Scientific Journal of Silesian University of Technology. Series Transport
Zeszyty Naukowe Politechniki Śląskiej. Seria Transport

Volume 123 **2024**

p-ISSN: 0209-3324

e-ISSN: 2450-1549

DOI: https://doi.org/10.20858/sjsutst.2024.123.5

Journal homepage: http://sjsutst.polsl.pl

Article citation information:
Krawczyk, T., Papis, M., Bielawski, R., Rządkowski, W. Possible applications of artificial intelligence algorithms in F-16 aircraft. *Scientific Journal of Silesian University of Technology. Series Transport*. 2024, **123**, 101-131. ISSN: 0209-3324.
DOI: https://doi.org/10.20858/sjsutst.2024.123.5.

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POSSIBLE APPLICATIONS OF ARTIFICIAL INTELLIGENCE ALGORITHMS IN F-16 AIRCRAFT

Summary. The F-16 aircraft, widely used by the Polish Army Air Force, requires modifications based on Artificial Intelligence (AI) algorithms to enhance its combat capabilities and performance. This study aims to develop comprehensive guidelines for this purpose by first describing F-16 systems and categorizing AI algorithms. Machine learning, deep learning, fuzzy logic, evolutionary algorithms, and swarm intelligence are reviewed for their potential applications in modern aircraft. Subsequently, specific algorithms applicable to F-16 systems are identified, with conclusions drawn on their suitability based on system features. The resultant analysis informs potential F-16 modifications and anticipates future AI applications in military aircraft, facilitating the guidance of new algorithmic developments and offering benefits to similar aircraft types. Moreover, directions for future research and development work are delineated.

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Keywords: F-16 aircraft, Artificial Intelligence (AI), machine learning, deep learning, AI algorithms, combat capabilities

1. INTRODUCTION

The F-16 Fighting Falcon is a 4^{th} generation fighter that is in service with many air forces. Currently, approximately 4,600 aircraft have been produced, out of which, 2280 are in active service. This aircraft is used in fighter missions as well as in assault missions. It is very popular due to its versatility of use in various military missions, as well as a favourable balance of shoot-downs of enemy aircraft – currently over 70 shoot-downs of enemy aircraft. [113, 120]. Despite the F-16 being replaced by the F-35, it is expected that the F-16 will continue to be in high demand, requiring modifications over time to meet battlefield tasks. One such modification is the possibility of using Artificial Intelligence (AI), mostly machine learning (ML) and deep learning (DL) algorithms in the F-16 aircraft. Work on such modifications has already been initiated by DARPA (Defense Advanced Research Projects Agency), which conducts research based on the F-16 aircraft in the field of self-piloting as well as air combat by artificial intelligence. The AI program of Heron Systems was used for this purpose. It should be noted that the current tests performed under the framework of research and development were conducted only in a virtual environment. As part of the test, a virtual 1-on-1, AI duel was organized against an experienced F-16 pilot, who was defeated in five duels by the AI. It is worth noting that the research and development program did not include the use of AI as a component supporting the pilot during air combat, which may be important for the users of F-16 aircraft. However, the DARPA program has opened a new direction for the implementation of AI algorithms in military aviation and in particular for the F-16 aircraft [41,50].

The considerable number of F-16 aircraft produced will provide a substantial amount of data to feed the prepared artificial intelligence algorithms. Ongoing research will enable these aircraft to adapt to meet the demands of modern air combat. Consequently, the F-16 aircraft will become an adaptive platform capable of utilizing AI technologies to optimize performance, decision-making, and mission execution.

The capability of AI to pilot and participate in air combats autonomously or for the AI component to assist the pilot of a military aircraft in the execution of a combat mission opens up new opportunities in military aviation [29]. Current AI algorithms can contribute to solving many problems in military aviation such as full "utilization" of aerodynamics and aircraft mechanics in the flight control system, optimization of armament use during air combat, operation of radar systems and Electronic Attack Jammer Pods (EAJP), aircraft control and decision-making at critical moments of flight or air combat, optimization of power unit control, optimization of fuel consumption, real-time generation and analysis of data from on-board sensors, predictive maintenance, etc. The area of application of AI algorithms can be considered modularly depending on the specific purpose of the aircraft, e.g.: fighter, assault, reconnaissance, or electronic warfare mission. The F-16 aircraft is a universal combat platform that allows for the modular implementation of AI algorithms in this respect.

The wide application of Artificial Intelligence algorithms in military and civil aviation and the characteristics of individual systems of the F-16 aircraft will allow detailing the possibilities of implementation of particular algorithms in the case of F-16 aircraft systems.

In this research, the focus was on exploring the possibilities of applying specific artificial intelligence algorithms to the functionalities of F-16 aircraft systems. Consequently, successive stages of the research were developed, which are described in the subsequent sections of this paper:

- characteristics of the F-16 aircraft systems in which AI algorithms can be applied;
- overview of artificial intelligence algorithms;
- overview of research on the application of AI algorithms in aviation;
- assessment of potential applications of artificial intelligence algorithms in F-16 to improve aircraft performance based on matrix analysis;
- discussion and conclusions.

2. CHARACTERISTICS OF THE F-16 AIRCRAFT

The capabilities of AI algorithms can be applied to the following systems of the F-16 aircraft:

- general characteristics of the airframe structure;
- aircraft engine;
- flight control system;
- fuel system;
- aircraft weapon;
- radar system.

In addition, airworthiness and maintenance management should be considered as a separate additional system.

Tab. 1 provides basic data on F-16 aircraft systems based on [1, 24, 79, 116, 130]. More detailed information can be found in [88].

Tab. 1

F-16 systems

General characteristics of the airframe structure
A single-engine, light fighter aircraft. It was built in a classic mid-wing configuration. Its basic dimensions are: wingspan of 9.8 m, aircraft length of 14.8 m, wing area: 27.87 m^2. The fuselage has a semi-monocoque construction, covering densely supported by frames and half frames.
Aircraft engine
The power unit (single-engine) of the F-16 aircraft consists of a Pratt & Whitney F100-PW-229 engine with 79.13 kN and 128.91 kN thrust with afterburning. It is a two-flow engine with a hydraulically regulated nozzle.
Flight control system
A fly-by-wire control system based on the Lear Siegler flight parameters computer, which uses data, among others from yoke (control column), control surface position transmitters, accelerometers, gyroscopes, angle of attack, and slide transmitters, aerodynamic data computer. Moreover, the system includes hydraulic actuators of control surfaces.
Fuel system
The F-16 engine is supplied with fuel from five fuselage tanks and two wing tanks, with a total capacity of 3,986 l. The fuel tanks have a self-sealing design. It is possible to mount additional fuel tanks.

Aircraft weapon
The primary weaponry is the General Electric M61 A1 six-barrel cannon (20 mm calibre). Suspended armament: medium-range AIM-120 AMRAAM air-to-air missiles, LAU-114 launchers for firing short-range Sidewinder, and medium-range AMRAAM air-to-air missiles. Guided air-to-ground armament consists of AGM-65A/B/D/G Maverick and AS30L missiles, AGM-88 HARM and AGM-45 Shrike anti-radiation guided missiles, AGM-84 Harpoon or AGM-119 Penguin Mk 3 air-to-air guided missiles. Unguided missiles of 70 mm calibre can be fired from LAU-68 and LAU-88 multi-barrel launchers. The aircraft's bombarding armament consists of Paveway II series guided bombs. The aircraft is also adapted to carry B43 nuclear bombs.
Radar system
A common radar used in F-16 aircraft is the Westinghouse AN/APG-68(V)5 (AN.APG-68 in older versions of the F-16C), operating in the I/J waveband. The (V)5 variant added an SA (Situation Awareness) module to warn the pilot of a threat. Starting with Block 50/52, a DTS digital map projector was added. Under ideal conditions, the maximum detection range for large targets (bombers) at high altitudes is 270 km. For small targets, it decreases to about 170 km. As regards targets visible on the ground, the analogous values are 230/130 km respectively. The radar can start tracking a target at a distance equal to about 60% of the detection distance. It is possible to track up to 10 targets simultaneously. The situation as seen by the radar is presented on multifunctional Honeywell indicators. The targets tracked by the station are also presented on the GEC-Arconi wide-angle head-up display (HUD). The AN/APG-68 radar prepares data necessary for air-to-air and air-to-ground missiles. The latest versions of the radar dedicated to F-16 are the AN/APG-80 and AN/APG-83, which can track more targets simultaneously.

3. ARTIFICIAL INTELLIGENCE ALGORITHMS AND THEIR APPLICATIONS IN AVIATION

The first major step in the ongoing research is a review of Artificial Intelligence algorithms. The next stages of the ongoing research are shown in the diagram (Fig. 1). AI algorithms that may be used in aviation were identified. For this purpose, a study of the literature's current state was conducted, which, combined with a review of AI algorithms, enabled the development of a summary presented in the form of a table, illustrating the applications of AI algorithms in specific areas of aircraft systems. The next step involved analysing the potential applications of AI algorithms in relation to the functionality of the F-16 aircraft's systems. The last step was to develop proposals for modifying the aircraft systems using selected algorithms.

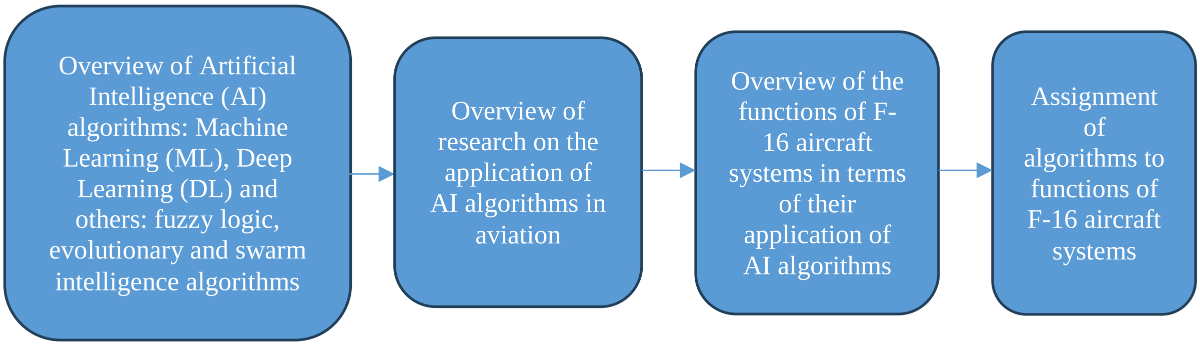

Fig. 1. Steps of the conducted analysis

3.1. Overview of artificial intelligence algorithms

The term Artificial Intelligence (AI) was pioneered by John McCarthy and presented at the Dartmouth Conference in 1956. In its shortened form, the term means “the intelligence exhibited by artificial devices” [80]. Since then, many definitions of the term AI have emerged. One of them was proposed by Andreas Kaplan and Michael Haenlein in 2019 [56]. They defined AI as “the ability of a system to correctly interpret data from external sources, learn from that data, and use that knowledge to perform specific tasks and achieve goals through flexible adaptation.” From the perspective of defining algorithms relating to the term artificial intelligence, the following can be identified: machine learning algorithms, deep learning algorithms, fuzzy logic, evolutionary algorithms, and swarm intelligence, among others. The overview of selected algorithms is presented below.

