Journal of Management & Techngy
e-ISSN: 2177-6652

DESENVOLVIMENTO E TESTE DE UM MODELO DIFUSO PARA PRIORIZAÇÃO RÁPIDA E PRECISA DE ALVOS AÉREOS EM TEMPO REAL PARA MELHORAR A EFETIVIDADE DOS SISTEMAS DE CONTROLE AUTOMATIZADOS

DEVELOP AND TEST A FUZZY MODEL FOR ACCURATE AND FAST AIR TARGET PRIORITIZATION IN REAL TIME TO IMPROVE THE EFFECTIVENESS OF AUTOMATED CONTROL SYSTEMS

DESARROLLAR Y PROBAR UN MODELO DIFUSO PARA LA PRIORIZACIÓN PRECISA Y RÁPIDA DE OBJETIVOS AÉREOS EN TIEMPO REAL CON EL FIN DE MEJORAR LA EFICACIA DE LOS SISTEMAS DE CONTROL AUTOMATIZADOS

Cited as:
Volkov A., Lezik, O., Oriehov, S., Korsunov, S., Oboronov, M., & Filippenkov O. (2024). Desenvolvimento e teste de um modelo difuso para priorização rápida e precisa de alvos aéreos em tempo real para melhorar a efetividade dos sistemas de controle automatizados. ***Revista Gestão & Tecnologia***, *24*(3), 280–300. https://doi.org/10.20397/2177-6652/2024.v24i3.3042

Andrii Volkov
Ivan Kozhedub Kharkiv National Air Force University, Ukraine
https://orcid.org//0000-0003-1566-9893

Oleksandr Lezik
PhD in Military Science, Ivan Kozhedub Kharkiv National Air Force University, Ukraine
https://orcid.org/0000-0002-7186-6683

Serhii Oriehov
PhD in Engineering, Ivan Kozhedub Kharkiv National Air Force University, Ukraine
https://orcid.org/0000-0001-6816-4720

Serhii Korsunov
Ivan Kozhedub Kharkiv National Air Force University, Ukraine
https://orcid.org/0000-0002-9769-4568

Mykola Oboronov
Ivan Kozhedub Kharkiv National Air Force University, Ukraine
https://orcid.org/0000-0002-5370-1375

Oleksii Filippenkov
PhD in Military Science, State Scientific Research Institute of testing and certification of the weapon and military equipment, Ukraine https://orcid.org/0000-0002-4027-6963

Scientific Editor: José Edson Lara
Organization Scientific Committee
Double Blind Review by SEER/OJS
Received on 19/04/2024
Approved on 10/07/2024

RESUMO

Objective: This study aims to enhance the accuracy and speed of air target prioritization in real-time through the development and testing of a fuzzy model, thus improving the effectiveness of automated control systems in military applications.

Methods: The research utilizes fuzzy logic and the Mamdani model to develop a system that incorporates expert knowledge and defuzzification processes using the center of gravity method. The methodology includes system analysis, simulation modeling, and a comprehensive review of fuzzy logic applications in complex control environments.

Results: The model demonstrates the ability to prioritize air targets accurately and quickly, confirming its effectiveness through simulations in Python. The model's architecture and the application of fuzzy IF-THEN rules enhance decision-making in air defense control systems.

Conclusions: The study validates the potential of fuzzy logic to improve air target prioritization, offering substantial benefits in terms of adaptability, precision, and operational efficiency. The findings support the integration of the model into existing air defense systems to optimize resource utilization and reduce response times in combat scenarios.

Palavras-chave: Alvo aéreo. Controlo automatizado. Meios de potência de fogo. Lógica difusa. Prioridade.

ABSTRACT

Objective: This study aims to enhance the accuracy and speed of air target prioritization in real-time through the development and testing of a fuzzy model, thus improving the effectiveness of automated control systems in military applications.

Methods: The research utilizes fuzzy logic and the Mamdani model to develop a system that incorporates expert knowledge and defuzzification processes using the center of gravity method. The methodology includes system analysis, simulation modeling, and a comprehensive review of fuzzy logic applications in complex control environments.

Results: The model demonstrates the ability to prioritize air targets accurately and quickly, confirming its effectiveness through simulations in Python. The model's architecture and the application of fuzzy IF-THEN rules enhance decision-making in air defense control systems.

Conclusions: The study validates the potential of fuzzy logic to improve air target prioritization, offering substantial benefits in terms of adaptability, precision, and operational efficiency. The findings support the integration of the model into existing air defense systems to optimize resource utilization and reduce response times in combat scenarios.

Keywords: Air target prioritization. Automated control systems. Fuzzy logic. Mamdani model. Real-time decision-making.

1 INTRODUCTION

In today's world of automated technologies, the efficiency of control systems depends on their ability to adapt to changing conditions and uncertainties in input data (Volkov et al., 2023).

One of the results of the air situation assessment is the prioritization of air targets involved in strikes against the state's troops and facilities. This process is complex and involves analyzing the flight parameters of air targets, as well as rapid processing and integration of various information, which often comes from unreliable and unverified sources. Subsequently, this information is the combat information used by firepower when selecting air targets for their timely destruction. Thus, to ensure the required reliability of information, it is important to use algorithms and models that can provide conclusions based on incomplete or unreliable data (Lezik et al., 2020).

It is proposed to prioritize air targets using the capabilities of fuzzy logic, which includes elements such as fuzzy sets and rules, membership functions, as well as inference methods and defuzzification processes. Using the capabilities of fuzzy logic allows control system users to use their experience and expertise to apply the necessary fuzzy rules. In addition, the process of fuzzification helps to smooth out variations in goal prioritization, especially at points where uncertainty prevails.

The use of fuzzy logic principles in the control of firepower can provide greater adaptability and accuracy in detecting and destroying air targets. This approach will optimize the use of firepower, minimize response time delays, and increase the likelihood of successful target destruction in various combat conditions.

A rule-based fuzzy system has proven effective and is widely used in decision support systems for threat assessment in air defense applications because it can model human expert knowledge. However, building such a system is labor-intensive and complex to adapt to changes in threat behavior in different operational contexts (Tuncer & Cirpan, 2023).

2 LITERATURE REVIEW

The study of this subject area emphasizes the growing importance of fuzzy set theory, as a fundamental concept within fuzzy logic, to improve the accuracy and efficiency of decision-making in military applications, especially in complex and uncertain scenarios such as air defense and air target engagement.

