Multi-Agent System for Courses of Action Comparison in Military Operations

Clara Maathuis
Open University of the Netherlands, Heerlen, The Netherlands

clara.maathuis@ou.nl

Abstract: In military operations, decision-making often involves evaluating multiple Courses of Action (COA) under conditions of uncertainty and complexity, requiring robust tools to support planners in this critical process. On this behalf, this research introduces a Multi-Agent System (MAS) that integrates the Fuzzy Analytic Hierarchy Process (fuzzy-AHP) method for CoA comparison, providing a dynamic and distributed approach to decision-making. The system models the decision environment through interacting autonomous agents, each representing decision-makers, operational variables, and contextual factors. By incorporating Fuzzy-AHP, the system combines the structured framework of Analytic Hierarchy Process (AHP) with the uncertainty handling capabilities of fuzzy logic, enabling agents to collaboratively evaluate hierarchical decision criteria. These criteria include key technological and operational factors, assessed using fuzzy representations of expert judgments and uncertain parameters. This approach facilitates an intelligent, nuanced, and adaptive comparisons of CoA, ensuring flexibility and consistency in multi-criteria scenarios. Experimental results demonstrate that the proposed MAS model not only enhances the accuracy and interpretability of COA evaluations, but also adapts effectively to changing operational conditions, providing actionable and trustworthy insights. This work contributes to advancing Artificial Intelligence (AI)-based military decision-support tools for military operations, addressing the complexities of CoA evaluation in dynamic and uncertain environments.

Keywords: Targeting, Courses of action, Military operations, Military decision-making, Multi-criteria decision-making, Multi-Agent system, Artificial Intelligence

1. Introduction

"Uncertainty is an uncomfortable position. But certainty is an absurd one." (Voltaire)

Military operations are becoming increasingly complex and uncertain, considering rapidly evolving geopolitical landscapes, technological advancements, and the asymmetric nature of modern conflicts. This growing complexity demands decision-making processes that can compile vast amounts of data and knowledge, adapt to unpredictable scenarios, and integrate diverse perspectives from multiple sources under time-critical conditions. Traditional methods often struggle to provide the transparency, adaptability, and reliability required in such high-stakes environments. To this end, the development of responsible, transparent, and trustworthy Artificial Intelligence (AI) models represents a reliable alternative (Kraska, 2021). These models already showed valuable results in various applications and activities, are able to support both decision-making by enhancing accuracy and speed of action, and to ensure that the ethical and operational dimensions of military actions are thoroughly considered. By building AI systems that foster accountability and interpretability (Maathuis, 2023), military operations can achieve a balance between efficiency and legal, social, ethical compliance, thereby enhancing the trust and reliability of AI-enabled strategies in complex operational settings.

In particular, in relation to capturing the variability, vagueness, and complexity of various military activities and tasks, defining, analysing, comparing, and selecting most effective CoA (Course of Action) is an important tasks when planning military operations (CALL, 2023), as the success of a mission often hinges on the ability to evaluate and compare multiple alternatives under complex and uncertain conditions. This decision-making process is further complicated by the dynamic nature of military environments, where criteria such as simplicity, maneuver, security, surprise, stealth, and proportionality need to be considered simultaneously. Taking these aspects into account, the development of corresponding AI models to tackle these decision-making processes has become in recent years relevant to both researchers and practitioners in this domain. To this end, AI-based decision-support systems, particularly those that consider multi-criteria decision-making (MCDM) methodologies (Meixner, 2009; Aruldoss, Lakshmi & Venkatesan, 2013; Temucin, 2021; Costa et al., 2022) that are able to work with both expert knowledge and data, offer a structured approach to addressing these challenges. On this behalf, this research builds a Multi-Agent System (MAS) (Uhrmacher & Weyns, 2018; Kewley, Argenta & Brawner, 2022) for CoA comparison and selection applying the fuzzy AHP (Analytic Hierarchy Process) which is a robust method. This is done in order to integrate and accommodate both subjective expert judgements and uncertainty through fuzzy logic. In addition, this approach is considered given (i) valuable results obtained in tackling various problems that deal with uncertainty and vagueness in various decision-making processes, (ii) the possibility of capturing and structuring multiple criteria to be accounted in the decision-making process in an adaptive manner, and (iii) the possibility of integrating this approach in a collaborative and distributed setting in the multi-agent system proposed. By systematically capturing pairwise comparisons of criteria and alternatives, transforming linguistic evaluations into fuzzy membership functions, and aggregating expert opinions, the fuzzy-AHP method ensures transparency, reliability, and adaptability in the decision-making process. This approach includes the normalization of weights and consistency checks to ensure logical coherence, ultimately identifying the optimal CoA based on its performance across all criteria. To demonstrate the effectiveness of the proposed model, the fuzzy-AHP-based system was implemented and evaluated through one use case focusing on counter-terrorism operations. The system's design captures the roles of experts, operational flow, and domain-specific requirements, as illustrated in the domain model and operational framework. At the same time, the robustness analysis was conducted to evaluate the system's reliability under varying input conditions, ensuring consistent outputs despite inherent uncertainties in expert judgments. By addressing the complexities of operational criteria and leveraging expert input in an agentic approach (Cil & Mala, 2010), the proposed system contributes to the ongoing developments that aim to build responsible and trustworthy AI-based military systems and provide proper decision-making support in dynamic and uncertain environments.