Machine learning (ML) algorithms analyse data, learn from it, and decide based on that data. Three techniques of machine learning algorithms can be identified — supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, the user provides the algorithm with a pair of input data and desired output data, and the algorithm itself finds a way to produce the desired output data given the indicated input data. In unsupervised learning, only the input data is known, and no known output data is provided to the algorithm [83]. Reinforcement learning is the third branch of machine learning, in which the agent determines its optimal behaviour (action) in the environment based on the feedback (reward) it receives. This feedback is known as a reinforcement signal. The agent's goal is to maximize its cumulative reward over time [89]. The overview of selected ML algorithms is presented in Table 2.

Tab. 2

Overview of selected ML algorithms

Group	Examples of algorithms
supervised learning [34, 83]	linear regression (LinR); logistic regression (LogR); Support-Vector Machines (SVM); decision trees and random forests (DT&RF); naive Bayes classifier (NBC); k-means algorithm (k-m S); neural networks (NN); ensemble learning (EL)
unsupervised learning [34, 89]	Hierarchical Cluster Analysis (HCS); Density-Based Spatial Clustering of Applications with Noise (DBSCAN), Hierarchical

	DBSCAN (HDBSCAN); novelty and outlier detection (NOD) — one-sided support vector machine, isolation forest algorithms; Dimensionality-reduction and visualization algorithms (D-R&V) - Principal Component Analysis, Locally Linear Embedding, t-Distributed Stochastic Neighbor Embedding; Independent Components Analysis (ICA) algorithm; k-means algorithm (k-m U); apriori algorithm (apriori); Singular Value Decomposition (SVD)
reinforcement learning [34, 94, 112]	Agent policy (AP); state value function (SVF); Q-learning and deep Q-learning (QL&DQL); value function (VF); Monte Carlo methods (MC); Temporal Difference learning (TD); REINFORCE algorithm (REINF); combined algorithms (CA)

The term Deep Learning (DL) refers to algorithms whose origins date back to attempts at modelling using neural networks. While in the case of Machine Learning, single-layer neural networks are used, in the case of Deep Learning, we are dealing with organized circuits consisting of many layers — at least two layers. Therefore, the term 'Deep learning' refers primarily to the extensive structure of a network consisting of many layers. The more layers, the deeper the network. A deeper network allows for better solutions to complex real-world problems, e.g., those that are characterized by significant non-linearity. When considering Deep Learning, it is necessary to indicate possible learning techniques that constitute the basis for building models of this class. Deep Learning is divided into three basic learning techniques:

- Supervised or discriminative learning — in which discriminative functions are used for supervision or classification. Supervised learning requires labelling the values of the target function. In supervised learning, labelled data must be provided by humans.
- Unsupervised or generative deep learning — which uses data without labelling it. The unsupervised learning process is carried out by sorting and classifying data. These processes involve correlation analysis or analysis of statistical distributions. In general, it can be said that in unsupervised learning, the system independently recognizes patterns through sorting and classification.
- Hybrid learning — a technique that is based on the construction of models based on combinations of the above-mentioned techniques.

The overview of selected DL algorithms based on [99] is presented in Table 3.

Tab. 3

Overview of selected DL algorithms, based on [99]

Group	Examples of algorithms
supervised or discriminative deep learning	multilayer perceptron (MLP); convolutional neural network (CVN), recurrent neural network (RNN);
unsupervised or generative deep learning	generative adversarial network (GAN); autoencoder (autoE); self-organizing /Kohonen map (SOM); restricted Boltzmann machine (RBM); deep belief network (DBN)
hybrid learning	hybrid deep neural networks (HDNN), deep transfer learning (DTL), deep reinforcement learning (DRL)

Other artificial intelligence algorithms include fuzzy logic, evolutionary algorithms, and swarm intelligence algorithms. Fuzzy logic is a form of multivalued logic in which the truth value of variables can be any real number between 0 and 1. It is used to handle the concept of partial truth, in which the truth value can range from completely true to completely false [87].

Among the Artificial Intelligence algorithms that can be used, there is an evolutionary algorithm that refers to the mechanisms of species development known from biology. This algorithm uses the principles of evolution to solve complex optimization problems. The evolutionary algorithm consists in iteratively determining the best solution in terms of the adopted quality criterion, e.g. reliability. Currently, the most famous evolutionary algorithm is the genetic algorithm, which uses mutations and recombination of chromosomes of individuals, their selection and generational replacement [123].

Swarm intelligence is found in biological systems such as ant colonies, bees, flocks of birds, animal husbandry, and bacterial growth. The operation of swarm intelligence is based on so-called agents that act according to specific rules, often in a decentralized structure. The action of a single agent does not manifest intelligence, but a group of agents acting according to the rules can be described as swarm intelligence. This community, operating on the basis of the above-mentioned principles, is capable of self-organization. This action is based on interactions between agents; for example, a swarm of ants creates specific paths in an organized manner. Swarm intelligence can be implemented in a similar way, such as for the operation of drones [44-46].

3.2.Overview of research on the application of AI algorithms in aviation

Interest in Artificial Intelligence techniques has contributed to many studies at the level of basic and development research. Below are presented selected studies related to possible applications of Artificial Intelligence algorithms in aviation divided into: machine learning, deep learning, and other Artificial Intelligence algorithms such as fuzzy logic, evolutionary algorithms, and swarm intelligence.

Tab. 4

Selected applications of ML algorithms – supervised learning

SUPERVISED LEARNING	
Algorithm	Selected applications
linear regression	1. Maintenance and aircraft equipment failure analysis [15]; 2. Wind prediction – fuel consumption [57]; 3. Identification of complex dynamic data-driven failure models for more accurate flight planning and control under emergency conditions [12]; 4. Modelling nonlinear and unstable aerodynamics during the design of future high-performance fighters and improving the angle of attack dynamics [14];
logistic regression	1. A digital twin of avionics systems – system performance and fault location [117]; 2. Predictive maintenance, aircraft repair, and overhaul [5];
Support-Vector Machines	1. Maintenance and aircraft equipment failure analysis [11]; 2. Wind prediction – fuel consumption [57];

	3. Modelling nonlinear and unstable aerodynamics during the design of future high-performance fighters and improving the angle of attack dynamics [14]; 4. A digital twin of avionics systems – system performance and fault location [117]; 5. Low-altitude obstacle detection and classification [3]; 6. Classification of different types of signals in radar systems [121]; 7. Identification of tactical manoeuvre of target based on air combat manoeuvre element [53]; 8. Recognition of tactical intent of multi-aircraft cooperative air combat [37]; 9. Target threat assessment model in air combat [38].
Decision trees and random forests	1. A digital twin of avionics systems – system performance and fault location [117]; 2. Fuel consumption analysis [6] 3. Aerodynamics modelling based on decision tree and random forest using flight data [64] 4. Modelling of aircraft nonlinear unsteady aerodynamics at high-angle attack 5. Identification of tactical manoeuvre of target based on air combat manoeuvre element [53]; 6. Improving the anti-jamming effectiveness of infrared air-to-air missiles [86]; 7. Recognition of tactical intent of multi-aircraft cooperative air combat [37]; 8. Engagement decision support tool for air combat engagement [21].
Naive Bayes classifier	1. Identification of complex dynamic data-driven failure models for more accurate flight planning and control under emergency conditions [12]; 2. A digital twin of avionics systems — system performance and fault location [117]; 3. Recognition of tactical intent of multi-aircraft cooperative air combat [37]; 4. Anti-interference recognition of aerial infrared targets [71].
K-means algorithm	1. A digital twin of avionics systems – system performance and fault location [117]; 2. Decision-making rules in air combat [76]; 3. Radar scanning, signal acquisition, and processing, one-dimensional range image, SAR radar, ISAR image recognition, radar tracking and guidance [74].
Neural networks	1. Modelling nonlinear and unstable aerodynamics during the design of future high-performance fighters and improving the angle of attack dynamics [14]; 2. Flight aerodynamic parameters' estimation of longitudinal and transverse directional motion [122]; 3. Cooperative attack for beyond-visual-range air combat [134]; 4. Reconfigurable flight control systems in case of aerodynamic coefficients changes or control surfaces failure [107]

	5. Detection, identification, and accommodation of sensor failures in a flight control system that assumes no physical redundancy in sensory capabilities [84]
Ensemble learning	1. Capability to break through air defence [141]; 2. Aircraft reliability prediction based on selected parameters of its operation [65]; 3. Targets (aircraft) classification using kinematic data only – ADS-B system [35].

Tab. 5

Selected applications of ML algorithms – unsupervised learning

UNSUPERVISED LEARNING	
Algorithm	Selected applications
Hierarchical Cluster Analysis	1. Anomaly detection from numerical and text data to enhance flight safety [96]; 2. Classification of aviation material consumption data [138]; 3. Data-driven prediction method to estimate turbofan engine's remaining life [105]; 4. Flight anomaly detection during the approach phase [104]; 5. Classification of the environment during combat [131].
DBSCAN, HDBSCAN	1. Flight anomaly detection during the approach phase [104]; 2. Diagnostics of aircraft engine faults [9]; 3. Detection of field data anomalies in automatic flight trajectories [124]; 4. Identification of flight manoeuvres considering flight data recorder data [108].
Novelty and outlier detection	1. Predictive maintenance, aircraft repair, and overhaul [5]; 2. Accurate combat identification – locate and identify critical air targets as friendly, hostile, or neutral [146]; 3. Track anomaly detection [126]; 4. Anomalies detection in the approach and take-off phases [69].
Dimensionality reduction and visualization algorithms	1. Target threat assessment in air combat [132, 133]; 2. Assessment of air defence capabilities [141]; 3. Air combat out of sight [135]; 4. Situation assessment model and formation combat capability model in air combat [72]; 5. Aircraft movement and position recognition[144].
Independent Components Analysis	1. Air pressure measurement [10]; 2. Flight dynamics and control effectiveness and missile guidance systems [148]; 3. Analysis of data collected from sensors during flight to assess aircraft condition [102]; 4. Radar target detection – objects background recognition in the airspace [36]
k-means algorithm	1. Classification of flights by manoeuvring conditions – analysis of human factors in aviation in the context of failure detection and identification [63].

