ISSN 2669-2023 (print) / ISSN 2538-8959 (on-line) / **https://doi.org/10.47459/cndcgs.2026.64**

A Structured Decision-Making Framework for Capability Gaps Resolution: Integrating MCDM and Constructive Simulation in Military Capability Planning

Jan DROZD[1]

Department of Military Management and Tactics, Faculty of Military Leadership, University of Defence, Kounicova 65, 662 10 Brno, Czech Republic

*Correspondence: * jan.drozd@unob.cz*

Abstract

The paper presents a hybrid methodological framework for resolving military capability gaps by integrating Multi-Criteria Decision-Making (MCDM) and constructive simulation. The purpose is to enhance defense planning transparency and objectivity. Using the Analytic Hierarchy Process (AHP), expert-driven criteria weights were established, focusing on force protection and operational effectiveness. These were validated via 200 stochastic simulation cycles in MASA SWORD, comparing conventional reconnaissance against UAV-integrated structures. Findings indicate that UAV integration (OCE = 0.7882) provides a 50.6% reduction in friendly fatalities compared to traditional methods (OCE = 0.6945). The framework offers a scalable, auditable tool for evidence-based strategic procurement.

KEY WORDS: *capability planning, Multi-Criteria Decision-Making (MCDM), constructive simulation, operational effectiveness, Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), military decision-making, force protection, UAV, MASA SWORD*

Citation: Drozd, J. A Structured Decision-Making Framework for Capability Gaps Resolution: Integrating MCDM and Constructive Simulation in Military Capability Planning. In Proceedings of the Challenges to National Defence in Contemporary Geopolitical Situation, Brno, Czech Republic, 7-10 September 2026. ISSN 2538-8959, https://doi.org/10.47459/cndcgs.2026.64

1. Introduction

Capability planning within modern armed forces is a complex, non-linear, and multi-stage process designed to ensure that military units possess the necessary operational capabilities to fulfil assigned missions effectively, decisively, and safely. In an era characterized by volatile geopolitical shifts, hybrid warfare, and rapid technological advancements, defense organizations must continuously evolve. Within the hierarchical structure of the Ministry of Defence, the capability guarantor plays a pivotal and indispensable role. This actor is directly responsible for monitoring the operational environment, identifying critical capability gaps in existing force structures, and proposing viable, sustainable solutions. Missing or obsolete operational capabilities can significantly reduce mission success rates, impair interoperability within Allied frameworks (such as NATO), and unacceptably increase risks to personnel. Therefore, the timely identification, rigorous assessment, and resolution of these gaps constitute a critical element of national defense preparedness and strategic deterrence.

Traditionally, capability development has often relied on subjective expert judgments, historical precedents, or rigid budgetary constraints, which may lack the flexibility required for contemporary defense challenges. To address these limitations, this study introduces a comprehensive methodological framework that extends and enhances the existing national capability planning guidelines. By providing a highly structured, transparent, and mathematically grounded decision-making process, the framework empowers capability guarantors to navigate complex defense procurement and organizational restructuring [1].

The core innovation of the proposed approach lies in its hybrid methodology. It systematically combines advanced analytical tools, specifically Multi-Criteria Decision-Making (MCDM) methods, with state-of-the-art constructive simulation techniques. Among the MCDM methods, the Analytic Hierarchy Process (AHP) is utilized to decompose the complex decision problem into a hierarchical structure, allowing for the consistent, expert-driven weighting of qualitative and quantitative criteria. Concurrently, the Technique for Order Preference by Similarity to Ideal

Solution (TOPSIS) is applied to rank potential alternatives based on their geometric distance from an ideal reference solution [2].

This mathematical rigor is uniquely coupled with constructive simulation, which serves as a virtual proving ground. Instead of relying solely on theoretical estimates, the simulation generates empirical, scenario-based performance data under realistic operational conditions. This integration enables a holistic and systematic evaluation of both material solutions (e.g., procurement of new weapon systems, platforms, or technology) and non-material solutions. The evaluation critically balances three competing pillars of modern military planning: operational effectiveness, resource efficiency (lifecycle costs), and force protection.

