Advances in Military Technology
Vol. 21, No. 2, 2026, pp. 395-412
ISSN 1802-2308, eISSN 2533-4123
DOI 10.3849/aimt.02083

UAS Flight Safety Risk Assessment Using Fuzzy Logic Approaches

Y. Honcharenko[1*], O. Radko[1], O. Blyskun[2], Y. Yaroshenko[1] and V. Yasinetskyi[1]

[1] *National Defence University of Ukraine, Kyiv, Ukraine*
[2] *Main Directorate for Aviation Capabilities Development, Kyiv, Ukraine*

The manuscript was received on 17 January 2026 and was accepted after revision for publication as an original research paper on 21 August 2026.

Abstract:

The paper proposes a method for assessing UAS flight safety risks based on fuzzy logic. The study aims to formalize risk assessment under conditions of uncertainty and the linguistic nature of data inherent in military operations. Existing approaches are analyzed, and their limitations in working with incomplete information are identified. The developed model includes linguistic variables, membership functions, and fuzzy inference rules that integrate key factors: technical condition, meteorology, operator training, task complexity, and enemy influence. Simulation shows that the method provides a smoother gradation of risk levels and can potentially support more informed decision-making under fuzzy data. The proposed approach is suitable for use in decision support systems and UAV flight planning.

Keywords:

flight safety, risk assessment, risk management, unmanned aerial vehicles, fuzzy logic, fuzzy sets, linguistic variables, membership functions, fuzzy inference, risk modeling, decision making, military UAS

1 Introduction

Unmanned aerial vehicles (UAVs) of the 2nd and 3rd class, controlled by external pilots, have become an indispensable tool of modern warfare. Their effectiveness in reconnaissance and striking targets is undeniable, but it is inextricably linked to the complexity of planning processes, where each decision is a balancing act on the verge of tactical advantage and potential aviation incident. A review of leading military doctrines, such as the NATO Joint Air and Space Doctrine (AJP-3.3) [1], shows that

* *Corresponding author: Aviation Department, National Defence University of Ukraine, Povitrianykh Syl Avenue, 28, Kyiv, Ukraine. Phone: +380 672 247 530, E-mail yev.v.honcharenko@gmail.com. ORCID: 0000-0001-7654-6083.*

risk management is a holistic and comprehensive process. However, there is a fundamental problem in this approach: specific issues of flight safety as such are not considered separately from other risks. They become one of many factors that are "weighed" on the scales along with the risk of failure to complete the combat mission, the threat from enemy air defense or electronic warfare. As a result, the priority of saving lives and avoiding harm, which is an axiom for civil aviation, is blurred and becomes a subject of compromise in military planning.

This problem is exacerbated by the fact that in the absence of a clearly defined and formalized procedure for assessing aviation risks, commanders and planners are forced to rely mainly on personal experience. Fundamental doctrines, such as the US Army's Joint Operations (JP 3-0) [2], emphasize the importance of commander's judgment, but this inevitably leads to a high degree of subjectivity in decisions. A plan that one commander will consider acceptable, another will reject as dangerous. Such variability of approaches is a direct threat, because it creates conditions in which potentially catastrophic risk can be underestimated due to the lack of objective criteria.

At the same time, global safety standards established by the International Civil Aviation Organization (ICAO) offer a radically different approach. The concept of a Safety Management System (SMS), as set out in Annex 19 to the Chicago Convention [3], requires a proactive, systematic and data-driven process where safety is the highest and unwavering priority. Moreover, ICAO has already developed detailed guidance on the safe integration of remotely piloted aircraft systems (RPAS) into the overall aviation ecosystem [4]. A critical gap is emerging while civil aviation is moving towards objectification and standardization of safety, military practice in combat environments often remains in the realm of subjective compromises.

The cost of this gap is extremely high. When flight safety is not an absolute priority, but only one of the competing factors in the decision-making process, the risk of catastrophic error increases exponentially. An incident involving a military unmanned aerial system (UAS) caused by an underestimation of aviation risks can lead to irreversible consequences: civilian casualties, destruction of critical infrastructure, and serious political and reputational losses for the state.

This article aims to analyze in detail the aforementioned conflict between an integrated military approach to risks and a priority approach to flight safety, as well as to suggest ways to harmonize these processes to increase both mission effectiveness and flight safety.

2 Analysis of Existing Methods for Assessing Flight Safety Risks

To ensure the proper level of flight safety, a significant number of risk assessment methods have been developed in global aviation practice, covering the spectrum from the simplest qualitative tools to complex structured methodologies approved by international aviation organizations. They form the foundation of any Flight Safety Management System (SMS), the functioning of which is regulated by the provisions of Annex 19 to the Convention on International Civil Aviation [3]. In the traditional, mainly civil context, these procedures demonstrate high efficiency, as they are based on the predictability of the operating environment, the availability of a developed infrastructure for collecting statistical data and the relative stability of operating conditions. However, the application of these methods in the military sphere, especially in the context of the operation of unmanned aircraft systems in combat conditions, reveals several significant conceptual and practical limitations. The level of uncertainty,

the fragmentation of input data, the dynamics of the operational situation, as well as the presence of an active adversary who deliberately creates threats, make classical approaches insufficiently accurate and unsuitable for realistic risk assessment. This is confirmed by the fundamental developments of Ukrainian researchers, who emphasize the objective need to improve methods for proactive assessment of flight safety risks in difficult situational conditions [5–7].

One of the most common tools that have become established in the practice of aviation organizations of various types is the risk matrix. It is based on calculating the risk level as a function of two key parameters – the probability of a dangerous event and the severity of its consequences [8]. Due to its simplicity, accessibility and clarity, this method has become a universal means of high-level risk assessment. However, a number of limitations that are of a fundamental nature accompany its application in a military environment. The significant dependence on the subjective assessments of experts who define linguistic categories such as "rarely", "probable" or "catastrophic consequences" creates the risk of significant differences in the results obtained by different analysts. The standard matrix, as a rule, contains only 25 combinations of categories, which causes low resolution and makes it impossible to reflect adequately the nuances of complex multifactorial situations. In addition, the boundary values of the categories are often of an uncertain, intermediate nature, which does not find an appropriate mathematical representation in the discrete structure of the matrix. One of the most critical problems is the requirement for clearly defined, formalized input data, which makes it impossible to assess correctly the risk when the information is unclear, incomplete or presented in the linguistic form in which it most often arrives in the context of military operations. In such situations, the risk matrix distorts the real picture, overestimating or underestimating important aspects of the operational situation [5].

