

Genetic Algorithms for Proportionality Assessment in Military Operations

Clara Maathuis

Open University of the Netherlands, Heerlen, The Netherlands

clara.maathuis@ou.nl

Abstract: This research proposes the application of Genetic Algorithms (GAs) as an effective computational approach for proportionality assessment in military operations. With this scope, two distinct GA-based models are proposed: one evaluating proportionality excluding psychological damage from collateral damage considerations, and another integrating psychological damage into the collateral damage component of this assessment. Each model encodes the operational assessment rules as binary classification policies, mapping multidimensional states defined by levels of injury, death, object damage, and military advantage to proportional or disproportional decisions. Through evolutionary optimization involving selection, crossover, mutation, and fitness evaluation across generation, the GAs search for classification rules that maximize alignment with expert-defined proportionality judgments. From the evaluation conducted which includes accuracy, fitness progression, population diversity, and confusion matrices, it is seen that the models converge reliably to high-performance solutions, achieving high classification accuracy within the deterministic rule sets. Further, the influence of psychological damage is assessed in relation to the behaviour convergence and classification outcomes. The results show the utility of GAs in automating this military decision-making process as a responsible, transparent, adaptive, and interpretable mechanism for proportionality assessment that is able to incorporate both legal and ethical considerations in operational environments.

Keywords: Military operations, Proportionality, Artificial intelligence, Genetic algorithms, Optimization

1. Introduction

Motto: "The world is in greater peril from those who tolerate or encourage evil than from those who actually commit it." (Albert Einstein)

Recent advances in the Artificial Intelligence (AI) domain are revolutionizing military capabilities across all operational domains (Rashid et al., 2023). Autonomous ground vehicles now traverse unstructured terrain using simultaneous localization and mapping (SLAM) algorithms, while sensor-to-shooter loops leverage convolutional and transformer-based networks for rapid target detection and tracking (Min et al., 2024; Kabir et al., 2024). At the same time, swarm robotics applications integrate decentralized multi-agent coordination protocols, enabling distributed teams of unmanned aerial and maritime systems to execute complex reconnaissance, electronic warfare, and counter-insurgency tasks under contested communications (Abro et al., 2024; Alqudsi & Makaraci, 2025). Meanwhile, the integration of digital twins and synthetic training environments has accelerated AI model validation through realistic scenario replay, reducing field-trial risks and speeding deployment cycles (Maathuis, 2022; Mahajan et al., 2024; Sajadieh & Noh, 2025). These technological strides, coupled with advances in the area of AI security and Explainable AI (XAI), position AI as a transformative force in the modern battlespace.

Nevertheless, the promise of AI-enabled decision-support comes with profound legal and ethical imperatives that must guide system design from the outset. International humanitarian Law (IHL) mandates distinction, proportionality, and precautions to be taken, requiring that autonomous or semi-autonomous systems discriminate combatants from civilians, weigh military advantage against collateral damage, and implement feasible mitigation measures (Egeland, 2016; Cohen, A., & Zlotogorski, 2021; Saxon, 2021). Ethical frameworks such as the IEEE's Ethically Aligned Design and NATO's Emerging and Disruptive Technologies principles contain requirements for algorithmic transparency, bias mitigation, and human-in-the-loop oversight to preserve accountability and public trust (Ray, 2023; Bur & Leslie, 2023; Maathuis & Chockalingam, 2022). Furthermore, AI governance models argue for continuous validation, auditability of decision logs, and robust fail-safe mechanisms in order to prevent unintended escalation or misuse of the AI systems developed and deployed (Sayles, 2024). Embedding these legal and ethical constraints into reward functions, policy priors, and system architectures ensures compliance with societal norms and upholds the moral legitimacy of military AI applications.

At the core of targeting decision-support lies the principle of proportionality, one of the most consequential judgments in the engagement cycle. Under Article 51(5)(b) of Additional Protocol I, commanders must refrain from attacks whose expected incidental collateral damage on civilians and civilian objects is excessive relative to the concrete and direct military advantage (Bellal & Casey-Maslen, 2022; Maathuis & Chockalingam, 2023).

Operationalizing this requirement demands AI solutions that synthesize heterogeneous data through sources such as electro-optical imagery, human intelligence reports, and probabilistic collateral-damage models under uncertainty and time pressure (Jafariandehkordi, 2024). To this end, adaptive Reinforcement Learning (RL) and evolutionary computational techniques can learn from after-action reviews, refining estimations of non-kinetic effects such as infrastructure disruption and psychological impacts (Gautam, 2023; Lin et al., 2025; Fard & Maathuis, 2021). By continuously updating proportionality metrics and providing transparent rationales for engagement recommendations, these intelligent systems can enhance human decision-making while rigorously adhering to both legal mandates and humanitarian values.