Apriori algorithm	1. Diagnostics of overload events resulting from such phenomena as strong turbulence, crosswind, overspeed [30]; 2. Aircraft control system [91].
Singular Value Decomposition	1. Control actuator failures [8]; 2. Fail-tolerant flight control system [26]; 3. Aircraft engine health diagnostics [67].

Tab. 6

Selected applications of ML algorithms – reinforcement learning

REINFORCEMENT LEARNING	
Algorithm	Selected applications
Agent policy	1. Highly intelligent air combat strategies for autonomous air combat missions – potential-based reward shaping methods to improve the effectiveness of the air combat strategy generation algorithm [59]; 2. Avoiding enemy threats and gaining an advantage over them in air combat [42]; 3. UCAV (*Unmanned Combat Aaerial Vehicle)* air combat autonomous manoeuvre decision for one-on-one within visual range [62].
State value function	1. Close air combat manoeuvre decision and taking a dominant position according to the opponent's strategy [78]; 2. Value function matching in a continuous state space using agent autoantagonism in human-machine confrontation — tactical decision-making to build a virtual AI pilot [43].
Q-learning and deep Q-learning	1. Independent decisions in air combat and effective decision-making policy in defeating the enemy [139]; 2. UCAV decision-making in air combat [73]; 3. Autonomous man-machine air combat system built from 3 subsystems: simulation of the air combat environment, simulation of manned aircraft operations, and a self-learning subsystem [15]; 4. Air combat target assignment [75]; 5. Stealthy engagement manoeuvring strategy [137].
Value function	1. Explicit risk mitigation in adversarial environments (aircraft and enemy missiles) using control barrier functions [103]; 2. Collision avoidance by unnamed ships in unknown environments [125].
Monte Carlo methods	1. Manoeuvring decisions in short-range air combat [81]; 2. UCAV fleet flight path planning [145]; 3. Influence of UCAV agility on short-range air combat effectiveness [128];
Temporal Difference learning	1. Real-time generation of intended flight paths for UAV in a complex air combat environment [13]; 2. Autonomous behaviour – the use of intelligent agents that enable the aircraft to adapt to unexpected situations and analyse past experiences to increase future mission performance [93]; 3. Intelligent systems that support system learning, control, and decision-making [92].

REINFORCE algorithm	1. Multi-agent hierarchical policy gradient (MAHPG) algorithm capable of learning different strategies and moving beyond expert cognition through adversarial learning – air combat method for both defensive and offensive capabilities [111]; 2. Autonomous air combat in sight [60]; 3. Air combat strategies generation [61]; 4. Maintaining of high-reliability target tracking in high-altitude dynamic 3D scenarios – various real-time navigation tasks in a dynamic and random electronic warfare environment [143]; 5. Deriving continuous and smooth control values to improve autonomous control accuracy – manoeuvring in aerial combat [140].
Combined algorithms	1. Effectively selecting a favourable manoeuvre action and taking a dominant position according to the opponent's strategy of action in air combat – value function and Q-learning [78]; 2. Intent prediction based on improved dual depth Q network (DDQN) for real-time generation (using temporal difference methods) of intended flight paths for UAVs in a complex air combat environment [13].

Tab. 7

Selected applications of DL algorithms

SUPERVISED OR DISCRIMINATIVE DEEP LEARNING	
Algorithm	Selected applications
Multilayer perceptron	1. Real-time detection of the level of faults in a turbine engine disk [33]; 2. Aircraft engine thrust control [142]; 3. Predicting the time required to capture an enemy aircraft in a combat situation [110].
Convolutional neural network	1. Aircraft target classification [77]; 2. Adverse event precursor – Identification of factors relevant to an adverse event and their signatures that can be tracked during flight [7]; 3. Terrain reconnaissance and warning system – low altitude flight [3]; 4. Flight approach phases – risk prediction and decision support [66]
Recurrent neural network	1. Aircraft manoeuvres – determining aircraft position, heading, acceleration, and other information [32]; 2. Aircraft engine vibration prediction [27]; 3. Flight dynamics of a highly manoeuvrable aircraft [97].
UNSUPERVISED OR GENERATIVE DEEP LEARNING	
Generative adversarial network	1. Trajectory planning [2]; 2. Detection of dynamic obstacles in the air and on the runway – applications in a HUD (Head-Up Display) system [58]; 3. Synthetic aperture radar for high-resolution images of stationary objects [100].
Autoencoder	1. Airspace tracking – detection and prediction of movement to indicate abnormal, dangerous situations in the airspace [115]; 2. Aircraft complex system anomaly detection and classification [85]; 3. Failure analysis of flight control actuators [52]; 4. Aircraft design, dynamics, and control [25].

Self-organizing (Kohonen) map	1. Condition assessment and diagnosis of a turbojet engine during operation using thermal imaging [4]; 2. Measuring signals from aircraft sensors during flight [28]; 3. Engine measurements based on variables such as core speed, oil pressure, and quantity, fan speed, etc., along with environmental variables such as external temperature, altitude, aircraft speed [16].
Restricted Boltzmann machine	1. Inertial navigation system – error parameter estimation [39]; 2. Predictive maintenance of an aircraft component [101]; 3. Aircraft auxiliary power unit (APU) – performance sensing data prediction [74].
Deep belief network	1. Fault detection in the aircraft fuel system [31]; 2. Fault diagnosis of essential aircraft parts [54]; 3. Identify hidden features responsible for system failure – particle filter in a turbofan engine [90]; 4. Aircraft design, dynamics, and control [25].
HYBRID LEARNING	
Hybrid deep neural networks	1. Impending failures' detection by predicting the future behavioural state of turbofan engines [95]; 2. Planning of fuel consumption [119].
Deep transfer learning	1. Target recognition using laser — real-time detection accuracy and speed [114].
Deep reinforcement learning	1. The problem of intelligent decision-making in multi-aircraft cooperative air combat [106]; 2. Control of the aircraft based on immediate observations of individual aircraft [55]; 3. Strategy generation for manoeuvring in pursuit in air combat [129]; 4. System of autonomously locating and navigating to an emitter and optically recognizing its associated vehicle [98].

Tab. 8

Selected applications of fuzzy logic, evolutionary, and swarm intelligence algorithms

Algorithms	Selected applications
Fuzzy logic (FL)	1. Air combat attack algorithm consisting of navigation steps and reference velocity calculations [51]; 2. Determining the optimal strategy for air combat at medium and long range. The parameters considered are: distance and azimuth position of the target, range, and projectile energy [118]; 3. Increasing manoeuvring effectiveness in air combat [48].
Evolutionary (E)	1. Making decisions regarding combat manoeuvres of unmanned aerial vehicles [136]; 2. Assign weapons targets in a dynamic, uncertain air combat environment [49, 109]; 3. Tactical combat against enemy formations — optimization of tactical attributes [82]; 4. Searching for optimal partition resource parameters for minimum CPU utilization – time partitioning mechanism to reduce errors between avionics applications [40].

Swarm intelligence (SI)	4. Weapon-Target Assignment (WTA) and minimizing threats from those targets [47]; 5. Multi-purpose air combat system – an autonomous control algorithm for multipurpose systems to improve the performance of UAVs in air combat [147]; 6. Autonomous manoeuvre decision-making – autonomous manoeuvre strategy of UAV swarms in out-of-sight aerial combat [127].

The conducted literature review of algorithms (Tables 4-8) shows that it is possible to develop objectives for a future aircraft equipped with advanced Artificial Intelligence. Depending on conditions, it may support the pilot during a combat mission or perform the mission independently.

4. POSSIBLE APPLICATIONS OF ARTIFICIAL INTELLIGENCE ALGORITHMS IN F-16

In this subsection, assumptions are made for the F-16 aircraft as the baseline combat platform where a specific set of Artificial Intelligence algorithms can be applied. The reason for choosing the F-16 aircraft is a large number of in-service aircraft in the Air Force, which provides the necessary input to the algorithms. Moreover, important is the knowledge about the F-16 aircraft gathered during the operation, the manufacturer's knowledge about realized modifications, and laboratory tests conducted by DARPA. Table 9 presents a comparison of F-16 aircraft functionality with its systems equipped with artificial intelligence algorithms. Table 10 shows in detail which algorithms can be applied in a given case. During assigning algorithms, the abbreviations defined in Tables 2, 3, and 8 were used.

Tab. 9

A feature overview of F-16 aircraft systems regarding Artificial Intelligence algorithms, based on [68]

Features	F-16 systems								
	I. Power unit	II. Electrical and electronic installation	III. Hydraulic system/ servo drives	IV. Control system	V. Safety systems	VI. Fuel system	VII. Avionics and digital equipment	VIII. Weapons	IX. Airframe
1. Engine thrust	x	x	x			x	x		x
2. Aerodynamics and flight mechanics	x	x	x	x		x	x		x
3. Communication (data transmission)		x			x		x		

4. Systems activation	x	x	x	x	x	x	x	x	x
5. Systems monitoring	x	x	x	x	x	x	x	x	x
6. Providing intelligence		x					x		
7. Maintaining a safe distance: ground, objects on the ground, objects in the air	x	x	x	x		x	x		x
8. IFF (Identification friend or foe) / WE (*electronic warfare)* systems		x					x		
9. Navigation		x					x		
10. Target detection and identification		x					x		
11. Use of weapons		x	x	x	x		x	x	x

Tab. 10

Assignment of algorithms to F-16 systems and features

Features	F-16 systems								
	I. Power unit	II. Electrical and electronic installation	III. Hydraulic system / servo drives	IV. Control system	V. Safety systems	VI. Fuel system	VII. Avionics and digital equipment	VIII. Weapons	IX. Airframe
1. Engine thrust	HCS; DBSCAN, HDB-SCAN; NOD; ICA; SVD; MLP; SOM	LinR; LogR; SVM; DT&RF; NBC; NN; HCS; DBSCAN, HDBSCAN; NOD; ICA; SVD; MLP; CVN; autoE; SOM; RBM; DBN; HDNN				LinR; SVM; DT&RF; MLP; SOM; HDNN	HCS; DBSCAN, HDB-SCAN; SVD; MLP; RNN; SOM; DBN; HDNN		same as for system VII
2. Aerodyna-mics and flight mechanics	NN; DT&RF; SVM; DBSCAN, HDB-SCAN; NOD; apriori; VF; MC; TD; REINF;	LinR; SVM; DT&RF; NN; NOD; ICA; SVD; apriori; AP; SVF; VF; MC; TD;	same as for syste m I	LinR; SVM; DT&RF; NN; DBSCAN, HDB-SCAN; ICA; apriori; AP; SVF; MC; TD;		LinR; SVM; DT&RF NN; NOD; apriori; VF; MC; TD; REINF; CA;	same as for system II		LinR; SVM; DT&RF NN; NOD; apriori; SVF; REINF; MLP; CVN; RNN;

