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Command-and-Control System Analysis and Delineation of Possible Areas for Machine Learning

P. Gallus*, and P. Františ

Department of Informatics and Cyber Operations, University of Defence, Brno, Czech Republic

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Abstract:

This paper explores AI and machine learning integration in military command-and-control (C2) systems, enhancing decision-making and operational efficiency. It examines AI applications across military levels, emphasizing predictive analytics, anomaly detection, and pattern recognition for improved situational awareness. Using the WASP simulation system, the study develops a neural network for scenario planning, highlighting simulators' role in AI training. Results show AI's potential to automate troop movement, command post deployment, and enemy maneuver recognition. The findings suggest AI-driven adaptability in dynamic battlefield environments. Future research will focus on advanced simulations and AI applications for military decision-making, reinforcing AI's strategic role in modern warfare.

Keywords:

command-and-control, artificial intelligence, machine learning, neural network, military system, simulation

1 Introduction

The rapid advancement of technology has significantly transformed modern military operations, with command-and-control (C2) systems playing a critical role in enhancing operational efficiency and decision-making. The integration of artificial intelligence (AI) and machine learning (ML) within these systems presents a unique opportunity to further advance military capabilities. By leveraging AI and ML, military organizations can process vast amounts of data with unprecedented speed and accuracy, enabling predictive analytics, anomaly detection, and enhanced situational awareness.

This research paper explores the integration of AI and ML into C2 military systems, focusing on their potential to revolutionize decision-making processes across tactical, operational, and strategic levels. The study delves into specific areas where AI can be effectively implemented within C2 frameworks, aiming to improve operational effectiveness and adaptivity in dynamic battlefield environments.

* *Corresponding author: Department of Informatics and Cyber Operations, University of Defence, Kounicova 156/65, CZ-662 10 Brno, Czech Republic. Phone: +420 973 44 23 35, E-mail: petr.gallus@unob.cz. ORCID 0000-0003-2270-073X.*

The study also presents an experiment utilizing the WASP simulation system, which demonstrates the creation and application of training data to develop a neural network for predictive analysis and scenario planning. The findings from this experiment suggest that AI can significantly enhance C2 systems' capabilities, offering insights into future battlefield scenarios and automating complex processes such as troop movement planning and enemy maneuver recognition.

This research contributes to ongoing modernization efforts within military operations by showcasing AI's strategic role in achieving operational superiority. It underscores the importance of continued research and development in this field, particularly in adopting advanced simulation software and developing AI-based applications that support military decision-making.

2 Command-and-Control Systems and AI

The Czech Army Command-and-Control System (C2) constitutes an advanced and integrated network designed to facilitate the efficient flow of information and enhance decision-making processes within the Czech military. Rooted in modern technology and standardized protocols, the system ensures seamless integration of various units, including operational, communication, and reconnaissance sectors. Its architecture employs both conventional and emerging digital communication tools, thereby providing military leaders at all levels with precise, real-time situational awareness. This capability significantly enhances the Czech Armed Forces' proficiency in coordinating complex missions, executing strategic plans, and rapidly adapting to dynamic battlefield environments [1].

Moreover, the system is engineered to enhance interoperability with NATO allies, a critical aspect given the Czech Republic's alliance commitment. By incorporating protocols and frameworks that align with NATO standards, the system facilitates effective coordination of multinational operations. This interoperability is further strengthened through regular training exercises, ensuring that personnel remain proficient in system usage. Consequently, the Czech Army Command-and-Control System not only exemplifies the modernization efforts within the Czech military but also serves as a strategic asset that augments the nation's defense capabilities within collaborative security initiatives [1].

2.1 Case Study

One of the significant challenges in modern warfare is the rapid and effective deployment of command posts while ensuring operational security. In a military operation, selecting optimal command post locations requires extensive manual planning, considering factors such as terrain, threat analysis, and logistic support. This process is time-consuming and prone to human error, potentially exposing command posts to enemy attacks.

To enhance the efficiency and accuracy of decision-making, ai-driven decision-support tools can be integrated into a C2 system to optimize command post deployment in complex battlefield scenarios. The AI model processes real-time satellite imagery, ISR sensor feeds, and logistic data to generate optimal command post placement recommendations.

- Input Data: Terrain maps, enemy movement patterns, troop logistics, communication coverage.

- AI Processing: Machine learning models analyze patterns, suggest secure locations, and adapt to dynamic battlefield changes.
- Implementation: the AI-assisted system provides recommendations to field commanders, who validate and execute the final deployment.

By leveraging AI for decision support, military operations can reduce planning time, improve the survivability of key assets, and enhance adaptability in rapidly changing battlefield environments.

2.2 Machine Learning Importance

Machine learning (ML) plays a crucial role in developing new features within NATO's C2 military systems due to its capacity to analyze and interpret vast streams of data at an unprecedented speed. As modern battlefields become increasingly complex and information-dense, ML algorithms can process surveillance data, signals intelligence, and other sensor inputs to deliver actionable insights. These insights empower military leaders with predictive analytics, anomaly detection, and pattern recognition to anticipate threats and opportunities. By integrating these ML capabilities, C2 systems significantly improve situational awareness, enabling faster decision-making that aligns with mission objectives in high-pressure environments [4].

Moreover, ML enhances the interoperability and adaptability of C2 systems within the NATO alliance. By employing algorithms capable of learning from diverse datasets collected across different member nations, these systems can create unified intelligence frameworks that improve collaborative defense efforts. This adaptability allows for the rapid customization of systems to suit evolving tactical needs, such as developing new models for emerging cyber threats or improving the efficiency of resource allocation. Thus, focusing on ML in C2 systems provides a strategic edge, ensuring NATO remains agile and effective in its collective defense responsibilities amidst changing technological and geopolitical landscapes.

2.3 Decision-Making Mechanisms in Human-AI Systems

Human-AI systems (HAIS) can be categorized into decision types based on the compositional balance of human and AI capabilities within the system. These systems aim to achieve objectives of effectiveness, efficiency, and quality. Key factors in balancing human and AI roles include the process of interactions (e.g., sequential, parallel, integrated) between human controls and AI controls, and the location of the final decision authority in the HAIS design. Human control aims for rational behavior, sound reasoning, and actionable decisions. AI handles large-scale data problems predictably through algorithms. Typically, AI generates decision outputs, while humans assess their fairness and generalizability. HAIS defines boundaries between human and machine actions based on the situation. Designers must balance human and machine strengths in HAIS. Human control can falter with complex decisions and information overload, while AI may lack empathy and broader understanding. Humans must ensure critical decisions are not made solely by AI. Effective human-AI systems require human supervision to maintain proper boundaries [6].

