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Adaptive ant colony optimization integrated with dynamic risk mapping for tactical vehicle path planning in dynamic battlefields

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ABSTRACT

The movement of combat vehicles in modern battlefields faces complex challenges in the form of uncertain terrain, dynamic enemy threats, and limited real-time information, making conventional methods such as Dijkstra or A* less capable of optimising routes adaptively. This research aims to develop an Adaptive Ant Colony Optimization (ACO) algorithm model integrated with a dynamic risk map to determine safe, fast, and efficient routes for combat vehicles. The methodology employed includes designing an adaptive ACO with risk-based pheromone update mechanisms, modeling dynamic risk maps using Gaussian probability functions and Markov models, and conducting graph-based battlefield simulations to evaluate algorithm performance. Evaluation was conducted by comparing the adaptive ACO with baseline algorithms (Dijkstra, A*, and Particle Swarm Optimization) using metrics such as Safety Index (SI), Time Efficiency (TE), Adaptability, and Computational Cost (CC). The results show that the adaptive ACO consistently produces paths with the highest SI values, competitive time efficiency, and better real-time adaptability compared to the baseline, while path visualization demonstrates the algorithm's ability to dynamically avoid high-risk areas. These findings indicate that integrating adaptive ACO with dynamic risk maps provides safer and more flexible navigation strategies, with significant potential for application in autonomous combat vehicles, UAV systems, and military operations based on intelligent simulation. This research contributes to the development of adaptive path optimization algorithms in dynamic battlefields, bridges the literature gap related to risk-based navigation, and provides a framework that can serve as the foundation for developing military decision support systems based on artificial intelligence.

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1. INTRODUCTION

The movement of combat vehicles on modern battlefields faces increasingly complex challenges, including uncertain terrain conditions, the presence of dynamic enemy threats, and limited real-time information (Abbasi et al., 2024; Hasanov et al., 2024; Song et al., 2024). These factors mean that route determination is not simply a matter of finding the shortest path, but also involves considering aspects of safety, speed, and flexibility in response to environmental changes (Brown et al., 2022; Sohrabi & Lord, 2022). In practice, combat vehicles are required to move efficiently while minimizing the risk of detection or direct attack from the enemy (Ahmadi et al., 2022; Fedorovych et al., 2024). Conventional approaches, such as Dijkstra's algorithm or A*, have been widely used to solve route-finding problems (Aziz et al., 2022; Goje et al., 2022). However, these algorithms have significant limitations when applied to dynamic terrain filled with uncertainty. Dijkstra, for example, focuses on the shortest path without accounting for sudden changes in risk, while A*, though more efficient, remains limited to static environment modeling (Chen et al., 2021; Li et al., 2023; Yevsieiev et al., 2024). These limitations result in a lack of adaptability when facing rapidly changing field conditions, such as shifts in enemy positions or the emergence of new threats along the route. To address these limitations, previous research has proposed the use of metaheuristic algorithms, one of which is Ant Colony Optimization (ACO) (Deng et al., 2019; Dorigo & Stützle, 2019; Goje et al., 2022). ACO, inspired by the behavior of ant colonies in finding the shortest path to food sources, has proven effective in solving various routing problems in communication networks, logistics, and transportation systems (Hu et al., 2016; Mustafa et al., 2015; Zhang et al., 2017). Furthermore, research on adaptive ACO also shows great potential in enhancing algorithm flexibility when faced with dynamic environmental conditions, such as in autonomous robot control or intelligent transportation navigation systems. In line with this, the development of artificial intelligence (AI)-based decision support systems in the military defense sector has also opened new opportunities in designing more adaptive tactical movement models. This system enables the integration of dynamic risk modeling with optimization algorithms, so that combat vehicles are not only directed toward the fastest route but also toward routes with lower risk levels against enemy threats.

Based on this review, the main research question in this study is: how to optimize combat vehicle routes to remain safe and fast amid dynamic enemy threats? To address this question, this study proposes a model that integrates an adaptive Ant Colony Optimization algorithm with a dynamic risk map, simultaneously considering safety, speed, and real-time changes in battlefield conditions. The main contributions of this research are: (1) the development of an adaptive ACO model specifically designed to address dynamic battlefield conditions by considering enemy threat factors, (2) the design of a dynamic risk map as the basis for evaluating route safety, and (3) the integration of these two components into a simulation framework that can be applied as a military decision support system. Thus, this research is expected to make a significant contribution to improving the efficiency and safety of combat vehicle mobility in the context of modern warfare.