	CA; CVN; RNN; DRL; FL	REINF; CA; RNN; DRL, FL; E; SI		REINF; CA; CVN; RNN; GAN; autoE; RBN; DRL; FL		RNN; DRL; FL			autoE; SOM; RBM; HDNN
3. Communi-cation (data trans-mission)		LinR; LogR; SVM; DT&RF; NBC; k-m S; NN; D-R&V; SVD; MLP; CVN; GAN			same as for system II		same as for system II		
4. Systems activation	NN; EL; AP; SVF; QL&DQL; VF; TD; REINF; CA; MLP; RNN; DRL; FL; E; SI								
5. Systems monitoring	supervised ML – all algorithms; unsupervised ML – all algorithms; supervised or discriminative DL – all algorithms; autoE; SOM; DBN, HDNN							SVM; DT&RF; NBC; NN; EL; unsupervised ML– all algorithms; MLP; CVN; autoE; DTL; DRL; FL; E; SI	LinR; LogR; SVM; NBC; NN; EL; HCS; NOD; ICA; SVD; MLP; CVN; autoE; SOM; DBN; hybrid learning – all algorithms
6. Providing intelligence		SVM; DT&RF; k-m S; EL; NOD; D-R&V; ICA; QL &DQL; TD; REINF; CA; CVN; GAN; autoE; DTL; DRL					same as for system II		

7. Maintaining a safe distance: ground, objects on the ground, objects in the air	SVM; DT&RF; NBC; k-m S; NN; EL; HCS; DBSCAN, HDBSCAN; NOD; D-R&V; k-m U; apriori; reinforcement ML – all algorithms; CVN; RNN; GAN; autoE; RBM; DTL; DRL; FL; E; SI					same as for systems I-IV			same as for systems I-IV
8. IFF (Identification friend or foe) / WE (electronic warfare) systems		SVM; DT&RF; NBC; k-m S; NOD; D-R&V; ICA; QL& DQL; GAN; autoE; DRL					same as for system II		
9. Naviagation		LinR; CVM; DT&RF; k-m S; NN; DBSCAN; HDB-SCAN; NOD; D-R&V; ICA; apriori; AP; QL&DQL; MC; TD; REINF; CA; MLP; CVN; RNN; GAN; autoE; RBM; HDNN; DRL; FL; E; SI					same as for system II		
10. Target detection and identification		SVM; DT&RF; NBC; NN; EL; HCS; D-R&V; ICA; AP; SVF; QL&DQL; REINF; CA; MLP; CVN; DTL; DRL; FL; E; SI					same as for system II		

11. Use of weapons		SVM; DT&RF; NBC; NN; EL; HCS; NOD; D-R&V; ICA; reinforcement ML – all algorithms; MLP; CVN; DTL; DRL; FL; E; SI		same as for systems II - V	SVM; DT& RF; NBC; NN; EL; HCS; NOD; D-R&V; ICA; QL& DQL; REINF; CVN; DTL; FL; E; SI	same as for systems II - V

Based on the compiled list of AI algorithms for the F-16 aircraft, a matrix analysis was performed – an analysis of the columns representing the systems of the F-16 aircraft and the rows representing the features. The main results of the analysis are as follows:

- Systems such as avionics and digital equipment, electrical and electronic installation are critical infrastructures. AI algorithms of these systems play an important role in every functionality of the F-16 aircraft. Both systems are interrelated and their reliability in individual functionalities is critical in the operation of the F-16 aircraft, for example: failure of any component of the electrical or electronic installation will prevent the correct operation of an algorithm responsible for specific functionality (feature). In turn, the malfunction of an algorithm from the area of avionics and digital equipment can also lead to the malfunction of a specific functionality leading to damage to a component of the electrical and electronic system, e.g.: the activation value set incorrectly by the algorithm for a given component may result in exceeding safe limits in the electrical or electronic installation.
- The systems activation and systems monitoring features, together with AI algorithms, are critical to the reliability and operation of all systems on the F-16 aircraft. For the systems' activation functionality, machine learning algorithms from the reinforcement learning group are particularly relevant, in turn, for the deep learning case, algorithms from the supervised deep Learning group. Fuzzy logic, evolutionary, and swarm intelligence are also applicable. In the case of the system's monitoring functionality, all supervised and unsupervised machine learning algorithms are distinguished, as well as all deep learning supervised or discriminative algorithms. They apply to systems such as power units, electrical and electronic installations, Hydraulic systems / servo drives, control systems, safety systems, fuel systems, avionics, and digital equipment. It should be noted that the two functionalities are interrelated. The algorithms responsible for monitoring enable the algorithms responsible for activating the systems to work properly.
- Functionalities such as aerodynamics and flight mechanics, maintaining a safe distance: the ground, objects on the ground, and objects in the air play a key role in the compilation. These features are associated with 7 of the 9 systems equipped with AI algorithms. In the case of the “aerodynamics and flight mechanics” functionality, such reinforcement learning algorithms in the respective systems can be distinguished: value function, Monte Carlo method, Time difference learning, REINFORCE, and combined algorithms. Supervised and unsupervised machine learning algorithms also play an important role. In turn, in the group of deep learning algorithms such as convolutional neural networks and recurrent neural networks. Fuzzy logic algorithms are also applicable. On the other hand, for the functionality of maintaining a safe distance, all the algorithms of reinforcement machine learning are applicable. For deep learning, all algorithms of supervised deep learning are applicable. Fuzzy logic, evolutionary, and

swarm intelligence are also applicable. It should be noted that the two functionalities are interrelated. In particular, the correct simultaneous operation of algorithms in the systems for these two functionalities is important in situations such as flight in formation and also close or medium-range combat.

- In the use of weapons functionality, all reinforcement machine learning algorithms stand out but also selected supervised machine learning algorithms like: Support-Vector Machines, decision trees, and random forests, naive Bayes classifiers, neural networks. Among unsupervised machine learning algorithms, the following stand out: Hierarchical Cluster Analysis, novelty and outlier detection algorithms, visualization and dimensionality-reduction and visualization algorithms, and Independent Components Analysis algorithm. Fuzzy logic, evolutionary, and swarm intelligence algorithms are also applied.

It is important to note that for a given functionality in comparison to a given system, there is a significant number of applications of different AI algorithms. This raises the question of which algorithms to choose. A suggestion could be a modular application, which involves the creation of sets and within them subsets of detailed algorithms for a given functionality within a given system. Another solution could be the wider use of combined algorithms within supervised machine learning, as well as unsupervised machine learning algorithms, combined algorithms within reinforcement machine learning, and hybrid deep learning networks. The area of the above applications requires further research in the near future.

5. DISCUSSION

The developed compilation of functions with systems equipped with machine learning, deep learning, fuzzy logic, evolutionary, and swarm intelligence made it possible to obtain a comprehensive view of the possible directions of research and development of the F-16 aircraft. The results of the analysis based on the compilation indicated the outstanding features and systems that will be critical for the reliability and operation of the F-16 aircraft equipped with artificial intelligence algorithms. Table 9 also allows determining the progress of research work on aircraft equipped with artificial intelligence algorithms. An important role is played by sensitivity analysis of AI algorithms, which allows us to determine the relevance of the data feeding into the algorithms and also minimizes the probability of the algorithms making incorrect decisions. This is particularly crucial in the case of aircraft designed for specific missions, such as assault operation. The authors plan to develop these matters in future research.

The matrix analysis prepared in this research enables an in-depth assessment of the application of artificial intelligence algorithms in specific cases. Presented below is one such example. So far, under DARPA's Air Combat Evolution (ACE) program, simulation tests of AlphaDogfigh in a laboratory environment (without real-world combat) were conducted. In this case, the AI agent algorithm which can quickly and effectively learn basic fighter manoeuvres and successfully employ them in a simulated dogfight was relevant here [22]. In December 2022, DARPA ACE algorithm developers installed their AI software onto a modified F-16 test aircraft called the X-62A or VISTA at the Air Force Test Pilot School in California. Over several days, they conducted multiple flights, showcasing the AI's capability to control a full-scale fighter jet and provide invaluable live-flight data [23]. According to the matrix analysis in this research, it enables such actions as: highly intelligent air combat strategies enabling autonomous execution of combat missions in the air, avoiding threats from the enemy, and gaining an advantage over the enemy in air combat. It can also be concluded that this algorithm belongs to the functionality responsible for “systems activation”. Moreover, this algorithm has an overriding function in the reliability and operation of an AI-equipped aircraft. However, there is no information in the DARPA reports that would indicate what are the algorithms with which the other systems are equipped. Based on our research, it can be concluded that this algorithm is certainly supported by a group of “systems monitoring” functionality algorithms. In turn, individual systems could be equipped with selected algorithms that are indicated in the compilation.

6. CONCLUSIONS

The presented compilation and analyses of the systems equipped with AI algorithms functions make it possible to develop objectives for the design structure to modify the F-16 aircraft. It is also possible to use this compilation for other military aircraft such as F-18, Rafael, Eurofighter Typhoon, and after completing the compilation with the features and systems of “STEALTH” technology also aircraft such as the F-22, and F-35. The overview can also be supplemented or detailed in the area of features and systems for aircraft versions whose tasks focus on assault missions, e.g.: tasks related to the neutralization of air defence systems, attack on moving columns of armoured warfare, attack on surface or underwater targets or electronic warfare missions. The compilation can also be a base for mapping future applications of AI algorithms in military aircraft, as well as for developing new AI algorithms.

It should also not be forgotten that when looking for solutions using artificial intelligence methods for aviation-related tasks, you can be supported by solutions designed for other fields of science. For example, when looking for non-invasive methods of diagnosing the condition of an internal combustion engine, you can obtain knowledge from articles about the automotive industry [17-20].

Based on this study, the following directions of research and development work can be indicated:

- development of dedicated ensemble learning methods based on machine learning algorithms or deep learning algorithms for the F-16 aircraft,
- development of sets of algorithms and their subsets for individual systems of the F-16 aircraft,
- development of hybrid learning algorithms in the area of deep learning for F-16 aircraft systems,
- development of AI algorithm configurations for dedicated variants of the F-16 aircraft (fighter, attack),
- advanced research on the application of reinforcement machine learning algorithms within the “systems activation” functionality in relation to the AI algorithms used in the systems for each functionality,
- advanced research in the area of “avionics and digital equipment” and “electrical and electronic installation” systems in relation to data sources that feed artificial intelligence algorithms,
- research and development studies regarding applications of artificial intelligence in relation to aerodynamics, flight mechanics, and maintaining a safe distance,
- development of applications of AI algorithms in weapon systems (short, medium, and long-range combat),
- research in the area of cybersecurity of aircraft equipped with AI algorithms,

- research and development studies in the area of pilot cooperation with artificial intelligence algorithms, e.g.: pilot surveillance of AI-controlled distributed UAVs or AI support of the pilot.