Human-AI Interaction Systems can be categorized into four distinct archetypes, each defined by the boundaries of control between human operators and AI systems. These archetypes reflect varying degrees of autonomy, collaboration, and innovation, shaping the roles and responsibilities of both AI and human counterparts.

Decision-Making Systems

Role of AI: in Decision-Making Systems, AI primarily handles tasks that involve sensing, data collection, and executing rapid decisions through automated algorithms. These systems are designed to function with minimal human intervention, capable of autonomous operations such as those seen in robotic process automation and self-driving vehicles. AI systems within this category are responsible for continuously monitoring safety regulations and managing repetitive activities, ensuring efficiency and adherence to predefined parameters.

Role of Humans: although AI takes on the primary role, human oversight remains crucial in Decision-Making Systems. Humans are responsible for ensuring that the AI behaves correctly and ethically, particularly in scenarios where safety or high-risk factors are involved. In such critical situations, humans have the authority to override AI decisions, thereby maintaining a safeguard against potential AI errors or ethical dilemmas.

Decision-Support Systems

Role of AI: Decision-Support Systems are designed to augment human cognitive abilities, enhance communication, and extend physical capabilities. In this archetype, AI systems assist by providing recommendations, insights, or diagnoses based on comprehensive data analysis. The AI's role is to serve as a tool that enhances the human decision-making process, offering data-driven guidance while leaving final decisions to human operators.

Role of Humans: humans in Decision-Support Systems play a pivotal role in interpreting AI-generated insights, making the final decisions, and ensuring that AI systems are appropriately trained. Additionally, humans are responsible for explaining AI outcomes to stakeholders and adapting the HAIS to evolving environments, ensuring that AI contributions remain relevant and effective.

Decision-Collaboration Systems

Role of AI: in Decision-Collaboration Systems, AI systems engage in a more interactive role with human partners. AI collaborates with humans in tasks such as sensing, organizing, reasoning, planning, and executing solutions. The interaction between AI and humans is characterized by rapid, nearly simultaneous exchanges, which lead to enhanced problem-solving capabilities and the development of new scientific and technological insights.

Role of Humans: humans in this context actively collaborate with AI, contributing to processes like deep learning and complex problem-solving. This collaboration enhances human understanding and fosters an environment where both AI and human intellects combine to tackle complex challenges, thereby expanding the boundaries of knowledge and innovation.

Decision-Innovation Systems

Role of AI: decision-Innovation Systems are geared towards supporting human endeavors in creativity and innovation. AI in this archetype assists humans in exploring new ideas and driving innovation by leveraging capabilities like Generative AI. These systems are designed to inspire continuous innovation, enabling humans to explore uncharted territories and develop novel solutions.

Role of Humans: the human role in Decision-Innovation Systems is centered around creativity, critical thinking, and applying value judgments. Humans use AI as a tool to push the limits of knowledge, transitioning from the known to the unknown. By integrating empathy and reasoning into the innovation process, humans ensure that AI-driven innovations align with societal values and ethical considerations.

Effective HAIS integration requires balancing human and AI strengths, ensuring human oversight for critical decisions, and maintaining proper boundaries. By leveraging both human and AI capabilities, HAIS can achieve superior decision outcomes across various domains. A comparison of all HAIS archetypes is summarized in Tab. 1 [7].

Tab. 1 HAIS archetypes – comparison and usage

Archetype	Pros	Cons	Usage
Decision-Making Systems	High efficiency, consistent monitoring	Limited human intervention, ethical issues	Autonomous vehicles, RPA
Decision-Support Systems	Enhanced human capabilities, iterative improvement	Requires continuous human involvement	Medical diagnostics, financial analysis
Decision-Collaboration Systems	Synergistic decision-making, improved problem understanding	Blurred control boundaries, complexity	Scientific research, complex problem-solving
Decision-Innovation Systems	Drives continuous innovation, explores new possibilities	High risk, ethical considerations	Generative AI, creative industries

3 Delineation of Possible AI Areas

Creating any system or application containing AI necessitates a substantial amount of training data, as the volume of data is directly proportional to the speed of learning in ML models. Due to the limited availability of “sharp” data from combat, peacekeeping operations, or exercises, developing AI becomes challenging. Consequently, the use of a supervised learning model appears to be adequate. In a real-world scenario, this could involve simulator-supported learning in collaboration with the Centre for Simulation and Simulator Technologies (CSTT) [3].

There are two possible guidelines for implementation:

- without ML - the fundamental elements of the C2 system, combined with simulators and an attached module that would automate and transform data in both directions,
- with ML (neural network) - the simulator linked to the C2 systems would initially train the neural network. Subsequently, the trained neural network would be integrated with the C2 systems in the deployment phase.

The potential implementation of AI in the Doppelganger system (Ground Forces ISMS) is organized into the following sections, logically divided according to the application area, namely the user level and the Army command levels (tactical, operational, and strategic).

3.1 User Level

The initial and unavoidable level for implementing AI within the Dolphin system is where the user interacts with the system. Although AI application within the Army's C2 is specific to an IT system, there are several parallels to practical applications in the civilian sector at the user level. The most relevant examples are detailed in the subsections below.

Virtual Assistant

The virtual assistant exemplifies the implementation of AI technology within the Integrated Management System (IMS) of the Army. It functions as an assistant to the operator, providing guidance in situations where the operator is unfamiliar with a procedure in the application. This alleviates the need to consult colleagues, supervisors, or staff from other departments for basic user-level issues. In practice, the virtual assistant would receive a request from the user and subsequently provide advice based on the information stored in its database or neural network.

User Authentication using Face Recognition

Another relevant application of AI at the user level is the creation and implementation of a security subsystem that authenticates the user before allowing system access through facial recognition.

The implementation of this AI element would not only enhance the physical security of the system but would also align with NATO's Federated Mission Networking (FMN) requirements and its developmental spirals. This approach ensures that user authentication is both robust and efficient, providing a higher level of security and meeting the stringent standards expected in military operations.

3.2 Tactical Level

Integration into ISR Sensor Outputs

A primary area for AI integration at the tactical level is within Intelligence, Surveillance, and Reconnaissance (ISR) sensor outputs. Advances in ISR sensor technology and the vast amount of data generated by these systems impose significant demands on data processing and utilization. For instance, an electro-optical system can generate several billion bits per second while scanning an area the size of a small city. This challenge has been well-documented by civilian companies supplying ISR systems to the U.S. military, as summarized in the AFA Warfare Symposium 2022 [8].

An expert team of scientists and engineers from the University of Defence and Brno University of Technology is working on a project aimed at designing and applying a drone swarm system equipped with ISR sensors. At an early stage of this project, a 3D model of an object of interest, including its interior, was successfully developed by flying around a point of interest (e.g., a car).