The study (Jin et al., 2020) developed a hierarchical bidirectional fuzzy reasoning mechanism by integrating hierarchical rule structures and forward/backward rule interpolation. The method proposed in this paper is based on the obtained hierarchical bidirectional fuzzy interpolation to maintain consistency in sparse fuzzy rule bases. The proposed methodologies are used to solve various decision support problems, successfully demonstrating their effectiveness.

The study (Volkov et al., 2022) considers the development of an automated decision support system using fuzzy networks to assess the air situation during combat preparation and conduct. Applying fuzzy network principles in fire control systems can provide higher adaptability and accuracy in detecting and destroying air targets.

To create a rule base used in fuzzy models, study (Kozlov, 2021) proposes a universal information technology for designing rule bases (RB) by forming optimal consequents for different types of fuzzy systems (FS) based on ant colony optimization methods (ACO). Applying the proposed information technology allows for designing an efficient RB with optimal consequences at low computational costs.

Due to the homogeneity and insufficiency of traditional methods of processing uncertain information, a new method of parallel processing is proposed in study (Уang et al., 2018). To obtain a dynamic threat value for working with quantitative indicators, the strong generalization ability of Back-Propagation is used, while the strong justification ability of the Bayesian network is used to analyze qualitative indicators to obtain a static threat value. The threat value is obtained by linearly weighting the two types of threat values. Through case analysis and forecasting ten batches of targets combined with simulation in Matlab and Genie software, the method has proven effective. The simulation results show that the comprehensive threat value is more reliable than that obtained by the traditional method.

The Extreme Learning Machine (ELM) neural network-based threat assessment method (Xu et al., 2022) allows for accurate and rapid target threat assessment during aerial reconnaissance, ensuring high accuracy and efficiency.

Study (Уu et al., 2019) reviewed the general process and types of threat assessment methods for air defense using a comparative research method, analyzing the application of fuzzy theory, neural networks, and genetic fuzzy trees in target threat assessment.

The comparison of air target threats using the multi-criteria decision-making method, Saaty Analytic Network Process (ANP), which was proposed in study (Ünver & Gürbüz, 2019), allows the obtained values to be used for sequencing or prioritizing targets in a military environment.

To address the problems of data distortion, errors, or even lack of situational information, study (Wang et al., 2022) proposes a method for assessing threats to air combat targets based on an enhanced evidence network (EN). First, for selected attribute variables closely related to the threat assessment of air combat targets and easy to obtain, a method for calculating the preference function was developed and an evidence network model was constructed. Then, for incomplete evidence information, a preprocessing and evidence correction method based on data prediction was proposed, and a method for transforming the structure of evidence beliefs based on triangular fuzzy ratio conversion was developed. Finally, network reasoning is realized by continuously merging information. The simulation results show that this method allows for fully utilizing target attribute information extracted and accurately assessing the threat level of an enemy fighter with random and incomplete data.

Based on the target detection capabilities of LSS and their threat characteristics in study (Luo et al., 2021) proposed a threat assessment factor and a threat degree quantification function according to LSS target characteristics. LSS targets not only have the same threat characteristics as traditional air targets but also unique characteristics of flexible mobility and dynamic mission planning.

Therefore, we use the Analytical Hierarchy Process (AHP) and information entropy to determine the subjective and objective weights of LSS target threat factors and use an optimization model to combine them to obtain more reliable assessment weights. Finally, the effectiveness and reliability of the proposed method are verified by experimental modeling.

Traditional threat assessment methods, such as the Analytical Hierarchy Process (AHP), are usually limited to individual air targets without considering air cluster targets. Additionally, due to the uncertainty and complexity of the battlefield environment, the data used for threat assessment is incomplete in many situations, such as interval values and probability values. Traditional methods cannot handle incomplete information.

To solve these problems, the study (Gong et al., 2024) proposes a threat assessment method for cluster targets based on the Dynamic Bayesian Network (DBN) with a cloud model. Based on the characteristics of air cluster targets, a DBN was built to infer the threat value for multiple air cluster targets using the Technique for Order of Preference by Similarity to Ideal

Solution (TOPSIS). Based on this, a cloud model with the ability to express uncertainty is used to handle incomplete information. Experiments show that the proposed method allows for assessing the threats of air cluster targets with incomplete information and is more accurate compared to traditional threat assessment methods.

Study (Han et al., 2019) proposed a TOPSIS method based on the cloud model and distance entropy for multi-target threat assessment, highlighting the complexity of threat assessment and the necessity for multifaceted approaches. Similarly, the method based on the Dynamic Bayesian Network addresses the problem of working with incomplete data in dynamic combat environments, emphasizing the need for reliable models that can handle such uncertainties (Wang et al., 2019). Dynamic Threat Assessment Method, which combines DBN and TOPSIS, presenting a comprehensive strategy for assessing multi-target threats, allows for the assessment of threat severity and distance, and provides a holistic picture, improving decision-making in air defense (Gong et al., 2021).

Stochastic dynamic assignment problem to improve air defense combat management using approximate dynamic programming techniques demonstrates an innovative approach to handling dynamic and stochastic elements in air defense scenarios (Liles et al., 2022).

Finally, the study of dynamic game strategies for optimal task management in military operations, provides insights into the application of game theory in air defense and includes matrix games and graph theory algorithms, emphasizing the potential of strategic optimization in combat situations (Zhang et al., 2021). Thus, the relevance of this research is driven by the need to enhance the efficiency of air defense control systems by improving air threat assessment methods. The aim of this research is to develop and validate fuzzy models to improve the efficiency of automated control systems by accurately and quickly determining the priority of air targets in real-time. The primary tasks include developing new approaches for target assessment and prioritization based on fuzzy systems and verifying the adequacy of the developed model through simulation.

3 SEARCH METHOD

The object of this research is the prioritization of air targets, the relevance of which has been confirmed by practical results from the Russian-Ukrainian war during the defense of troops and critical objects, including objects of Ukraine's energy system. After conducting the analysis, it was established that this process is complex and involves analyzing the flight parameters of air targets, as well as the rapid processing and integration of diverse information, which often comes from unreliable and unverified sources. This information is subsequently used by fire control systems to select air targets for timely neutralization.