The compilation presented in the article including analyses of functions and systems equipped with AI algorithms can also be used for modifications in the area of material and structure strength of the F-16 aircraft.

References

1. Adamski M. 2009. „Analiza możliwości bojowych samolotów F-16 i MiG-29". *Problemy Techniki Uzbrojenia* 110(38): 41-46. [In English: „Analysis of combat capabilities of F-16 and MiG-29 aircraft". *Issues of Armament Technology*].
2. Aksoy M., O. Ozdemir, G. Guner, et al. 2021. „Flight Trajectory Pattern Generalization and Abnormal Flight Detection with Generative Adversarial Network". *AIAA Scitech 2021 Forum*. Reston, Virginia, American Institute of Aeronautics and Astronautics. DOI: https://doi.org/10.2514/6.2021-0775.
3. Ammalladene-Venkata M., O. Halbe, C. Seidel, et al. 2021. „Deep Learning based obstacle awareness from airborne optical sensors". *77th Annual Vertical Flight Society Forum and Technology Display, FORUM 2021: The Future of Vertical Flight*.
4. Andoga R., L. Főző, M. Schrötter, et al. 2019. „Intelligent Thermal Imaging-Based Diagnostics of Turbojet Engines". *Applied Sciences* 9(11): 2253. DOI: https://doi.org/10.3390/app9112253.
5. Apostolidis A., M. Pelt, K. P. Stamoulis. 2020. „Aviation Data Analytics in MRO Operations: Prospects and Pitfalls". *2020 Annual Reliability and Maintainability Symposium (RAMS)*, IEEE: 1-7. DOI: https://doi.org/10.1109/RAMS48030.2020.9153694.
6. Baumann S., U. Klingauf. 2020. „Modeling of aircraft fuel consumption using machine learning algorithms". *CEAS Aeronautical Journal* 11(1): 277-287. DOI: https://doi.org/10.1007/s13272-019-00422-0.
7. Bleu Laine M.-H., T. G. Puranik, D. N. Mavris, B. Matthews. 2020. „Multiclass Multiple-Instance Learning for Predicting Precursors to Aviation Safety Events". *Journal of Aerospace Information Systems* 19(1): 22-36. DOI: https://doi.org/10.2514/1.I010971.
8. Boskovic J., J. Redding. 2009. „Accommodation of Control Actuator Failures in Morphing Aircraft". *AIAA Guidance, Navigation, and Control Conference*. Reston, Virigina, American Institute of Aeronautics and Astronautics. DOI: https://doi.org/10.2514/6.2009-5759.
9. Buraimah I. J. 2020 „Using modern clustering techniques for parametric fault diagnostics of turbofan engines". *Civil Aviation High Technologie*s 23(6): 20-27. DOI: https://doi.org/10.26467/2079-0619-2020-23-6-20-27.
10. Carassale L. 2012. „Analysis of aerodynamic pressure measurements by dynamic coherent structures". *Probabilistic Engineering Mechanics* 28: 66-74. DOI: https://doi.org/10.1016/j.probengmech.2011.08.010.
11. Celikmih K., O. Inan, H. Uguz. 2020. „Failure Prediction of Aircraft Equipment Using Machine Learning with a Hybrid Data Preparation Method". *Scientific Programming* 2020: 1-10. DOI: https://doi.org/10.1155/2020/8616039.

12. Chen S., S. Imai, W. Zhu, C. A.Varela. 2018. „Towards Learning Spatio-Temporal Data Stream Relationships for Failure Detection in Avionics". *Handbook of Dynamic Data Driven Applications Systems*. Cham, Springer International Publishing: 97-121. DOI: https://doi.org/10.1007/978-3-319-95504-9_5.
13. Chen T., H. Liu, Y. Wang. 2021. „Intention prediction of UAVs based on improved DDQN". *Journal of Physics: Conference Series* 2010(1): 012129. DOI: https://doi.org/10.1088/1742-6596/2010/1/012129.
14. Chen Y. 2012. „Modeling of longitudinal unsteady aerodynamics at high angle-of-attack based on support vector machines". *8th International Conference on Natural Computation*, IEEE: 431-435. DOI: https://doi.org/10.1109/ICNC.2012.6234640.
15. Chen Y., J. Zhang, Q. Yang, et al. 2020. „Design and Verification of UAV Maneuver Decision Simulation System Based on Deep Q-learning Network". *16th International Conference on Control, Automation, Robotics and Vision (ICARCV)*, IEEE: 817-823. DOI: https://doi.org/10.1109/ICARCV50220.2020.9305467.
16. Cottrell M., P. Gaubert, C. Eloy, et al. 2009. „Fault Prediction in Aircraft Engines Using Self-Organizing Maps". *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*: 37-44. DOI: https://doi.org/10.1007/978-3-642-02397-2_5.
17. Czech Piotr. 2013. „Diagnosing a car engine fuel injectors' damage". Communications in Computer and Information Science 395: 243-250. DOI: https://doi.org/10.1007/978-3-642-41647-7_30. Springer, Berlin, Heidelberg. ISBN: 978-3-642-41646-0; 978-3-642-41647-7. ISSN: 1865-0929. In: Mikulski Jerzy (eds), *Activities of transport telematics*, 13th International Conference on Transport Systems Telematics, Katowice Ustron, Poland, October 23-26, 2013.
18. Czech Piotr. 2011. „Diagnosing of disturbances in the ignition system by vibroacoustic signals and radial basis function - preliminary research". Communications in Computer and Information Science 239: 110-117. DOI: https://doi.org/10.1007/978-3-642-24660-9_13. Springer, Berlin, Heidelberg. ISBN: 978-3-642-24659-3. ISSN: 1865-0929. In: Mikulski Jerzy (eds), *Modern transport telematics*, 11th International Conference on Transport Systems Telematics, Katowice Ustron, Poland, October 19-22, 2011.
19. Czech Piotr. 2012. „Identification of Leakages in the Inlet System of an Internal Combustion Engine with the Use of Wigner-Ville Transform and RBF Neural Networks". Communications in Computer and Information Science 329: 175-182. DOI: https://doi.org/10.1007/978-3-642-34050-5_47. Springer, Berlin, Heidelberg. ISBN: 978-3-642-34049-9; 978-3-642-34050-5. ISSN: 1865-0929. In: Mikulski Jerzy (eds), *Telematics in the transport environment*, 12th International Conference on Transport Systems Telematics, Katowice Ustron, Poland, October 10-13, 2012.
20. Czech Piotr. 2013. „Intelligent Approach to Valve Clearance Diagnostic in Cars". Communications in Computer and Information Science 395: 384-391. DOI: https://doi.org/10.1007/978-3-642-41647-7_47. Springer, Berlin, Heidelberg. ISBN: 978-3-642-41646-0; 978-3-642-41647-7. ISSN: 1865-0929. In: Mikulski Jerzy (eds), *Activities of transport telematics*, 13th International Conference on Transport Systems Telematics, Katowice Ustron, Poland, October 23-26, 2013.

21. Dantas J. P. A., A. N. Costa, D. Geraldo, et al. 2021. „Engagement Decision Support for Beyond Visual Range Air Combat". *2021 Latin American Robotics Symposium (LARS), 2021 Brazilian Symposium on Robotics (SBR), and 2021 Workshop on Robotics in Education (WRE)*, IEEE: 96-101. DOI: https://doi.org/10.1109/LARS/SBR/WRE54079.2021.9605380.
22. DARPA. 2020. „AlphaDogfight Trials Foreshadow Future of Human-Machine Symbiosis". Available at: https://www.darpa.mil/news-events/2020-08-26.
23. DARPA. 2023. „ACE Program's AI Agents Transition from Simulation to Live Flight". Available at: https://www.darpa.mil/news-events/2023-02-13.
24. Davis S. 2014. *General Dynamics F-16 Fighting Falcon Manual*. Sparford, Hayness Publishing.
25. Dong Y., J. Tao, Y. Zhang, et al. 2021. „Deep Learning in Aircraft Design, Dynamics, and Control: Review and Prospects". *IEEE Transactions on Aerospace and Electronic Systems* 57(4): 2346-2368. DOI: https://doi.org/10.1109/TAES.2021.3056086.
26. Drouot A., H. Noura, L. Goerig, P. Piot. 2015. „Actuators additive SVD-based fault-tolerant control for a combat aircraft". *2015 IEEE Conference on Control Applications (CCA), IEEE*: 960-965. DOI: https://doi.org/10.1109/CCA.2015.7320736.
27. ElSaid A., F. El Jamiy, J. Higgins, et al. 2018. „Optimizing long short-term memory recurrent neural networks using ant colony optimization to predict turbine engine vibration". *Applied Soft Computing* 73: 969-991. DOI: https://doi.org/10.1016/j.asoc.2018.09.013.
28. Faure C., M. Olteanu, J.-M. Bardet, J. Lacaille. 2017. „Using self-organizing maps for clustering anc labelling aircraft engine data phases". *12th International Workshop on Self-Organizing Maps and Learning Vector Quantization, Clustering and Data Visualization (WSOM)*, IEEE: 1-8. DOI: https://doi.org/10.1109/WSOM.2017.8020013.
29. Fawkes A.J., L.C.M. Menzel. 2018. „The Future Role of Artificial Intelligence Military Opportunities and Challenges". *JAPCC* 27: 70-77.
30. Gao X., W. Huo, X. Feng. 2014. „Civil aircraft's exceedance event diagnosis method based on fuzzy associative classifier". *Beijing Hangkong Hangtian Daxue Xuebao/Journal of Beijing University of Aeronautics and Astronautics* 10: 1366-1371. DOI: https://doi.org/10.13700/j.bh.1001-5965.2013.0656.
31. Gao Z., C. Ma, D. Song, Y. Liu. 2017. „Deep quantum inspired neural network with application to aircraft fuel system fault diagnosis". *Neurocomputing* 238: 13-23. DOI: https://doi.org/10.1016/j.neucom.2017.01.032.
32. Gao Z., A. Song. 2019. „Aviation Surveillance Information Fusion Technology Based on Recurrent Neural Network". *Proceedings the 9th International Workshop on Computer Science and Engineering, WCSE*. DOI: https://doi.org/10.18178/wcse.2019.06.050.
33. Garcia C.E., M.R. Camana, I. Koo. 2021. „Machine learning-based scheme for multi-class fault detection in turbine engine disks". *ICT Express* 7(1): 15-22. DOI: https://doi.org/10.1016/j.icte.2021.01.009.
34. Géron A. 2019. *Hands-on machine learning with Scikit-Learn, Keras and TensorFlow: concepts, tools, and techniques to build intelligent systems*. O'Reilly Media.
35. Ginoulhac R., F. Barbaresco, J.-Y. Schneider, et al. 2019. „Target Classification Based On Kinematic Data From AIS/ADS-B, Using Statistical Features Extraction and Boosting". *20th International Radar Symposium (IRS)*, IEEE: 1-10. DOI: https://doi.org/10.23919/IRS.2019.8768094.

