerial systems (UAS) have come to be used in military operations, demonstrating high efficiency and a relatively low cost - in the case of large drones -, particularly when compared to traditional military assets used in previous modern conflicts. This aspect of their utility and efficiency was immediately noted by both experts and decision-makers, so that these unmanned aerial platforms have increasingly become a critical element in modern conflicts. Their development in engineering and military terms has experienced an interdependence that has materialized through the manufacture of increasingly high-performance drone models, but also through the implementation of artificial intelligence (AI) at their level, so that the horizon of advantages and opportunities for the military environment has increased. The notion of "drone swarms" emerged due to communication and network techniques that allow information exchange, multiple coordination, and dynamic topology, demonstrating much greater efficiency and low cost in contested environments [1].

### 1.1 Problem statement

Referring to these drone swarms in a military environment characterized by dynamism and the need for continuous adaptation to anticipated or unforeseen situations, it is necessary to use artificial intelligence oriented towards machine learning (ML), so as to support decision-makers and troops implicitly by delegating to these systems the capacity to analyze risks and carry out an integrated management through which they autonomously select an optimal course of action to adopt, based on the best option that the internal intelligent analysis offers, in real time. This capability can translate into many opportunities that have as their central goal the continuity of the mission and the increase of effectiveness including in the case of dysfunction of individual drones [2].

The resulting challenge is the implementation of such an integrated risk management approach

at the drone system level, beginning with the risk analysis stage.

### 1.2 Application context and operational scenario

Researching this perspective of integrating risk management and assessment mechanisms is of interest because it provides a deeper analysis within the military context and with the implication of the concept of autonomous drone swarms, an area in which critical awareness should be encouraged for multi-UAV coordination.

Drone limitations, disadvantages or vulnerabilities may exhibit different levels of operational tolerance depending on the tactical situation in the field. In other words, some of these may be fatal if they occur during the operation, while others may be negligible, and the mission can still be accomplished with a high success rate. For this reason, a personalized FMEA (Failure Modes and Effects Analysis) assessment with the criticality mode is suitable for implementation at the drone system level, to operate automatically in a dynamic environment, such as armed conflict, thereby enhancing operational effectiveness for allied forces. Within the analysis, the vulnerabilities of unmanned systems are considered failures, and their analysis determines the effects on the performance of the equipment or system [3].

## 2. RELATED WORK

Most recent work in the drone field highlights the complexity of multi-objective mission planning for drone swarms, especially in contested environments [4]. Other studies address the issue of identifying critical communication nodes within drone swarms [5]. However, such works mainly focus on network-level properties and do not explicitly quantify the operational impact of communication failures.

Regarding risk analysis methods, previous studies highlight FMEA as an effective method, widely applied in industrial environments, often relying on predefined RPN (Risk Priority Number) thresholds and qualitative criticality assessments to guide mitigation efforts [6][7]. Techniques such as HAZOP (Hazard and Operability Study), FMEA, and what-if analysis based on expert judgment and structured reasoning are used to identify failure modes and assess risk levels [8]. Other studies perform systematic risk classifications of drone delivery systems and highlight mitigation strategies such as redundancy, fail-safe mechanisms, robust communication networks, and adaptive routing in adverse weather conditions [9][10][11]. While these studies provide comprehensive risk taxonomies and solution-oriented perspectives, they predominantly focus on civil and urban logistics contexts, addressing risks in isolation rather than analyzing their propagation at the individual, system, and mission levels.

Previous research involving FMEA/FMECA methods demonstrates that these analysis techniques can support maintenance decision-making by quantifying how prediction accuracy and monitoring frequency influence system-level risk indicators [12]. Hierarchical FMEA frameworks identify component-specific risk factors, guide the calibration of preventive thresholds, and optimize cost-reliability trade-offs [12].

In the field of artificial intelligence, recent scientific articles propose AI-augmented tools to support FMECA by automatically generating failure modes and effects through statistical modeling and interactive interfaces, significantly reducing the effort and time required for analysis [13]. These approaches focus on assisting human analysts, rather than focusing on real-time decision support in autonomous multi-agent environments, such as mUAV-S systems.