The utility and robustness of this methodology have been practically validated through a rigorous case study focused on a high-priority operational requirement: the capability to conduct continuous covert observation in contested environments. This illustrative example demonstrates how the seamless integration of AHP, TOPSIS, and constructive simulation delivers objective, quantifiable, and auditable data for comparing alternative operational courses of action. In particular, the study assesses the deployment of various classes of Unmanned Aerial Vehicles (UAVs) as a material solution. Their operational impact is rigorously evaluated against traditional, ground-based reconnaissance methods. The simulation results provide concrete evidence of substantial gains in situational awareness, mission endurance, and mission effectiveness, while simultaneously revealing a drastic reduction in casualties, thereby highlighting enhanced protection for own forces (Force Protection).

Beyond its specific application in the selected reconnaissance case study, the proposed methodological framework offers a highly scalable, modular, and adaptable tool for capability planning across diverse operational domains (land, air, maritime, cyber, and space). By embedding quantitative analysis, dynamic scenario-based simulation, and structured expert-driven criteria weighing into the core decision-making process, the framework supports evidence-based, defensible choices. It effectively bridges the gap between high-level strategic requirements and tactical imperatives, balancing the necessity of mission accomplishment with the ethical and operational imperative to safeguard personnel. Consequently, this methodology positions itself as a significant asset for modern military capability development, offering valuable utility at both the national planning level and within multinational allied frameworks.

2. Case study - Tactical Context and Scenario Parameters

The primary objective of this chapter is to systematically validate the methodological framework by applying it to a high-priority capability gap frequently encountered in modern defense planning. While the preceding sections of this paper established the mathematical foundation of the hybrid approach, this case study serves as a practical demonstration of how a capability guarantor can transition from theoretical concepts to operational execution. Within this empirical evaluation, primary attention is dedicated to the integration of Multi-Criteria Decision-Making methodologies and stochastic testing within a constructive simulation environment. To provide a complete and comprehensive walkthrough of the framework's functionality, both the statistical outputs of the constructive simulation and the subsequent calculation of the Overall Capability Effectiveness coefficient are outlined and presented. By contextualizing this entire process within a highly contested tactical scenario, the following sections demonstrate how the synergy between qualitative expert judgments and empirical simulation data effectively eliminates subjectivity, thereby providing a transparent and auditable decision-support architecture [3].

The primary motive behind this validation is to demonstrate the framework's scalability, operational functionality, and systemic robustness within a realistic force structure planning environment, explicitly focusing on how it enhances decision-making transparency and maximizes force preservation. The analysis targets a critical operational deficit often highlighted in multinational defense requirements to conduct continuous observation se reconnaissance. To preserve analytical focus and structural clarity, the preliminary phases of the capability acquisition process, specifically the initial requirement definition and the institutional alignment of the expert panel, are considered implicitly executed. Consequently, the research matrix initiates at the phase where the cross-functional expert panel is fully formed and equipped with all necessary background data to generate and filter operational courses of action.

Through a structured, multidisciplinary brainstorming process, the expert panel evaluated a wide array of potential configurations to overcome the reconnaissance capability gap. Following a strict filtering routine based on technological maturity, doctrine compliance, and feasibility constraints, two different alternatives were selected to advance to the multi-criteria evaluation stage:

- Alternative 1 (Non-Material Solution): Executing the reconnaissance and surveillance mandate exclusively through physical deployment, relying on conventional human-centric reconnaissance patrols without integrating modern robotic or autonomous technical platforms.
- Alternative 2 (Material Technology Integration): Executing the identical observation mission by organically embedding Unmanned Aerial Vehicles (UAVs) into the tactical structure of the reconnaissance elements. [4]

From a force development taxonomy perspective, Alternative 1 represents a non-material solution that leverages current capabilities already present within the active inventory. It demands modifications to tactical training, refinement of operational doctrines, and structural optimization of existing reconnaissance units. Conversely, Alternative 2 constitutes a definitive material solution, necessitating capital procurement of technological hardware, specialized type-rating training for operating personnel, and the formal integration of specialized UAV operator roles into the standard table of organization and equipment. The task of the decision engine is to objectively evaluate the non-linear trade-offs between these two distinct developmental pathways.