36. Greet L.D., S. Harris. 2011. „Detection and clutter suppression using fusion of conventional CFAR and two parameter CFAR". *3rd International Conference on Electronics Computer Technology, IEEE*: 216-219. DOI: https://doi.org/10.1109/ICECTECH.2011.5941740.
37. Guanglei M., Z. Runnan, W. Biao, et al. 2021. „Target Tactical Intention Recognition in Multiaircraft Cooperative Air Combat". *International Journal of Aerospace Engineering* 2021: 1-18. DOI: https://doi.org/10.1155/2021/9558838.
38. Guo H., H. Xu, L. Liu. 2010 „Target threat assessment of air combat based on support vector machines for regression". *Beijing Hangkong Hangtian Daxue Xuebao/Journal of Beijing University of Aeronautics and Astronautics* 36(1): 123-126.
39. Guo W., Y. Xian, D. Zhang, et al. 2019. „Hybrid IRBM-BPNN approach for error parameter estimation of SINS on aircraft". *Sensors* 19(17): 3682. DOI: https://doi.org/10.3390/s19173682.
40. Han P., Z. Zhai, L. Zhang. 2020. „A Model-Based Approach to Optimizing Partition Scheduling of Integrated Modular Avionics Systems". *Electronics* 9(8): 1281. DOI: https://doi.org/10.3390/electronics9081281.
41. Hitchens T. 2020. „AI Slays Top F-16 Pilot In DARPA Dogfight Simulation". Available at: https://breakingdefense.com/2020/08/ai-slays-top-f-16-pilot-in-darpa-dogfight-simulation/.
42. Hu D., R. Yang, J. Zuo, et al. 2021. „Application of Deep Reinforcement Learning in Maneuver Planning of Beyond-Visual-Range Air Combat". *IEEE Access* 9: 32282-32297. DOI: https://doi.org/10.1109/ACCESS.2021.3060426.
43. Hu D., J. Zuo, W. Zheng, et al. 2021. „Research on Application of LSTM-QDN in Intelligent Air Combat Simulation". *Journal of Physics: Conference Series* 1746(1): 012028. DOI: https://doi.org/10.1088/1742-6596/1746/1/012028.
44. Hu J., P. Bhowmick, I. Jang, et al. 2021. „A Decentralized Cluster Formation Containment Framework for Multirobot Systems". *IEEE Transactions on Robotics* 37(6): 1936-1955. DOI: https://doi.org/10.1109/TRO.2021.3071615.
45. Hu J., A.E. Turgut, T. Krajnik, et al. 2022. „Occlusion-Based Coordination Protocol Design for Autonomous Robotic Shepherding Tasks". *IEEE Transactions on Cognitive and Developmental Systems* 14(1): 126-135. DOI: https://doi.org/10.1109/TCDS.2020.3018549.
46. Hu J., A.E. Turgut, B. Lennox, F. Arvin 2022. „Robust Formation Coordination of Robot Swarms With Nonlinear Dynamics and Unknown Disturbances: Design and Experiments". *IEEE Transactions on Circuits and Systems II: Express Briefs* 69(1): 114-118. DOI: https://doi.org/10.1109/TCSII.2021.3074705.
47. Hu X., P. Luo, X. Zhang, J. Wang. 2018. „Improved Ant Colony Optimization for Weapon-Target Assignment". *Mathematical Problems in Engineering* 2018: 1-14. DOI: https://doi.org/10.1155/2018/6481635.
48. Huang C., K. Dong, H. Huang, S. Tang. 2018. „Autonomous air combat maneuver decision using Bayesian inference and moving horizon optimization. *Journal of Systems Engineering and Electronics* 29(1): 86-97. DOI: https://doi.org/10.21629/JSEE.2018.01.09.
49. Huang J., X. Li, Z. Yang, et al. 2021. „A Novel Elitism Co-Evolutionary Algorithm for Antagonistic Weapon-Target Assignment". *IEEE Access* 9: 139668-139684. DOI: https://doi.org/10.1109/ACCESS.2021.3119363.
50. Hunt E. 2021. „AI and the future of air combat". Available at: https://www.aerosociety.com/news/ai-and-the-future-of-air-combat/.

51. İşci H., G.Ö. Günel. 2022. „Fuzzy logic based air-to-air combat algorithm for unmanned air vehicles”. *International Journal of Dynamics and Control* 10(1): 230-242. DOI: https://doi.org/10.1007/s40435-021-00803-6.
52. Jia Z., Z. Liu, Y. Cai. 2021. „A novel fault diagnosis method for aircraft actuator based on ensemble model”. *Measurement* 176: 109235. DOI: https://doi.org/10.1016/j.measurement.2021.109235.
53. Jia Z.Z., X.G. Fan, M.H. Xue, S. Zhang 2018. „Online Identification Method for Tactical Maneuver of Target Based on Air Combat Maneuver Element”. *Beijing Ligong Daxue Xuebao/Transaction of Beijing Institute of Technology* 38(8): 820-827. DOI: https://doi.org/10.15918/j.tbit1001-0645.2018.08.009.
54. Jiang H. 2019. „Deep Learning Theory with Application in Intelligent Fault Diagnosis of Aircraft”. *Journal of Mechanical Engineering* 55(7): 27. DOI: https://doi.org/10.3901/JME.2019.07.027.
55. Julian K.D., M.J. Kochenderfer. 2019. „Distributed Wildfire Surveillance with Autonomous Aircraft Using Deep Reinforcement Learning”. *Journal of Guidance, Control, and Dynamics* 42(8): 1768-1778. DOI: https://doi.org/10.2514/1.G004106.
56. Kaplan A., M. Haenlein. 2019. „Siri, Siri, in my hand: Who’s the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence”. *Business Horizons* 62(1): 15-25. DOI: https://doi.org/10.1016/j.bushor.2018.08.004.
57. Kim J., C. Zhang, S.I. Briceno, D.N. Mavris. 2021. „Supervised Machine Learning-based Wind Prediction to Enable Real-Time Flight Path Planning”. *AIAA Scitech 2021 Forum*. Reston, Virginia, American Institute of Aeronautics and Astronautics. DOI: https://doi.org/10.2514/6.2021-0519.
58. Kniaz V.V., M.I. Kozyrev, A.N. Bordodymov, et al. 2019. „Segmentation and visualization of obstacles for the enhanced vision system using generative adversarial networks”. *Scientific Visualization* 11(4): 43-52. DOI: https://doi.org/10.26583/sv.11.4.04.
59. Kong W., D. Zhou, Z. Yang, et al. 2020. „Maneuver Strategy Generation of UCAV for within Visual Range Air Combat Based on Multi-Agent Reinforcement Learning and Target Position Prediction”. *Applied Sciences* 10(15): 5198. DOI: https://doi.org/10.3390/app10155198.
60. Kong W., D. Zhou, Z. Yang, et al. 2020. „UAV autonomous aerial combat maneuver strategy generation with observation error based on state-adversarial deep deterministic policy gradient and inverse reinforcement learning”. *Electronics* 9(7): 1121. DOI: https://doi.org/10.3390/electronics9071121.
61. Kong W., D. Zhou, Z. Yang. 2020. „Air Combat Strategies Generation of CGF Based on MADDPG and Reward Shaping”. *Proceedings – 2020 International Conference on Computer Vision, Image and Deep Learning, CVIDL 2020*, IEEE: 651-655. DOI: https://doi.org/10.1109/CVIDL51233.2020.000-7.
62. Kong W., D. Zhou, K. Zhang, Z. Yang. 2020. „Air combat autonomous maneuver decision for one-on-one within visual range engagement base on robust multi-agent reinforcement learning”. *IEEE 16th International Conference on Control & Automation (ICCA)*, IEEE: 506-512. DOI: https://doi.org/10.1109/ICCA51439.2020.9264567.
63. Kraemer A.D., E. Villani, D.H. Arjoni. 2019. „Aircraft FDI and human factors analysis of a take-off maneuvre using SIVOR flight simulator”. *IFAC-PapersOnLine*. DOI: https://doi.org/10.1016/j.ifacol.2019.01.063.

64. Kumar A., A.K. Ghosh. 2019. „Decision Tree– and Random Forest-Based Novel Unsteady Aerodynamics Modeling Using Flight Data". *Journal of Aircraft* 56(1): 403-409. DOI: https://doi.org/10.2514/1.C035034.
65. Kuvayskova Y.E. 2021. „Application of Ensemble Machine Leearnings Methods for Predicting the Technical State of an Object". *Izvestiya of Samara Scientific Center of the Russian Academy of Sciences* 23(1): 111-114. DOI: https://doi.org/10.37313/1990-5378-2021-23-1-111-114.
66. Lee H., T.G. Puranik, D.N. Mavris. 2021. „Deep Spatio-Temporal Neural Networks for Risk Prediction and Decision Support in Aviation Operations". *Journal of Computing and Information Science in Engineering* 21(4): 1-21. DOI: https://doi.org/10.1115/1.4049992.
67. Lei D., S.S. Zhong. 2013. „Aircraft engine health signal denoising based on singular value decomposition and empirical mode decomposition methods". *Jilin Daxue Xuebao (Gongxueban)/Journal of Jilin University (Engineering and Technology Edition)* 43(3): 764-770. DOI: https://doi.org/10.7964/jdxbgxb201303034.
68. Lewitowicz J. 2021. *Podstawy eksploatacji statków powietrznych. Tom 1. Statek powietrzny i elementy teorii*. Warsaw, Wydawnictwo Instytutu Technicznego Wojsk Lotniczych. [In English: *Fundamentals of aircraft operations. Volume 1. Aircraft and elements of theory*].
69. Li G., H. Lee, A. Rai, A. Chattopadhyay. 2020. „Analysis of operational and mechanical anomalies in scheduled commercial flights using a logarithmic multivariate Gaussian model". *Transportation Research Part C: Emerging Technologies* 110: 20-39. DOI: https://doi.org/10.1016/j.trc.2019.11.011.
70. Li P. 2020. „Research on radar signal recognition based on automatic machine learning". *Neural Computing and Applications* 32(7): 1959-1969. DOI: https://doi.org/10.1007/s00521-019-04494-1.
71. Li S., K. Yang., J. Ma, et al. 2021. „Anti-interference recognition method of aerial infrared targets based on the Bayesian network". *Journal of Optics* 50(2): 264-277. DOI: https://doi.org/10.1007/s12596-021-00701-2.
72. Liang X., J. Huang, Y. Zhou. 2010. „Study on the effectiveness evaluation method of formation Beyond Visual Range air combat based on genetic BP Neural Network". *Proceedings of 2010 Asia-Pacific International Symposium on Aerospace Technology APISAT 2010*.
73. Liu P., Y. Ma 2017. „A Deep Reinforcement Learning Based Intelligent Decision Method for UCAV Air Combat". *Communications in Computer and Information Science* 751: 274-286. DOI: https://doi.org/10.1007/978-981-10-6463-0_24.
74. Liu X., L. Liu, L. Wang, et al. 2019. „Performance Sensing Data Prediction for an Aircraft Auxiliary Power Unit Using the Optimized Extreme Learning Machine". *Sensors* 19(18): 3935. DOI: https://doi.org/10.3390/s19183935.
75. Luo P., J. Xie, W. Che. 2016. „Q-learning based air combat target assignment algorithm". *2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, IEEE: 000779-000783. DOI: https://doi.org/10.1109/SMC.2016.7844336.
76. Lyu Y., A. Yang, Z. Li, Z. Xi. 2021. „Research on the construction method of air combat decision knowledge". *Xi Tong Gong Cheng Yu Dian Zi Ji Shu/Systems Engineering and Electronics* 43(7): 1866-1874. DOI: https://doi.org/10.12305/j.issn.1001-506X.2021.07.18.