While various research and practitioner efforts were dedicated to understand, capture, and model various dimensions of the proportionality assessment and the assessment itself, most contributions do not account a continuous refinement mechanism. While legal, ethical, and philosophical efforts delineated the contours of permissible force under IHL (Boutin, B., & Woodcock, 2024; Capone, 2025) and analyses further expanded the discourse to include concepts such as collateral psychological harm and infrastructure resilience, other efforts have translated these norms into threshold heuristics or weighted scoring models. Nevertheless, a limited number of studies incorporate adaptive learning or feedback loops that enable a system to evolve its proportionality judgments in response to operational outcomes or shifting tactical contexts. As a result, existing methods often deal with various challenges when dealing with novel scenarios or ambiguous evidence, underscoring the need for models that can self-improve and generalize beyond their initial rule sets. To address this gap, a Genetic Algorithms-based model (Pétrowski, A., & Ben-Hamida, 2017; Gerges et al., 2018) is proposed in this research for conducting the proportionality assessment in military operations as an evolutionary search for optimal classification policies. In this way, each candidate policy is encoded as a binary chromosome over the 54 possible engagement states that evolves through selection, crossover, and mutation to maximize fidelity to the proportionality rules. From here, the system is evaluated under two distinct paradigms. In the first case, collateral damage is narrowly defined by physical injury, death, and object destruction, reflecting a traditional kinetic perspective. And in the second case, the damage vector is expanded in order to include psychological harm as well, thereby embedding a more expansive humanitarian calculus. By comparing convergence dynamics, classification accuracy, and policy robustness across these two cases, the GAs system proposed demonstrates both the feasibility of adaptive proportionality modelling and the capacity to integrate evolving ethical considerations into responsible AI-enabled targeting decision-making support.

The outline of this article is structured as follows. Section 2 discusses the theoretical background of GAs and a series of relevant related studies conducted in this domain. Section 3 presents the methodological approach taken in this research. Section 4 presents the modelling context and decisions made for both use cases considered in the implementation and evaluation processes. Section 5 discusses the evaluation process and the results obtained for both cases considered. At the end, in Section 6, concluding remarks and future research perspectives are provided.

2. Research Background

Genetic Algorithms are a prominent class of optimization and search heuristics inspired by the biological principles of natural selection and genetic evolution, situated within the broader artificial intelligence paradigm. They operate by simulating the evolutionary process to progressively improve a population of candidate solutions to a given problem over successive generations. This process embodies the principle of survival of the fittest where solutions, encoded as chromosomes consisting of genes, are evaluated according to a fitness function that measures their quality or performance (Back, 1996; Sloss, A. N., & Gustafson, 2020). Through iterative genetic operations such as selection, crossover (recombination), and mutation, GAs explore the solution space by favouring higher-fitness individuals for reproduction and introducing diversity to prevent premature convergence (Pandey, H. M., Chaudhary, A., & Mehrotra, 2014; Felix-Saul et al., 2024). The population-based, stochastic nature of GAs allows them to effectively search complex, multimodal, and nonlinear problem landscapes which are often challenging for traditional deterministic or gradient-based optimization methods.

The core elements of a genetic algorithm include an initial population of encoded candidate solutions, a fitness function to evaluate solution quality, and genetic operators that evolve the population mathematically. Selection mechanisms, such as tournament or roulette wheel selection, probabilistically choose the most fit individuals to parent the next generation. In this process, the crossover operator exchanges genetic material between parents to produce offspring potentially combining advantageous traits, while mutation introduces random alterations to genes, ensuring genetic diversity and exploration of the search space (Alhijawi &

Awajan, 2024). These iterative generations continue until stopping criteria, e.g., convergence of fitness, maximum generations, or computational budget are met. Because GAs function without requiring gradient information or explicit modelling of the problem environment, they are well-suited to optimization tasks where objective functions are discontinuous, nondifferentiable, or noisy.

Further, GAs have various applications due to their flexibility, robustness, and global search capability. They are frequently employed in combinatorial optimization, machine learning model tuning, scheduling, and complex system design (Hamdia, Zhuang & Rabczuk, 2021; Zhang et al., 2023). While classic GAs rely on relatively simple encodings and operators, ongoing research focuses on hybridizing GAs with other AI approaches such as neural networks, reinforcement learning, or multi-objective optimization in order to address high-dimensional, dynamic, or uncertain environments. In supply chain management, GAs have been applied to multi-objective network design by minimizing costs and emissions while maximizing reliability, and through demonstrating significant improvements in closed-loop logistics under demand uncertainty and uncovering Pareto-optimal trade-offs in multi-echelon structure (Wu et al., 2022; Gen & Lin, 2023; Maathuis, Pieters & van den Berg, 2018). In healthcare operations, supplier selection and resource allocation problems have been formulated as multi-objective GA tasks, optimizing cost, quality, and delivery time for critical medical supplies (Mohamed et al., 2023). At the same time, in the context of environmental management during the COVID-19 pandemic, GAs optimized municipal waste collection routes and resource allocation in emergency response, achieving up to 15 % performance gains over traditional heuristics (Andelić et al., 2021; Li et al., 2021). Furthermore, for innovative product design applications such as NASA's ST5 spacecraft antenna, whose complex shape was evolved entirely by GA to meet stringent radiation-pattern requirements highlighting their versatility in engineering design tasks (Alyammahi, 2023).