Traditional FMECA implementations have been criticized for limitations related to parameter subjectivity, equivalent risk priority values, and the lack of explicit modeling of interdependencies between risk factors. As a result, several studies have integrated probabilistic reasoning techniques, such as Bayesian networks, Dempster-Shafer theory, and fuzzy logic, especially in the field of cyber attacks, in order to assess risks [14][15][16][17].

The problem described at the beginning of the current paper has received limited attention in

existing research, particularly within the military context.

Although FMEA/FMECA methods have been extensively applied in industrial and civil UAV contexts, limited research addresses mission-centric criticality propagation in coordinated military multi-UAV systems operating in contested environments. Addressing this gap, the present study proposes a structured FMECA-based framework to support rapid tactical decision-making and enhance system-level resilience in autonomous multi-UAV operations.

## 3. RESEARCH METHODOLOGY AND STAGES

### 3.1 Research approach

The research is based on a qualitative analysis of open-source materials represented by scientific publications in the current field, technical reports and official documentation of drone manufacturers, in order to identify failure modes that may occur in military missions. Unlike existing descriptive analyses, this work translates qualitative operational perspectives into a structured assessment of critical awareness based on FMECA. The sources found through the platforms IEEE Xplore, ScienceDirect, etc., were filtered based on their indexing, relevance to the researched topic and their topicality.

The proposed approach focuses on a conceptual modeling and critical criteria analysis, with the aim of supporting the subsequent design of such an AI system based on FMECA analysis in which the scores for the specific indicators were established following the responses collected based on responses collected from ten domain experts, including military officers, ISR (S-2) and communications and informatics (S-6) specialists, as well as system engineers, using structured questionnaires.

The objective of this analysis is to identify mission-critical failure modes and their propagation between UAVs at the individual level, enhancing multi-UAV coordination in a tactical mission context, supporting rapid decision-making in contested environments.

Most studies validate the resilience of a technological system based on simulations, ignoring the early identification of critical failures that may subsequently affect the entire system. Therefore, this paper focuses on this gap by providing a structured framework based on the criticality analysis (CA) component inclusive. The proposed framework is analytically evaluated using scenario-based modeling combined with Monte Carlo experiments. Each UAV failure mode is assigned a probability of occurrence, and its impact on mission success is calculated through criticality numbers. Multiple iterations allow for the statistical assessment of mission resilience and UAV loss frequency, without relying on high-fidelity flight simulators.

### 3.2 Research stages

In order to achieve the research objective, previously highlighted through conceptual modeling and analytical assessment of the problem, the following activities are envisaged:

**A1.** Identification of operational requirements and constraints of UAVs in missions;

**A2.** Identification of failure modes and effects for multi-UAV systems;

**A3.** Criticality analysis using a mission-involving FMECA framework;

**A4.** Integration of criticality indicators into the multi-UAV decision-making process;

**A5.** Analytical assessment based on scenarios and Monte Carlo.

The activities are carried out throughout the following chapters, fulfilling the objective previously mentioned in section *3.1. Research approach*.

## 4. FMECA FRAMEWORK FOR MULTI-UAV SYSTEMS

While the notion of mUAV-S and that of swarms overlap at the level of quantity, as the former refers to a minimum of two UAVs, while a swarm is represented by a minimum of three and up to a thousand such devices [18], the basic criterion that is required for this research is that the drone system should be intelligent, autonomous, focused on coordination and synchronization and using efficient 4G wireless networks to achieve the described performance

[19], so that the implementation of a specific management for the proposed one is possible.

According to the flowchart below, the defect identification process, FMECA analysis and critical decisions for multi-UAV can be observed illustrated at a basic level. This framework enables proactive risk management and rapid decision-making across all UAVs in the system.