The remainder of this article is structured as follows. In Section 2 are discussed relevant studies conducted in this research context. In Section 3, the methodological approach following for building the model proposed in this research is presented. In Section 4 the design, implementation, and evaluation results for the model proposed are discussed. At the end, in Section 5, concluding remarks and future research perspectives are tackled.

2. Related Research

Military operations represent a rapidly changing environment characterized by multiple intertwined factors such as adversary actions, resource constraints, and shifting geopolitical realities. Their planning and execution phases are thus shaped by high levels of complexity, uncertainty, and dynamism, demanding robust frameworks for intelligence gathering, risk assessment, and strategic decision-making. These frameworks need to account for both numerous operational variables ranging from personnel readiness to technological capabilities, and for the adaptability required to respond promptly to evolving threats. Thus, in this section an in-depth analysis is provided in relation to various AI mechanisms and techniques grounded in multi-agent systems and fuzzy AHP methods. Through this analysis, existing research is discussed in order to understand how these approaches enhance situational awareness, prioritize objectives, navigate the uncertainties inherent to modern military contexts, and are able to support various relevant military decision-making processes.

Multi-Agent Systems represent a relevant framework for addressing the nonlinear and dynamic nature of military operations. As discussed by Cil and Mala (2010), MAS simulate real-world systems through autonomous agents that adapt, evolve, and interact with their environment. This feature makes MAS highly effective for modelling combat scenarios and analysing interdependent problems. Furthermore, these systems allow decentralized computation and asynchronous operations, making them suitable for addressing unpredictable combat environments and enhancing decision-making in CoA analysis, comparison, and selection. In particular, military networks face unique challenges, such as increased attack surfaces and the necessity for integrating fault-tolerant systems. Hancock and Lemont (2011) emphasize the role of MAS in enhancing network defence by addressing vulnerabilities such as limited flexibility, susceptibility to direct attacks, and deception tactics. By developing distributed classifying agents, MAS improve threat detection and response, particularly in reconnaissance and cyber-attack scenarios, thereby safeguarding critical military networks. Moreover, modern combat and asymmetric warfare demand rapid and precise information dissemination in highly complex environments. Cil and Mala (2010) propose a two-layer hybrid MAS architecture to model and simulate the dynamic nature of warfare. This system integrates cognitive and reactive agents, enabling simulation of planning results for multidimensional combat needs. At the same time, the architecture offers effective decision-making support for small-unit combat scenarios, aligning with the demands of future warfare. The integration of MAS in CoA planning enhances military training and decision-making through realistic virtual simulations. Kewley, Argenta, and Brawner (2022) describe the use of MAS for generating diverse and repeatable CoA while maintaining consistency with doctrine. This model anticipates future states and provide explainable behaviours, improving after-action reviews and decision-making efficiency in virtual training environments.

Concurrently, the application of cognitive agents in military command systems facilitates advanced modelling of command behaviours in information-dense battlefields. To this end, Li et al. (2006) describe a distributed system of cognitive agents that map military command entities to autonomous functions, enabling efficient analysis and interaction through modified contract net protocols. These agents are pivotal in representing and simulating military command behaviours, providing commanders actionable insights for decision-making in complex and fast-paced scenarios.