The SORA (Specific Operations Risk Assessment) methodology, developed by the international group of aviation regulators JARUS, is today the most detailed and influential approach to risk assessment in the field of civil UAS operation [9]. It involves a step-by-step analysis of risks on the ground and in the air with a consistent establishment of levels of requirements for operational procedures, equipment reliability and personnel training (SAIL I–VI). Despite the high structure, clarity and regulatory correctness of this method, its adaptation to military tasks is limited. The SORA methodology does not include mechanisms for taking into account an active intelligent enemy capable of conducting electronic suppression, cyberattacks, using air defense means or using maneuverable interception means. The strict discreteness of classifications, the requirement to unambiguously attribute a situation to a certain risk class and the significant complexity of the procedures create serious difficulties when trying to use the SORA methodology in the conditions of limited time inherent in operational flight planning in a combat zone. Thus, despite its high value in the civilian environment, this method cannot meet the needs of assessing the safety risks of military UAS flights.

Bow-Tie Analysis occupies an important place among modern approaches to risk modeling due to its ability to reflect clearly the structure of threats, cause-and-effect relationships, and existing security barriers [10]. This method allows you to build a structural model of the central undesirable event and determine a set of preventive and protective measures aimed at preventing the incident and minimizing its consequences. At the same time, it has a pronounced static nature, which does not allow taking into account dynamic changes in threats in real time, as well as the mutual influence of several risk factors that arise simultaneously. The complexity of adequate modeling of

personnel behavior under stress, the limited qualitative characteristics of barriers and threats, and the lack of mechanisms for processing fuzzy and incomplete data determine the low effectiveness of this approach in combat operations, where the situation can change every minute. Research in the field of applied risk analysis emphasizes the limitations of Bow-Tie as a tool for calculating the complex multifactorial interaction of threats in unmanned systems.

Standard safety assessments are often too static and boxed-in to reflect real-world risks. That's why recent studies have moved away from these rigid categories, opting instead for dynamic, hybrid models. A good example is the use of Bayesian Networks (BN) in autonomous systems; they allow us to map out complex dependencies and update risk levels on the fly as new data comes in [11].

By weaving Bayesian Networks into the SORA framework, Babetto et al. [12] showed that hybrid models can handle multi-state variables and practical mitigations. This approach effectively moves past the rigid "pass-fail" logic that usually limits standard Fault Tree Analysis (FTA).

Along similar lines, Abtahi et al. [13] developed a hybrid framework that blends FTA and FMEA with fuzzy logic and Bayesian Networks. This multi-layered approach was designed specifically to tackle the messy data and shifting operational conditions often found in critical systems.

To deal with the guesswork and subjectivity that come with limited data, some studies have turned to Dempster-Shafer evidence theory. This allows for more reliable data fusion across multiple sensors, especially when paired with advanced fuzzy-logic models [14].

Kiss et al. [15] point out that fuzzy logic is a game-changer for UAVs because it uses rule-based inference. This approach is particularly good at managing the messy, unpredictable environmental factors that are otherwise nearly impossible to model accurately.

Banerjee et al. [16] further emphasize that in low-altitude airspace, it is critical to tell the difference between a real drone failure and simple environmental noise. Their work calls for robust detection frameworks that can distinguish internal vehicle faults from external hits, like sudden wind gusts.

The catch with these advanced BN and hybrid models is their overhead. While they offer excellent dynamic capabilities, they demand heavy computational power and continuous streams of complex data. In the middle of time-sensitive military mission planning, pulling that kind of information together is rarely an option.

Hadjimichael [17] highlights the Flight Operations Risk Assessment System (FORAS) as a prime example of a fuzzy expert system in action. Instead of relying purely on probabilities, FORAS takes a proactive, knowledge-driven route by organizing human experience into a clear hierarchy of risk factors. It is designed to be versatile – whether its safety departments tracking long-term trends, flight crews evaluating a specific route, or management weighing the impact of new safety protocols. Ultimately, FORAS proves that fuzzy inference can successfully break past the stiff, "black-and-white" boundaries of older models, offering a much stronger foundation for handling risk in complex aviation scenarios.

Beyond just risk assessment, fuzzy logic has proven its worth in other UAV support tools, particularly for predicting flight times and handling shifting environmental factors [18, 19]. Some of these setups also fold in advanced control strategies to keep the drone stable when hit with unexpected mid-air disruptions.

Taking a step back, it becomes clear that none of these existing frameworks are truly built for military UAS operations. They all share deep, systemic flaws. Risk matrices, for instance, rely too heavily on subjective guesswork and overly simplistic, blocky categories. SORA, while thorough, is far too bureaucratic to survive the fast-paced reality of combat. Meanwhile, the Bow-Tie method simply falls flat when trying to map out rapidly shifting threats or make sense of ambiguous, subjective data.

At its core, the real bottleneck is the absence of tools built for the realities of operational planning – a space where incomplete intelligence and qualitative, linguistic assessments are the norm. We urgently need a new breed of methodologies that can mathematically digest this uncertainty, interpret flexible human parameters, and map out complex risk dependencies. Fuzzy logic stands out as the most viable solution here. It bridges the gap by mimicking intuitive human reasoning yet anchors it in rigorous mathematics. To address this, we propose expanding the use of fuzzy logic specifically to secure and manage military UAV operations.

3 UAS Flight Safety Risk Assessment

3.1 UAS Flight Safety Fuzzy Logic Risk Modelling

For quantitative assessment of flight safety risk during UAS usage, it is advisable to investigate the factors that affect flight safety (hazards) of all its elements. In general, risk does not have clear boundaries, so the authors propose the use of fuzzy logic approaches. When solving analytical problems for the formalization of uncertain information, one of the most developed mathematical theories in engineering is the theory of fuzzy sets. The algorithm of this technique is implemented by the MATLAB software package: Simulink and Fuzzy Logic Designer.