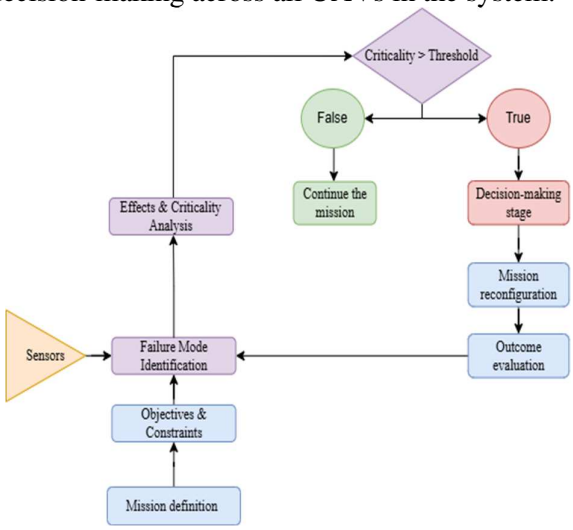



**Fig. 1.** Analytical framework for multi-UAV resilience using FMECA

Moreover, the framework is suitable for tactical military missions, where adversary actions can disrupt communication, navigation, sensors, or maneuverability, potentially affecting the UAVs' autonomous decision-making. These attacks define operational constraints, as UAVs must avoid entering high-risk areas. The framework is intended for implementation as a software module at the mission management layer, processing real-time sensor and telemetry data to influence high-level decisions, such as task reassignment, formation adjustments, or fallback strategies, without interfering with low-level flight control or stabilization. The analyses abstract from specific flight dynamics, focusing on supporting the design of such systems for future deployment.

### 4.1 Ground rules and assumptions

To ensure clarity and reproducibility of the analysis, a set of ground rules and assumptions approved by both parties to the paper – the authors and the interviewed experts – were established. The analysis considers drones operating within the limits of their specified technical capabilities, including energy autonomy, sensor performance, navigation and communication functions. The operational environment is limited to contested ground and air scenarios, characterized by electronic warfare, attacks on communications and threats from anti-aircraft weapons, while extreme weather conditions are not included. Mission objectives are defined as area coverage, mission continuity and communications integrity, with limited tolerance for loss and degradation of drone performance. All failure modes are treated as functional, rather than hardware-specific, and their criticality is assessed taking into account both severity, probability of occurrence and impact on the mission [20]. These assumptions provide a consistent framework for interpreting FMECA results and supporting rapid tactical decision-making in multi-drone operations.

### 4.2 Multi-level system decomposition

While failure mode analysis traditionally focuses on singular elements, analyzing them individually, we chose to conduct the research on three levels to cover the initiated issue. The three components are at the individual (UAV), overall (mUAV-S) and context (tactical mission environment) levels, each having vulnerabilities translated through risk management into failure modes, as well as a related criticality level, which will be discussed.

In Table 1 below, the division of the failure modes found for a series of functions specific to each level can be observed on the three levels. In this way, the problem data can be better visualized and data interpretations can be made. The function column defines the intended operational objectives of each component, in particular: maintained navigation, increased energy management and durability, and functional sensors with respect to an individual drone; an automatic and efficient task allocation that would provide the coordination of a drone system, easy data exchange and formation maintenance, also for better coordination and synchronization among multi-agent drones; last but not least, in order to successfully carry out a

*Table 1*

**Failure modes divided into three levels and their effects reported at each level**

| Level | Function | Failure Mode | Cause | Individual effect | System effect | Mission effect |
|---|---|---|---|---|---|---|
| UAV | Navigation (1) | GNSS degradation | Jamming | Position error | Loss of coordination | Reduced mission coverage |
| | Energy management (2) | Battery depletion | Extended mission time | Forced landing | UAV loss | |
| | Sensor (3) | Sensor failure | Hardware fault | Loss of target detection | Degraded situational awareness | Lower mission intelligence |
| Multi-UAV | Task allocation (4) | Delayed reconfiguration | Communication loss | Task mismatch | Coverage imbalance | Partial failure to complete objectives |
| | Data sharing (5) | Intermittent links | EW interference | Data inconsistency | Decision latency | Slower response rate |
| | Formation maintenance (6) | Collision avoidance failure | Sensor error / Communication loss | Collision | UAV loss / Reduced coordination | Delayed mission adaptation |
| Mission context | Area coverage (7) | Coverage gap | UAV loss | Uncovered area | Uncovered area | Mission success degradation |
| | Mission continuity (8) | Critical loss of UAV | Air defense | UAV loss | Reduced coordination | Mission failure |
| | Communication integrity (9) | Complete comms failure | EW / Jamming | UAV isolation | Multi-UAV coordination collapse | Mission coordination breakdown |

military operation at the tactical level, when UAV assets are available either at the individual or system level, the greatest possible coverage of the area of operations (AO) is desired, ensuring the continuity of the mission throughout its duration, but also the integrity of communications that facilitates the performance of a drone ensemble in the form of an intelligent autonomous system.