The development of CoA involves evaluating potential solutions to military challenges based on feasibility, acceptability, and suitability. Bélanger and Guitouni (2000) propose a systematic decision support framework for CoA planning, incorporating models for event descriptions, CoA development, and evaluation criteria. This framework ensures a thorough analysis and comparison of CoA, facilitating informed decisions during contingency operations. As this is positioned in the area of MCDM, a well-known mechanism that is based on fuzzy logic and AHP is the fuzzy AHP mechanism. The Fuzzy AHP method was proposed as an effective extension of the classic AHP for tackling decision-making challenges under uncertainty. According to Aliyev, Temizkan, and Aliyev (2020), the incorporation of fuzzy sets into pairwise comparisons addresses the inherent ambiguity and inconsistencies in human judgment. This enhances decision-making processes, particularly for ranking alternatives based on a set of criteria. In the context of military decision-making, Fuzzy-AHP has proven effective for addressing issues like rank reversal and imprecise evaluations, which are common in complex, uncertain environments. Specifically, Chen et al. (2024) present an evaluation model based on Fuzzy-AHP to analyse combat outcomes and provide decision support to policymakers. This methodology bridges the gap between human and unmanned systems, offering reliable assessments for collaborative combat scenarios. Another challenging problem in this domain is the selection of the optimal Unmanned Aerial Vehicle (UAV) for military operations is a multi-criteria decision-making challenge. On this behalf, Ardil (2023) demonstrates the use of fuzzy sets to define linguistic terms for criteria evaluation, enabling decision-makers to effectively rank UAV alternatives. This methodology provides a systematic approach to UAV selection, considering payload capacity, speed, endurance, and other critical factors. Moreover, hybrid fuzzy AHP models are used for military decision-making support by combining multiple decision-making methods. In this area, Radovanović et al. (2021) integrate fuzzy AHP with VIKOR to evaluate UAV alternatives based on tactical, technical, and economic criteria. This approach enhances decision-making accuracy and supports the strategic implementation of UAVs in tactical military units.

Traditional decision-support systems, such as rule-based or static multi-criteria decision analysis (MCDA) tools, often lack the flexibility and adaptability required to handle rapidly changing, uncertain environments. By contrast, the MAS architecture, combined with fuzzy-AHP, dynamically integrates distributed, context-aware inputs from multiple autonomous agents, allowing for real-time updates and nuanced decision-making. As this extensive literature study shows, multi-agent systems and fuzzy AHP mechanisms have been used with success in various activities in the military domain for decision-making support. Nevertheless, merging these two mechanisms for developing an intelligent solution for CoA analysis, comparison, and selection is a topic that needs further attention and represents the scope of the present research.

3. Research Methodology

The aim of this research is to design a MAS for selecting the most effective CoA in military operations. On this behalf, the model was developed under the guidance of the Design Science Research methodology Peffers et al., 2007; Hevner et al., 2010). This approach integrates iterative design, implementation, and evaluation phases, focusing on creating and validating the proposed model as an artifact that addresses a practical problem in a societal context. On this behalf, given the uncertainty, complexity, and dynamism that characterize this context, the fuzzy-AHP method is applied to facilitate decision-making under uncertainty and subjectivity. The hierarchical structure of the fuzzy-AHP model includes criteria critical to military operations: simplicity, maneuver, security, surprise, stealth, and proportionality (Maathuis & Chockalingam, 2023). These criteria reflect essential dimensions of operational effectiveness, ensuring that the system aligns with tactical and strategic goals. The artifact's design phase emphasized modularity and scalability, allowing for dynamic integration of expert inputs from multiple agents and adapting to evolving operational contexts.

During the evaluation phase, for both evaluation and demonstration purposes, a use focused on conducting a counter-terrorism Cyber Operation is considered to demonstrate the system's effectiveness in a high-stakes, real-world scenario. Accordingly, the pairwise comparisons of criteria and alternatives are embedded and processed by the system to rank CoA based on their overall performance across the defined criteria. To evaluate the reliability of the system, a robustness analysis is performed for assessing the sensitivity of the CoA rankings to perturbations in expert inputs. This analysis revealed that the system maintains consistent outputs under slight variations in the input data, confirming its reliability and robustness in uncertain and dynamic environments. By combining a rigorous methodological framework with AI techniques, the system offers a transparent, adaptive, and reliable solution for selecting the most effective CoA in military operations.

4. Model Implementation

The process of defining, comparing, and selecting CoA in military operations is a systematic approach grounded in operational art and decision-making theory. A CoA is a feasible, suitable, and acceptable plan that achieves the mission while balancing risk and resource allocation. Defining a COA begins with a comprehensive analysis of the mission, enemy capabilities, terrain, and other operational factors (CALL, 2023). Once potential COA are developed, they are compared using criteria such as simplicity, maneuver, security, surprise, stealth, and proportionality. On this behalf, various methods at disposal are used to simulate the outcomes of each CoA under various scenarios for assessing how the enemy might respond and identifying vulnerabilities in each plan. In this process, decision matrices and metrics are used to assign weights to each criterion, helping prioritize options based on their relative importance to mission success. This further implies a rigorous evaluation of trade-offs, guided by principles of mission command and the operational environment's dynamics. The final CoA is then selected based on its ability to achieve military objectives effectively while minimizing associated potential risks and maximizing the use of available resources (Osoba, 2024; Fard & Maathuis, 2021; de Reus et al., 2024).