Planning Assistant

Another relevant and beneficial application of AI at the tactical level is a sub-application that assists the C2 operator in developing various plans. Scheduling is a daily activity for staff members. One possible sub-application could plan the movement of troops over communication networks, referred to as “navigation” in working terms. Another critical planning sub-application might generate a radio-relay link plan, essential for organizing any military exercise or operation.

In these domains, the entire process would not be driven solely by AI. Hence, an AI-based sub-application would propose the most cost-effective options to the operator (staffer), but the final decision on executing the plan or building the link nodes would rest with the operator.

The two figures below illustrate distinct AI-driven tactical planning processes. Fig. 1 focuses on planning the movement of units and vehicles by considering factors such as operation type, priority, and terrain to determine the optimal convoy route. In contrast, Fig. 2 emphasizes the strategic placement of communication units based on similar criteria – operation type, priority, and terrain – but with a focus on establishing effective communication networks rather than troop movement. Both figures highlight the role of AI in optimizing different aspects of tactical operations, yet each serves a unique function within the overall military planning framework.

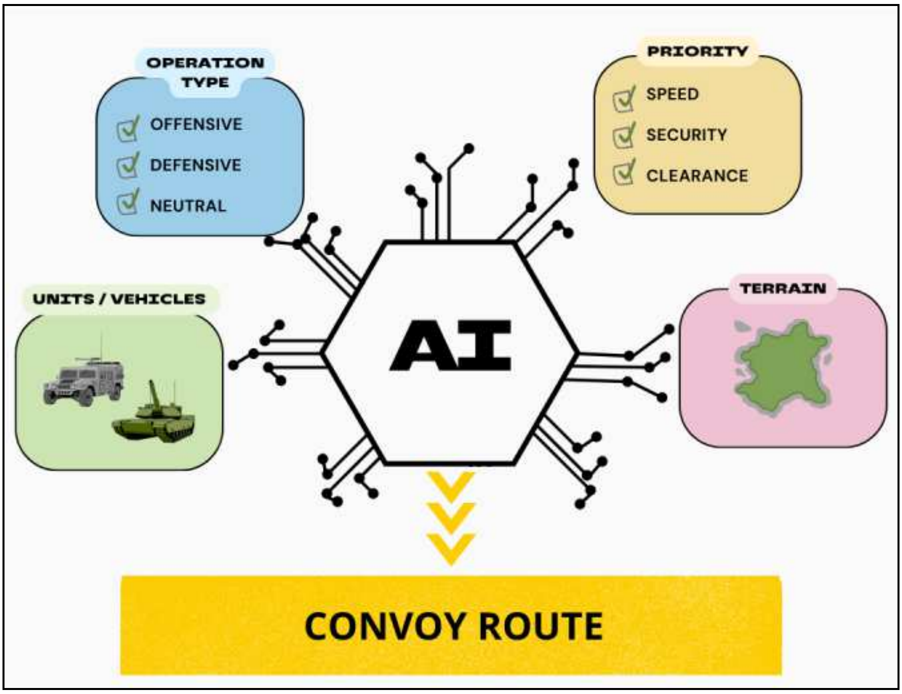

Fig. 1 Convoy route input data

3.3 Operational Level

The operational level of military planning is critical in ensuring the effectiveness of tactical decisions and battlefield outcomes. This article explores advanced tools and methodologies that enhance operational efficiency, focusing on key areas such as time transparency simulations, command post deployment, and enemy maneuver recognition. By leveraging neural networks, AI automation, and cutting-edge simulation technologies, these tools provide military staff with the ability to anticipate short-term future scenarios, optimize command post locations, and accurately predict enemy actions.

These innovations offer significant strategic advantages in dynamic and complex operational environments.

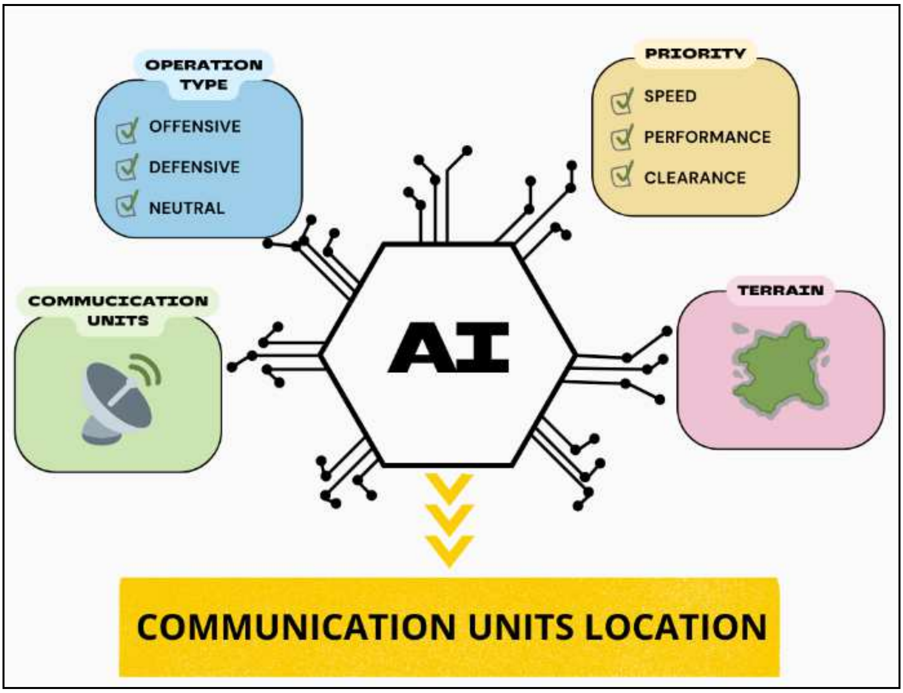

Fig. 2 Communication units location input data

Insight into the Short Future Using Time Transparencies

Staff would significantly benefit from functionality that allows them to run simulations to preview short-term future scenarios. The input data would consist of a plot of the tactical situation. The trained neural network would provide a glimpse into the short-term future of the battlefield situation in the form of transparency. Staff could thus view the preliminary evolution of the situation at various time horizons (e.g., t +1, 3, 6, 12, or 24 hours), aiding in the assessment of whether the proposed battle plan is worth pursuing.

The NVG-Client is designed to transfer tactical transparencies from a NATO NVG standard web service to the visualization program in use. During this transfer, individual graphical elements (tactical markers) are categorized, and the symbols (tactical markers) in the transferred transparencies are converted according to the APP6b code (NATO marking standard) into their graphical forms. Simultaneously, the tactical markings of the units are supplemented with information from the relevant database regarding their status (e.g., fuel amount, manning, ammunition, and equipment). The wiring implementation is illustrated in Fig. 3.