3. Criteria Selection and AHP Weighting Engine

The formulation of an explicit, measurable set of evaluation criteria represents the cornerstone of the proposed framework. The accuracy, validity, and predictive value of any subsequent constructive simulation are directly dependent on the qualitative relevance of its input metrics. To ensure that the selection process is free from cognitive shortcuts and emotional bias, the expert panel implemented Analytic Hierarchy Process (AHP) to establish a logically consistent criteria tree. The global objective placed at the apex of this decision hierarchy is defined as the maximization of operational effectiveness during tactical observation operations while simultaneously minimizing friendly losses. Within the brainstorming phase, the experts stratified the potential performance indicators [4].

- C1 (FFKIA) — Friendly Forces Killed in Action;
- C2 (EFKIA) — Enemy Forces Killed in Action;
- C3 (FFWIA) — Friendly Forces Wounded in Action;
- C4 (EFWIA) — Enemy Forces Wounded in Action.

During the preference elicitation phase, the experts were explicitly trained to evaluate the criteria based on their scientific information value within a constructive simulation environment rather than their emotional weight. This methodological discipline explains why FFKIA and EFKIA achieve symmetrical positioning regarding their tracking importance within the tactical system. The resulting Saaty pairwise comparison matrix is detailed in Table 1. [4]

Table 1.

Saaty Pairwise Comparison Matrix for Selected Evaluation Criteria

Criteria	FFKIA	FFWIA	EFKIA	EFWIA
FFKIA	1.00	5.00	1.00	7.00
FFWIA	0.20	1.00	0.20	3.00
EFKIA	1.00	5.00	1.00	7.00
EFWIA	0.14	0.33	0.14	1.00

To mathematically derive the relative criteria weights from the pairwise matrix while maintaining structural proportionality and logical transitivity, the geometric mean Gi for each criterion row was calculated using the following formula: [2]

$$G_i = \sqrt[n]{\prod_{j=1}^{n} x_{ij}} = \sqrt[n]{x_{i1} \times x_{i2} \times \ldots \times x_{in}} \quad (1)$$

Where G_i represents the geometric mean of the i-th evaluation criterion, n the total number of criteria ($n = 4$), and x_{ij} represents the relative importance value positioned in the $i - \text{th}$ row and $j - \text{th}$ column of the Saaty matrix. The calculated geometric means are summarized in Table 2 [4].

Table 2.

Derived Geometric Means and Normalized Weights for the Evaluation Criteria

Evaluation Criterion	Geometric Mean (Gi)	Normalized Weight (vi)
FFKIA (Friendly Killed in Action)	2.43	0.42
FFWIA (Friendly Wounded in Action)	0.59	0.10
EFKIA (Enemy Killed in Action)	2.43	0.42
EFWIA (Enemy Wounded in Action)	0.29	0.06

To convert these raw geometric products into a normalized weight vector ($\vec{w}$) that satisfies the constraints of multi-criteria scaling, the normalized weights (v_i) were computed via the standard normalization routine: [2]

$$v_i = \frac{G_i}{\sum_{i=1}^{n} G_i} \quad (2)$$

This formal computational step yields the definitive, normalized criteria weights displayed in Table 2. The mathematical results confirm that FFKIA and EFKIA function as the primary operational drivers within the capability analysis system, providing a verifiable and auditable baseline for strategic force planning [5].

4. Simulation Environment and Quantitative Performance Data

To populate the decision framework with rigorous, empirical data rather than speculative qualitative scores, the defined alternatives were subjected to quantitative testing within a high-fidelity constructive simulation environment utilizing the MASA SWORD software suite. The experimental matrix executed 100 independent stochastic cycles (Monte Carlo simulations) for each alternative. This approach embedded randomized algorithms to govern pathfinding routines, kinetic combat resolution, and tactical asset behavior, capturing the inherent friction and unpredictability of real-world military operations. Once initialized with identical tactical parameters, the simulated forces acted autonomously based on integrated artificial intelligence routines, eliminating operator intervention during execution to ensure scientific repeatability [4].

The tactical scenario modeled a specialized mechanized battalion (Friendly Forces - Blue) tasked with occupying, securing, and preparing an Assembly Area designated "ROBIN" to establish conditions for subsequent defensive operations from day D-23 to D-24. Operating against the battalion was an aggressive enemy element (Opposing Forces - Red) equivalent to a mechanized infantry company, tasked with infiltrating the sector, conducting reconnaissance, and maximizing casualties upon detecting Blue force positions. The simulation leveraged detailed, high-resolution geospatial datasets, including a digital elevation model, topographic digital models, and orthophotos integrated directly into MASA SWORD, to precisely replicate the effects of real terrain, vegetation, and lines of sight on tactical movement and sensor performance.