The table also shows the implicit propagation of failures from the individual to the system level [21], on the principle of the effect from inside to outside, from the ensemble to the entire mission context, from local to global.

## 5. CRITICALITY-AWARE DECISION-MAKING UAV

### 5.1 Criticality analysis

To perform this assessment, we must define the usual FMEA (Failure Mode Effects Analysis) criteria, in which we replace the D - Detection criterion with a new component that prioritizes failures according to the impact they have in the context of a tactical mission, favoring the quantification of criticality (or criticality number), as follows:

- S – Severity;
- O – Occurrence;
- $W_m$ – Mission Impact Weight;
- $C_n$ – Criticality Number.

The criticality number will have the formula:

$$C_n = S \cdot O \cdot W_m \quad (1)$$

In the military field, a defect may be impossible to detect in a timely manner, especially in critical situations, so that it can be prevented, which is why a parameter $W_m$ is more relevant than the classic detection one. The personalized method still remains attributed to the FMECA analysis, because it represents a qualitative criticality analysis adapted to the mission.

To create the criticality analysis table, the scores provided by the questionnaire participants were given on a scale from 1 to 5, instead of the traditional scale from 1 to 10, allowing a clearer discrimination between low, moderate and high-risk levels, remaining sufficient to classify failure

modes and identify critical thresholds. The score scale is presented in Table 2.

*Table 2*

**Scale definition**

| Scale | Indicator | | |
|---|---|---|---|
| | S | O | $W_m$ |
| 1 | Minor effect | Very improbably (<5%) | Minor impact |
| 2 | Impaired function | Low probability (6 – 20%) | Limited impact |
| 3 | Impaired function | Medium probability (21 – 40%) | Significant impact |
| 4 | Impaired critical function | High probability (41 – 60%) | Major impact |
| 5 | Impaired essential function | Very probably (>60%) | Critical impact |

A severity score of 1 indicates no impairment of UAV function; scores of 2 and 3 indicate partial impairment, either not directly observable or observable within the drone system, respectively. A score of 4 indicates significant degradation of system and mission performance, while a score of 5 represents mission failure or UAV loss.

From the $W_m$ category, the scores reflect the following: no impairment of the main mission objectives, minor delays in mission execution, medium degradation, significant degradation, and mission compromised in the extreme case.

### 5.2 Criticality indicators in the decision-making process

Following the questionnaire, the responses were recorded and the median was calculated for each of the functions presented, the results being those in Figure 2.

With these results, courses of action can be designed for each situation, autonomous decisions that can be logically implemented at the drone level so as to achieve the automation and machine learning that is essential for the successful conduct of military operations. Thus, scenarios leading to prevention, system reconfiguration, task reassignment or mission cancellation can be established depending on the value of the $C_n$ indicator. This will be discussed in the next chapter.

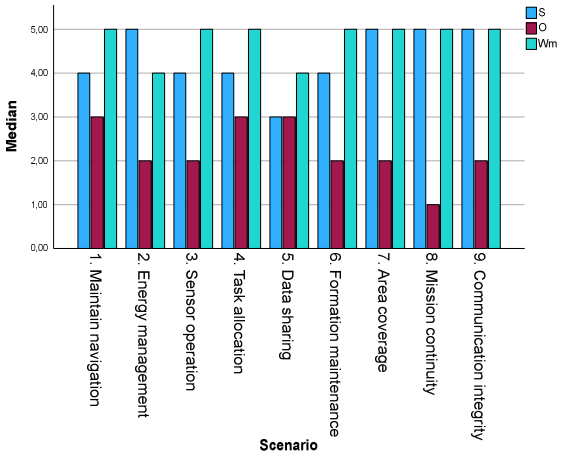



**Fig. 2.** Median score for each function

The following table highlights the criticality analysis, providing the calculation for criticality ($C_n$) and prioritization options.