In the military domain, GAs have been effectively deployed for autonomous UAV path planning, where safety constraints, dynamic obstacles, and multi-objective goals (e.g., fuel efficiency, stealth) create highly nonconvex search spaces (Pan et al., 2021; Liu, 2022). Early studies solved three-dimensional waypoint routing as a Traveling Salesman Problem, using GAs to avoid radars and terrain hazards, thereby enhancing mission success and reducing pilot workload (Ramasamy et al., 2022). More recent work integrates GA with geometric obstacle-avoidance algorithms (e.g., QuickNav), producing advance mission plans that simultaneously respect no-fly zones and real-time sensor updates, resulting in collision-free trajectories with near-optimal path length (Aizat et al., 2023; Debnath et al., 2024). At the same time, parallel implementations on multicore architectures have further improved computation speed, enabling real-time replanning in contested environments.

Moreover, in the context of multi-UAV mission planning, GAs were used for coordinated task allocation and path optimization as multi-objective evolutionary problems (Bai et al., 2022). A hybrid GA with constraint-satisfaction checks and Pareto front analysis efficiently balances makespan, fuel consumption, and coverage metrics across UAV teams, reflecting scalable performance on complex mission datasets (Alqahtani, H., & Kumar, 2024; Özer, 2024). Moreover, in emergency response scenarios such as coordinated search-and-rescue operations, improved GAs (e.g., ERRT-GA) integrate expert heuristics to escape local optima, showing faster convergence and enhanced task throughput in high-pressure, multi-agent settings (Zhan et al., 2024). These studies show GAs' ability to navigate rugged fitness landscapes inherent to joint-operations planning. Furthermore, GAs are used for sensor placement and coverage path planning for both reconnaissance and structural inspection. In one study, a Biased Random Key Genetic Algorithm (BRKGA) solved a Set-Covering Vehicle Routing Problem (SC-VRP), reducing inspection path length by up to 48 % for large 3D structures, thereby optimizing surveillance efficacy in complex terrain (Huang et al., 2023; Oliveira et al., 2024). Such applications demonstrate GAs' strength in producing high-quality, interpretable solutions for discrete, combinatorial military decision-making processes, making them to be considered valuable tools for evolving the next generation of autonomous and semi-autonomous defence systems.

3. Research Methodology

In this research, the Design Science Research methodology is applied in order to develop, evaluate, and communicate a GA-based model for proportionality assessment in military operations (Kuechler & Vaishnavi, 2012; Peffers, Tuunanen & Niehaves, 2018). The research process started with problem identification and motivation, recognizing the need for building computational models that can encode complex proportionality rules and constraints involving collateral damage and psychosocial injury considerations which serves the base for the data and rules used in this research (Maathuis, Pieters & van den Berg, 2018; Maathuis, 2022b). Following this, clear objectives were set to design and implement a GA-based decision-support artifact capable

of mapping state configurations to proportionality decisions through evolutionary optimization. Furthermore, the design and development phase involved encoding these mappings as chromosomes, defining a fitness function aligned with rule-based correctness, and iteratively applying genetic operators such as selection, crossover, and mutation. The model obtained was then instantiated and tested on representative scenarios of varying complexity to ensure it effectively internalizes target classification constraints.

From this stage, the evaluation phase comprised systematic experimentation to measure the artifact's performance through metrics like classification accuracy, fitness progression, and population diversity. The iterative nature of the GA allowed for continuous monitoring of convergence behaviours and robustness to feature complexity, exemplifying the design-as-a-search-process principle. Insights from these evaluations informed refinements of genetic parameters to balance exploration and exploitation. At the same time, the artifact's contribution to design knowledge was articulated with dual audiences in mind: technology developers aiming for implementable AI solutions, and military decision-makers requiring reliable and interpretable proportionality assessment tools. In addition, documentation and communication of the artifact's design rationale, evaluation results, and limitations complete the DSR cycle, ensuring that the GA model serves as both a practical tool and a research contribution to building responsible and trustworthy military AI (Maathuis, 2024) decision-support systems.