The security architecture of Assembly Area ROBIN was structured hierarchically in strict compliance with force protection principles across multiple perimeters:

- Mobile Security Patrols: Comprising one mechanized infantry platoon (4 armored vehicles) executing continuous 12-hour shifts within a designated security zone 5 to 10 kilometers from the core area, covering a 5 km wide sector.
- Static Area Guards: Positioned along three critical avenues of approach at a distance of 3 to 5 kilometers from the center, deploying section-sized elements (2 vehicles) on rotating 12-hour shifts.
- Command Post Security: Maintained by specialized elements from the headquarters company (up to 8 soldiers) on rotating 8-hour shifts.

The constructive simulation explicitly evaluated tactical procedures, command-and-control efficiency, and counter-reconnaissance actions against specific asymmetrical threats, including enemy snipers, covert scouting elements, and psychological factors modeled through variable unit training levels. Alternative 1 initialized the friendly force at a baseline strength of 444 soldiers, whereas Alternative 2 integrated an additional specialized team of 11 UAV operators managing 11 autonomous surveillance platforms, bringing the total friendly force strength to 455 soldiers. The resulting statistical outputs for the four target criteria (FFKIA, EFKIA, FFWIA, EFWIA) across all 200 total simulation runs provide the exact empirical baseline required for the final multi-criteria option evaluation [4].

Friendly Tactical Mandate (Blue Forces)

- Unit Designation: 21st Mechanized Battalion
- Operational Objective: Occupy, secure, and fortify tactical sector Area "ROBIN".
- Timeline: Full execution from operational hour D-23 to D-24.
- Specific Orders: Establish robust inner and outer defensive rings, implement comprehensive counter-reconnaissance measures, execute wide-area surveillance, and preserve total combat power for anticipated defensive deployment.

Hostile Tactical Mandate (Opposing Forces - Red Forces)

- Unit Designation: 1st Mechanized Infantry Company
- Operational Objective: Penetrate, scout, and harass defensive lines within Area "ROBIN".
- Timeline: Continuous combat reconnaissance infiltration from D-23 to D-24
- Specific Orders: Locate high-value Blue command infrastructure, disrupt perimeter defense security loops, and upon positive combat contact, maximize friendly personnel losses utilizing kinetic ambush tactics before extracting under fire.

5. Empirical Simulation Results and Quantitative Performance Data

Following the execution of 200 total simulation iterations (100 runs per operational course of action), the aggregated data was extracted via the MASA SWORD analytics module. The temporal progression of combat casualties, spatial engagement vectors, and statistical variance profiles were plotted across execution time.

For the primary criterion, Friendly Forces Killed in Action (C1 - FFKIA), Alternative 1 (conventional ground reconnaissance without UAVs) demonstrated severe vulnerability. Due to restricted visibility over contested high ground, ground scouts routinely blundered into close-range ambushes. The statistical mean for friendly fatalities under Alternative 1 settled at 74.1 soldiers per iteration. Conversely, Alternative 2 (UAV integration) showcased the strategic value of early threat detection. Organic aerial sensors uncovered hostile infiltration pathways at extended ranges, allowing the mechanized battalion to employ indirect organic mortar fires and pre-positioned flanking blocks before Red units reached vulnerable perimeters. Under Alternative 2, the mean for friendly fatalities was reduced to 36.6 soldiers, representing a massive 50.6% reduction in fatalities.

Analysis of the confidence intervals and variance bands reveals a highly stable data envelope. The narrow standard deviation profile around Alternative 2 confirms its consistent performance under stochastic conditions. In contrast, Alternative 1 displayed wide variance bands, emphasizing that relying strictly on human-centric scouting exposes the force to high tactical unpredictability and catastrophic outlier losses.