The subject of this research is the use of fuzzy logic to determine the priority of air targets. The research included the development of a model structure that encompasses defining input and output data and the processor's work as a mechanism for mapping the dependencies of output variables on input variables. It also involved developing a specific fuzzy model for analyzing and determining the priority of air targets, considering parameters such as distance, speed, altitude, target type, etc. The use of the systems analysis method allowed the identification of the most significant flight parameters of targets that can influence the determination of priority levels. Systems analysis also determined that the assessment rule used to establish the priority of an air target is based on the minimum membership degree among the fuzzy sets associated with each input parameter.

In this research, the determination of air target priority was performed using the capabilities of fuzzy logic, which includes elements such as fuzzy sets and rules, membership functions, inference methods, and defuzzification processes. The use of fuzzy logic capabilities allows system users to apply their experience and expert knowledge to formulate necessary fuzzy rules. Additionally, the fuzzification process helps smooth out variations in priority determination, especially in areas where uncertainty prevails.

The principles of fuzzy logic in fire control management can ensure greater adaptability and accuracy in detecting and destroying air targets. This approach will optimize the use of fire resources, minimize response time delays, and increase the likelihood of successfully neutralizing targets under various combat conditions.

In the course of the research, a fuzzy model was created, structured to include input data containing information about the flight parameters of air targets and the fire means designated for their destruction. Flight parameters of air targets are obtained by processing information from target detection means (radar stations, observers, acoustic sensors, etc.), which include data such as target range, speed, altitude, course, and so on.

The method of simulation modeling allowed for the consideration of various factors, such as the diversity of air targets and the characteristics of their flight parameters, the location of the fire means, possible attack routes, and risk dynamics. Through simulation modeling, the accuracy of the proposed fuzzy model based on the Mamdani model and fuzzy rules was evaluated.

4 RESULTS

The fundamental architecture of a fuzzy model encompasses several components: fuzzy logic, fuzzy arithmetic, mathematical programming, graph theory, and data analysis under the umbrella of fuzzy set theory (Xu et al., 2022). The primary goal of this theory is to introduce the concept of fuzzy sets, a mathematical concept that extends traditional set theory for more realistic data processing and system complexity handling.

In conventional terms, a fuzzy set is characterized by a membership function that determines the degree to which each element belongs to the set. The degree of membership varies from 0 to 1, where 0 indicates no membership and 1 indicates full membership.

Assume there is a fuzzy set A on a universal set X. Then, the fuzzy set A can be denoted as a set of pairs:

$$A = \left\{ \left(x, \mu_A(x) \right) \middle| x \in X \right\},$$

where x – element of the universal set X; $\mu_A(x)$ – membership function of the fuzzy set A, which defines the degree of membership of element x to the set A.

The membership function $\mu_A(x)$ can take any value in the interval [0,1], reflecting the fuzziness of the degree to which an element is considered part of the set. This distinguishes fuzzy sets from traditional sets, where the membership function can only take values 0 or 1, corresponding to the absence or presence of an element in the set, respectively (Ruiz-García et al., 2019).

The inference mechanism serves as the “brain” of the system, responsible for processing input data according to defined rules and methods of fuzzy logic to obtain useful conclusions or actions. It illustrates how the output variables depend on the input variables in the system. In the context of a fuzzy model, the input data can be represented by specific numerical values, while the output data can be either a fuzzy set or a precise numerical value. Instead of relying on an explicit function, the relationship between the output and input in a fuzzy model is determined through a set of fuzzy rules. To achieve the goal of this work, it is proposed to consider an expert fuzzy model variant which enables reasoning using expert experience (Fig. 1).

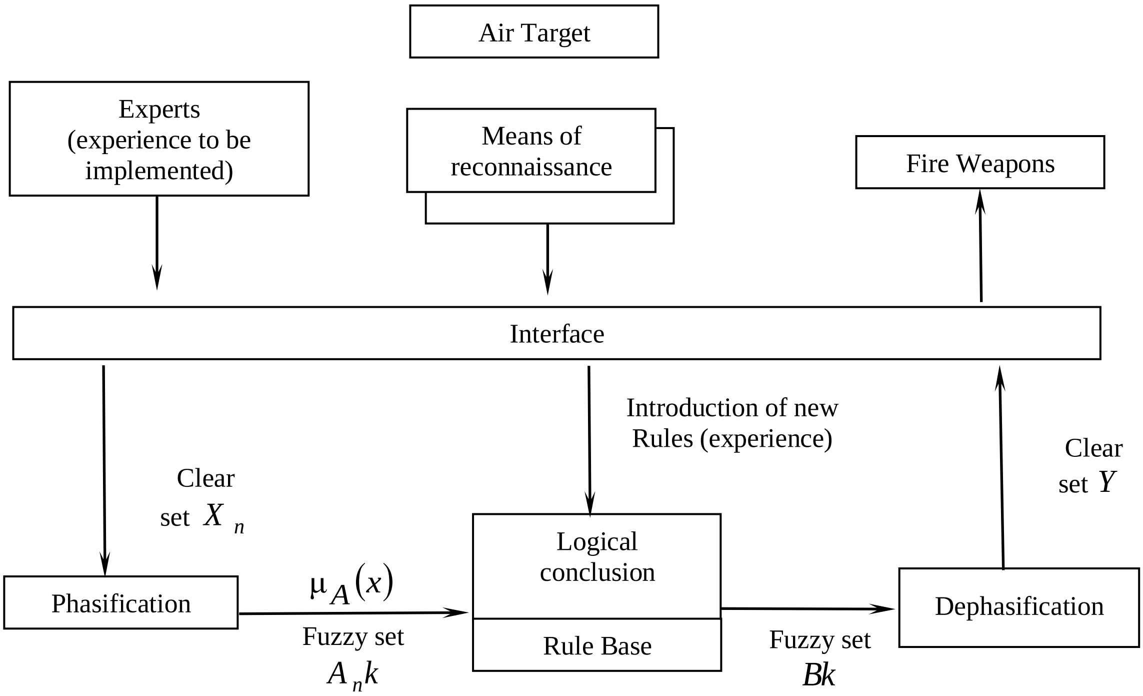

Figure 1: Expert Fuzzy Model Option.
Source: Prepared by the authors (2024).

From Figure 1, it is evident that the rule base serves as a repository for fuzzy IF-THEN production rules. These rules consist of statements written in the language of qualitative concepts by experts in the process, which is weakly formalized. In the case of a fuzzy model with "n inputs – one output" each fuzzy rule can be described as follows:

$$R(k)\text{: if } X_1 \in A_1 k \text{ and } X_2 \in A_2 k \text{ and } \dots X_n \in A_n k \text{, that } Y \in Bk \text{ ,}$$

where $R(k)$– k-th rule in the system; $X_1, X_2, \dots, X_n$ – input variables; $A_1 k, A_2 k, \dots, A_n k$ – fuzzy sets for the corresponding input variables in the k-th rule; Y – output variables; Bk – fuzzy sets for the original variable in the k-th rule.