4. Model Implementation

In this research, the proportionality assessment is conceptualized as a combinatorial optimization challenge solvable via GAs. To this end, each candidate solution, i.e., a chromosome, encodes a complete classification policy over the 54 discrete engagement states defined by collateral-damage severity and military advantage. Furthermore, considerations for both cases are provided as follows. In Case 1, the first gene dimension represents only physical injury (Low/Medium/High) as collateral damage, whereas in Case 2 it encompasses both physical and psychological harm as collateral damage. Each gene allele takes one of two values, P (Proportional) or DP (Disproportional), thus forming a 54-bit binary string which corresponds to the number of distinct engagement states of the model. This representation ensures direct interpretability: a chromosome's complete policy can be decoded state by state to yield actionable targeting recommendations.

The process starts with the initialization of a random population of 50–100 chromosomes. Here, the fitness function quantitatively measures how closely each candidate's state–action mapping matches the expert rule set: +1 for each of the 54 correct classifications, and 0 for mismatches, yielding integer fitness in [0,54]. This dense feedback drives selection pressure toward high-accuracy policies, while preserving genetic diversity in early generations. We track both the best fitness and the average population fitness per generation to monitor convergence behaviour and population health. To evolve solutions, the following GA operators are applied:

- Selection via tournament or roulette-wheel, probabilistically favouring higher-fitness chromosomes yet allowing occasional selection of weaker candidates to prevent premature convergence.
- Crossover, implemented as one-point or uniform which recombines parental bit-strings to produce offspring that blend state decisions across both lineages.
- Mutation, executed with a low bit-flip probability (~0.01) which introduces random gene perturbations, enabling exploration of novel policy variants and maintaining genetic diversity. These operations are iterated for 500–1 000 generations (or until fitness stagnation), dynamically recording the population's diversity index, computed as the mean pairwise Hamming distance between chromosomes, to ensure a balance of exploration and exploitation .

From here, the model is executed for both use cases. Although GA hyperparameters (population size, crossover rate ≈ 0.8 , mutation rate ≈ 0.01) remain constant, the expanded semantics of Case 2 typically demand more generations to converge. Upon completion, the best chromosome is extracted and the final accuracy is computed, the confusion matrix is generated to assess misclassification patterns, and a plot for fitness and diversity curves over generations is considered. This comprehensive design facilitates the comparison of GA's capacity to discover robust proportionality policies under both strict kinetic and enriched humanitarian perspectives.

5. Model Evaluation

From the evaluation process, the GA model for Case 1 attained rapid convergence to the proportionality rules, with the best-fitness chromosome reaching the maximum score of 54 (100 % classification accuracy) by generation 120. The fitness trajectory (mean and best over generations) exhibited a steep ascent in early

generations, reflecting effective selection and crossover pressure, followed by a gradual plateau as mutation refined boundary cases. At the same time, the population diversity, measured via mean pairwise Hamming distance, declined sharply until generation 80 which shows consensus on high-fitness genes and stabilized thereafter, confirming that exploitation had overtaken exploration without complete genetic homogenization. On this point, the confusion matrix shows zero false positives or negatives across the 54 scenarios, demonstrating the GA's capacity to fully recover the deterministic rule mapping when only physical collateral damage is considered.

Furthermore, by introducing psychological harm in Case 2 increased rule complexity and expanded the semantic burden on the GA. Here, the best chromosome achieved a fitness of 52 out of 54 ($\approx 96.3\%$ accuracy) by generation 250, with the remaining mismatches concentrated in Medium psychological-damage states with High military advantage. Here, the fitness curve rose more slowly and with greater variance which reflects a more rugged fitness landscape while diversity persisted at moderate levels through generation 150, indicating prolonged exploration of alternate policy variants before convergence. Moreover, the confusion matrix depicts two misclassified states, underscoring that GA can approximate the enriched ethical calculus, but may require enhanced parameter settings (e.g., larger population or higher mutation) to guarantee full rule coverage.

From the comparative analysis conducted in this research, Case 1's simpler state semantics yielded faster convergence (≈ 120 vs. 250 generations) and sharper diversity reduction, as the fitness landscape contained a single, easily discoverable global optimum. In contrast, Case 2's enriched state space generated a multimodal landscape, delaying the discovery of near-optimal chromosomes and sustaining higher diversity to avoid premature convergence (Figure 1 and Figure 2). This difference illustrates the sensitivity of GA search efficiency to problem complexity and highlights the need for adaptive genetic operator rates or niching strategies when incorporating additional ethical dimensions into the input.