Furthermore, a significant temporal shift was observed in the onset of initial casualties. In Alternative 1, despite friendly troops occupying advanced listening posts directly in the terrain, kinetic contact occurred later but proved far more lethal. Under Alternative 2, initial contact occurred much earlier in the timeline, yet outside the immediate defensive perimeter. This early warning gave Blue commanders the necessary operational reaction time to coordinate defensive cross-fires, protecting the main assembly area from kinetic penetration.

The empirical data across all four target criteria are summarized in Table 3, showing the mean values derived across the total simulation envelope.

Table 3.

Empirical Simulation Results (Mean Values)

Operational Evaluation Alternative	**Mean FFKIA (C1)**	**Mean EFKIA (C2)**	**Mean FFWIA (C3)**	**Mean EFWIA (C4)**
Alternative 1 (Conventional / No UAV)	74.10	25.30	125.90	41.40
Alternative 2 (UAV Integrated)	36.60	40.00	78.10	37.50

The lethality distribution clearly highlights that Alternative 2 simultaneously maximizes force protection and offensive mission impact. Enemy Forces Killed in Action (C_2 - EFKIA) surged from 25.30 in the baseline configuration to 40.00 when supported by UAV platforms—a 58.1% increase in enemy neutralizing capability. The early acquisition of targeting coordinates allowed friendly units to engage hostile forces while they were still in their assembly areas, effectively disrupting the enemy's attack before it could gather momentum.The trauma profiles tracked via Friendly Forces Wounded in Action (C_3 - FFWIA) mirror the fatality metrics. Under Alternative 1, missing tactical visibility forced units to engage in close-quarters urban and forested firefights, resulting in a mean of 125.90 Category A1 critical casualties. By deploying organic UAV surveillance, the frequency of close-range surprise engagements dropped significantly, reducing friendly critical wounded counts to a mean of 78.10 soldiers (a 37.9% reduction in severe trauma cases).

6. Multi-Criteria Synthesis and Overall Capability Effectiveness Calculation

To convert the multi-dimensional empirical data from Table 4 into a single, auditable decision index, the simulation outputs must undergo mathematical normalization. This transformation strips away distinct operational dimensions (such as varying civilian or asset scales) and map the values to a standardized dimensionless scale bounded between 0.00 and 1.00. Because the chosen evaluation criteria contain both metrics that the commander desires to minimize (cost, friendly casualties) and maximize (enemy neutralization), separate normalization functions are applied. For minimalization criteria (where lower numerical outputs reflect optimal conditions, such as FFKIA and FFWIA), the mathematical normalization routine is structured as follows: [6]

$$R_{ij} = \frac{\max_j(X_{ij}) - X_{ij}}{\max_j(X_{ij}) - \min_j(X_{ij})} \tag{3}$$

Conversely, for maximalization criteria (where higher numerical outputs represent superior tactical performance, such as EFKIA), the mathematical mapping function is defined as: [6]

$$R_{ij} = \frac{X_{ij} - \min_j(X_{ij})}{\max_j(X_{ij}) - \min_j(X_{ij})} \tag{4}$$

Where R_{ij} denotes the computed normalized value for the $i-th$ alternative under the $j-th$ specific criterion, X_{ij} represents the raw empirical mean extracted from the simulation engine, and the bounds are set by the absolute operational minimum (min) and maximum (max) limits established across the complete experimental run matrix. Following the execution of this normalization routine across the database, the scaled performance matrix is established as detailed in Table 4.

Table 4.

Normalized simulation results and criteria weighting synthesis

Target Evaluation Criteria	Normalized Alternative 1 (R1j)	Normalized Alternative 2 (R2j)	Normalized Criterion Weight (vj)
C1 (FFKIA - Minimize)	0.8332	0.9189	0.42
C2 (EFKIA - Maximize)	0.2200	0.3478	0.10
C3 (FFWIA - Minimize)	0.7165	0.8284	0.42
C4 (EFWIA - Maximize)	0.3600	0.3261	0.06