On this behalf, a MAS model is proposed in this research in order to model and simulate the agentic environment (Dorri, Kanhere & Jundak, 2018; Zhu, Dastani & Wang, 2022; Maathuis, 2022) where three different agents (i.e., military advisor, military-technical, and military-legal) are advising the military decision-maker (i.e., military commander) for selecting the most effective CoA. Each agent contributes domain-specific expertise, ensuring that CoA are evaluated comprehensively across strategic, logistical, and legal dimensions. In order to do that, under the MCDM framework, the fuzzy-AHP method is applied so that the system proposed handles uncertainty and provides a structured evaluation, enabling decision makers to make informed decisions even under incomplete information. Additionally, MAS supports the planning phase by simulating potential future states and behaviours, improving operational foresight. In this system, the models have a shared knowledge base that contains mission data, intelligence, constraints, legal guidelines, resource information, and historical lessons learned where each agent accesses the relevant part of the knowledge base to perform its assessment. To propose the decision, the outputs from the three agents are modelled into a recommendation using the fuzzy-AHP mechanism that will be further explained. This implies going through the following steps:

Step 1 (Selection of experts): the agents (i.e., experts) are selected to provide their evaluations through own judgement, which form the foundation for pairwise comparisons in the subsequent steps. The quality of the decision process depends significantly on their background.

Step 2 (Criteria determination and hierarchy construction): The decision problem is broken down into a hierarchy of criteria and alternatives. The hierarchy structure starts with the overall goal, followed by the evaluation criteria, and ends with the alternatives. This ensures that the decision process is systematically organized.

Step 3 (Matrix comparison): the importance of each criterion is compared alternative in pairs, relative to the decision goal, forming pairwise comparison matrices, as defined in Equation 1. These matrices quantify the subjective importance of criteria and alternatives using linguistic terms (e.g., "more important," "equally important").

$$\tilde{C}_{\mathrm{k}} = \begin{bmatrix} 1 & \tilde{c}_{12} & \cdots & \tilde{c}_{1\mathrm{n}} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{c}_{\mathrm{n}1} & \tilde{c}_{\mathrm{n}2} & \cdots & 1 \end{bmatrix} \tag{1}$$

Step 4 (Fuzzification and Aggregation of options): the linguistic evaluations are transformed into triangular fuzzy membership functions to handle vagueness and uncertainty. The opinions of all experts are aggregated using the arithmetic mean, ensuring a unified representation of group judgment.

Step 5 (Fuzzy Weight Matrix calculation and consistency check): the fuzzy weight matrix is calculated from the aggregated fuzzy evaluations. Consistency is then checked to ensure that subjective judgments are logically coherent. This step verifies the reliability of the input data by ensuring the consistency ratio meets acceptable thresholds.

Step 6 (Weights normalization): the fuzzy weights are normalized to maintain consistency and comparability across criteria. This step ensures that the decision-making process is unbiased and mathematically sound, aligning the weights with the overall hierarchy.

Step 7 (Selection of the best alternative): the final scores for each alternative are calculated by multiplying the weights of the criteria with the scores of the alternatives on those criteria. The total scores are summed to rank the alternatives, with the one having the highest score being selected as the best choice.

For demonstration and evaluation, a Cyber Operation that was built and simulated with military experts in a virtual environment is used (Maathuis, Pieters & van den Berg, 2018; Maathuis, Pieters & van den Berg, 2021; Maathuis & Ambtman, 2025). In this operation, a counter-terrorism Cyber Operation is conducted by a Coalition of 12 countries in order to prevent a terrorist attack of the Terrmisous group on a commercial cargo ship which contains chemical agents, being positioned near the civilian port AricikPortus. Accordingly, the following three CoA are considered:

- CoA 1 aims to bring down the power grid of VicikPortus where the terrorist group aims to load their cargo ship. In this CoA, during a previous intelligence operation, a BlackEnergy3-based malware was injected and would be used.
- CoA 2 aims to temporally neutralize the services of the civilian pump station from VIcikPortus where the terrorist group aims to load their cargo ship with fuel. This implies conducted a DDoS attack based on a previously unpatched software vulnerability.
- CoA 3 aims to alter the ship course so that it would not reach its intended target after leaving the VicikPortus. This would be conducted through a GNSS spoofing that would alter its location, velocity, and heading.