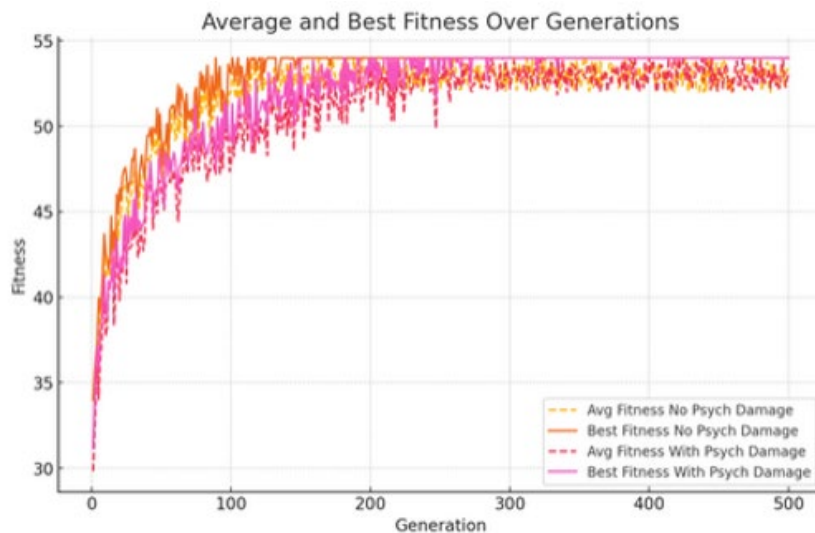


Figure 1: Best fitness over generations

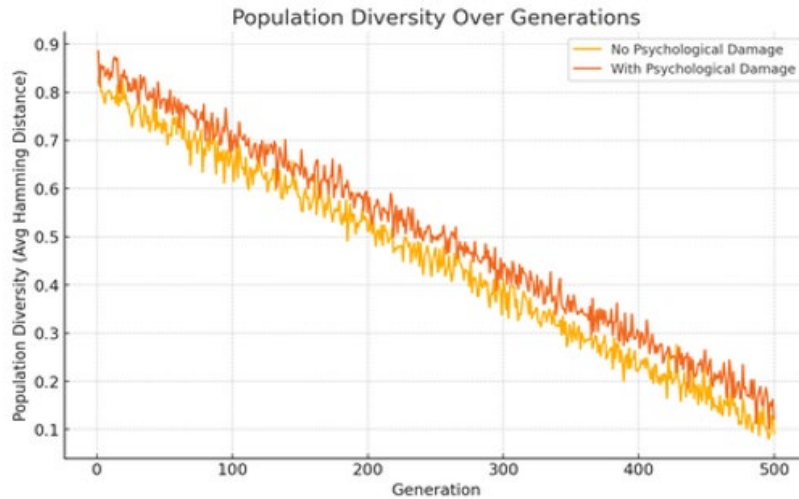


Figure 2: Population diversity over generations

Furthermore, both GA models effectively uncovered high-fidelity policies, Case 2's residual misclassifications point to the limits of fixed GA hyperparameters under more nuanced proportionality rules. The 96.3 % accuracy in Case 2, although high, falls short of the 100 % achieved in Case 1, suggesting that supplementary techniques such as hybridizing GA with local search or increasing mutation rates could bolster robustness (Figure 3 and Figure 4). Nevertheless, the GA framework demonstrates their capability for encoding both strict kinetic and expanded humanitarian perspectives by providing an interpretable, parallel search mechanism that can be tailored to balance convergence speed, diversity retention, and classification accuracy.