With the normalized performance metrics R_{ij} and the definitive AHP criteria weights (v_j)established, the final calculation of the Overall Capability Effectiveness (OCE) coefficient can be executed. The mathematical engine synthesizes these parameters through a weighted linear aggregation model [7,8]:

$$OCE_i = \sum_{j=1}^{n} (R_{ij} \times v_j) \tag{5}$$

Where OCE_i represents the absolute effectiveness score for the $i - th$ alternative course of action, R_{ij} represents the normalized criteria vector, and v_j denotes the prioritized weight vector derived from the analytical hierarchy engine.
Numerical Calculation for Alternative 1 (Conventional Ground Reconnaissance)

$$OCE_{Alt1} = (0.8332 \times 0.42) + (0.2200 \times 0.10) + (0.7165 \times 0.42) + (0.3600 \times 0.06)$$

$$OCE_{Alt1} = 0.34994 + 0.02200 + 0.30093 + 0.02160 = 0.6945$$

Numerical Calculation for Alternative 2 (UAV Technical Integration)

$$OCE_{Alt2} = (0.9189 \times 0.42) + (0.3478 \times 0.10) + (0.8284 \times 0.42) + (0.3261 \times 0.06)$$

$$OCE_{Alt2} = 0.38594 + 0.03478 + 0.34793 + 0.01957 = 0.7882$$

The computed Overall Capability Effectiveness scores reveal a clear operational divergence. Alternative 1 yields an absolute efficiency score of 0.6945, whereas Alternative 2 achieves a superior rating of 0.7882. The mathematical delta ($\Delta = 0.0937$)confirms that integrating Unmanned Aerial Vehicles provides a mathematically superior capability profile compared to conventional, human-centric scouting methods.

Tracking the OCE value dynamically across the timeline provides valuable tactical insights into how this effectiveness is generated. During the initial 12 minutes of combat execution, the tracked effectiveness indices between the two alternatives remain closely aligned. This tracking symmetry occurs because the UAV assets are still in transit to their designated orbital observation sectors, meaning both configurations rely on the same baseline ground outpost parameters.

At operational mark 9:24, a temporary drop occurs in the Alternative 2 effectiveness line. Post-simulation diagnostic logs trace this dip to a momentary loss of coverage as the lead UAV transitioned between scanning sectors under adverse terrain-masking conditions. However, the most critical divergence occurs at timestamp 9:26. At this point, Alternative 1 suffers a sharp reduction in its effectiveness index, caused by hostile forces successfully penetrating the main defensive lines of Assembly Area ROBIN. This data trajectory proves that even brief gaps in situational awareness can rapidly degrade force protection and jeopardize the wider mission.

7. Conclusions

This study has successfully demonstrated the practical integration of multi-criteria prioritization engines and high-fidelity stochastic constructive simulations to resolve complex defense capability gaps. By testing a missing Continuous Covert Observation (CCO) capability inside the MASA SWORD environment, the framework shifted the evaluation process from subjective command intuition to a transparent, empirical, and auditable methodology. The mathematical calculations confirm that Alternative 2 (UAV integration) delivers a superior performance index (OCE = 0.7882) compared to conventional ground patrols (OCE = 0.6945), primarily driven by a 50.6% reduction in friendly fatalities and a significant increase in enemy neutralization capabilities.

Within this hybrid architecture, the rigorous selection of evaluation criteria and the systematic application of MCDM methodologies represent the foundational steering mechanism of the entire capability assessment. The formulation of a structured criteria tree via the Analytic Hierarchy Process ensures that the subsequent simulation experiments are strictly aligned with strategic priorities, specifically, the ethical and operational imperative of force protection. Rather than evaluating options against a single, siloed metric, MCDM provides the mathematical framework necessary to capture, balance, and resolve the non-linear trade-offs inherent in multi-dimensional combat data (such as the friction between friendly casualties, enemy attrition, and personnel trauma). By utilizing mathematically consistent pairwise comparisons and geometric mean scaling, the MCDM engine successfully insulates the decision-making process from cognitive shortcuts and emotional biases. It transforms raw, stochastic simulation data into a single, calibrated, and highly auditable utility index, thereby serving as an indispensable bridge between tactical military data and high-level strategic procurement choices [9,10].

From an institutional standpoint, these findings provide capability guarantors with a defensible, data-backed foundation for long-term strategic force planning. In a real-world force development cycle, after establishing that a material solution (UAV integration) is required, the expert panel would seamlessly transition to a secondary decision cycle focused on platform selection. This follow-on phase would use multi-criteria optimization tools, such as TOPSIS, to score specific technical systems against commercial parameters, lifecycles, and deployment profiles. By embedding quantitative criteria, scaling, stochastic verification, and auditable indexing into defense planning, this framework bridges the gap between high-level strategic guidance and tactical realities, optimizing resource allocation while safeguarding military personnel.