To perform assessment using a fuzzy logic device, a fuzzy algorithm is created (Fig. 1), which consists of [20]:

- fuzzier, converts fixed vectors groups of risk factors that affect the input data (pilot (readiness), UAV, environment and organization),
- fuzzy knowledge rules base that determines the relationship between input and output data in the form of a linguistic rule "IF – THEN",
- fuzzy inference block, based on the rules of the knowledge base, determines the value of the output variable in the form of a fuzzy set that corresponds to the input values,
- defuzzier, converts the fuzzy initial value into crisp output risk values.

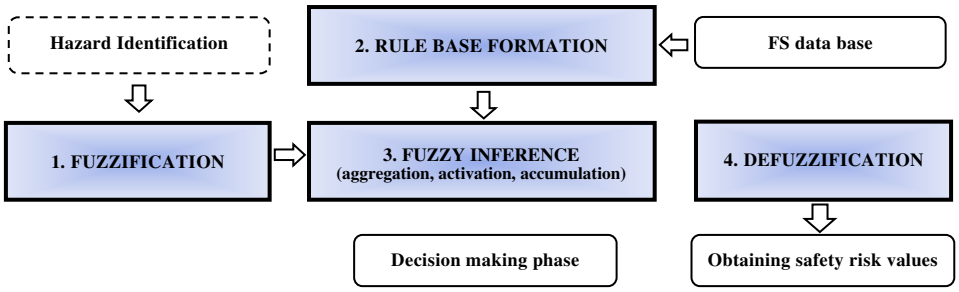


Fig. 1 Fuzzy logic safety risk assessment algorithm

Next, the input risk factors (subfactors) are formalized (fuzzified) in the form of a tuple of fuzzy input data $< \mathcal{E}_i, T_i, K_i, G_i >$, where $\mathcal{E}_j$ is the name of the risk factor; T – is linguistic terms; K – is the range of values of risk factor indicators; $G = \{\mu_\mathcal{E}(X)|X\}$ – is the membership function (hereinafter referred to as the MF) of the linguistic risk variable [21]. The construction of the MF is carried out taking into account the requirements of aviation legislation, statistical indicators of UAS operation and the experience of experts who use and operate aviation-unmanned systems. The theory of fuzzy sets does not oblige to choose the type of MF absolutely clearly or precisely [9]. It can be refined in the process of research based on the results of solving the problem. The most common are Gaussian surfaces, trapezoidal and triangular MFs, which will be used in the proposed model.

The intervals of values pre-defined by experts for each indicator of the risk factor in the form of fuzzy sets are the basis for constructing MFs of input linguistic variables.

Further, in the environment of the Fuzzy Logic Designer graphical toolkit, from the MATLAB program suite, fuzzy control modeling is performed using the FIS (Fuzzy Inference System). For each FIS block of flight safety risk calculation, it is necessary to define a system of fuzzy rules.

Based on the flight safety information database (FS database), fuzzy input and output data interdependence rules are created in the form of "IF – THEN":

$$\textbf{IF } x_1 \text{ is } T_1,\ x_2 \text{ is } T_2, \cdots, x_n \text{ is } T_n$$

$$\textbf{THEN } y \text{ is } B$$

where T_i ($i = 1, 2, \cdots, n$) and B are fuzzy sets.

Fuzzy IF – THEN rules are the core of a fuzzy logic system, as they connect all other components and determine the output of the system. In flight safety risk assessment, inputs are often designated as risk factors and outcomes as consequences. Fuzzy IF – THEN rules are then established to relate consequences to a set of risk factors with a certain level of linguistic risk. For example, the following fuzzy IF – THEN rule, consisting of two inputs and one output, is: "IF risk factor x_1 is T_1 (low), AND risk factor x_2 is T_2 (high), THEN consequences y is B (medium)".

The rules are constructed systematically, by iterating over all possible combinations of fuzzy sets of each input from smallest to largest. The consequences are adjusted so that the smallest sum of the fuzzy sets is equal to the minimum and the largest to the maximum value of the risk. Intermediate sums are interpolated between these two values. The number of rules is the product of the number of fuzzy sets of each input. For example, for FIS "Pilot" the number of logical inputs is 5, the number of terms of the output function is 3, therefore the number of rules N is $3^5 = 243$.

The rules are built considering the weight coefficients of the input functions W. Weighting coefficients are usually determined by experts, however, to assess the risk to UAS flight safety, it is advisable to take into account experience in operating UAS. For example, for FIS "UAV-Risk" the input values are the level of training of the external crew "Pilot", the state of the UAV "UAV", the environment "Environment" and the organization (planning) of the use of the UAS "Organization". From the analysis of the state of flight safety, the weight coefficients $W_{\text{Pil}} = 0.3$; $W_{\text{UAV}} = 0.4$; $W_{\text{Env}} = 0.2$; $W_{\text{Org}} = 0.1$ (Tab. 2). For each FIS, a separate fuzzy rule base is defined.

The next step is to form a fuzzy inference mechanism. In the Fuzzy Logic Designer application in the MATLAB environment, the Mamdani and Sugeno

mathematical apparatuses (also known as Takagi-Sugeno-Kang, TSK) are used. In this work, TSK was chosen due to its following advantages:

- since the output is not a fuzzy set, there is no need for a complex defuzzification process (as in Mamdani), which makes calculations faster,
- the linear nature of the consequences allows for easy integration of Sugeno systems with optimization methods,
- the continuity of the output surface is guaranteed, which is important for solving control problems.

The Sugeno fuzzy inference algorithm in Fuzzy Logic Designer MATLAB uses the following mathematical apparatus. The form of the first-order Sugeno rules for the AND operator for four antecedents in our study is as follows:

$$\textbf{IF } x_1 \in A_{i1} \textbf{ AND } x_2 \in A_{i2} \textbf{ AND } x_3 \in A_{i3} \textbf{ AND } x_4 \in A_{i4} \textbf{ THEN}$$

$$z_i = c_{i0} + c_{i1}x_1 + c_{i2}x_2 + c_{i3}x_3 + c_{i4}x_4$$

where

i – the rule number,

x_1, x_2, x_3, x_4 – the input variables (antecedent),

$A_{i1}, A_{i2}, A_{i3}, A_{i4}$ – the fuzzy sets (with corresponding membership functions) that define the linguistic values for each input variable in the i-th rule,

z_i – the output variable for the i-th rule (consequent),

$c_{i0}, c_{i1}, c_{i2}, c_{i3}, c_{i4}$ – the constant coefficients for the i-th rule. These coefficients define a linear function that relates the input variables to the output variable for a given rule. They can be determined by an expert or trained using optimization algorithms (for example, the least squares method within ANFIS).