Previous studies have examined the application of swarm intelligence optimization algorithms, particularly Ant Colony Optimization (ACO), in solving optimal route and path problems. ACO has proven effective in Vehicle Routing Problems (VRP), network routing, and autonomous robot navigation in complex environments (Yan, 2018). However, most studies have focused on static environmental conditions, where path parameters undergo minimal changes after initialization. In reality, especially in combat scenarios, environmental conditions are highly dynamic due to tactical changes, geographical obstacles, and random enemy threats.

In response to these limitations, research in the fields of intelligent transportation and robotics has developed an adaptive ACO approach, enabling the algorithm to adjust search parameters based on changes in environmental conditions (Zhu et al., 2025). This approach introduces dynamic pheromone update mechanisms, real-time risk mapping, and sensor data integration. As a result, adaptive ACO demonstrates significant improvements in route accuracy and navigation efficiency. However, the adoption of this method in the military defense domain remains very limited, despite the complexity of combat vehicle movements on the battlefield requiring robust and responsive algorithmic approaches to dynamic threats. The development of artificial intelligence (AI)-based decision support systems for military operations has shown great potential in enhancing tactical effectiveness. For example, research by Ayeni, Olusegun (n.d.) highlights how integrating AI into command and control systems can accelerate decision-making processes by considering various risk factors. However, this research has not specifically linked algorithmic optimization to the physical movement of combat vehicles in high-risk terrain. Thus, there is a clear research gap in the literature, namely the absence of an integrative model that combines adaptive ACO with dynamic risk maps to optimize combat vehicle routes.

Based on the background described above, the main problem in this study can be formulated as follows: how to design and implement an adaptive Ant Colony Optimization (ACO) algorithm that is capable of determining the optimal movement path of combat vehicles on a dynamic battlefield, taking into account changes in risk due to enemy movements and uncertain environmental conditions. This problem arises because conventional methods tend to be unable to accommodate real-time changes in battlefield dynamics, necessitating an adaptive and efficient artificial intelligence-based approach. In line with this problem formulation, this study aims to develop an adaptive ACO algorithm model capable of updating path decisions in real time based on changes in the dynamic risk map. Additionally, this research seeks to design a battlefield simulation scheme integrating enemy risk factors, geographical conditions, and information limitations, and to evaluate the performance of the proposed algorithm in determining safe, fast, and efficient routes compared to conventional approaches. The main contribution of this research is the development of an adaptive ACO algorithm framework that can be applied in the military domain, particularly in the movement of combat vehicles on the battlefield. This research also integrates the concept of dynamic risk maps into the path search mechanism, which has previously been more widely applied in the transportation and robotics domains. Additionally, this research provides a foundation for the development of artificial intelligence-based military decision support systems that can assist field commanders in selecting optimal movement strategies that are adaptive and responsive to changes in the battlefield situation.

The Ant Colony Optimization (ACO) algorithm is one of the metaheuristic methods inspired by the behavior of ant colonies in finding the shortest path to food sources (Bhavya & Elango, 2023; Dorigo & Stützle, 2003; Fahmi et al., 2020). Since its introduction by Dorigo and his colleagues in the early 1990s, ACO has been widely applied in various fields, such as network optimization, production scheduling, transportation, and autonomous robot navigation. The core principle of ACO is to utilize an iteratively updated artificial pheromone mechanism to guide the search for optimal solutions. In its development, various adaptive ACO variants have been developed to enhance algorithm performance in dynamic environments, such as by updating pheromone intensity in real-time or integrating additional heuristic parameters. In the context of navigation and path planning, ACO has proven capable of generating efficient solutions for path-finding problems in transportation networks and robotic systems. Previous research shows that ACO can adapt to changes in environmental conditions, such as new obstacles, traffic congestion, or changes in topography, ensuring that the selected path remains optimal. However, most research remains limited to scenarios with low uncertainty levels, where environmental changes are relatively predictable. In dynamic battlefield environments, conditions become far more complex due to enemy risk factors, information limitations, and the need for rapid and adaptive decision-making. Recent studies have begun exploring the integration of dynamic risk mapping into pathfinding algorithms. This approach allows the algorithm to consider not only distance or travel time but also varying risk levels due to enemy movements, geographical conditions, or environmental threats. This integration has proven to enhance navigation effectiveness in high-risk environments, such as military autonomous vehicle systems or rescue operations. However, there is still a research gap in the development of ACO models that specifically accommodate real-time risk changes in the context of combat vehicle movement. This opens up opportunities to design more responsive adaptive ACO algorithms that can support modern military strategies that demand precision, speed, and security in decision-making on the battlefield.