The primary purpose of NVG-Client is to decouple the decoding and transformation of tactical transparencies from the visualization itself. This approach makes the visualization independent of the operational/tactical system used or its version or increment. The acronym NVG stands for NATO's Vector Graphic, a file extension specifically designed for graphical interaction with NATO military systems. NVG-Client also includes a graphical user interface allowing the user to select individual tactical transparencies available through the NVG service, set conversion parameters, and further control their display in the visualization program.

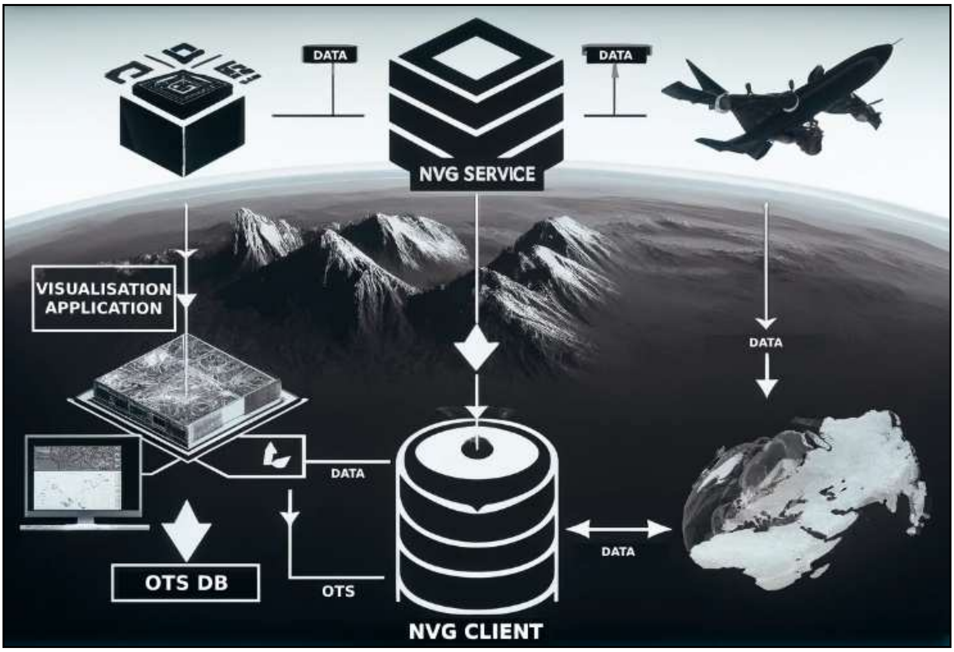

Fig. 3 NVG system wiring diagram into OTS implementation

Appropriate Deployment of Command Posts

The deployment of command posts is a crucial aspect of any military operation or exercise. During the current conflict in Ukraine, this aspect of battle planning has proven essential, as Ukrainian troops often maneuver command posts to avoid remaining in one location for security reasons. The automation and potential involvement of AI could significantly accelerate the process of selecting and establishing command posts for various command levels. The relevant input data used for this AI-based planning is shown in Fig. 4.

This process would resemble the sub-applications outlined in the Planning Assistant section. The operator would input the composition of troops with equipment, type of operation, and priority, and the AI would then determine suitable coordinates for command locations, primarily based on the terrain's nature. According to the inputted military units and equipment, the application would evaluate the command level (company, battalion, brigade, division, etc.) and propose appropriate command post deployments suitable for the current situation.

Enemy Combat Maneuvers Recognition The CSTT currently employs various live, virtual, and constructive simulation tools to cover the training of planning, control, and execution processes for combat, peacekeeping, and crisis management operations from the brigade level to individual soldiers. This training utilizes views created directly from the latest battlefield situations combined with historical data from databases [9].

The following figure illustrates this application, where data is transferred from a constructive One-SAF Testbed Baseline (OTB) simulator, which incorporates ACCS and BVIS technologies and software, to train the model. For training, it was necessary to interface with the OTS of the DG, leading to the creation of the connection project. This project facilitated data transformation from the synthetic simulator environment (DIS protocol) to a proprietary protocol format. A “gateway” is used to transform the data from the simulator into XML format and then into the OTS DG Ground Forces ISMS protocol. This intermediate step may benefit other systems to which it connects. In this application, the proprietary OTS DG is utilized. The simulator data is divided into training and test data in a 2:1 ratio. The training data is used for learning, and the model is tested with the remaining data. Once the model is built, actual battlefield data is input, and the distribution is predicted. The result is then evaluated by a credentialed expert for correctness, and accurate predictions are used as feedback and training data to update the model [1].

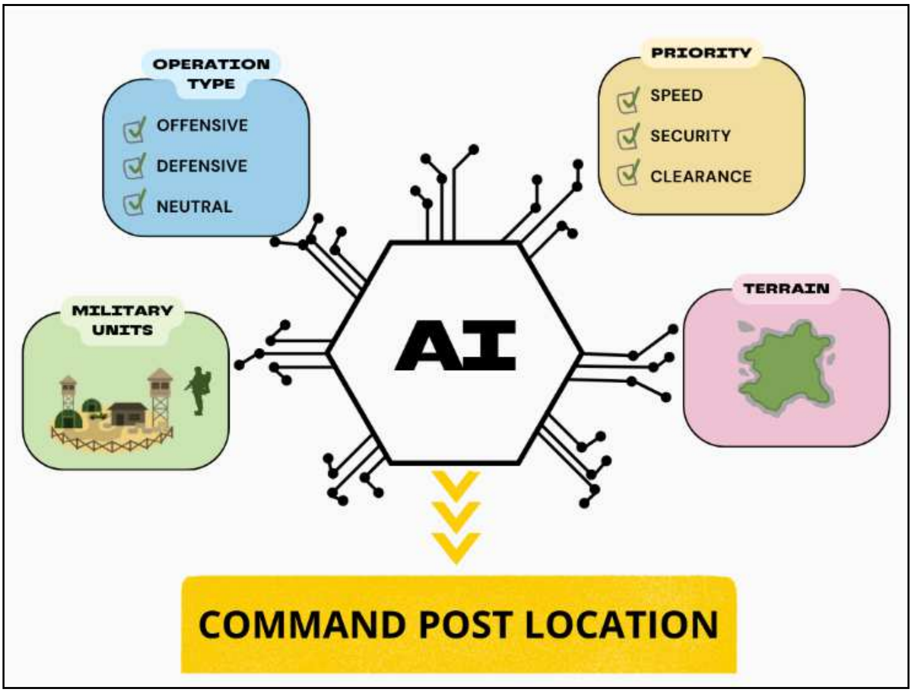

Fig. 4 Command post location input data

Additionally, Fig. 5 below illustrates the integration of AI within the Command-and-Control (C2) system, emphasizing its role in enhancing situational awareness, decision-making, and operational efficiency. The AI model interacts with various components of the system by processing real-time battlefield data, detecting patterns, predicting enemy maneuvers, and providing decision support. The AI-driven analysis assists human operators in planning troop movements and allocating resources effectively. Furthermore, AI models leverage data from simulations, such as the WASP system, to improve predictive accuracy. This integration enables faster, data-driven decisions while maintaining human oversight in critical operations.