77. Ma J., H. Zhao, D. Yang, Q. Kang. 2019. „Design and Optimization of Deep Convolutional Neural Network for Aircraft Target Classification". *Laser & Optoelectronics Progress* 56(23): 231006. DOI: https://doi.org/10.3788/LOP56.231006.
78. Ma W., H. Li, Z. Wang, et al. 2021. „Close air combat maneuver decision based on deep stochastic game". *Xi Tong Gong Cheng Yu Dian Zi Ji Shu/Systems Engineering and Electronics* 9: 14. DOI: https://doi.org/10.12305/j.issn.1001-506X.2021.02.19.
79. Matusiak W. 1996. „F-16 C". *Przegląd Konstrukcji Lotniczych*. [In English: „F-16 C". *Aircraft Structures Review*].
80. McCarthy J., M.L. Minsky., C.E. Shannon. 1955. „A proposal for the Dartmouth summer research project on artificial intelligence". *AI Magazine* 27(4).
81. Minglang C., D. Haiwen, W. Zhenglei, S. QingPeng. 2018. „Maneuvering decision in short range air combat for unmanned combat aerial vehicles". *2018 Chinese Control And Decision Conference (CCDC)*, IEEE: 1783-1788. DOI: https://doi.org/10.1109/CCDC.2018.8407416.
82. Mulgund S., K. Harper, G. Zacharias, K. Krishnakumar. 2001. „Large-Scale Air Combat Tactics Optimization Using Genetic Algorithms". *Journal of Guidance, Control, and Dynamics* 24(1): 140-142. DOI: https://doi.org/10.2514/2.4689.
83. Müller A., S. Guido. 2018. *Introduction to Machine Learning with Python: A Guide for Data Scientists*. O'Reilly Media.
84. Napolitano M.R., D.A. Windon, J.L. Casanova, et al. 1998. „Kalman filters and neural-network schemes for sensor validation in flight control systems". *IEEE Transactions on Control Systems Technology* 6(5): 596-611. DOI: https://doi.org/10.1109/87.709495.
85. Ning S., J. Sun, C. Liu, Y. Yi. 2021. „Applications of deep learning in big data analytics for aircraft complex system anomaly detection". *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability* 235(5): 923-940. DOI: https://doi.org/10.1177/1748006X211001979.
86. Niu D., Y. Wu, Y. Xu, et al. 2021. „Modeling of anti-jamming effectiveness evaluation of infrared air-to-air missile". *Beijing Hangkong Hangtian Daxue Xuebao/Journal of Beijing University of Aeronautics and Astronautics* 47(9): 1874-1883. DOI: https://doi.org/10.13700/j.bh.1001-5965.2020.033.
87. Novák V., I. Perfilieva, J. Močkoř. 1999. *Mathematical Principles of Fuzzy Logic*. Boston, MA, Springer US. DOI: https://doi.org/10.1007/978-1-4615-5217-8.
88. Papis M., T. Krawczyk. 2022. „Comparison of MiG-29 and F-16 aircraft in the field of susceptibility to destruction in combat". *Aviation* 26(3): 131-137. DOI: https://doi.org/10.3846/aviation.2022.17592.
89. Patel A .A. 2019. *Hands-On Unsupervised Learning Using Python*. O'Reilly Media.
90. Peng K., R. Jiao, J. Dong, Y. Pi. 2019. „A deep belief network based health indicator construction and remaining useful life prediction using improved particle filter". *Neurocomputing* 361: 19-28. DOI: https://doi.org/10.1016/j.neucom.2019.07.075.
91. Qian X., Y. Kai, B. Ya, et al. 2018. „Data Mining and Simulation Analysis of Aircraft Control System Based on Apriori Algorithm". *IEEE CSAA Guidance, Navigation and Control Conference (CGNCC)*, IEEE: 1-6. DOI: https://doi.org/10.1109/GNCC42960.2018.9019047.
92. Quirion N., D. Liu. 2021. „Effect of Sensor Sensitivity on Autonomous Aerial Vehicle Target Localization". *Unmanned Systems* 09(01): 11-21. DOI: https://doi.org/10.1142/S2301385021500023.

93. Quirion N., D. Liu, A. Ludu, D. Vincenzi. 2015. „Sensor sensitivity and reinforcement learning models on target acquisition task for autonomous vehicle”. *IIE Annual Conference and Expo 2015*.
94. Recht B.A. 2019. „Tour of Reinforcement Learning: The View from Continuous Control”. *Annual Review of Control, Robotics, and Autonomous Systems*. DOI: https://doi.org/10.1146/annurev-control-053018-023825.
95. Remadna I., L.S. Terrissa, S. Ayad, N. Zerhouni. 2021. „RUL Estimation Enhancement using Hybrid Deep Learning Methods”. *International Journal of Prognostics and Health Management* 12(1). DOI: https://doi.org/10.36001/ijphm.2021.v12i1.2378.
96. Rose R.L., T.G. Puranik, D.N. Mavris. 2020. „Natural Language Processing Based Method for Clustering and Analysis of Aviation Safety Narratives”. *Aerospace* 7(10): 143. DOI: https://doi.org/10.3390/aerospace7100143.
97. Roudbari A., F. Saghafi. 2014. „Intelligent modeling and identification of aircraft nonlinear flight”. *Chinese Journal of Aeronautics* 27(4): 759-771. DOI: https://doi.org/10.1016/j.cja.2014.03.017.
98. Rountree J., P. Hipelius, B. Dienst, et al. 2021. „Testing Artificial Intelligence in High-Performance, Tactical Aircraft”. *2021 IEEE Aerospace Conference* (50100), IEEE: 1-15. DOI: https://doi.org/10.1109/AERO50100.2021.9438308.
99. Sarker I.H. 2021. „Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions”. *SN Computer Science* 2(6): 420. DOI: https://doi.org/10.1007/s42979-021-00815-1.
100. Sasaki H., C.G. Willcocks, T.P. Breckon. 2021. „Data Augmentation via Mixed Class Interpolation using Cycle-Consistent Generative Adversarial Networks Applied to Cross-Domain Imagery”. *25th International Conference on Pattern Recognition (ICPR),* IEEE: 5083-5090. DOI: https://doi.org/10.1109/ICPR48806.2021.9413023.
101. Savitha R., A. Ambikapathi, K. Rajaraman. 2020. „Online RBM: Growing Restricted Boltzmann Machine on the fly for unsupervised representation”. *Applied Soft Computing* 92: 106278. DOI: https://doi.org/10.1016/j.asoc.2020.106278.
102. Schimert J. 2008. „Data-driven fault detection based on process monitoring using dimension reduction techniques”. *IEEE Aerospace Conference Proceedings*. DOI: https://doi.org/10.1109/AERO.2008.4526621.
103. Scukins E, P. Ogren. 2021. „Using Reinforcement Learning to Create Control Barrier Functions for Explicit Risk Mitigation in Adversarial Environments”. *IEEE International Conference on Robotics and Automation (ICRA),* IEEE: 10734-10740. DOI: https://doi.org/10.1109/ICRA48506.2021.9561853.
104. Sheridan K., T.G. Puranik, E. Mangortey, et al. 2020. „An Application of DBSCAN Clustering for Flight Anomaly Detection During the Approach Phase”. *AIAA Scitech 2020 Forum.* Reston, Virginia, American Institute of Aeronautics and Astronautics. DOI: https://doi.org/10.2514/6.2020-1851.
105. Shi J., Y. Li, G. Wang, X. Li. 2016. „Health index synthetization and remaining useful life estimation for turbofan engines based on run-to-failure datasets”. *Eksploatacja i Niezawodnosc - Maintenance and Reliability* 18(4): 621-631. DOI: https://doi.org/10.17531/ein.2016.4.18.
106. Shi W., Y.H. Feng, G.Q. Cheng, et al. 2021. „Research on Multi-aircraft Cooperative Air Combat Method Based on Deep Reinforcement Learning”. *Zidonghua Xuebao/Acta Automatica Sinica* 47(7): 1610-1623. DOI: https://doi.org/10.16383/j.aas.c201059.