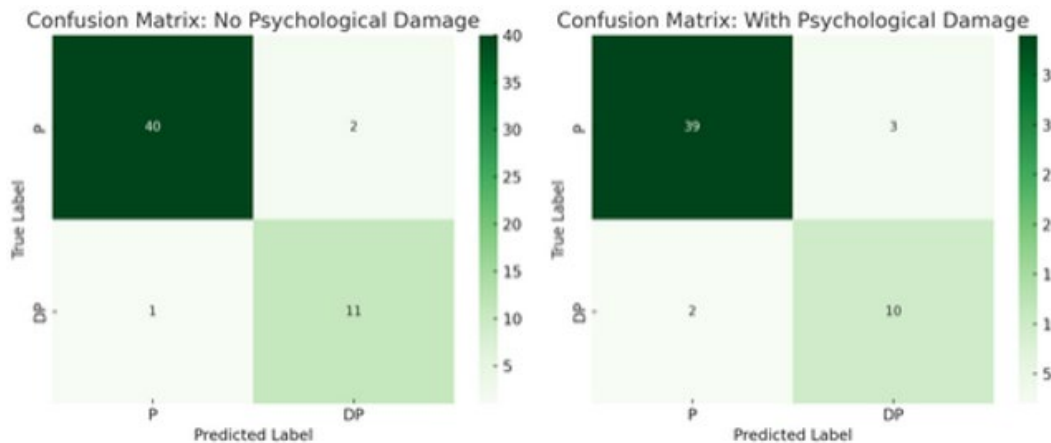


Figure 3: Confusion matrix for both cases

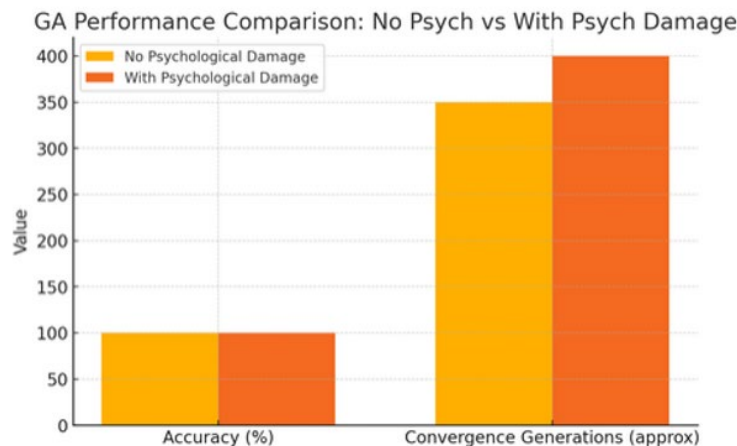


Figure 4: Accuracy and convergence for both cases

6. Conclusions

The application of GA for proportionality assessment in military operations provides a robust evolutionary computation approach capable of discovering effective classification policies for complex legal and ethical decision-making. In this research, this approach encodes candidate solutions as chromosomes representing mappings from states defined by collateral damage and military advantage attributes to proportionality decisions, i.e., being Proportional or Disproportional. The evolutionary process iteratively refines these mappings through fitness-based selection, crossover, and mutation, guided by a fitness function that rewards accurate classification against deterministic rule sets. The experimental implementation conducted in two cases, one excluding psychological damage as part of the collateral damage component and another including it, showed convergence towards near-perfect classification accuracy. In this process, the GA's global search capabilities allow it to explore alternative policy mappings, providing resilience and adaptability in the presence of potential noise or partial rule knowledge, which commonly characterizes real-world military operational contexts and environments. Visualization of fitness curves, population diversity, and confusion matrices demonstrates the GA's progressive learning and convergence stability in both simpler and enriched feature spaces, reinforcing its utility as a decision-support artifact in proportionality assessment.

From an AI and military operational perspective, this application of GAs shows the potential of evolutionary algorithms to balance exploration and exploitation within the challenge of ethically sensitive military targeting decisions. The success in both case scenarios highlights the GA's capacity to handle combinatorially large state-action spaces without requiring gradient information or explicit environment models, a critical advantage in uncertain and dynamic combat settings. Furthermore, the maintenance of population diversity throughout the evolutionary runs safeguards against premature convergence, ensuring robustness as the proportionality constraints increase in complexity with psychosocial injury considerations. From here, future research includes extending the GA framework with multi-objective optimization to integrate additional criteria such as minimizing civilian risk variance and dynamically evolving rules of engagement, which would better reflect operational realities. Another promising direction involves hybridizing GAs with deep learning or reinforcement learning techniques to leverage function approximation for continuous state spaces and enable real-time adaptability in high-stakes battlefield environments. Both the current approach and future extensions aim to enhance the practical applicability and ethical reliability of AI-enabled proportionality assessment systems in future military decision-support platforms to ensure the development and deployment of responsible and trustworthy military AI systems.

Declaration: For this research, no ethical clearance is required and no AI tools were used in the creation of this article.

References

- Abro, G. E. M., Ali, Z. A., & Masood, R. J. (2024). Synergistic UAV motion: A comprehensive review on advancing multi-agent coordination. *ICCK Transactions on Sensing, Communication, and Control*, 1(2), 72-88.
- Aizat, M., Qistina, N., & Rahiman, W. (2023). A comprehensive review of recent advances in automated guided vehicle technologies: Dynamic obstacle avoidance in complex environment toward autonomous capability. *IEEE Transactions on Instrumentation and Measurement*, 73, 1-25.
- Alqahtani, H., & Kumar, G. (2024). Efficient routing strategies for electric and flying vehicles: A comprehensive hybrid metaheuristic review. *IEEE Transactions on Intelligent Vehicles*.
- Alhijawi, B., & Awajan, A. (2024). Genetic algorithms: Theory, genetic operators, solutions, and applications. *Evolutionary Intelligence*, 17(3), 1245-1256.
- Alqudsi, Y., & Makaraci, M. (2025). UAV swarms: research, challenges, and future directions. *Journal of Engineering and Applied Science*, 72(1), 12.
- Alyammahi, E. R. A. (2023). *Antenna Design Optimization Using Evolutionary and Swarm Intelligence Algorithms* (Doctoral dissertation, Khalifa University of Science).
- Anđelić, N., Baresi Šegota, S., Lorencin, I., Mrzljak, V., & Car, Z. (2021). Estimation of COVID-19 epidemic curves using genetic programming algorithm. *Health informatics journal*, 27(1), 1460458220976728.
- Back, T. (1996). *Evolutionary algorithms in theory and practice: evolution strategies, evolutionary programming, genetic algorithms*. Oxford university press.
- Bai, H., Fan, T., Niu, Y., & Cui, Z. (2022). Multi-UAV cooperative trajectory planning based on many-objective evolutionary algorithm. *Complex System Modeling and Simulation*, 2(2), 130-141.
- Bellal, A., & Casey-Maslen, S. (2022). *The Additional Protocols to the Geneva Conventions in Context*. Oxford University Press.
- Boutin, B., & Woodcock, T. (2024). Aspects of realizing (meaningful) human control: a legal perspective. In *Research Handbook on Warfare and Artificial Intelligence* (pp. 179-196). Edward Elgar Publishing.