The AND operator in the antecedent combines the degrees of membership of each input variable to its corresponding fuzzy set. This operator is usually implemented using the T-norm, most often the minimum or product. The rule activation strength (weight coefficient – WC) w_i for the minimum:

$$w_i = \textbf{min}[\mu A_{i1}(x_1), \mu A_{i2}(x_2), \mu A_{i3}(x_3), \mu A_{i4}(x_4)]$$

Aggregation of consequences in TSK systems always occurs using a weighted average. The output values z_i for each rule are weighted by their triggering strength w_i.

The final risk output value R (Defuzzified Output) has the form:

$$Final\ Output = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i}$$

where N is the number of rules.

At the stage of obtaining safety risk values, a clear output is calculated – UAS Flight Safety Risk, which can take values in the range from 0 to 1. Currently, there are many approaches to determining criteria for assessing the level of risk. For example, Doc 9859 defines three levels of risk tolerance for Flight Safety: acceptable, permissible, unacceptable [8], MIL-STD-882 – four levels: Low, Medium, Serious, High [22], and APP-28.1 – four zones: comfort zone, cautious zone, concerned zone, critical zone [23]. The authors proposed to divide the range of possible values of UAS Flight Safety

Risk into the following four zones: $0 < R \leq 0.4$ – Low; $0.4 < R \leq 0.6$ – Medium; $0.6 < R \leq 0.85$ – Serious; $0.85 < R \leq 1$ – High. However, depending on the operating conditions of the unmanned aircraft systems, decision makers can adjust the boundaries of these zones.

During the final phase (Decision making phase), a decision is made on the appropriate way to perform the UAS mission depending on the level (zone) of risk:

- if R is in the Low zone – "at an acceptable level", then additional risk management measures are not required, the mission is performed without restrictions,
- if R is in the Medium zone – "at a warning level", then minor additional risk management measures are required to perform the mission,
- if R is in the Serious zone – "at a threatening level", then significant additional risk management measures are required to perform the mission,
- if R is in the High zone – "at a critical level", then immediate radical risk management measures are required to perform the mission or its abandonment altogether.

3.2 Factors Affecting the Risk Components for UAS

To build a UAS Flight Safety Fuzzy Logic Risk model, we determine the factors that affect the safety of UAV flights.

For military UAVs of class 2 and 3, these factors are similar to those for civilian ones, but with some significant differences. In particular, the peculiarities of the military regulatory environment are taken into account, since the importance of resistance to enemy actions, the ability to perform specific combat missions and compliance with military standards, etc. is increasing.

For any element of the UAS, factors can be identified that determine the quality of functioning of this system from the point of view of flight safety. According to the authors, among the variety of factors for UAS flight safety, it is advisable to identify the influence of the following main groups of factors with the simultaneous determination of the ranges of their possible values:

- human factor (pilot), under which in this study we consider the level of readiness of the external pilot (operator) of the UAV, in the range from 0 to 1,
- UAV state (UAV), from 0 to 1,
- environment factor (Environment), from 0 to 1,
- organization (planning) of the use of UAS (Organization), from 0 to 1.

The input parameters described below are evaluated using either physical units (total flight hours in hours, visibility in meters) or normalized scales and indices.

To handle qualitative factors that resist direct physical measurement, we built normalized scales grounded in field experience and expert judgment. For continuous variables – like a pilot's psychophysiological state, situational awareness, or remaining equipment lifespan – we applied a standard 0 to 100 % scale representing the spectrum from minimum to maximum capability. For discrete environmental and operational factors (such as terrain complexity, enemy air defense density, or organizational readiness), we translated expert input into a simple 0–3 index. We tied this index directly to everyday linguistic assessments (where 0 = no threat / excellent condition, 1 = low threat / good condition, 2 = medium threat / satisfactory condition, and 3 = high threat / poor condition).

The readiness of the external pilot depends on many factors. However, for conducting the study, the authors identified the following 5 main ones that have a greater impact on flight safety:

- general experience – total flight hours of the pilot (total flight hours), from 0 to 2 000 h,
- current experience (flight breaks), from 0 to 100 h,
- situational awareness of the external crew – the operator's availability of relevant information (mission tasks, procedures for their troops, enemy air defense and electronic warfare systems, etc.) regarding the current situation in the mission area (situational awareness), from 0 to 100 %. It is characterized by three components [24]: perception (Perception) – awareness of the current state of the environment and the state of the UAV (position, altitude, speed, system status, sensor data, etc.); understanding (Comprehension) – adequacy of interpretation of perceived information, its meaning in the context of the goals of the current mission; projection (Projection) – ability to predict future states of the system (situation) based on current understanding,
- cognitive load on the crew depends on the complexity of the mission, the amount of information that needs to be processed, and the number of management decisions (cognitive load), from 0 to 100 %,
- psychophysiological state of the crew – emotional and physiological stress, monotony of work, and mission duration, lead to fatigue and stress, which negatively affects productivity (psy state), from 0 to 100 %.

The state of the UAV is characterized by the following factors:

- remaining resource (resource), from 0 to 100 %,
- dependability of UAV systems (dependability), from 10 to 150 failures per 1 000 hours of operation (flight),
- storage conditions (storage), from 0 to 100 %,
- stability of UAV communication and control channels (control channel stability), from 0 to 100 %,
- qualification and level of training of personnel maintaining the UAV (Maintenance Personal qualification – MPQ), from 0 to 3.

The group of factors "Environment" (from 0 to 1) consists of two subgroups (enemy influence (from 0 to 10) and weather influence (from 0 to 10)) and three separate factors – ornithology (from 0 to 3), terrain features in the mission area (terrain) (from 0 to 3) and mission complexity (from 0 to 3).