The output can be utilized to evaluate the enemy’s combat maneuvers preparations or predict the success or failure probability of military actions. The output can be visualized through graphs, models, or decision support tables. The Microsoft Cognitive

Toolkit, compatible with other applications from the same company, can serve as an AI library. Additionally, other tools such as TensorFlow or Scikit-learn can be employed, depending on the author's programming language and compatibility preferences [1].

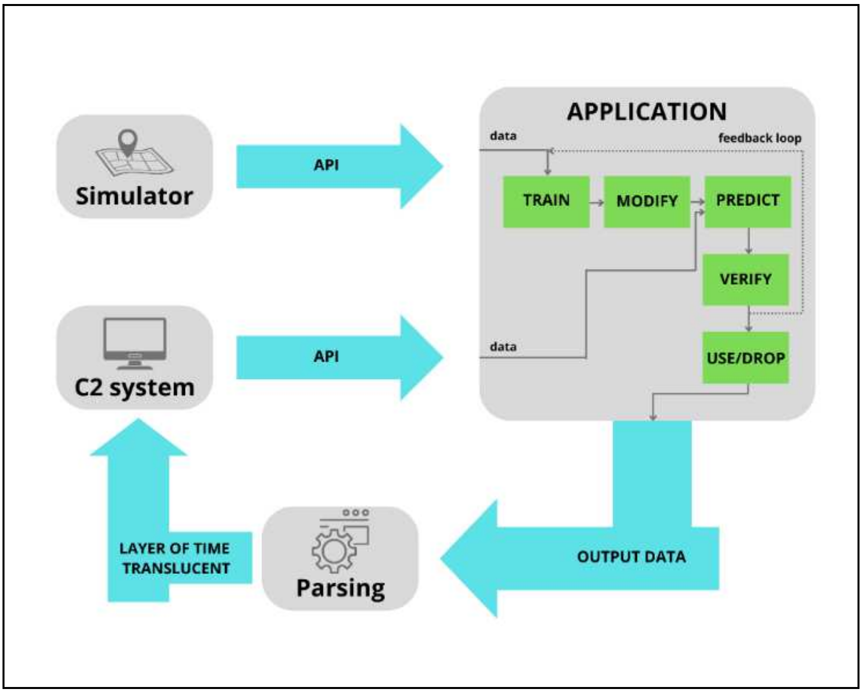

Fig. 5 Simulator system wiring diagram into OTS implementation

3.4 Strategic Level

The strategic level of military planning integrates advanced AI applications to enhance decision-making and operational effectiveness. This section explores how AI can be utilized to simulate entire operations, calculate winning probabilities, and enhance intelligence gathering. By leveraging extensive simulations and predictive analytics, these AI tools provide commanders with actionable insights, helping them maneuver troops efficiently, predict outcomes with greater accuracy, and analyze complex intelligence data. These capabilities are crucial for achieving strategic objectives while minimizing risks and uncertainties in the battlefield.

Operation Result according to the Plan

A significant inspiration for this potential AI implementation is the "Peering through the Fog of War" project by U.S. companies in collaboration with the Department of Defence (2022). The developers successfully created a comprehensive simulator of entire operations, providing realistic solutions for how commanders could maneuver troops to achieve the intended objective with minimal losses. Essentially, this would involve performing an extended simulation of the application, referred to as "Preview of the Short Future", described in the chapter on time slides (e.g., t +1, 6, 12, 24 hours).

The simulation would not run solely within a fixed time horizon but would calculate all possible variations, proceeding as follows:

- the input data would be a plot of the combat situation,
- data from the OTS database (Dolphin) would be merged with the NVG service within the NVG client and projected into a 3D visualization,
- thousands of simulations would be conducted, where the simulator evaluates the consequences of proposed unit actions and learns from them,
- a reverse process would return data from the NVG client to the OTS (Dolphin) database.

The resulting data (proposed plan of operation) would be projected to the Dolphin user in a plot. This ambitious and challenging proposal, if successfully implemented, would likely become a highly desired product not only for the Czech Army but also for other NATO allied forces.

Winning Probability

Another potential AI application is the Force Ratio application, which calculates the ratio of forces between one's own troops and those of the enemy. The calculation includes the numbers of all groups of combat assets multiplied by their combat value and adjusted by coefficients reflecting parameters such as terrain, weather, training and combat experience, air superiority, surprise attack, defense type, and command quality.

This application could use AI to calculate, for instance, the number of enemy units needed to secure victory or cause defeat. It would also provide the probability of such outcomes, acknowledging that the exact locations and statuses of all operating forces are often unknown. In this scenario, AI could simulate both defeat and victory scenarios, which could then be integrated into the War Games application. A war game is any simulation of a military operation involving two or more opposing armed forces, conducted under specified rules using data and procedures designed to represent actual or anticipated operational situations.

Intelligence – Enemy Hierarchical Structure

A critical sub-area in combat operations contributing to the overall battlefield picture is intelligence. There are numerous AI applications with significant potential in the intelligence domain, particularly in filtering large volumes of data to extract intelligence-relevant information. Without AI systems, two main problems arise: the annual increase in data production and the limited human capacity to analyze data based on only a few key characteristics.

An example of an advanced AI system for intelligence purposes is the Israeli system known as The Gospel. This AI system generates lists of individuals for elimination. Israel utilizes this system to create lists of Hamas members within the Gaza Strip as part of Operation Iron Sword, initiated at the end of 2023. The input to the neural network is data obtained by intelligence reconnaissance, such as transcripts from wiretaps, ground photos of operatives, space photos from satellites, or information from an insider – a person inside the organization. Prior to the deployment of these AI systems (The Gospel was not the first), Israeli intelligence agencies could produce a list of 50 targets annually. The Gospel, however, generates 100 targets daily, including predictions of collateral damage to the civilian population. This AI-driven process is demonstrated in Fig. 6 [10].