107. Shin D.-H., Y. Kim. 2004. „Reconfigurable Flight Control System Design Using Adaptive Neural Networks". *IEEE Transactions on Control Systems Technology* 12(1): 87-100. DOI: https://doi.org/10.1109/TCST.2003.821957.
108. Socha V., L. Hanakova, L. Socha, et al. 2018. „Automatic Detection of Flight Maneuvers with the Use of Density-based Clustering Algorithm". *XIII International Scientific Conference – New Trends in Aviation Development (NTAD)*, IEEE: 132–136. DOI: https://doi.org/10.1109/NTAD.2018.8551680.
109. Song X., J. Jiang, H. Xu. 2017. „Application of improved simulated annealing genetic algorithm in cooperative air combat". *Harbin Gongcheng Daxue Xuebao/Journal of Harbin Engineering University* 38(11): 1762-1768. DOI: https://doi.org/10.11990/jheu.201606094.
110. Su M.-C., S.-C. Lai, S.-C. Lin, L.-F. You. 2012. „A new approach to multi-aircraft air combat assignments". *Swarm and Evolutionary Computation* 6: 39-46. DOI: https://doi.org/10.1016/j.swevo.2012.03.003.
111. Sun Z., H. Piao, Z. Yang, et al. 2021. „Multi-agent hierarchical policy gradient for Air Combat Tactics emergence via self-play". *Engineering Applications of Artificial Intelligence* 98: 104112. DOI: https://doi.org/10.1016/j.engappai.2020.104112.
112. Sutton R., A. Barto. 2018. *Reinforcment Learning: An Introduction*. MIT Press Cambridge.
113. Szopa M. 2020. „F-16 nadal popularny". Available at: https://defence24.pl/przemysl/f-16-nadal-popularny-analiza. [In English: „F-16 still popular"].
114. Tang Q., W. He. 2021. „Target Recognition Method of Laser Imaging Fuze Based on Deep Transfer Learning". *3rd International Conference on Natural Language Processing (ICNLP)*, IEEE: 202-207. DOI: https://doi.org/10.1109/ICNLP52887.2021.00040.
115. Taşdelen O., L. Çarkacioglu, B.U. Töreyin. 2021. „Anomaly Detection on ADS-B Flight Data Using Machine Learning Techniques". *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*: 771-783. DOI: https://doi.org/10.1007/978-3-030-88081-1_58.
116. Tomaszek H., M. Wróblewski 2001. *Podstawy oceny efektywności eksploatacji systemów uzbrojenia lotniczego*. Warsaw, Bellona. [In English: *Basics of evaluating the effectiveness of the operation of aircraft weapon systems*].
117. Trusova K.V. 2021. „Machine Learning Methods Application for the Avionics Systems Health Analysis and Faults Localization Challenges". *Springer Proceedings in Physics*: 383-397. DOI: https://doi.org/10.1007/978-3-030-58868-7_44.
118. Ummah K., H. Setiadi, H.M. Pasaribu, D. Anandito. 2020. „A Simple Fight Decision Support System for BVR Air Combat Using Fuzzy Logic Algorithm". *AVIA* 1(1). DOI: https://doi.org/10.47355/avia.v1i1.8.
119. Uzun M., M. Umut Demirezen, E. Koyuncu, G. Inalhan. 2019. „Design of a Hybrid Digital-Twin Flight Performance Model Through Machine Learning". *IEEE Aerospace Conference*, IEEE: 1-14. DOI: https://doi.org/10.1109/AERO.2019.8741729.
120. Valiant Air Command. „F-16 Fighting Falcon". Available at: https://www.valiantaircommand.com/f-16-fighting-falcon.
121. Vanhoy G., T. Schucker, T. Bose. 2017. „Classification of LPI radar signals using spectral correlation and support vector machines". *Analog Integrated Circuits and Signal Processing* 91(2): 305-313. DOI: https://doi.org/10.1007/s10470-017-0944-0.

122. Verma H.O., N.K. Peyada. 2020. „Parameter estimation of aircraft using extreme learning machine and Gauss-Newton algorithm”. *The Aeronautical Journal* 124(1272): 271–295. DOI: https://doi.org/10.1017/aer.2019.123.
123. Vikhar P.A. 2016. „Evolutionary algorithms: A critical review and its future prospects”. *2016 International Conference on Global Trends in Signal Processing, Information Computing and Communication (ICGTSPICC)*, IEEE: 261-265. DOI: https://doi.org/10.1109/ICGTSPICC.2016.7955308.
124. Wang B. 2020. „Data cleaning method of ADS-B historical flight trajectories”. *Jiaotong Yunshu Gongcheng Xuebao/Journal of Traffic and Transportation Engineering* 20(4): 217-226. DOI: https://doi.org/10.19818/j.cnki.1671-1637.2020.04.018.
125. Wang C., X. Zhang, L. Cong, et al. 2019. „Research on intelligent collision avoidance decision-making of unmanned ship in unknown environments”. *Evolving Systems* 10(4): 649-658. DOI: https://doi.org/10.1007/s12530-018-9253-9.
126. Wang L., P. Lucic, K. Campbell, C. Wanke. 2021. „Autoencoding Features for Aviation Machine Learning Problems”. *AIAA AVIATION 2021 FORUM*. DOI: https://doi.org/10.2514/6.2021-2388.
127. Wang L., J. Hu, Z. Xu, C. Zhao. 2021. „Autonomous maneuver strategy of swarm air combat based on DDPG”. *Autonomous Intelligent Systems* 1(1): 15. DOI: https://doi.org/10.1007/s43684-021-00013-z.
128. Wang M., L. Wang, T. Yue, H. Liu. 2020. „Influence of unmanned combat aerial vehicle agility on short-range aerial combat effectiveness”. *Aerospace Science and Technology* 96: 105534. DOI: https://doi.org/10.1016/j.ast.2019.105534.
129. Wang Z., H. Li, H. Wu, Z. Wu. 2020. „Improving Maneuver Strategy in Air Combat by Alternate Freeze Games with a Deep Reinforcement Learning Algorithm”. *Mathematical Problems in Engineering* 2020: 1-17. DOI: https://doi.org/10.1155/2020/7180639.
130. Wasilewski A. 2004. „Samolot myśliwski F-16 C/D Block 52+”. *Typy Broni i Uzbrojenia*. [In English: „F-16 C/D Block 52+ fighter aircraft”. *Types of Weapons and Armaments*].
131. Wu X., Y. Wu, B. Chen, et al. 2021. „Hierarchical Prediction of Infrared interference Environment based on Mutual Information and Random Forest”. *Journal of Physics: Conference Series* 1883(1): 012091. DOI: https://doi.org/10.1088/1742-6596/1883/1/012091.
132. Xi Z., A. Xu, Y. Kou, et al. 2020. „Target threat assessment in air combat based on PCA-MPSO-ELM algorithm”. *Hangkong Xuebao/Acta Aeronautica et Astronautica Sinica* 41(9): 323895-323895. DOI: https://doi.org/10.7527/S1000-6893.2020.23895.
133. Xi Z., A. Xu, Y. Kou, et al. 2021. „Air combat target threat assessment based on gray principal component”. *Xi Tong Gong Cheng Yu Dian Zi Ji Shu/Systems Engineering and Electronics* 43(1): 147-155. DOI: https://doi.org/10.3969/j.issn.1001-506X.2021.01.18.
134. Xiao L., J. Huang, Z. S. Xu. 2013. „Cooperative attack decision for BVR air combat based on neural network”. *Shenyang Gongye Daxue Xuebao/Journal of Shenyang University of Technology* 35(3): 338-344. DOI: https://doi.org/10.7688/j.issn.1000-1646.2013.03.18.
135. Xiao L., J. Huang, Z. Xu. 2013. „Modeling air combat situation assessment based on combat area division”. *Beijing Hangkong Hangtian Daxue Xuebao/Journal of Beijing University of Aeronautics and Astronautics* 39(10): 1309-1313.

136. Xie J., Q. Yang, S. Dai, et al. 2020. „Air Combat Maneuver Decision Based on Reinforcement Genetic Algorithm”. *Xibei Gongye Daxue Xuebao/Journal of Northwestern Polytechnical University* 38(6): 1330-1338. DOI: https://doi.org/10.1051/jnwpu/20203861330.
137. Xu A., Y.X. Kou, L. Yu, Z.W. Li. 2012. „Stealthy engagement maneuvering strategy with Q-learning based on RBFNN for air vehicles”. *Xi Tong Gong Cheng Yu Dian Zi Ji Shu/Systems Engineering and Electronics* 34(1): 97-101. DOI: https://doi.org/10.3969/j.issn.1001-506X.2012.01.18.
138. Xue Y., Z. Chen. 2019. „Aviation material classification research based on consumption volatility clustering analysis”. *Xi Tong Gong Cheng Yu Dian Zi Ji Shu/Systems Engineering and Electronics* 41(12): 2802-2806. DOI: https://doi.org/10.3969/j.issn.1001-506X.2019.12.19.
139. Yang Q., J. Zhang, G. Shi, et al. 2020. „Maneuver Decision of UAV in Short-Range Air Combat Based on Deep Reinforcement Learning”. *IEEE Access* 8. DOI: https://doi.org/10.1109/ACCESS.2019.2961426.
140. Yang Q., Y. Zhu, J. Zhang, et al. 2019. „UAV Air Combat Autonomous Maneuver Decision Based on DDPG Algorithm”. *IEEE 15th International Conference on Control and Automation (ICCA)*, IEEE: 37-42. DOI: https://doi.org/10.1109/ICCA.2019.8899703.
141. Yang Y., X. Hu, M. Rong, et al. 2019. „Characteristic Index Digging of Combat SoS Capability Based on Machine Learning”. *Xitong Fangzhen Xuebao / Journal of System Simulation* 31(6): 1048-1054. DOI: https://doi.org/10.16182/j.issn1004731x.joss.19-0238.
142. Yildirim Dalkiran F., M. Toraman. 2021. „Predicting thrust of aircraft using artificial neural networks”. *Aircraft Engineering and Aerospace Technology* 93(1): 35-41. DOI: https://doi.org/10.1108/AEAT-05-2020-0089.
143. You S., M. Diao, L. Gao, et al. 2020. „Target tracking strategy using deep deterministic policy gradient”. *Applied Soft Computing* 95: 106490. DOI: https://doi.org/10.1016/j.asoc.2020.106490.
144. Yuan W., P. Jia, L. Wang, L. Shao. 2009. „Aircraft Pose Recognition Using Locally Linear Embedding”. *2009 International Conference on Measuring Technology and Mechatronics Automation*, IEEE: 454-457. DOI: https://doi.org/10.1109/ICMTMA.2009.637.
145. Yuksek B., U.M. Demirezen, G. Inalhan. 2021. „Development of UCAV Fleet Autonomy by Reinforcement Learning in a Wargame Simulation Environment”. *AIAA Scitech 2021 Forum.* Reston, Virginia, American Institute of Aeronautics and Astronautics. DOI: https://doi.org/10.2514/6.2021-0175.
146. Zhao Y., T. Kendall, B. Johnson. 2016. „Big Data and Deep Analytics Applied to the Common Tactical Air Picture (CTAP) and Combat Identification (CID)”. *Proceedings of the 8th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management, SCITEPRESS - Science and Technology Publications*: 443-449. DOI: https://doi.org/10.5220/0006086904430449.
147. Zhou W., M. Kuang, J. Zhu. 2020. „An unmanned air combat system based on swarm intelligence”. *SCIENTIA SINICA Informationis* 50(3): 363-374. DOI: https://doi.org/10.1360/SSI-2019-0196.
148. Zou Y. M., B. Wang. 2008. „Estimation of the attitude of a rolling missile based on independent component analysis”. *Xi Tong Gong Cheng Yu Dian Zi Ji Shu/Systems Engineering and Electronics* 7: 1301-1303.

Received 01.04.2024; accepted in revised form 30.05.2024