In turn, the subgroup "Enemy Influence" includes the following factors: the enemy's ability to hinder the mission through electronic warfare (EW) (from 0 to 100 %), air defense (AD) (from 0 to 3), and interceptor aircraft (drones) (from 0 to 3).

The subgroup "Weather Influence" includes the following factors: visibility along the route and in the mission area (visibility) (from 0 to 1 000 m), cloud height (from 0 to 800 m), icing conditions (from 0 to 1 mm), wind direction and force (wind) (from 0 to 1 m/s).

The group "Organization of UAS use (Organization)" includes the following factors:

- availability and quality of standard operating procedures (protocols) defined by regulatory documents for the preparation and execution of UAV flight tasks and crew actions in emergency situations (procedures and protocols), from 0 to 3,
- quality of personnel training and preparation, from 0 to 3,

- degree of implementation and effectiveness of the flight safety management system (SMS) and flight safety culture (RM & FS culture), from 0 to 3,
- efficiency and quality of communication and coordination between all interested officials who make decisions, provide and use UAS (communication and coordination), from 0 to 3,
- degree of implementation and effectiveness of the quality management system (QMS), from 0 to 3.

3.3 Risk Evaluation

After determining the risk factors, a risk assessment model for flight safety is built in the Simulink environment from the MATLAB program suite (Fig. 2) and these factors are formalized as a tuple of fuzzy input data.

For example, for the risk factor "Total flight hours of the pilot" the formalization will look like this:

$\mathcal{E}_1$ – "total flight hours",

T_1 – "low", "medium", "high",

K_1 – [0…2 000], h,

G_1 – membership functions in the work are selected in a triangular shape, the boundaries of which are determined by experts taking into account their experience and the requirements of regulatory documents regarding the training of external pilots to fly UAVs of a certain type. Thus, for the selected variant of the MF form, its values μ will be calculated using the mathematical equation:

$$f(x;a,b,c)=\begin{cases}0, & x\le a\\ \dfrac{x-a}{b-a}, & a<x\le b\\ \dfrac{c-x}{c-b}, & b<x\le c\\ 0, & x>c\end{cases}$$

where x – the actual value of the input parameter (e.g., total flight hours of the pilot), a, b, c – the parameters of the triangular membership function (where a is the lower bound, b is the peak, and c is the upper bound). Taking into account the above, we obtain the following parameter values, Tab. 1 and the form of FIS (Fig. 3).

Similarly, the values and limits of the input parameters are set for the remaining factors that affect the risks for UAS Flight Safety Risk.

The next step is to build a library of fuzzy rules "IF – THEN" (Rule Base Formation), taking into account the weight coefficients w_i (Tab. 2). Graphic visualization of the built rules for FIS "Pilot" depending on the total flight and situational awareness is shown in Fig. 4, and for FIS "UAS Flight Safety Risk" depending on the pilot's readiness level and UAV state in Fig. 5.

Fig. 4 maps out the rule base for the "Pilot" FIS block, highlighting a clear, nonlinear relationship between the operator's readiness and two main variables: total flight hours and situational awareness. Since pilot readiness essentially acts as the inverse of human-factor risk, the 3D surface plot gives us a realistic look at how these elements interact. As expected, readiness bottoms out near zero when a pilot lacks both flight experience and a grasp of the tactical environment. Conversely, as operators log more hours and build better situational awareness, we see a smooth, nonlinear climb in readiness, safely driving down the overall human-centric risk.

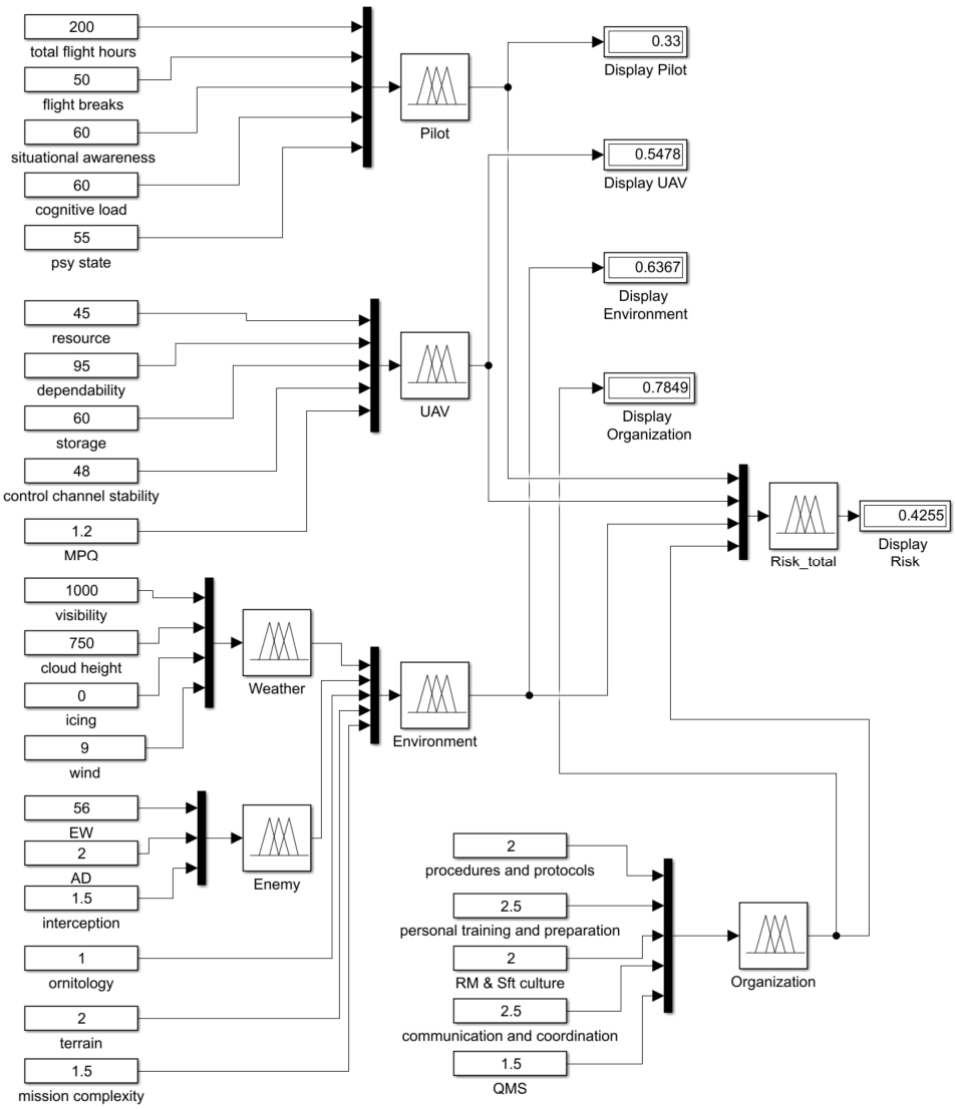


Fig. 2 UAS Risk Simulink model

Tab. 1 MF parameter values for "total flight hours"