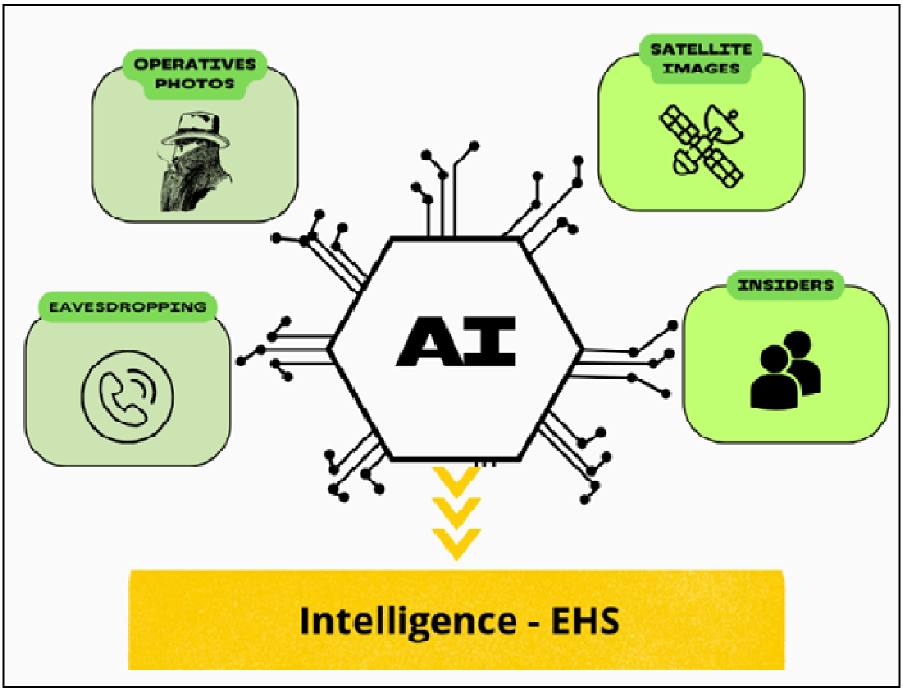

Fig. 6 Intelligence Enemy Hierarchical Structure input data

4 Experiment

The integration of AI within C2 military systems represents a pivotal advancement in modern warfare. The primary objective of the experiment is to delineate various AI applications within C2 frameworks, aiming to enhance decision-making and operational effectiveness. By leveraging the WASP Simulator, hundreds of simulated operations have been conducted to analyze the dynamic interplay of multiple variables, including unit locations, troop numbers on both friendly and enemy sides, and tactical maneuvers.

The significance of employing simulators within C2 systems cannot be overstated, especially within NATO's strategic trajectory toward utilizing AI subsystems. Simulators provide a controlled environment in which diverse scenarios can be replicated, offering invaluable insights into complex operational landscapes without the risks associated with live exercises. By harnessing the power of simulation, military commanders and strategists can explore numerous potential outcomes, test hypotheses, and refine strategies in a cost-effective and scalable manner.

The central objective of the experiment was the utilization of a custom neural network trained on simulation logs. This approach enabled the neural network to autonomously learn from input parameters and corresponding outputs, effectively capturing the intricacies of decision-making processes within C2 systems. The trained neural network serves as a powerful tool for predictive analysis and scenario planning, empowering military leaders to anticipate and adapt to evolving battlefield dynamics with unprecedented agility.

4.1 WASP Simulations and Custom Neural Network

One of the applications of ML is to support user decision-making. For such an application to yield relevant output, it requires a well-constructed neural network with a substantial amount of historical training data. Obtaining such training data was crucial for this research. Unfortunately, there is no regulation within NATO that mandates Czech or coalition troops to record and store historical data from exercises or operations. Consequently, it was decided to generate artificial data for the research by using a simulator to perform hundreds of military operations. These simulations recorded, stored, and parsed data at every second of combat, capturing the state of military equipment, supplies, attack progress, maneuvers, and the final state of each operation according to the various tactical actions of the allied forces [12].

For collecting training data, the constructive simulation system WASP, developed by the Czech company VRGroup, was selected. The advantage of this simulator lies in its ability to operate in layers, like the well-known Photoshop software. These layers, referred to as temporal transparencies, allow for the use of individual, separate transparencies from any second of the simulation [13].

Fig. 7 illustrates the wiring diagram of the experiment. A WASP simulator was connected to the existing C2 system used in the Czech Army using an API interface, which facilitated the execution of hundreds of simulations based on the created scenario. The simulator also includes a graphical interface with a real-time overview of the combat situation and the actual orders executed by each entity participating in the combat which can be seen on Fig. 8.

In addition to the simulation results, the log stores crucial parameters such as unit ID, unit type, current damage, current position in three coordinate systems, degree of rotation, and the current command being executed by the entity. These parameters are recorded every second during combat, allowing for subsequent data analysis to examine the effectiveness and impact of each commander’s decisions.

Fig. 9 illustrates a simplified tactical situation with a limited number of entities to clearly demonstrate the problem being addressed. The outcome of hundreds of simulations is an optimized offensive plan for the blue team. Initially, five allied units (blue squares marked with numbers 1 to 5) face four enemy troop entities (red squares marked with numbers 1 to 4). The situation is depicted in three phases of combat: the initial deployment of units in dark colors, the subsequent advance by allied units, and the reaction of enemy units forming a defensive line. The offensive culminates with the allied units developing into a V-shaped offensive formation.

After hundreds of simulation interventions, the simulator identified the most effective offensive strategy as a V-type offensive formation, as indicated by the neon line. It is also noteworthy that the final enemy unit deployment splits the four-entity formation into pairs, with one pair targeting the upper portion of the allied units (blue squares 1 to 3) and the other pair targeting the lower portion of the allied units (blue squares 4 and 5). Simultaneously, red entity 2 has moved closer to the pair of red entities 3 and 4 due to the numerical superiority of the blue entities from the northwest.

The example provided in the figure above serves as a simplified illustration to facilitate the description of the problem; however, the simulator can conduct more extensive operations involving a greater number of entities. Crucially, the thousands of lines of code generated from the simulation logs will be used to develop a custom neural network. The availability of historical data from which the neural network can learn is generally critical, enabling it to provide commanders with relevant data for decision-making.