Each rule $R(k_n)$ associates a specific combination of fuzzy input variable values with a specific fuzzy output variable value. The rule hypothesis is constructed through the intersection, performed by the fuzzy AND, of linguistic statements known as antecedents. The rule's conclusion is derived from the hypothesis using fuzzy inference (IF-THEN). Each rule has a relative importance $\alpha_k \in [0,1]$.

The rule base is created by combining all fuzzy rules using the fuzzy OR. These rules are generated based on expert knowledge or empirical data samples. The rule base is the most crucial component of any fuzzy model.

The model parameter set defines the characteristics of membership functions used to represent linguistic terms of fuzzy variables and rules. These parameters can be set based on expert assessments or through knowledge extraction from experimental data. The combination of the rule base and the model parameter set is usually called the knowledge base. The inference mechanism is responsible for conducting the fuzzy logical inference process, using this knowledge base and input data, ultimately providing the predicted output value. The fuzzification interface converts crisp input data into degrees of membership in the corresponding linguistic terms, while the defuzzification interface converts the fuzzy inference back into a crisp output value.

In the context of prioritizing air targets, the fuzzy model is built such that the input data includes information about the flight parameters of air targets and the fire means intended to destroy them. The flight parameters of air targets are obtained by processing information from target detection means (radar stations, observers, acoustic sensors, etc.), which include data such as target range, speed, altitude, course, etc.

In turn, data on fire means intended to destroy air targets include information about the type of means, their location, ammunition availability, hit probability, etc (Volkov et al., 2021). The relationship between some air target parameters and fire means information is shown in Figure 2.

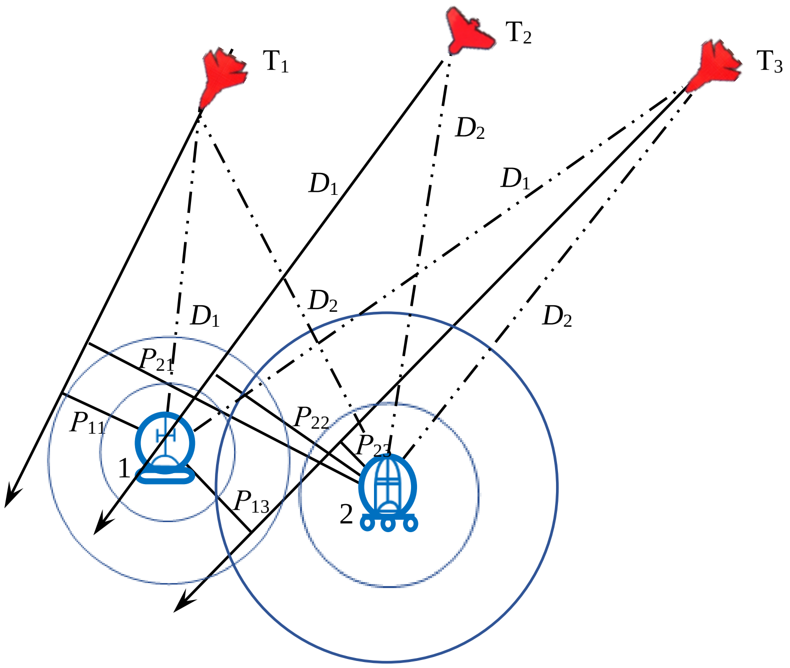

Figure 2: Relationship between the flight parameters of air targets and firepower means.
Source: Prepared by the authors (2024).

To determine the priority of an air target, it is proposed to use a fuzzy model, which is implemented in the processing unit of a fuzzy expert system (Fig. 3).

Based on the information about the flight parameters of air targets and the data on fire means, the range of the *i*-th target to the j-th fire means, the course parameter, the time the *i*-th target stays in the strike zone of the *j*-th fire means, and the target priority for optimal target allocation are determined.