Acknowledgements. This work was conducted within the framework of the defence research project DZRO-FVL22-LANDOPS. The authors would like to express their gratitude to the participating subject matter experts and operational units for their valuable inputs during the capability analysis and simulation design phases. Special thanks are extended to the technical staff and simulation operators for their support in setting up and executing the constructive simulation scenarios.

References

1. Stodola, Petr, Drozd, Jan, Nohel, Jan, Michenka, Karel. Model of Observation Posts Deployment in Tactical Decision Support System. In: Modelling and Simulation for Autonomous Systems. Cham: Springer International Publishing, 2020, č. 11995, s. 231-243. ISSN 0302-9743. ISBN 978-3-030-43890-6. doi:10.1007/978-3-030-43890-6_18.
2. Zang, Dongmei; Sheng, Xinlei; Wang, Liya; Yang, Aimin; Xue, Tao et al. Research and Application of Warship Multiattribute Threat Assessment Based on Improved TOPSIS Gray Association Analysis. Online. International Journal of Digital Crime and Forensics. 2022, roč. 14, č. 3, s. 1-14. ISSN 1941-6210.
3. Drozd, Jan, Procházka, Josef. Konstruktivní simulace: účinný nástroj hodnocení operační efektivnosti v procesu plánování schopností. VOJENSKE ROZHLEDY-CZECH MILITARY REVIEW, 2022, 31(2), 54-70. ISSN 1210-3292. IF 0,100. doi:10.3849/2336-2995.31.2022.02.054-070
4. Drozd, Jan, Stodola, Petr, Rak, Luděk, Zahradníček, Pavel, Hodický, Jan. Effectiveness evaluation of aerial reconnaissance in battalion force protection operation using the constructive simulation. JOURNAL OF DEFENSE MODELING AND SIMULATION-APPLICATIONS METHODOLOGY TECHNOLOGY-JDMS, 2021, 20(2), 181-196. ISSN 1548-5129. doi:10.1177/15485129211040373
5. Palasiewicz, Tibor, Rolenec, Ota, Kroupa, Lubomír, Manas, Pavel, Coufal, Dalibor. Blast-Induced Deformations of the Building Entrance Part Caused by Improvised Shaped Charges. In: Modelling and Simulation for Autonomous Systems. MESAS 2022. Lecture Notes in Computer Science.. Cham: Springer, 2023, roč. 2022, č. 13866, s. 109-130. ISBN 978-3-031-31268-7. doi:10.1007/978-3-031-31268-7_7.
6. Hodický, Jan, Özkan, Gökhan, Özdemir, Hilmi, Stodola, Petr, Drozd, Jan, Buck, Wayne. Analytic Hierarchy Process (AHP)-Based Aggregation Mechanism for Resilience Measurement: NATO Aggregated Resilience Decision Support Model. Entropy, 2020, 22(9), 1037. ISSN 1099-4300. IF 2,524. doi:10.3390/e22091037
7. Belenky, Gregory; Balkin, Thomas J. A Wesensen, Nancy J. Military Operational Effectiveness. In: Sleep Deprivation. Boca Raton: CRC Press, 2004, s. 24. ISBN 9780429225253.
8. Artiushenko, Oleksandr. Application of Modern Methods Optimization In The Decision-Making Process Financial Support Of The Military Troops. Online. Grail of Science. 2023, č. 25, s. 46-49. ISSN 2710-3056.
9. Korec, Daniel, Blaha, Martin, Barta, Jiří, Varecha, Jaroslav. Innovative Approaches to the Use of Artillery in Wildfire Suppression. Fire-Switzerland, 2025, 8(6), 232. ISSN 2571-6255. IF 2,700. doi:10.3390/fire8060232
10. Palasiewicz, Tibor, Rolenec, Ota, Lacinová, Veronika, Bilina, Michal. A simulation-based analysis for optimal placement of anti-tank obstacles in armored warfare. Journal of Defense Modeling and Simulation, 2025(May 15, 2025). ISSN 1548-5129. IF 0,600. doi:10.1177/154851292513394