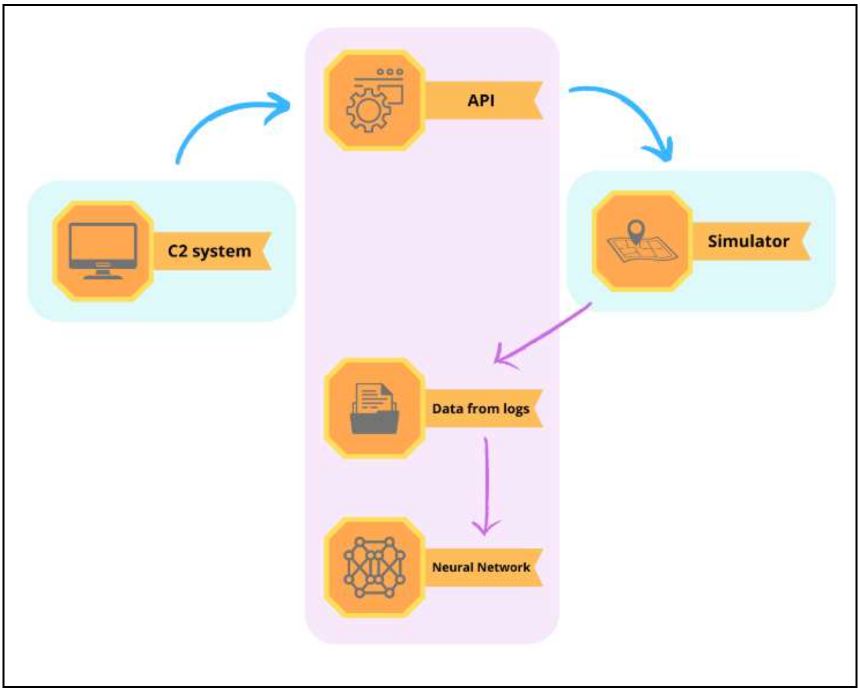

Fig. 7 Data flow between C2 system, simulator and neural network

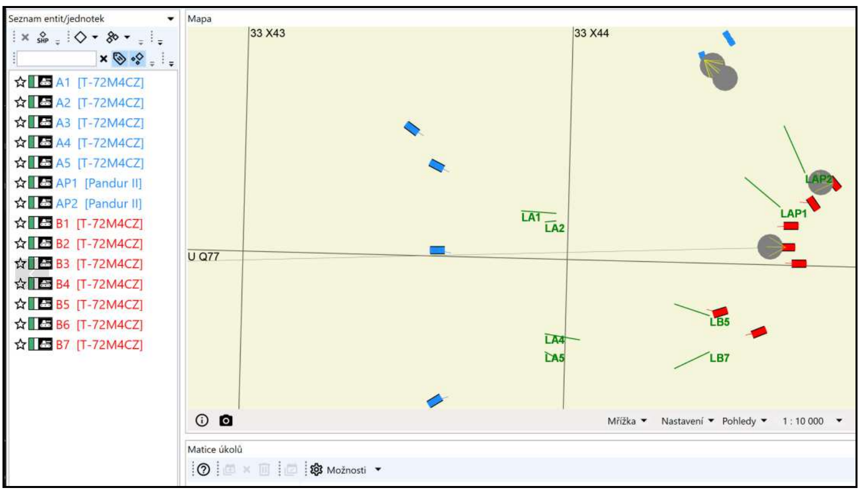

Fig. 8 Graphic User Interface (GUI) of WASP simulator

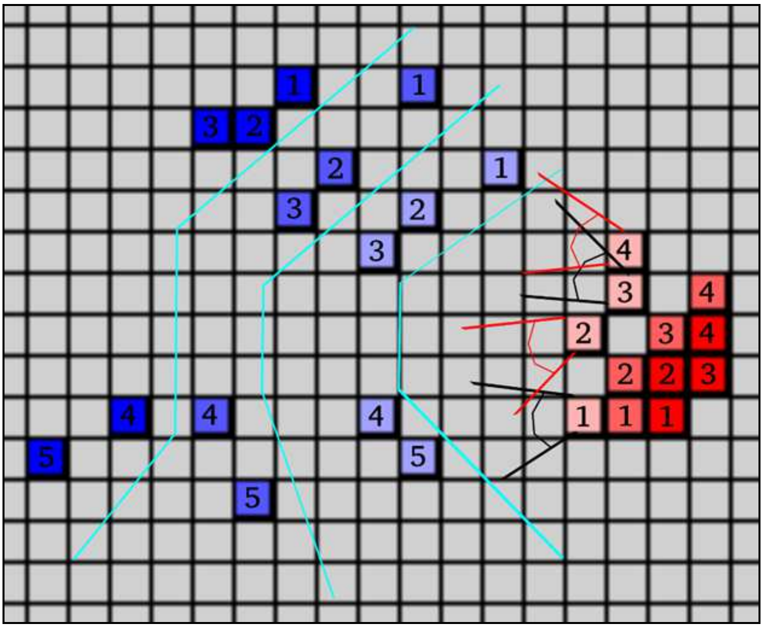

Fig. 9 NN output for the most appropriate tactical unit location

4.2 Data Generation Time Consumption

There exists a direct proportionality between the relevant output of neural networks and the amount of training data. In an experiment, the generation of scenarios and training data underwent temporal testing, with each iteration measured to evaluate efficiency. The relationship between AI systems and the volume of their training datasets is pivotal, as the quantity and quality of data directly influence the performance and accuracy of neural networks. The manual generation of training data is a time-consuming and labor-intensive process, often resulting in slower development cycles and potential data inconsistencies. In contrast, utilizing AI to automate data generation accelerates the process, ensuring the creation of larger, more diverse datasets that enhance the neural network's learning capabilities. This efficiency is of paramount importance in Command and Control (C2) systems, where AI subsystems facilitate rapid data processing, real-time decision-making, and adaptive responses to dynamic environments, thereby ensuring operational superiority and mission success. A significant drawback of the data generation approach used in this experiment is that the creation of scenarios was manually coded in the simulator's source code. In the subsequent phases of the research, a different simulator will be utilized, capable of generating data much faster due to Protocol Buffers serialization. This time efficiency comparison is visualized in Fig. 10 [13].

The lack of automation for generating training data for the simulator highlighted a critical aspect of the research: the time-consuming nature of data preparation. When manual changes were made to the source code for each simulation, it took 220 minutes (3 hours and 40 minutes) to generate 200 simulation scenarios. In contrast, using a different simulator, such as MASA SWORD (which will be the subject of a subsequent chapter in the next scientific paper), the estimated time required to generate the same number of scenarios is approximately 60 minutes, representing a time reduction of approximately 73 %.