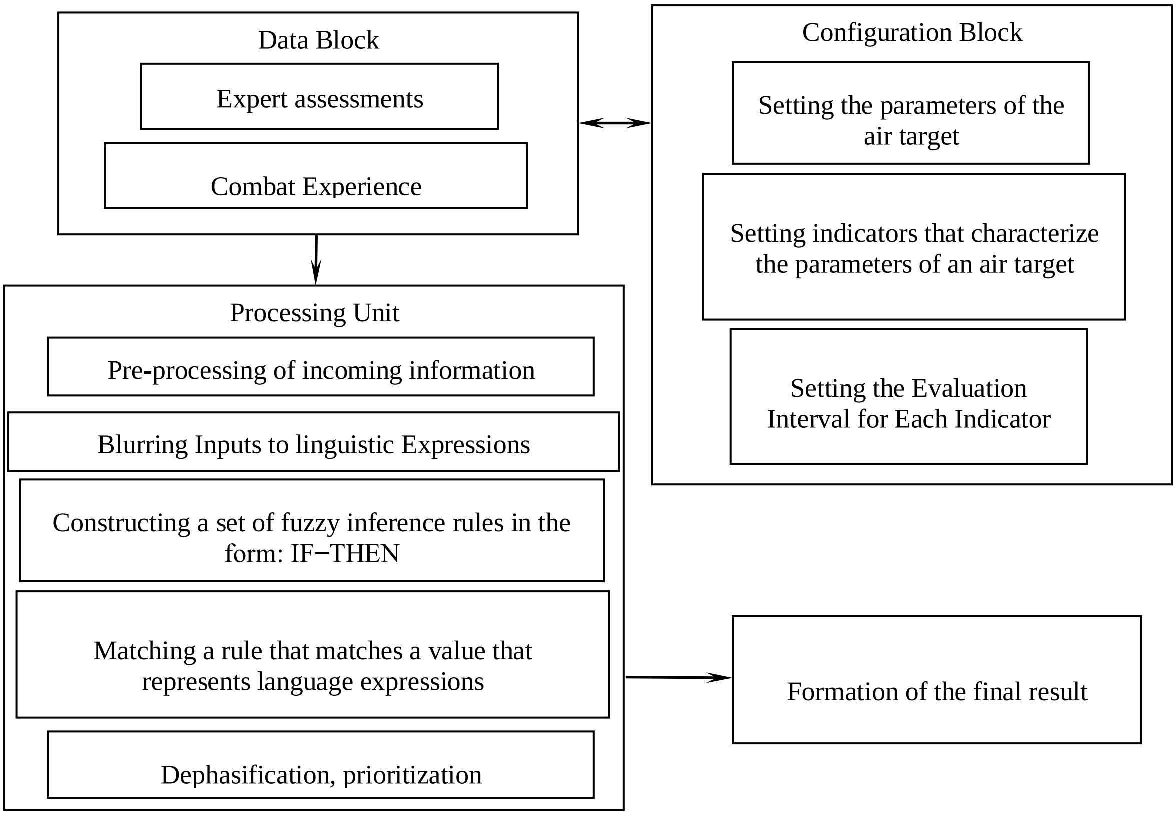

Figure 3: Structure of the fuzzy system algorithm to prioritize air targets.
Source: Prepared by the authors (2024).

The fuzzy information received at the input is processed by determining the degrees of membership for the linguistic variables that describe the input data. Precise input values are then used as parameters for membership functions, assigning these values to linguistic terms involved in the conditions of each fuzzy logic rule. According to the approach described in (Lezik et al., 2020) and the standards used in NATO countries, the flight parameters of the target are classified at different levels. For example, the target flight altitude is divided into very low (up to 150 m), low (150–1,500 m), medium (1,500–7,600 m), and high (7,600–15,200 m). Similarly, the target speed is divided into low (up to 102 m/s), low (102–206 m/s), medium (206–308 m/s), and high (over 308 m/s). Based on this classification of air target flight parameters, membership functions are formed, resulting in input data and linguistic expressions for the proposed fuzzy model.

Subsequently, a set of fuzzy inference rules in the form of IF-THEN operators is formed by fuzzily converting the input information into linguistic expressions. It should be noted that shorter distances to the target and lower flight altitudes correspond to an increased priority of the air target. Thus, the language used to determine the air target's priority level based on the input information is directly proportional to the speed and inversely proportional to the distance, altitude, course, and time the target remains in the strike zone. The set of fuzzy inference rules, which evaluates the input information using the fuzzy AND operator, is created based on a combination of expert knowledge and the relative importance of each rule $\alpha_k \in [0, 1]$, represented in Table I. According to Table I, each evaluation rule applied to establish the air target's priority is based on the minimum value of membership degrees among the fuzzy sets associated with each input parameter.

Table 1

A set of fuzzy output rules in the form of IF-THEN for evaluating input data by the AND operator based on expert knowledge

№	Relative importance	AND							Level Priority
		Target range, m.	Target Height, m.	Target azimuth, °	Target speed, m/s	Exchange rate parameter, m	Time spent by the target in the kill zone, s	Target Type	
1	1,0	L	L	H	L	M	L	L	H
2	1,0	H	H	L	H	H	H	H	L
3	0,8	L	M	L	M	M	M	L	M
4	0,5	H	L	H	L	L	M	L	M
5	0,5	M	L	H	L	L	M	H	H
6	0,1	L	H	M	H	H	M	M	L

Source: research data

Then the satisfaction H_k for each input parameter, using the Mamdani method, is calculated as follows:

$$H_k = \min(\mu_{kl}(x)),$$

where $\mu_{kl}(x)$ the degree of affiliation, which determines how well the input value corresponds to the linguistic term l for the rule.

Such an approach ensures that the evaluation of each parameter reflects the most important factor influencing the overall priority assessment. In the evaluation process, the compliance of each rule, which correlates with the given linguistic terms, requires the determination of the degree of satisfaction. This degree reflects how well the input parameters meet the conditions set for each rule, as presented in Table 1. In cases where all the rules in Table 1 are activated simultaneously, there may be rules that yield the same satisfaction value H_k. For example, rules 1 and 5 generate a goal priority level with the linguistic expression "High (H)", rules 3 and 4 generate a priority level with the linguistic expression "Medium (M)", and rules 2 and 6 determine the priority level with the linguistic expression "Low (L)". Therefore, there arises a need to combine rules that create the same linguistic expression of priority level using the fuzzy operator ProbOR, according to the formula:

$$\beta_l = \oplus\, k\,(H_k \otimes \alpha_k),$$

where β_l – aggregated priority level for a linguistic term l; $\oplus$ – represents the fuzzy ProbOR operator used for aggregation; H_k – the degree of satisfaction for the k-th rule; $\otimes$ – denotes the operation of combining the degree of satisfaction with the relative importance of the rule; α_k – the relative importance of the k-th rule.

Then, for the rules given in Table 2, their cumulative affiliation is calculated as follows:

for $l = 1$ (High Priority)

$$\beta_{\mathrm{H}} = (H_1 \otimes \alpha_1) \oplus (H_2 \otimes \alpha_2) \oplus \ldots \oplus (H_k \otimes \alpha_k);$$

for $l = 2$ (Medium Priority):

$$\beta_{\mathrm{M}} = (M_1 \otimes \alpha_1) \oplus (M_2 \otimes \alpha_2) \oplus \ldots \oplus (M_k \otimes \alpha_k);$$

for $l = 3$ (Low priority):

$$\beta_L = (L_1 \otimes \alpha_1) \oplus (L_2 \otimes \alpha_2) \oplus \ldots \oplus (L_k \otimes \alpha_k),$$

where H_k, M_k, L_k – correspond to the degrees of satisfaction of each rule for high, medium and low levels, respectively; k – the number of rules corresponding to each linguistic level.

To apply the specified formulas, it is necessary to use the degrees of correspondence of each linguistic term and the relative importance of each rule.

Then, using these formulas, the aggregated degrees of membership are calculated, which allows for obtaining an overall assessment for each air target. This process integrates various input data and assessments into a single output value, reflecting the priority of the targets considering the established rules and criteria.

The defuzzification process to calculate the target priority value of an air target is proposed to be carried out using the Center of Gravity (CoG) method, taking into account nput parameters such as range, speed, altitude, course, and other characteristics that affect the determination of target priority. This method integrates input fuzzy data to obtain a single crisp numerical value that reflects the priority of air targets.