MF name		MF parameter values		
total flight hours		*a*	*b*	*c*
μ_{11}	low	0	0	400
μ_{12}	medium	200	600	1 200
μ_{13}	high	200	2 000	2 000

DOI 10.3849/aimt.02083

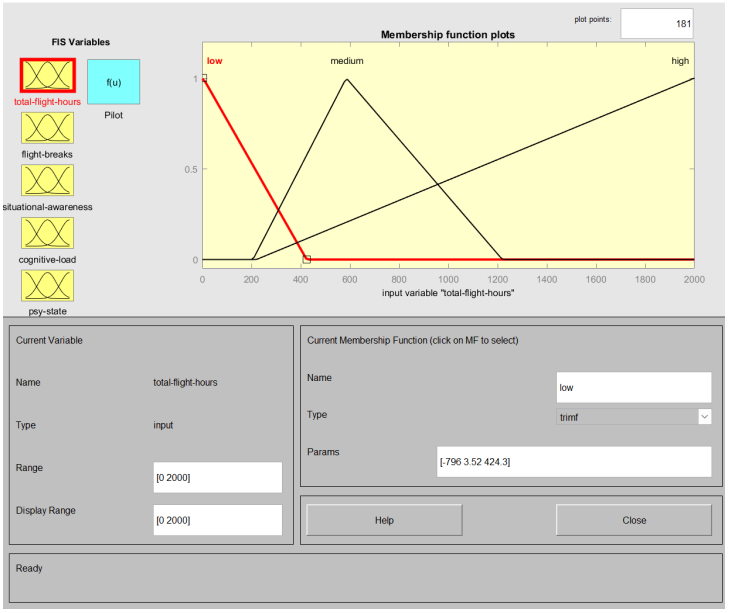


Fig. 3 Example of Fuzzy Inference System for flight safety risks calculation

Tab. 2 UAS FS Risk Evaluation results

Inputs name, $\mathcal{E}_1$	WC w_i	Inputs, x_i			Outputs, y_i			UAV Risk, z_i		
		x_1	x_2	x_3	y_1	y_2	y_3	z_1	z_2	z_3
Pilot	**0.3**				0.937	0.33	0.018	**0.01**	**0.426**	**0.95**
total flight hours	0.4	950	200	20						
flight breaks	0.1	10	50	35						
situational awareness	0.2	85	60	10						
cognitive load	0.1	15	60	97						
psy state	0.2	95	55	10						
UAV	**0.4**				1.00	0.548	0.15			
resource	0.2	90	45	12						
dependability	0.2	15	95	50						
storage	0.2	85	60	5						
control channel stability	0.15	90	48	5						
MPQ	0.25	3	1.2	0.1						

Inputs name, $\mathcal{E}_1$	WC w_i	Inputs, x_i			Outputs, y_i			UAV Risk, z_i		
		x_1	x_2	x_3	y_1	y_2	y_3	z_1	z_2	z_3
Environment	**0.2**				0.738	0.637	0.356			
Weather	0.3									
visibility	0.1	950	1000	200						
cloud height	0.2	750	750	50						
icing	0.35	0	0	0.1						
wind	0.35	3	9	7						
Enemy	0.3									
EW	0.5	5	56	30						
AD	0.3	0.5	2	1.4						
interception	0.2	0.3	1.5	2.2						
Ornithology	0.3	0.3	1	0.3						
Terrain	0.3	0.5	2	2.7						
Mission complexity	0.3	0.5	1.5	2.5						
Organization	**0.1**				0.972	0.785	0.585			
procedures and protocols	0.2	2.5	2.0	2						
personal training and preparation	0.2	2.5	2.5	2						
RM & Sft culture	0.2	3	2	1						
Com & Coord	0.2	2.5	2.5	2						
QMS	0.2	2.5	1.5	1						

Each fuzzy logic block is tested to ensure that it produces the expected output values and therefore confirms that the developed analysis method is acceptable. After this, several runs should be performed with different input values and the results compared with each other. The aim is to determine whether the results are adequate so that the model produces realistic and consistent results. Once this is confirmed, the results should be checked against the acceptable limits K_i set for the i-th input parameter (antecedent). Appropriate adjustments are made if necessary.

DOI 10.3849/aimt.02083

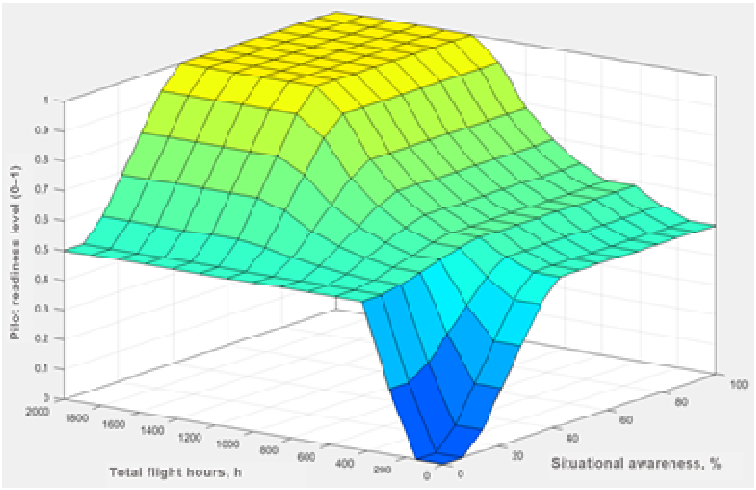


Fig. 4 Graphical visualization of the constructed rules for FIS "Pilot"