On this behalf, the three agents are considered for comparing the alternatives, and for each of them, the pairwise comparison of criteria is depicted in Figure 1. Accordingly, the values considered for all alternatives given the criteria established (i.e., simplicity, maneuver, security, surprise, stealth, and proportionality) are depicted in this picture.

	Simplicity	Maneuver	Security	Surprise	Stealth	Proportionality
Simplicity	9	7	11	10	12	5
Maneuver	11	9	13	13	15	8
Security	7	5	9	8	10	4
Surprise	8	5	10	9	11	6
Stealth	6	3	8	7	9	4
Proportionality	13	10	14	12	14	9

	Simplicity	Maneuver	Security	Surprise	Stealth	Proportionality
Simplicity	9	8	9	10	13	7
Maneuver	10	9	10	12	16	9
Security	9	8	9	10	12	8
Surprise	8	6	8	9	12	5
Stealth	5	2	6	6	9	3
Proportionality	11	9	10	13	15	9

	Simplicity	Maneuver	Security	Surprise	Stealth	Proportionality
Simplicity	9	7	9	9	12	11
Maneuver	11	9	11	9	14	13
Security	9	7	9	9	11	11
Surprise	9	9	9	9	13	13
Stealth	6	4	7	5	9	9
Proportionality	7	5	7	5	9	9

Figure 1: Pairwise comparison of criteria for the three experts

Furthermore, in Figure 2 the final scores are displayed scores as crisp (non-fuzzy) values, representing the aggregated overall performance of each alternative across all evaluation criteria. The alternative with the highest final score is identified as the preferred or optimal choice, which, in this case, corresponds to CoA 2.

	Simplicity	Maneuver	Security	Surprise	Stealth	Proportionality	
Weights	0.13	0.063	0.169	0.148	0.43	0.061	
	Scores						Total
CoA 1	0.32	0.32	0.24	0.34	0.14	0.59	0.249
CoA 2	0.49	0.5	0.47	0.35	0.39	0.97	0.453
CoA 3	0.19	0.18	0.29	0.31	0.46	0.88	0.382

Figure 2: Weights for the criteria considered for all three alternatives together with their overall total score

The distribution of the criteria weights is further depicted in the chart below:

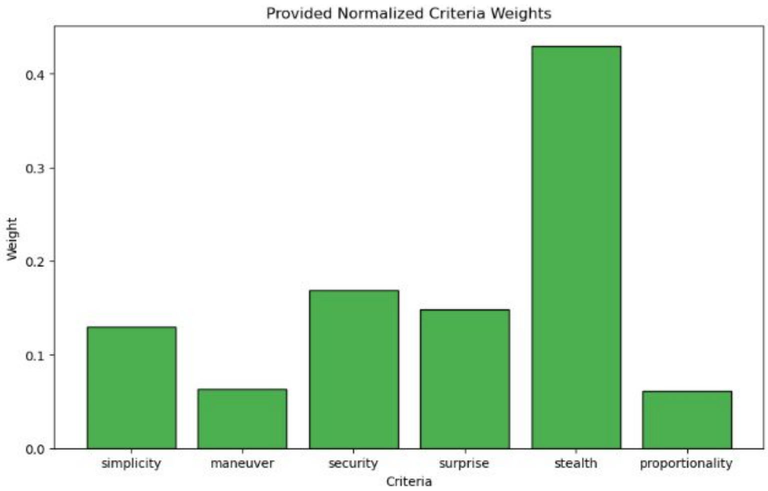

Figure 3: Weights for the criteria considered

Shortly, criteria weight derivation is achieved through the integration of the fuzzy-AHP method within the MAS framework to ensure that decision-making accounts for both the hierarchical structure of criteria and the inherent uncertainty in this operational context. The process begins with pairwise comparisons of decision criteria, where autonomous agents provide judgments using linguistic variables that are represented by fuzzy numbers to capture uncertainty and imprecision. These fuzzy pairwise comparisons are then synthesized using fuzzy comparison matrices, which are processed to calculate the fuzzy weights of each criterion. To ensure consistency and reliability in the derived weights, defuzzification is applied to convert fuzzy outputs into crisp weights.

At the same time, the preference among the agents for selecting CoA 2 as being the most effective one is illustrated in Figure 4. Here it can be seen that the preference score obtained by CoA 1 is 22.9%, by CoA 2 is 41.8%, and by CoA 3 is 35.3%.