To calculate a specific value $\beta_H, \beta_M, \beta_L$ it is necessary to combine the corresponding members and then transform them into a scalar value through reduction to remove indeterminate components. This results in the final form of the membership function representing a certain level of priority. Then, the priority value of the air target relative to the fire means can be calculated as follows

$$\upsilon_{ij}^{CoG} = \frac{\sum_{i=1}^{n}\left(\upsilon_z \cdot \mu_c\left(\upsilon_z\right) \cdot S_z\right) + \lambda \cdot \sum_{k=1}^{m}\left(d_{jk} \cdot \mu_d\left(d_{ij}\right) \cdot W_j\right)}{\sum_{i=1}^{n}\left(\mu_c\left(\upsilon_z\right) \cdot S_z\right) + \lambda \cdot \sum_{k=1}^{m}\left(\mu_d\left(d_{ij}\right) \cdot W_j\right)},$$

where υ_{ij}^{CoG} the calculated priority value for the *i*-th air target using the center of gravity method, taking into account the interaction with the *j*-th fire weapon; υ_z – the value of the *z*-th parameter, which affects the priority (for example, range, speed); $\mu_c\left(\upsilon_z\right)$ – accessory function for the *z*-th parameter; S_z – the weight or significance of the *z*-th parameter; d_{ij} – the distance between the *i*-th target and the *j*-th fire weapon; $\mu_d\left(d_{ji}\right)$ – accessory function, which reflects the degree of suitability of the *j*-th fire weapon for destroying the *i*-th target, taking into account the distance; W_j – the weight or significance of the *j*-th fire weapon in the context of the ability to destroy the target; λ – a coefficient that regulates the influence of the distance to the firing assets on the overall priority of the target; n – the number of parameters that affect the priority; m – the number of fire weapons. For conducting the simulation modeling of the proposed fuzzy model in determining and comparing priority levels, we will consider the experience of the russian-Ukrainian war and define a scenario for the engagement of critical infrastructure targets protected by a single fire weapon. This scenario replicates an air situation with 6 air targets ($T_1, T_2, \ldots, T_6$) with variable flight parameters and one fire weapon (F_1). The flight parameters of the targets during the simulation are presented in Table 2.

Table 2.

Information on the flight parameters of the targets

Target ID	Range to the target, m	Height target, m	Azimuth target,°	Course target,°	Speed target, m/s
T_1	2 000	300	25	195	30
T_2	1 200	230	45	200	50
T_3	800	700	120	300	55
T_4	1 560	450	10	90	100
T_5	3 800	1 000	100	200	20
T_6	3 200	1 200	90	20	70

Source: research data

In the process of conducting simulation modeling, we will evaluate the accuracy of the proposed fuzzy model based on the Mamdani model and the fuzzy rules presented in Table 2. For this, we will use the SCIKIT-FUZZY PYTHON library set. The fuzzy rules are established based on the values of the input information. After determining the fuzzy rules, fuzzy models are created using SCIKIT-FUZZY PYTHON to determine the priority levels of the targets, as indicated in Table 2. The results of testing this model, considering the target trajectory parameters, are presented in Figure 4. To evaluate the effectiveness of the proposed fuzzy model, we will create a test model in the GOOGLE COLAB environment, which provides a platform for executing PYTHON code in the cloud. The results of the simulation modeling show that target T_2 demonstrates the highest priority with a value of 0.712, while target T_4 has the lowest priority, measured at 0.124.

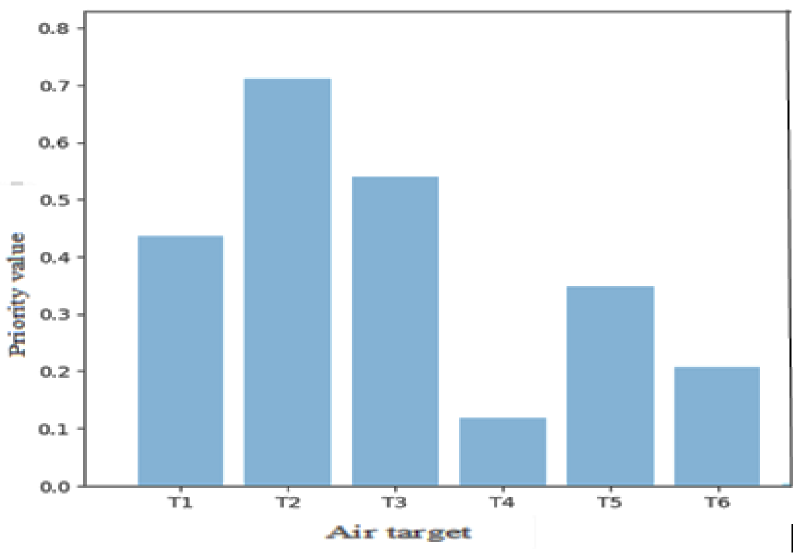

Figure 4: Target Threat Level Values in the Air Defense Scenario.
Source: Prepared by the authors (2024).

The calculated priority values of the targets allow for ordering the targets in descending priority level, which simplifies the automatic assignment of target data to the fire units.

The developed model is capable of calculating and updating the priority values of targets during each data update cycle and demonstrates its ability to operate in real-time. Furthermore, there is potential to integrate this model into existing software products, where target priority values can be directly displayed on a digital map.

5 DISCUSSION

The proposed fuzzy logic model for prioritizing air targets demonstrates significant progress in real-time target assessment in air defense systems. Key findings from the simulation modeling confirm the effectiveness of the Mamdani fuzzy model, which was implemented using the SCIKIT-FUZZУ РYTHON library. The model's ability to accurately evaluate target priorities based on variable flight parameters demonstrates its potential for integration into modern air defense management systems.

Modeling results indicate that the model effectively prioritizes targets, assigning the highest priority to the most threatening target (priority value 0.712) and the lowest priority to the least threatening target (priority value 0.124). This differentiation allows for a systematic approach to target engagement, ensuring that the most threatening targets are neutralized first. This conclusion aligns with previous research emphasizing the importance of accurate threat assessment for enhancing the efficiency of air defense operations.

The performance of the presented model is comparable to existing methods, such as those using Bayesian networks and the Analytical Network Process (ANP) for threat assessment (Wang et al., 2019). However, our fuzzy logic approach offers an advantage in processing multiple input parameters and expert knowledge through IF-THEN rules, which traditional methods may not handle as flexibly. Studies have shown that fuzzy logic systems similar to ours can provide more nuanced and adaptive assessments in complex and dynamic environments (Beser et al., 2018).