- Capone, F. (2025). The Centrality of the “Reasonable Military Commander Standard” in the Paradigm Shift. In *Dual-use Objects under International Humanitarian Law: Towards a Paradigm Shift* (pp. 157-194). The Hague: TMC Asser Press.
- Cohen, A., & Zlotogorski, D. (2021). *Proportionality in international humanitarian law: Consequences, precautions, and procedures*. Oxford University Press.
- Debnath, D., Vanegas, F., Boiteau, S., & Gonzalez, F. (2024). An integrated geometric obstacle avoidance and genetic algorithm tsp model for uav path planning. *Drones*, 8(7), 302.
- Egeland, K. (2016). Lethal autonomous weapon systems under international humanitarian law. *Nordic Journal of International Law*, 85(2), 89-118.
- Fard, A. E., & Maathuis, C. (2021). Toward Capturing the Underlying Offensive Mechanisms of Social Manipulation: A Data Model Approach.
- Felix-Saul, J. C., García-Valdez, M., Merelo Guervós, J. J., & Castillo, O. (2024). Extending Genetic Algorithms with Biological Life-Cycle Dynamics. *Biomimetics*, 9(8), 476.
- Gautam, M. (2023). Deep Reinforcement learning for resilient power and energy systems: Progress, prospects, and future avenues. *Electricity*, 4(4), 336-380.
- Gen, M., & Lin, L. (2023). Genetic algorithms and their applications. In *Springer handbook of engineering statistics* (pp. 635-674). London: Springer London.
- Gerges, F., Zouein, G., & Azar, D. (2018, March). Genetic algorithms with local optima handling to solve sudoku puzzles. In *Proceedings of the 2018 international conference on computing and artificial intelligence* (pp. 19-22).
- Hamdia, K. M., Zhuang, X., & Rabczuk, T. (2021). An efficient optimization approach for designing machine learning models based on genetic algorithm. *Neural Computing and Applications*, 33(6), 1923-1933.
- Huang, Y., Chen, B., Lu, W., Jin, Z. X., & Zheng, R. (2022). Asynchronous optimization of part logistics routing problem. *Journal of Global Optimization*, 82(4), 803-834.
- Jafariandehkordi, M. (2024). The AI Battlefield: Legal Challenges of Autonomous Weapon Systems under International Humanitarian Law.
- Lin, Y., Lin, F., Cai, G., Chen, H., Zou, L., Liu, Y., & Wu, P. (2025). Evolutionary reinforcement learning: A systematic review and future directions. *Mathematics*, 13(5), 833.
- Liu, J. (2022). An improved genetic algorithm for rapid uav path planning. In *Journal of Physics: Conference Series* (Vol. 2216, No. 1, p. 012035). IOP Publishing.
- Kabir, M. M., Jim, J. R., & Istenes, Z. (2024) Fusion-enhanced terrain detection and segmentation for autonomous vehicle navigation: A state-of-the-art systematic review. Available at SSRN 4797592.
- Kuechler, W., & Vaishnavi, V. (2012). A framework for theory development in design science research: multiple perspectives. *Journal of the Association for Information systems*, 13(6), 3.
- Li, D., Zhou, H., Hui, X., He, X., & Mu, X. (2021). Plasmonic biosensor augmented by a genetic algorithm for ultra-rapid, label-free, and multi-functional detection of COVID-19. *Analytical Chemistry*, 93(27), 9437-9444.
- 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. (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. (2022b). On the road to designing responsible AI systems in military cyber operations. In *European Conference on Cyber Warfare and Security* (Vol. 21, No. 1, pp. 170-177).
- Maathuis, C., & Chockalingam, S. (2022). Responsible digital security behaviour: Definition and assessment model. In *European Conference on Cyber Warfare and Security* (Vol. 21, No. 1).
- 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. (2024). Trustworthy Human-Autonomy Teaming for Proportionality Assessment in Military Operations. In *2024 4th International Conference on Applied Artificial Intelligence (ICAPAI)* (pp. 1-8). IEEE.
- Mahajan, S., Raj, P., & Pandit, A. K. (Eds.). (2024). *Deep Reinforcement Learning and Its Industrial Use Cases: AI for Real-World Applications*. John Wiley & Sons.
- Min, C., Si, S., Wang, X., Xue, H., Jiang, W., Liu, Y., ... & Li, X. (2024). Autonomous driving in unstructured environments: How far have we come?. *arXiv preprint arXiv:2410.07701*.
- Mohamed, M. F., Eltoukhy, M. M., Al Ruqeishi, K., & Salah, A. (2023). An adapted multi-objective genetic algorithm for healthcare supplier selection decision. *Mathematics*, 11(6), 1537.
- Oliveira, J. L. A., Aquino, A. L., Pinheiro, R. G., & Nogueira, B. (2024). Optimizing public transport system using biased random-key genetic algorithm. *Applied Soft Computing*, 158, 111578.
- Özer, M. M. (2024). Hybrid Genetic Algorithm Based on Machine Learning and Fitness Function Estimation Proposal for Ground Vehicle and Drone Cooperative Delivery Problem. In *Artificial Intelligence in Prescriptive Analytics: Innovations in Decision Analysis, Intelligent Optimization, and Data-Driven Decisions* (pp. 171-210). Cham: Springer Nature Switzerland.
- Pan, Y., Yang, Y., & Li, W. (2021). A deep learning trained by genetic algorithm to improve the efficiency of path planning for data collection with multi-UAV. *Ieee Access*, 9, 7994-8005.
- Pandey, H. M., Chaudhary, A., & Mehrotra, D. (2014). A comparative review of approaches to prevent premature convergence in GA. *Applied Soft Computing*, 24, 1047-1077.