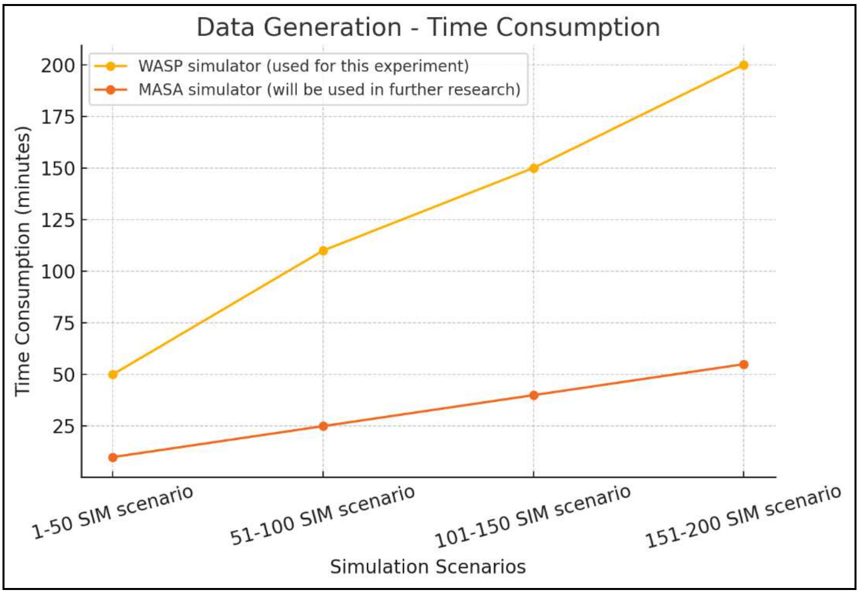

Fig. 10 Comparison of data generation time consumption

5 Conclusion and Future Approach

The primary aim of this paper was to analyze the Army's Command-and-Control system and identify potential areas within IT systems where future development could be supported by machine learning. The paper highlights several key domains within the Army where machine learning could significantly accelerate the Command-and-Control decision-making process. The experiment section practically verifies the feasibility of linking a simulator with hundreds of tactical scenarios, from which the Command Corps can derive essential insights.

In the next phase, the research will focus on employing different simulation software that utilizes Protocol Buffers serialization, which will substantially expedite the generation of training data for the simulator. Following this, an API link will be developed, incorporating a user interface for commanders to validate the new ML-based subapplication during exercises and provide critical feedback to the researchers.

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Abbreviation list

ACCS	Automated Command and Control System
AI	Artificial Intelligence
API	Application Programming Interface
BVIS	Battlefield Visualization Information System
C2	Command-and-Control

C4ISTAR	Command, Control, Communications, Computers, Intelligence, Surveillance, Target Acquisition, Reconnaissance
CSTT	Centre for Simulation and Training Technologies
DIS	Distributed Interactive Simulation
EHS	Enemy Hierarchical Structure
FMN	Federated mission Networking
GF	Ground Forces
GUI	Graphical User Interface
HAIS	Human-AI-Systems
ISR	Intelligence, Surveillance, Reconnaissance
MASA	MASA Group (company)
ML	Machine Learning
NATO	North Atlantic Treaty Organization
NVG	NATO Vector Graphics
OTS	Operational/Tactical System
RPA	Robotic Process Automation
WASP	WASP Simulation System (company)

References

[1] MEDKOVÁ, D. *Possibilities of Using Artificial Intelligence Tools over Ground Forces Battlefield Data.* [Master Thesis]. 2019, University of Defence, Brno, Czech Republic.

[2] BURITA, L. and M. HOPJAN. The Czech Army C2 and Simulation Systems and Decision-Making Support Architecture. In: *2004 Command and Control Research and Technology Symposium.* San Diego: CCRTS, 2004.

[3] HUBÁČEK, M., D. HAUSNER and V. VRÁB. The Use of Simulation Technologies in the Preparation for New Types of Operations. *Czech Military Review*, 2013, **22**(1), pp. 149-159. DOI 10.3849/2336-2995.22.2013.01.149-159.

[4] LI, H., L. YU, J. ZHANG and M. LYU. Fusion Deep Learning and Machine Learning for Heterogeneous Military Entity Recognition. *Wireless Communications and Mobile Computing*, 2022, **2022**, 103022. DOI 10.1155/2022/1103022.

[5] TURČANÍK, M. and J. BARÁTH. Intrusion Detection by Artificial Neural Networks. *New Trends in Signal Processing (NTSP)*, **2022**, 9920388. DOI 10.23919/NTSP54843.2022.9920388.

[6] LIANG, Y., X. WANG, T. YUE, S. XU, C. YAO, D. LIU and Q. LIU. Review of Live-Virtual-Constructive Simulation Technology. *Journal of Physics: Conference Series*, **2478**(12), 122080. DOI 10.1088/1742-6596/2478/12/122080.

[7] STOREY, V.C., A.R. HEVNER and V.Y. YOON. The Design of Human-Artificial Intelligence Systems in Decision Sciences: A Look Back and Directions Forward. *Decision Support Systems*, 2024, **182**, 114230. DOI 10.1016/j.dss.2024.114230.

[8] YOUN, J., K. KIM, D. KANG, J. LEE, M. PARK and D. SHIN. Research on Cyber ISR Visualization Method Based on BGP Archive Data through Hacking Case Analysis of North Korean Cyber-Attack Groups. *Electronics*, 2022, **11**(24), 4142. DOI 10.3390/electronics11244142.

[9] GIACHOS, I., E. PAPAKITSOS, P. SAVVIDIS and N. LASKARIS. Inquiring Natural Language Processing Capabilities on Robotic Systems through Virtual Assistants: A Systemic Approach. *Journal of Computer Science Research*, 2023, **5**(2), pp. 28-36. DOI 10.30564/jcsr.v5i2.5537.

[10] *Annual Report 2023 – Military Intelligence* [online]. 2023 [viewed 2024-03-18]. Available from: https://www.vzcr.cz/uploads/41-Vyrocni-zprava-2023.pdf

[11] McKERNAN, B. and H. DAVIES. *The Gospel: How Israel Uses AI to Select Bombing Targets*. *The Guardian* [online]. 2023 [viewed 2024-06-24]. Available from: https://www.theguardian.com/world/2023/dec/01/the-gospel-how-israel-uses-ai-to-select-bombing-targets

[12] *C4ISTAR Ground Force Systems* [online]. [viewed 2024-04-06]. Available from: https://www.iczgroup.com/en/products-and-services/defense/c4istar-ground-force-systems/

[13] *Company Brochure* [online]. 2018 [viewed 2024-07-25]. Available from: https://www.vrg.cz/doc/company_brochure.pdf

[14] *MASA SWORD White Paper – Multi-Site Command Post Exercise* [online]. 2024 [viewed 2024-07-11]. Available from: https://www.masasim.com/en/_files/ugd/8d4563_976b60c77bb64a068f7c722309f8a318.pdf