*Table 3*

***Criticality indicators average scores based on polls***

| Level | Function | Indicators | | | |
|---|---|---|---|---|---|
| | | S | O | $W_m$ | $C_n$ |
| Individual | 1 | 4 | 3 | 5 | 60 |
| | 2 | 5 | 2 | 4 | 40 |
| | 3 | 4 | 2 | 5 | 40 |
| Multi-UAV | 4 | 4 | 3 | 5 | 60 |
| | 5 | 3 | 3 | 4 | 36 |
| | 6 | 4 | 2 | 5 | 40 |
| Mission | 7 | 5 | 2 | 5 | 50 |
| | 8 | 5 | 1 | 5 | 25 |
| | 9 | 5 | 2 | 5 | 50 |

## 6. RESULTS AND DISCUSSION

### 6.1 Scenario-based analysis

This study's contribution is reflected in the addition of the Mission Impact Weight ($W_m$) element, and the analytical approach does not include criticality at the technical level, but at the tactical level.

This impact on the mission is a component exclusively specific to the military environment since the reporting is made to the tactical situations that the experts, who provided the answer to the questionnaires, know. From this point, it is possible to establish thresholds within which the $C_n$ value can fall, thus resulting in the actions that a drone system will take.

For example:

- $1 \leq C_n < 30$, represents a threshold where the mission can continue normally;

- $30 \leq C_n < 50$, represents a threshold where the system requires thorough supervision, and if necessary, a reconfiguration depending on the situation;
- $50 \leq C_n \leq 125$, represents a critical threshold where the system requires immediate action, an urgent tactical decision. Otherwise, the mission has the highest chance of being compromised.

Proceeding on a concrete and plausible scenario, that of a drone system approaching enemy lines whose positions are reinforced by electronic warfare means, it is found that the signal level decreases, so the O indicator increases. Increasing the occurrence, the criticality automatically increases.

### 6.2 Implementation strategies

There are two options through which this FMECA method can be implemented within a multi-UAV system: default or online. Default by determining the scores by the decision-makers before the start of the mission, according to the knowledge and data they have at their disposal, according to the SALUTE principle (Size, Activity, Location, Unit, Time, Equipment). A plan of measures will result in intelligence that the system can use when it is deployed in the field.

In the context where missions and tactical situations are predominantly very difficult to predict in terms of their outcome, it is necessary to implement this risk management method at the software level.

Thus, drones whose sensors detect signal fluctuations, low battery level or a reduction in the number of UAVs within the system, as they are interconnected and can identify each other, can modify the parameters of the analysis model, especially that of occurrence (while the severity and impact remain pre-established by the operators), and recalculate the criticality, so as to make autonomous decisions based on the mentioned thresholds. Also, the other parameters S and $W_m$ should be able to be modified, if necessary.

The dynamic update of the FMECA parameters can be implemented within a supervisory mission management layer integrated into the UAV autonomy architecture. This module continuously processes data from onboard sensors and from other UAVs in the network, enabling periodic or event-triggered recalculation of the criticality index $C_n$. The occurrence parameter (O) can be adjusted using rule-based or threshold-driven estimations derived from signal degradation, rapid energy depletion, or formation losses, allowing the model to reflect evolving operational risks in real time.

Although severity (S) is generally predefined during mission planning, it may be contextually adapted in degraded operational conditions where redundancy is reduced.

### 6.3 Monte Carlo Experiment

Since the scores assigned to each function can be subjective, in order to quantify how the uncertainty of the FMECA parameters translates into the probability of exceeding the critical risk thresholds for the mission, the Monte Carlo method was used.

By running 1000 iterations, the following was found:

Starting from the premise of the previously established thresholds and keeping their value, it can be seen that the maximum scores allowed to consider the drone system safe (<50% critical situations) are 3-3-5, regardless of their order (Figure 3). This case provides a percentage of $C_n$ >50 of approximately 40%. If any of the indicators increases by just one value, the percentage doubles (Figure 4).

The figures below are histogram-type graphs that show the frequency of cases in which the criticality takes the value according to the intervals on the X-axis. The difference between the two figures at the level of frequency of criticality exceeding the previously established threshold of 50 can be observed.