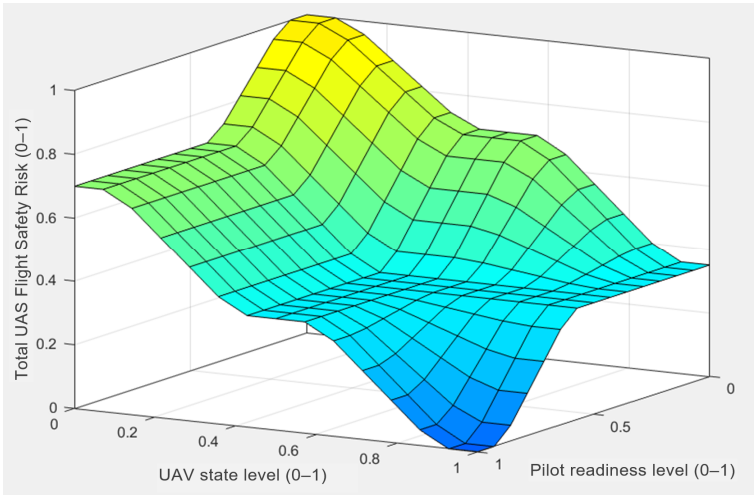


Fig. 5 Graphical visualization of the constructed rules for FIS "UAS Flight Safety Risk"

3.4 Simulation Results Analysis and Decision Making

Simulation of flight safety risk assessment is performed in the Simulink environment by entering different values (from a specified range) of factors affecting flight safety for each planned UAS mission. For example, in Tab. 2, the simulation results are presented for three variants of combinations of factors affecting UAS flight safety. Analysis of the obtained results makes it possible to determine the level of risk to UAS flight safety and to take timely (operational) decisions aimed at reducing that risk through the implementation of corrective measures, namely:

- for z_1 (R = 0.01) additional risk management measures are not required, the mission is performed without restrictions,
- for z_2 (R = 0.426) minor additional risk management measures are required for the mission,
- for z_3 (R = 0.95) immediate radical risk management measures are required for the mission or its cancellation altogether.

4 Conclusions

The study proposes a conceptual approach aimed at improving the efficiency of the flight safety risk assessment process during the performance of flight tasks by unmanned aerial vehicles in a dynamic operational environment. The central goal of the work was to substantiate and develop a methodology that is able to adequately work with uncertain, vague, incomplete and linguistically formulated data typical of military operations, and to ensure consistency in decision-making based on formalized risk criteria.

In the process of the study, a comprehensive analysis of existing approaches to risk assessment used in the aviation industry was carried out. It was shown that traditional methods such as risk matrices, models such as SORA or types of scenario analysis have limitations associated mainly with their discreteness, categoricalness, subjectivity of assessments or orientation to the expected conditions of activity. Although these methods remain important in classical aviation, they are insufficiently sensitive to the multifactorial nature, incomplete data, and high rates of change in the operational environment characteristic of modern UAS applications in the military environment.

Given the established limitations, the paper develops a new approach to flight safety risk assessment, built on the principles of fuzzy logic theory. The proposed model takes into account key risk parameters, such as the technical condition of the UAV, the operator's level of training, the complexity of the task, meteorological conditions, the enemy's influence and other relevant factors. For each of the parameters, membership functions are formed that allow describing the input information in a linguistic form, with a high level of detail and considering intermediate states that cannot be reflected in traditional discrete models. Based on the constructed set of "If-Then" rules, a fuzzy inference mechanism is implemented, which provides a comprehensive integration of all input factors and forms a generalized quantitative assessment of the flight risk level. This approach allows for a flexible, adaptive and stable solution even in conditions of fragmentary information, contradictory data and high uncertainty, which is especially important in the context of operational planning for the use of UAS in combat conditions.

The scientific novelty of the work lies in the creation of a formalized fuzzy risk assessment model, which allows combining expert knowledge, real parameters of the operating environment and the mathematical apparatus of fuzzy logic into a single system of support for decision-making on flight safety. The proposed methodology is characterized by high flexibility, the ability to scale and adapt to different types of missions, platforms and operating conditions. Simulation results suggest that the proposed methodology has the potential to provide a more nuanced and flexible risk assessment compared to traditional discrete models, providing higher sensitivity to changing conditions and allowing to take into account a wide range of factors that previously remained outside the formalized assessment.

The practical significance of the proposed methodology lies in the possibility of its integration into flight planning procedures, the UAV operator training system, algorithms of automated control complexes and the risk management system of units operating unmanned systems. The results of the work can be used in military units, training centers, research institutions, as well as in structures responsible for the development of regulatory documents in the field of aviation safety.

Further development of the study involves expanding the set of model parameters, refining membership functions, and testing the methodology on real data from UAS flight operations in various application scenarios. Important areas of future work are the integration of the model with intelligent flight control systems, the development of adaptive models for real-time risk prediction, and the creation of software that will automate the risk assessment process at all stages of flight planning and execution.

Thus, the study demonstrates that the use of fuzzy logic in assessing UAS flight safety risks is a promising and practically significant direction that can serve as an effective complementary decision-support tool for flight task planning on the performance of flight tasks in the complex and dynamic conditions of the modern combat environment.

References

[1] *Allied Joint Doctrine for Air and Space Operations* [online]. 2026 [viewed 2026-03-01]. Available from: https://assets.publishing.service.gov.uk/media/698ef9fb7da91680ad7f4389/AJP_3_3_EdC_V1.pdf

[2] *Joint Operations* [online]. 2017 [viewed 2026-01-17]. Available from: https://geopolitica.iiec.unam.mx/sites/default/files/2017-05/joint%20operations%202017.pdf

[3] *Safety Management.* 2nd ed. [online]. 2016 [viewed 2026-01-17]. Available from: https://dasa.defence.gov.au/sites/default/files/AN19_2ed-publication.pdf

[4] *Manual on Remotely Piloted Aircraft Systems (RPAS)* [online]. 2015 [viewed 2026-00-17]. Available from: https://www.dhmi.gov.tr/PublishingImages/Sayfalar/Ssd/InsansizHavaTrafikSbMd/KurumsalBilgiveDokumanlar/ICAO%20Doc.10019.pdf

[5] HONCHARENKO, Y., O. MARTYNIUK, O. RADKO and P. OPEN'KO. The Method of Proactive Risk Assessment for Flight Safety Based on the Rate of Dangerous Events. *Advances in Military Technology*, 2020, **15**(2), pp. 365–377. DOI 10.3849/aimt.01424.