- Peffer, K., Tuunanen, T., & Niehaves, B. (2018). Design science research genres: introduction to the special issue on exemplars and criteria for applicable design science research.
- Pérowski, A., & Ben-Hamida, S. (2017). *Evolutionary algorithms* (Vol. 9). John Wiley & Sons.
- Ramasamy, S., Reddinger, J. P. F., Dotterweich, J. M., Childers, M. A., & Bhounsule, P. A. (2022). Coordinated route planning of multiple fuel-constrained unmanned aerial systems with recharging on an unmanned ground vehicle for mission coverage. *Journal of Intelligent & Robotic Systems*, 106(1), 30.
- Rashid, A. B., Kausik, A. K., Al Hassan Sunny, A., & Bappy, M. H. (2023). Artificial intelligence in the military: An overview of the capabilities, applications, and challenges. *International journal of intelligent systems*, 2023(1), 8676366.
- Ray, P. P. (2023). Benchmarking, ethical alignment, and evaluation framework for conversational AI: Advancing responsible development of ChatGPT. *BenchCouncil Transactions on Benchmarks, Standards and Evaluations*, 3(3), 100136.
- Sajadieh, S. M. M., & Noh, S. D. (2025). From Simulation to Autonomy: Reviews of the Integration of Artificial Intelligence and Digital Twins. *International Journal of Precision Engineering and Manufacturing-Green Technology*, 1-32.
- Saxon, D. (2021). *Fighting Machines: Autonomous Weapons and Human Dignity*. University of Pennsylvania Press.
- Sayles, J. (2024). Aligning AI Governance with Other Internal Governance Models for Trustworthy AI: "The Convergence of Governance Frameworks". In *Principles of AI Governance and Model Risk Management: Master the Techniques for Ethical and Transparent AI Systems* (pp. 113-172). Berkeley, CA: Apress.
- Sloss, A. N., & Gustafson, S. (2020). 2019 evolutionary algorithms review. *Genetic programming Theory and practice XVII*, 307-344.
- Wu, Y., Li, X., Liu, Q., & Tong, G. (2022). The analysis of credit risks in agricultural supply chain finance assessment model based on genetic algorithm and backpropagation neural network. *Computational Economics*, 60(4), 1269-1292.
- Zhan, H., Zhang, Y., Huang, J., Song, Y., Xing, L., Wu, J., & Gao, Z. (2024). A reinforcement learning-based evolutionary algorithm for the unmanned aerial vehicles maritime search and rescue path planning problem considering multiple rescue centers. *Memetic Computing*, 16(3), 373-386.
- Zhang, F., Mei, Y., Nguyen, S., & Zhang, M. (2023). Survey on genetic programming and machine learning techniques for heuristic design in job shop scheduling. *IEEE Transactions on Evolutionary Computation*, 28(1), 147-167.