Finally, if an indicator is further increased, out of the 1000 iterations, almost 100% of them exceed the threshold set for $C_n$, the mission having a high chance of being compromised (Figure 5).

It is understood that for such a UAV system based on FMECA to be relatively safe, it must, based on machine learning, be able to act from a

level of 3-3-5, so as not to reach a critical area where the probability of multiple function failures is very high.

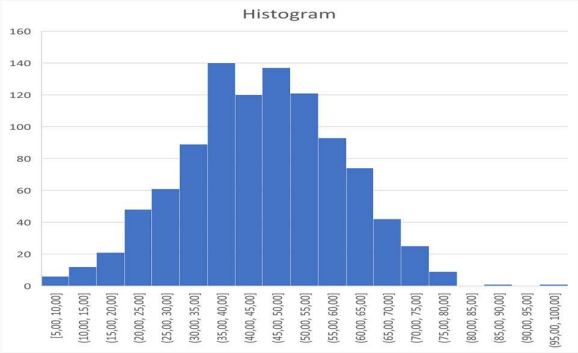



**Fig. 3.** Frequency of cases in which $C_n$>50 when indicators are 3-3-5 (not necessarily in this order)

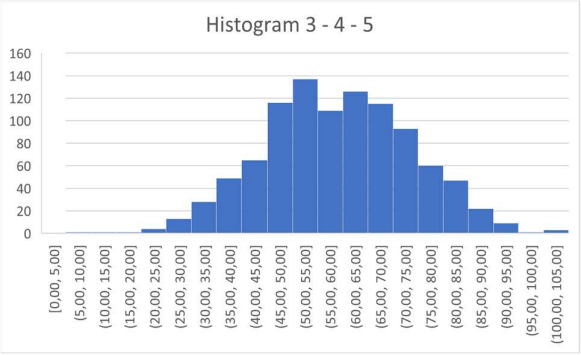



**Fig. 4**. Frequency of cases in which $C_n$>50 when indicators are 3-4-5 (not necessarily in this order)

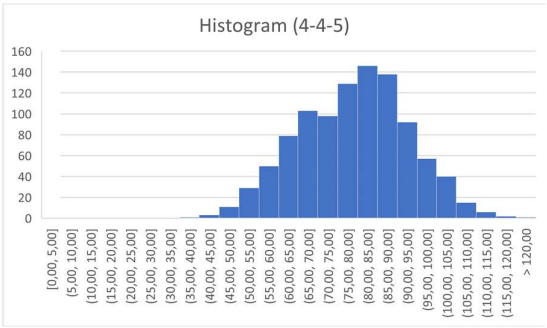



**Fig. 5.** Frequency of cases in which $C_n$>50 when indicators are 4-4-5 (not necessarily in this order)

## 7. LIMITATIONS AND FURTHER RESEARCH

The framework for failure modes, effects and criticality analysis is based on the assignment of scores by experts or decision makers for the three parameters: severity, occurrence and mission impact, which inextricably introduces subjectivity into the analysis.

However, this limitation is mitigated by median-based analysis and Monte Carlo uncertainty propagation, as a method of quantifying the uncertainty of input variables that can affect the final outcome, which very well describes the uncertain military environment in the context of tactical-level missions.

A real-flight experiment with multi-UAV systems could not be conducted due to safety, cost, and operational constraints, as well as the difficulty of replicating contested tactical conditions. Therefore, the study relies on analytical assessment, expert input, and Monte Carlo uncertainty propagation to explore scenarios safely and efficiently. It intentionally focuses on the analytical assessment of risks at an early stage and proposes a risk management framework in an uncertain environment to be implemented at the software level with the help of artificial intelligence and subsequent machine learning.

Another limitation is that only a part of the possible military scenarios was covered in this study, but the analysis model is applicable to any of the tactical situations.

Additionally, constraints regarding computers performance and latency aspects associated with real-time recalculation of criticality indices in large UAV networks require further investigation.

Future work will focus on integrating the now proposed FMECA framework into the internal decision loops of low-cost, autonomous multi-UAV systems. Dynamic and autonomous updating of scores based on real-time sensor data remains a possibility. These concepts must be validated through simulation and testing.