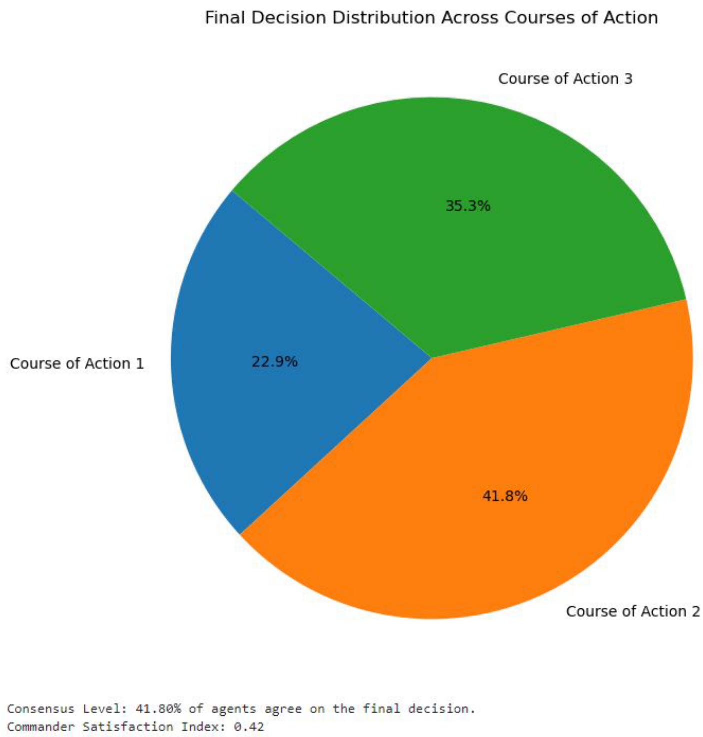

Figure 4: CoA selection result

Furthermore, an important evaluation component is the robustness analysis of the system. This evaluates the stability and realiability of the system when subjected to variations or perturbations in input data for assuring that the system's recommendations remain consistent despite changes in expert evaluations. This is especially necessary as the system relies on pairwise comparisons that may be nfluenced by differing expertise levels, biases, or incomplete information. Perturbations in the input data, such as minor changes in the evaluations of criteria or alternatives, could potentially affect the final rankings. Accordingly, the robustness analysis quantitatively measures how sensitive the system's output is to such perturbations, ensuring confidence in the selected CoA. The results of the robustness analysis conducted are presented in Figure 5. Specifically, the 0.06 score indicates that the multi-agent system effectively integrates the evaluations from the three agents, maintaining consistent rankings even under reasonable uncertainty or slight differences in judgments. At the same time, this shows that the system's recommendations are stable and reliable, even under slight variations in expert evaluations.