A notable addition to the body of literature is the study by (Jin et al., 2020), which presented a bidirectional reasoning-based approximation approach for decision support. This method underscores the importance of incorporating bidirectional reasoning to enhance decision-making, complementing our fuzzy logic model by potentially providing a more comprehensive understanding of threat scenarios.

There is currently a substantial body of research on prioritization through various methods. For example, R. J. Zhao et al. (2021), aiming to reduce the uncertainty of target threat assessment results and improve the accurate assessment of targets in complex and changing air combat environments, proposed a method based on the combination of interval-valued intuitionistic fuzzy sets (IVIFS), game theory, and evidence reasoning methodology. The study represents the imprecise and fuzzy information of air targets on the battlefield with IVIFS, determines the optimal index weight using interval-valued intuitionistic fuzzy entropy and game theory, and calculates the time series weight using the inverse Poisson distribution method. Similar approaches were used by J. Feng et al. (2019) and M. Iasechko et al. (2021) in their work, where they proposed an improved generalized intuitionistic fuzzy soft set (GIFSS) method for dynamic threat assessment of air targets.

Firstly, the threat assessment index is reasonably determined by analyzing the typical characteristics of air targets. Secondly, after obtaining GIFSS at different times, the index weight is determined using intuitionistic fuzzy entropy and relative entropy theory. The inverse Poisson distribution method is then used to determine the time series weight, and a time-weighted GIFSS is obtained. Finally, the threat assessment of five air targets is carried out using improved GIFSS (I-GIFSS) methods, and their comparison proves the validity and advantage of the proposed method.

У. Gao et al. (2020) developed a target threat assessment method based on triadic decisions in an intuitionistic fuzzy multi-attribute decision-making environment. The key components include the conditional probability of each target evaluated by intuitionistic fuzzy TOPSIS and the decision thresholds of each target constructed using intuitionistic fuzzy evaluation values. Results from two numerical examples indicate that the proposed method effectively handles dynamic uncertain situation information, transforming traditional two-sided decision ranking results into objective triadic decision classification results, and can flexibly reflect situation information acquisition by setting the risk avoidance coefficient.

To overcome the shortcomings of traditional threat assessment methods, such as one-sidedness, subjectivity, and low accuracy, L. Уue et al. (2019) proposed a new air target threat assessment method based on a gray neural network model (GNNM) optimized by an improved moth-flame optimization algorithm (IMFO). The model fully combines the excellent optimization performance of IMFO with the strong learning performance of GNNM.

Additionally, V. Koval et al. (2023) proposed a classification of air threats for warning, recognition, and alert systems, prioritizing threats based on predicted losses. Their findings align with our approach, emphasizing the importance of parameters such as minimum engagement range and maximum flight speed in determining threat priority.

The real-time operational capabilities of the presented model are crucial for modern air defense systems, which require quick and reliable target assessments to respond to rapidly evolving threats. The model's ability to dynamically update priority values ensures continuous optimization of defense strategies necessary for effective air defense management. This feature aligns with the findings of recent studies, highlighting the need for adaptive and responsive systems in air defense scenarios (Tuncer & Cirpan, 2023).

One of the most promising aspects of the developed model is its potential integration into existing tactical software modules. By displaying target priority values directly on digital maps, operators can make informed decisions quickly, enhancing situational awareness and decision-making efficiency. This integration potential was confirmed by previous research on decision support systems in air defense (Volkov et al., 2020).

Future research should focus on refining the model by incorporating additional parameters, such as electronic countermeasures and environmental factors that may affect target prioritization. Extending the model to account for joint engagement scenarios involving multiple air defense units could significantly enhance its applicability. Collaboration with defense technology developers can facilitate the practical implementation and testing of the model under real-world conditions.

In conclusion, the developed fuzzy logic model represents a significant advancement in the field of air defense. Its ability to accurately determine target priorities in real-time, combined with its integration potential, makes it a valuable tool for enhancing the efficiency and effectiveness of air defense operations. Recent research contributions further underscore the need for adaptive, reliable, and multifaceted approaches in threat assessment and decision support systems.

6 CONCLUSION

This work represents an innovative approach to determining the priority level of air targets using fuzzy logic and technical terminology. The application of the Mamdani model enabled effective processing of multiple input data to determine a single output value - the priority level. The foundation of this method lies in fuzzy logic inference rules IF-THEN, which take into account expert knowledge through the use of the AND operator. The defuzzification process, conducted using the limited center of gravity method, in conjunction with fuzzy rules, determined the final priority value of the target.

The effectiveness of the model was validated through simulations in PYTHON on various target trajectories. The results demonstrated that the model is capable of promptly assessing the priority level of each target, making it highly promising for integration into tactical software modules for real-time control and management of air defense systems.

Overall, the developed fuzzy model represents a significant advancement in the development of automated control systems for military applications. It provides flexibility, speed, and precision in decision-making, crucial in dynamic and unpredictable conditions of the modern battlefield.

REFERENCES

Beser, F., Adiguzel, D., Уildirim, O., & Уildirim, T. (2018). Air defence decision support system design using fuzzy logic. *Journal of Intelligent Systems with Applications*, *1*(2), 135–139. https://doi.org/10.54856/jiswa.201812042.

Feng, J., Zhang, Q., Hu, J., & Liu, A. (2019). Dynamic assessment method of air target threat based on improved GIFSS. Journal of Systems Engineering and Electronics, *30*(3), 525–534. https://doi.org/10.21629/jsee.2019.03.10.

Gao, У., Li, D., & Zhong, H. (2020). A novel target threat assessment method based on three-way decisions under intuitionistic fuzzy multi-attribute decision making environment. *Engineering Applications of Artificial Intelligence*, 87, 103276. https://doi.org/10.1016/j.engappai.2019.103276.

Gong, C., Уang, L., & Huang, Q. (2024). Threat assessment of air cluster targets based on dynamic Bayesian network with cloud model. *In Lecture Notes in Electrical Engineering*, 1171, 372–381. https://doi.org/10.1007/978-981-97-1083-6_35.

Gong, H., Уu, X., Zhang, У., & Liu, F. (2021). Dynamic threat assessment of air multi-target based on DBN-TOPSIS method. *In 2021 China Automation Congress (CAC), Beijing, China.* IEEE. https://doi.org/10.1109/cac53003.2021.9727672.

Han, Q., Уu, M., Gao, У., Song, S., & Chen, S. (2019). TOPSIS method based on cloud model and distance entropy in evaluating the air multi-target threat. *Fire Control. Command. Control*, 44, 136–141.