## 8. CONCLUSION

The resilience of multi-UAV systems during military operations characterized by contested environments and constantly evolving in terms of technology, strategies and doctrines, remains a critical aspect to ensure and maintain.

This paper proposed a structured framework based on failure mode and effects analysis, for

mission-oriented criticality assessment, as a model for subsequent implementation at the software level within an intelligent drone system, specifically as a supervisory module at the mission management layer. The FMECA-based module can influence task allocation, formation control, and fallback strategies, providing real-time risk evaluation and decision support without interfering with low-level stabilization loops.

Assessing criticality probabilities enables rapid tactical decisions by identifying failure patterns, with severity thresholds guiding actionable responses.

This approach lays the foundation for integrating analytical risk assessment into future autonomous multi-UAV architectures.

## 9. REFERENCES


[1] Chen, W., Liu, J., Guo, H.,Kato, N., *Toward Robust and Intelligent Drone Swarm: Challenges and Future Directions*, in IEEE Network, vol. 34, no. 4, pp. 278-283, 2020, doi: 10.1109/MNET.001.1900521;

[2] Zhang, J., Zhang, Q., Wu, J., Du, J., Liu, Y., *Optimizing redundancy of UAVs system by targeting risk-significant components for improved mission success probability*, Reliability Engineering & System Safety, Volume 270, 2026, ISSN 0951-8320, https://doi.org/10.1016/j.ress.2025.112131;

[3] Borgovini, R., Pemberton, S., Rossi, M., *Failure mode, effects and criticality analysis (FMECA)*, Reliability Analysis Center, 1993, Available at: https://s3vi.ndc.nasa.gov/ssri-kb/static/resources/a278508.pdf;

[4] Checker, L., Xie, H., Khaksar, S., Murray, I. *Systematic Review of Multi-Objective UAV Swarm Mission Planning Systems from Regulatory Perspective*, *Drones*, *9*(7), 509, (2025), https://doi.org/10.3390/drones9070509;

[5] Teng, M., Gao, C., Wang, Z., Li, X., *A communication-based identification of critical drones in malicious drone swarm networks*, Complex & Intelligent Systems, *10*, 3197 – 3211, 2024, https://doi.org/10.1007/s40747-023-01316-9;

[6] Damanab, S., Alizadeh, S.S., Rasoulzadeh, Y., Moshashaie, P., Varmazyar, S., *Failure modes and effects analysis (FMEA) technique: A literature review,* Scientific Journal of Review 4 (1): 1–6, 2015, Available at: https://files01.core.ac.uk/download/45271091.pdf;

[7] Jovanović, I., Perčić, M., Vladimir, N., *Combined FMECA-BN analysis for reliability assessment of marine systems*, Ocean Engineering, Volume 341, Part 1, 122465, ISSN 0029-8018, 2025, https://doi.org/10.1016/j.oceaneng.2025.122465;

[8] Moussa, A., Hassini, E., Ezzeldin, M., El-Dakhakhni, W., *Machine learning-enabled real-time risk prediction and mitigation in drone-based hazmat delivery*, Research in Transportation Business & Management, Volume 65, 101585, ISSN 2210-5395, 2026, https://doi.org/10.1016/j.rtbm.2025.101585;

[9] Tubis, A.A., Ryczynski, J., Zurek, A., *Risk assessment for the use of drones in warehouse operations in the first phase of introducing the service to the market*, Sensors 21, 2021, https://doi.org/10.3390/s21206713;

[10] Borghetti, F., Caballini, C., Carboni, A., Grossato, G., Maja, R., Barabino, B., *The use of drones for last-mile delivery: A numerical case study in Milan, Italy*, Sustain Switz 14 2022, https://doi.org/10.3390/su14031766;

[11] Kumbhani, C., Kant, R., Shankar, R., *Prioritizing sustainable solutions to mitigate risks in drone-based last-mile delivery*, Sustainable Futures, Volume 9, 100536, ISSN 2666-1888, 2025, https://doi.org/10.1016/j.sftr.2025.100536;