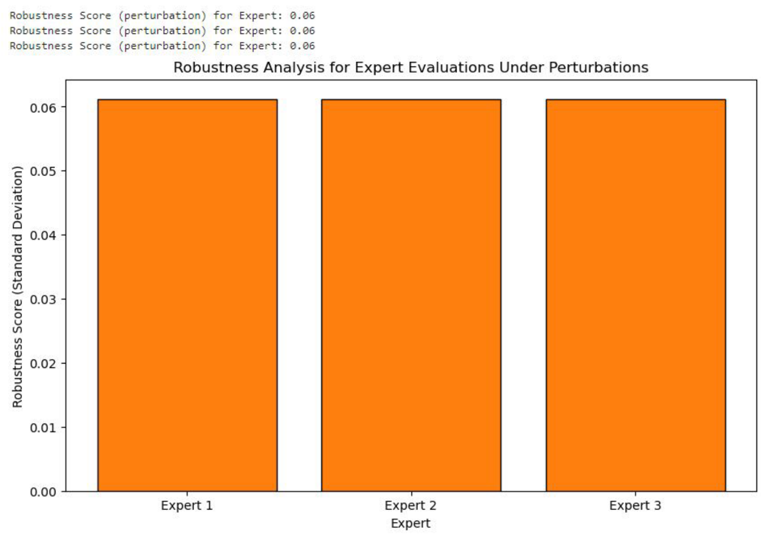

Figure 5: System’s robusntess analysis

5. Conclusions

Military operations are characterized by uncertainty, complexity, and time-critical constraints which require the development and deployment of intelligent, adaptive, reliable, and scalable decision-making support tools and capabilities. Multi-agent systems are suitable in these contexts because they allow for decentralized, cooperative problem-solving among multiple autonomous agents, each specialized in collecting intelligence, evaluating threats, or managing resources. By distributing responsibilities and enabling agents to communicate with each other, MAS provide situational awareness that would be difficult to achieve only through centralized methods. This collaboration capacity, coupled with the flexibility to incorporate diverse data sources and decision-making paradigms, makes MAS particularly valuable for supporting evidence-based CoA analysis, comparison, and selection in order to achieve intended effects and military goals. To this end, this article addresses these challenges by proposing a MAS that integrates the Fuzzy Analytic Hierarchy Process (Fuzzy-AHP) to enable a dynamic, distributed approach to military CoA comparison, analysis, and selection. This system models the decision environment via interacting agents, each representing different stakeholders and operational parameters, and leverages fuzzy logic to cope with uncertainty in expert-based assessments. By considering the Fuzzy-AHP approach, the system systematically breaks down and weighs decision criteria while incorporating imprecise or ambiguous inputs. Experimental results show that such a system represents a suitable mechanism that could be further developed in this domain. In these lines, future research could be consider in relation to (i) expanding the current architecture considering even more decision criteria or a hierarchical agent structure to manage large-scale problems efficiently, (ii) expanding the proposed system with real-time data from various sources, thereby enhancing responsiveness to rapidly evolving battlefields, goals, and perspectives, and (ii) investigating how other tangent AI techniques based on Reinforcement Learning and Machine Learning techniques could be layered or adapted onto the fuzzy decision framework to support continuous agent-level learning and further refine collaborative solution optimization.

References

Aliyev, R., Temizkan, H., & Aliyev, R. (2020). Fuzzy analytic hierarchy process-based multi-criteria decision making for universities ranking. *Symmetry*, *12*(8), 1351.

Ardil, C. (2023). Unmanned Aerial Vehicle Selection Using Fuzzy Multiple Criteria Decision Making Analysis. *International Journal of Aerospace and Mechanical Engineering*, *17*(8), 303-311.

Aruldoss, M., Lakshmi, T. M., & Venkatesan, V. P. (2013). A survey on multi criteria decision making methods and its applications. *American Journal of Information Systems*, *1*(1), 31-43.

Bélanger, M., & Guitouni, A. (2000). A decision support system for CoA selection. In *Proceedings of the 5th International Command and Control Research and Technology Symposium*.

Božanić, D., Tešić, D., & Milićević, J. (2018). A hybrid fuzzy AHP-MABAC model: Application in the Serbian Army—The selection of the location for deep wading as a technique of crossing the river by tanks. *Decision Making: Applications in Management and Engineering*, *1*(1), 143-164.

CALL (2023). Military Decision-Making Process. Center for Lessons Learned.

Chen, W., Wang, X., Yu, C., & Liang, Y. (2024). The Fuzzy Analytic Hierarchy Process for Evaluating the Effectiveness of Manned and Unmanned Collaborative Combat. In *2024 27th International Conference on Computer Supported Cooperative Work in Design (CSCWD)* (pp. 2812-2815). IEEE.

Cil, I., & Mala, M. (2009). MABSIM: A multi agent based simulation model of military unit combat. In *2009 Second International Conference on the Applications of Digital Information and Web Technologies* (pp. 731-736). IEEE.

Cil, I., & Mala, M. (2010). A multi-agent architecture for modelling and simulation of small military unit combat in asymmetric warfare. *Expert Systems with Applications*, *37*(2), 1331-1343.

Costa, I. P. D. A., Costa, A. P. D. A., Sanseverino, A. M., Gomes, C. F. S., & Santos, M. D. (2022). Bibliometric studies on multi-criteria decision analysis (MCDA) methods applied in military problems. *Pesquisa Operacional*, *42*, e249414.

Dorri, A., Kanhere, S. S., & Jurdak, R. (2018). Multi-agent systems: A survey. *Ieee Access*, *6*, 28573-28593.

Ekanayake, S. W., & Pathirana, P. N. (2007). Smart cluster bombs-control of multi-agent systems for military applications. In *2007 IEEE International Conference on Networking, Sensing and Control* (pp. 471-476). IEEE.

Fard, A. E., & Maathuis, C. (2021). Toward Capturing the Underlying Offensive Mechanisms of Social Manipulation: A Data Model Approach.

Goztepe, K., & Kahraman, C. (2015). A new approach to military decision making process: Suggestions from MCDM point of view. In *Proceedings of The International Conference on Military and Security Studies* (pp. 118-122).

Heinze, G. T. C., Goss, S., Murray, G., Appla, D., & Lloyd, I. (2000). Using Intelligent Agents in Military Simulation or “Using Agents Intelligently”.

Hevner, A., Chatterjee, S., Hevner, A., & Chatterjee, S. (2010). Design science research in information systems. *Design research in information systems: theory and practice*, 9-22.

Hancock, D. L., & Lamont, G. B. (2011, April). Multi agent systems on military networks. In *2011 IEEE Symposium on Computational Intelligence in Cyber Security (CICS)* (pp. 100-107). IEEE.