[6] LUTSKYI, M., R. KHRASHCHEVSKYI, O. IVANETS and K. NESTERENKO. Information Technologies for Managing Aviation Systems. *Science-Based Technologies*, 2022, **54**(2), pp. 105–112. DOI 10.18372/2310-5461.54.16745.

[7] BARTULOVIĆ, D. and S. STEINER. Liaison between Proactive and Predictive Methodology of Aviation Safety Management System. In: *ICTS 2020 Conference Proceedings*. Portorož: University of Ljubljana, 2020, pp. 34–41.

[8] *Safety Management Manual.* 4th ed. [online]. 2018 [viewed 2026-01-17]. Available from: https://dspace.caanepal.gov.np/handle/123456789/400

[9] *JARUS Guidelines on Specific Operations Risk Assessment* (SORA) [online]. 2024 [viewed 2026-01-17]. Available from: http://jarus-rpas.org/wp-content/uploads/2024/06/SORA-v2.5-Main-Body-Release-JAR_doc_25.pdf

[10] de RUIJTER, A. and F. GULDENMUND. The Bowtie Method: A review. *Safety and Security Science*, 2016, **88**, pp. 211–218. DOI 10.1016/j.ssci.2016.03.001.

[11] DAI, L. and B. KANTARCI. *Advancing Autonomous Vehicle Safety: A Combined Fault Tree Analysis and Bayesian Network Approach* [online]. 2025 [viewed 2026-04-23]. DOI 10.48550/arXiv.2504.08206. Available from: https://arxiv.org/abs/2504.08206.

[12] BABETTO, L., R. KÖNIG, J. FASSNACHT and E. STUMPF. *Study on Public Acceptance of EVTOL: Safety & Noise* [online]. 2023 [viewed 2026-03-24]. Available from: https://www.dglr.de/publikationen/2024/610319.pdf

[13] ABTAHI, A.R., F. HAGHIGHI-RAD, M. SOHRABI RAD and M. SOORI. Fault Lines Due to Ignored Early Warnings: Lessons from the Cheshmeh-Khosh Oil Transmission System. *International Journal of Reliability, Risk and Safety: Theory and Application*, 2024, **8**(1), pp. 98–113. DOI 10.22034/IJRRS.2024.8.1.9.

[14] HAMBARDZUMYAN, A. and R. GHASABYAN. *Real-Time Fatigue Crack Growth Monitoring Using High-Precision Control and Data Acquisition Systems* [online]. 2025 [viewed 2026-04-23]. DOI 10.48550/arXiv.2509.23710. Available from: https://arxiv.org/abs/2509.23710

[15] KISS, B., Á. BALLAGI and M. KUCZMANN. PID Control and Alternative Control Approaches in UAV Systems. *International Journal of Medical Networks* [online]. 2025, **3**(5) [viewed 2026-03-24]. Available from: https://www.opastpublishers.com/open-access-articles/pid-control-and-alternative-control-approaches-in-uav-systems.pdf

[16] BANERJEE, P., R. GHIMIRE and E. HALE. *Vibration Anomaly Detection by Clustering in Unmanned Aerial Vehicles* [online]. 2023 [viewed 2026-03-24]. Available from: https://ntrs.nasa.gov/api/citations/20230007262/downloads/Aviation2023_vibration_Banerjee_v3.pdf

[17] HADJIMICHAEL, M. A Fuzzy Expert System for Aviation Risk Assessment. *Expert Systems with Applications*, 2009, **36**(3), pp. 6512–6519. DOI 10.1016/j.eswa.2008.07.081.

[18] NUZHAT, T. and F. MACHIDA. Fuzzy-Based Risk Assessment for UAV Deforestation Monitoring Under Adverse Weather [online]. 2025 [viewed 2026-04-23]. DOI 10.2139/ssrn.5374246. Available from: https://ssrn.com/abstract=5374246.

[19] MEDVEDIEV, I., D. MUZYLYOV and J. MONTEWKA. Towards the Risk Assessment Framework Conceptualization Using Fuzzy Logic for Last-Mile Cargo Drones. In*: Proceedings of the 35th European Safety and Reliability & the 33rd Society for Risk Analysis Europe Conference* [online]. Singapore: Research Publishing, 2025, pp. 2532–2539 [viewed 2026-04-23]. DOI 10.3850/978-981-94-3281-3_ESREL-SRA-E2025-P1657-cd. Available from: https://rpsonline.com.sg/proceedings/esrel-sra-e2025/pdf/ESREL-SRA-E2025-P1657.pdf

[20] SHTOVBA, S.D. *Design of Fuzzy Systems by Means Matlab* (in Russian). Moscow: Hot Line-Telecom, 2007. ISBN 5-93517-359-X.

[21] HONCHARENKO, Y., O. MARTYNIUK, O. RADKO, O. BLYSKUN, Y. KOLOMIIETS and M. BILOKUR. Flight Safety Fuzzy Risk Assessment for Combat Aviation System. In: *Proceedings of the 2nd IEEE International Conference on Advanced Trends in Information Theory*. Kyiv: IEEE, 2020, pp. 132–137.

[22] *Department of Defense Standard Practice: System Safety* [online]. 2012 [viewed 2025-07-29]. Available from: https://www.nde-ed.org/NDEEngineering/SafeDesign/MIL-STD-882E.pdf

[23] *APP-28.1 Risk Management*. Brussels: NATO Standardization Office, 2023.

[24] CHEN, J., A. CHEN, B. JIANG and X. ZHANG. Physiological Records-Based Situation Awareness Evaluation Under Aviation Context: A Comparative Analysis. *Heliyon*, 2024, **10**(5), e26409. DOI 10.1016/j.heliyon.2024.e26409.