[12] Tao, Z., Zhu, R., Hu, J., Wang, M., Chen, Q., Wang, C., *A novel hierarchical failure analysis approach targeting the operation and maintenance of floating offshore wind turbines*, Renewable Energy, Volume 24, 122267, ISSN 0960-1481, 2025, https://doi.org/10.1016/j.renene.2024.122267;

[13] Grabill, N., Wang, S., Olayinka, H.A., De Alwis, T., Khalil, Y., Zou, J., *AI-augmented failure modes, effects, and criticality analysis (AI-FMECA) for industrial applications*,

Reliability Engineering & System Safety, Volume 250, 110308, ISSN 0951-8320, 2024, https://doi.org/10.1016/j.ress.2024.110308;

[14] Uflaz, E., Sezer, S.I., Tunçel, A.L., Aydin, M., Akyuz, E., Arslan, O., *Quantifying potential cyber-attack risks in maritime transportation under Dempster–Shafer theory FMECA and rule-based Bayesian network modelling*, Reliability Engineering & System Safety, Volume 243, 109825, ISSN 0951-8320, 2024, https://doi.org/10.1016/j.ress.2023.109825.

[15] Gulen, M.F., Soares, C.G., Arslan, O., *A comprehensive risk assessment of enclosed space operations on ships*, Reliability Engineering & System Safety, Volume 265, Part B, 111543, ISSN 0951-8320, 2026, https://doi.org/10.1016/j.ress.2025.111543;

[16] Chakhrit, A., Benharkat, N., Guetarni, I.H.M., Guedri, A., Chennoufi, M., *A literature review of risk assessment approaches in failure mode and effects analysis*, International Journal of Quality & Reliability Management, Volume 42, Issue 9, Pages 2415-2454, ISSN 0265-671X, 2025, https://doi.org/10.1108/IJQRM-01-2025-0042;

[17] Matosek, M., Prokopowicz, D., *The question of the scope of decision-making of combat systems based on generative artificial intelligence technology as an important element of risk management of the potential risks arising from it,* International Journal of Legal Studies (IJOLS), 20, 283-313, 2025, 10.5604/01.3001.0055.5726;

[18] U.S. Government Accountability Office, *Drone swarm technologies*, (GAO-23-106930), 2023, Available at: https://www.gao.gov/assets/gao-23-106930.pdf;

[19] Tahir, A., Böling, J., Haghbayan, M.H., Toivonen, H., Plosila, J., *Swarms of Unmanned Aerial Vehicles - A Survey*, Journal of Industrial Information Integration, Volume 16,2019, 100106, ISSN 2452-414X, https://doi.org/10.1016/j.jii.2019.100106;

[20] Yousaf, A., Amro, A., Kwa, P.H.T., Li, M., Zhou, J., *Cyber risk assessment of cyber-enabled autonomous cargo vessel,* International Journal of Critical Infrastructure Protection, Volume 46, 100695, ISSN 1874-5482, 2024, https://doi.org/10.1016/j.ijcip.2024.100695;

[21] Sun, Y., Tian, H., He, J., Chen, C., Liu, Z., Yang, Z., *Dynamic failure modes and effects analysis method considering synergistic standards of failure correlation and expert evaluation,* Expert Systems with Applications, Volume 279, 127461, ISSN 0957-4174, 2025, https://doi.org/10.1016/j.eswa.2025.127461.

**Descifrarea rezilienței sistemelor militare multi-UAV: un cadru bazat pe FMECA pentru decizii tactice rapide**

**Rezumat**: Dat fiind faptul că în conflictele moderne sistemele tehnologice de tip dronă sunt tot mai folosite, evoluând de la utilizarea lor singulară la cea reprezentată de sisteme multi-UAV și roiuri, implementându-se la nivelul lor inteligența artificială prin capabilități de învățare automată, este necesară o aplecare spre managementul lor la nivel decizional, însă prin posibilitatea efectuării unei analize automate a riscurilor și după care să se ghideze un sistem de drone. Această lucrare are rolul de a aprofunda înțelegerea implementării si menținerii rezilienței sistemelor multi-UAV. Pornind de la metoda FMECA de management al riscului se oferă un cadru decizonal inedit de dezvoltare a deciziilor specifice utilizării tactice a sistemelor de roboți aerieni inteligenți pentru sprijinul forțelor armate în operații militare.

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