Hawkins, T., & Orechovesky, A. (2024). Applying Abstraction Techniques to Military Courses of Action. In *International Conference on Human-Computer Interaction* (pp. 368-380). Cham: Springer Nature Switzerland.

Kewley, R., Argenta, C., & Brawner, K. (2022). Behaving like soldiers: A multi-agent system approach to course of action planning for simulated military units. In *The International FLAIRS Conference Proceedings* (Vol. 35).

Kraska, J. (2021). Command Accountability for AI Weapon Systems in the Law of Armed Conflict. *International Law Studies*, *97*(1), 22.

Li, X., Wu, Y., Cao, Y., & Dong, Z. (2006). Cognitive Agents for Modeling Military Command Entities. In *2006 5th IEEE International Conference on Cognitive Informatics* (Vol. 1, pp. 176-184). IEEE.

Maathuis, C., Pieters, W., & van den Berg, J. (2018). A knowledge-based model for assessing the effects of cyber warfare. In *Proceedings of the 12th NATO Conference on Operations Research and Analysis*.

Maathuis, C., Pieters, W., & van den Berg, J. (2021). Decision support model for effects estimation and proportionality assessment for targeting in cyber operations. *Defence Technology*, *17*(2), 352-374.

Maathuis, C. (2022). An Outlook of Digital Twins in Offensive Military Cyber Operations. In *European Conference on the Impact of Artificial Intelligence and Robotics* (Vol. 4, No. 1, pp. 45-53).

Maathuis, C. (2023). Human Centered Explainable AI Framework for Military Cyber Operations. In *MILCOM 2023-2023 IEEE Military Communications Conference (MILCOM)* (pp. 260-267). IEEE.

Maathuis, C., & Chockalingam, S. (2023). Modelling the influential factors embedded in the proportionality assessment in military operations. In *International Conference on Cyber Warfare and Security* (Vol. 18, No. 1, pp. 218-226).

Maathuis, C. & Ambtman, L. (2025). Fuzzy AHP model for Courses of Action comparison in Military Operations. In *International Conference on Cyber Warfare and Security* 2025, *To Appear.*

Meixner, O. (2009). Fuzzy AHP group decision analysis and its application for the evaluation of energy sources. In *Proceedings of the 10th International Symposium on the Analytic Hierarchy/Network Process, Pittsburgh, PA, USA* (Vol. 29, pp. 2-16).

Mosadeghi, R., Warnken, J., Tomlinson, R., & Mirfenderesk, H. (2015). Comparison of Fuzzy-AHP and AHP in a spatial multi-criteria decision making model for urban land-use planning. *Computers, Environment and Urban Systems*, *49*, 54-65.

Osoba, O. A. (2024). A complex-systems view on military decision making. *Australian Journal of International Affairs*, *78*(2), 237-246.

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. *Journal of management information systems*, *24*(3), 45-77.

Radovanović, M., Petrovski, A., Žindrašič, V., & Ranđelović, A. (2021). Application of the fuzzy AHP-VIKOR hybrid model in the selection of an unmanned aircraft for the needs of tactical units of the armed forces. *Scientific Technical Review*, *71*(2), 26-35.

de Reus, N., Schadd, M. P., Maaiveld, T. M., Nyegaard, D. D. N., van den Broek, C. A. A., van der Waa, J., & Trantas, A. (2024, April). Generating Explainable Military Courses of Action. In *2024 International Conference on Military Communication and Information Systems (ICMCIS)* (pp. 1-10). IEEE.

Temucin, T. (2021). Multi-criteria decision making: A cast light upon the usage in military decision process. In *Research Anthology on Military and Defense Applications, Utilization, Education, and Ethics* (pp. 469-497). IGI Global.

Tidhar, G., Heinze, C., Goss, S., Murray, G., Appla, D., & Lloyd, I. (1999, July). Using Intelligent Agents in Military Simulation or" Using Agents Intelligently". In *AAAI/IAAI* (pp. 829-836).

Uhrmacher, A. M., & Weyns, D. (Eds.). (2018). *Multi-Agent systems: Simulation and applications*. CRC press.

Üsküdar, A., Türkan, Y. S., Özdemir, Y. S., & Öz, A. H. (2019). Fuzzy ahp-center of gravity method helicopter selection and application. In *2019 8th International Conference on Industrial Technology and Management (ICITM)* (pp. 170-174). IEEE.

Zhu, C., Dastani, M., & Wang, S. (2022). A survey of multi-agent reinforcement learning with communication. *arXiv preprint arXiv:2203.08975*, *1*.