Iasechko, M., Shelukhin, O., Maranov, A., Lukianenko, S., Basarab, O., & Hutchenko, O. (2021). Evaluation of The Use of Inertial Navigation Systems to Improve The Accuracy of

Object Navigation. *International Journal Of Computer Science And Network Security*, *21*(3), 71-75. https://doi.org/10.22937/IJCSNS.2021.21.3.10/

Jin, S., Peng, J., Li, Z., & She, Q. (2020). Bidirectional approximate reasoning-based approach for decision support. *Information Sciences*, 506, 99–112. https://doi.org/10.1016/j.ins.2019.08.019.

Koval, V., Oleksenko, O., Lupandin, V., & Nos, I. (2023). General approach to determine air threat prioritization according to forecasted losses for notification, identification and warning systems of population. *Science and Technology of the Air Force of the Armed Forces of Ukraine*, *1*(50), 7–14. https://doi.org/10.30748/nitps.2023.50.01.

Kozlov, O. (2021). Information technology for designing rule bases of fuzzy systems using ant colony optimization. *International Journal of Computing*, *20*(4), 471–486. https://doi.org/10.47839/ijc.20.4.2434.

Lezik, O., Volkov, A., Tokar, O., & Stadnichenko, V. (2020). Essence, content and evaluation of management efficiency air defense of land forces and fire in battle. *Systems of Arms and Military Equipment*, *62*(2), 119–128. https://doi.org/10.30748/soivt.2020.62.15.

Liles, J., Robbins, M., & Lunday, B. (2022). Improving defensive air battle management by solving a stochastic dynamic assignment problem via approximate dynamic programming. *European Journal of Operational Research*, *305*(3), 1435–1449. https://doi.org/10.1016/j.ejor.2022.06.031.

Luo, R., Huang, S., Zhao, Y., & Song, Y. (2021). Threat assessment method of low altitude slow small (LSS) targets based on information entropy and AHP. *Entropy*, *23*(10), 1292. https://doi.org/10.3390/e23101292.

Ruiz-García, G., Hagras, H., Pomares, H., & Ruiz, I. (2019). Toward a fuzzy logic system based on general forms of interval type-2 fuzzy sets. *IEEE Transactions on Fuzzy Systems*, *27*(12), 2381–2395. https://doi.org/10.1109/TFUZZ.2019.2898582.

Tuncer, O., & Cirpan, H. A. (2023). Adaptive fuzzy-based threat evaluation method for air and missile defense systems. *Information Sciences*, 643, 119191. https://doi.org/10.1016/j.ins.2023.119191.

Tuncer, O., & Cirpan, H. A. (2023). A networked radar resource management approach utilizing target priority and maneuver for cooperative air defense fire control radars. *IEEE Access*, *11*, 136279–136291. https://doi.org/10.1109/ACCESS.2023.3337799.

Ünver, S., & Gürbüz, T. (2019). Threat evaluation in air defense systems using analytic network process. *Journal of Military and Strategic Studies*, *4*(19), 10–39. https://jmss.org/article/view/58229/53341.

Volkov, A., Bazilo, S., Tokar, O., Horbachov, K., Lutsyshyn, A., Zaitsev, I., & Iasechko, M. (2022). Automated assessment of the air situation during the preparation and conduct of combat operations using a decision support system based on fuzzy networks of target installations. *International Journal of Computer Science and Network Security*, *22*(11), 184–188. https://doi.org/10.22937/IJCSNS.2022.22.11.26.

Volkov, A., Brechka, M., Stadnichenko, V., Yaroshchuk, V., & Cherkashyn, S. (2023). The protection of critical infrastructure facilities from air strikes due to compatible use of various forces and means. *Machinery & Energetics, 14*(4), 23–32. https://doi.org/10.31548/machinery/4.2023.23.

Volkov, A., Lezik, O., Dolyna, M., Korsunov, S., Fedchenko, S., & Hulenov, I. (2021). Analysis, rating and packing effectivity systems management of subrecessions of air defense units a score of unproperty functioning. *Digest of Scientific Works Scientific Works of Kharkiv National Air Force University*, *3*(69), 7–15. https://doi.org/10.30748/zhups.2021.69.01.

Wang, X., Zuo, J., Yang, R., Zhang, Z., Yue, L., & Liu, H. (2019). Target threat assessment based on dynamic Bayesian network. *Journal of Physics: Conference Series*, *1302*(4), 042023. https://doi.org/10.1088/1742-6596/1302/4/042023.

Wang, Y., Fan, Z., Ren, T., & Wang, X. (2022). Target threat assessment in air combat with incomplete information. *In 2022 34th Chinese Control and Decision Conference (CCDC), Hefei, China*. IEEE. https://doi.org/10.1109/ccdc55256.2022.10033869.

Xu, J., Xu, X., & Tian, W. (2022). Aerial target threat estimation in unmanned aerial vehicle reconnaissance based on neural network. *In ICNSER 2022: The 3rd International Conference On Industrial Control Network And System Engineering Research.* ACM. https://doi.org/10.1145/3556055.3556065.

Yang, H., Han, C., & Tu, C. (2018). Air targets threat assessment based on BP-BN. *Journal of Communications*, *13*(1), 21–26. https://doi.org/10.12720/jcm.13.1.21-26.

Yu, R., Liu, G., & Li, G. (2019). Comparative analysis and development exploration of threat assessment methods for warship air defense. *System and Control Engineering*, 291, 01006. https://doi.org/10.1051/matecconf/201929101006.

Zhang, T., Li, C., Ma, D., Wang, X., & Li, C. (2021). An optimal task management and control scheme for military operations with dynamic game strategy. Aerospace Science and Technology, 115, 106815. https://doi.org/10.1016/j.ast.2021.106815.

Zhao, R., Yang, F., Ji, L., & Bai, Y. (2021). Dynamic air target threat assessment based on interval-valued intuitionistic fuzzy sets, game theory, and evidential reasoning methodology. *Mathematical Problems in Engineering*, *2021*(1), 1–13. https://doi.org/10.1155/2021/6652706.

Yue, L., Yang, R., Zuo, J., Luo, H., & Li, Q. (2019). Air target threat assessment based on improved moth flame optimization gray neural network model. *Mathematical Problems in Engineering*, *2019*(1), 1–14. https://doi.org/10.1155/2019/4203538.