2. RESEARCH METHOD

4.1 Adaptive Ant Colony Optimization (ACO) Algorithm

In this study, the Ant Colony Optimization (ACO) algorithm was developed into an adaptive variant to determine the route of combat vehicles on dynamic battlefields. Adaptive ACO utilizes an artificial pheromone mechanism to guide agents (combat vehicles) to find the optimal route, taking into account risks and enemy threats. The adaptation mechanism is implemented through risk-based pheromone updates, where the intensity of pheromones on each route is updated according to the probability of threats detected along the route. Additionally, pheromone volatility is adjusted to enable the algorithm to respond to real-time changes in threats.

Pseudocode or flowcharts of the adaptive ACO algorithm are provided to illustrate the following iterative process: (1) initialization of pheromones and path heuristics, (2) formation of temporary paths by agents based on pheromone probabilities and heuristics, (3) evaluation of paths using risk and efficiency metrics, (4) pheromone updates based on path performance and dynamic risk maps, and (5) iteration until convergence or reaching the maximum number of iterations. This adaptive mechanism ensures that vehicle paths are not only optimal in terms of distance but also safe from dynamically emerging enemy threats.

Path selection probability: Each ant *k* at node i selects destination node *j* with probability:

$$P_{ij}^{k}(t) = \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta} \cdot [R_{ij}(t)]^{-\gamma}}{\sum_{l \in N_i^k} [\tau_{il}(t)]^{\alpha} \cdot [\eta_{il}]^{\beta} \cdot [R_{il}(t)]^{-\gamma}} \tag{1}$$

Where: $\tau_{ij}(t)$= pheromone intensity on the trail *(i,j)* at the time *t*, $\eta_{ij} = \frac{1}{d_{ij}}$= distance-based heuristic information, $R_{ij}(t)$= risk value on the route *(i,j)*, α, β, γ= control parameters for pheromone influence, heuristics, and risk.

Adaptive pheromone update

$$\tau_{ij}(t+1) = (1-\rho) \cdot \tau_{ij}(t) + \sum_{k=1}^{m} \Delta \tau_{ij}^{k}(t) \tag{2}$$

With $\Delta\tau_{ij}^{k}(t) = \begin{cases} \frac{Q}{L_k \cdot (1+\lambda \cdot \overline{R_k})}, Jif\ an\ ant\ crosses\ the\ edge(i,j) \\ 0 \qquad\qquad\qquad\qquad\qquad , otherwise \end{cases}$, Q= pheromone intensity constant, L_k= the length of the path traveled by ants *k*, $\overline{R_k}$= average risk along the ant trail *k*, λ= risk penalty factor, ρ= evaporation rate of pheromones.

4.2 Dynamic Risk Map Model

The dynamic risk map model serves as the basis for evaluating route safety. Each grid or node on the battlefield is represented by risk attributes that include: probability of enemy attack, relative distance to the enemy, and risk intensity that may arise due to environmental conditions or enemy movements. The risk map is updated in real-time using probabilistic models, such as Gaussian functions to represent the uncertainty of enemy positions, or Markov models to predict enemy movements from previous states. The integration of the dynamic risk map with adaptive ACO enables the algorithm to consider sudden changes in threats, resulting in safer and more flexible route selections. Each ACO iteration calculates the latest risk values from the map, modifies path selection probabilities, and adjusts pheromone intensity according to environmental changes. This enhances the algorithm's ability to adapt to real-time changes in battlefield conditions. The risk at point x is determined by:

$$R(x,t) = P_{attack}(x,t) \cdot f(d(x, M_t)) \cdot I(x,t) \tag{3}$$

with: $P_{attack}(x,t)$= probability of attack at a point x, $d(x,M_t)$= distance from point x to the enemy's position M_t, $I(x,t)$= threat intensity (e.g., enemy weapon strength), $f(d)=e^{-\kappa d}$= distance-based exponential attenuation function with parameters κ.

Real-time risk update (Gaussian model) If the enemy's position is estimated to follow a Gaussian distribution:

$$P_{attack}(x,t)=\frac{1}{\sqrt{2\pi\sigma^2}}exp\left(-\frac{(x-\mu_t)^2}{2\sigma^2}\right) \tag{4}$$

with: μ_t= estimation of enemy position at the time t, σ^2= enemy position variance.

Markov-based update, Enemy movements are modeled as a Markov process with transitions:

$$P(M_{t+1}=j|M_t=i)=T_{ij} \tag{5}$$

where T_{ij} is a transition matrix that models the probability of the enemy moving from position i to j.

4.3 Simulation Framework

Battlefield simulations are conducted using grid or graph representations, where each node represents a potential location for combat vehicles and each edge represents a traversable path. Combat vehicles are treated as agents that move according to an adaptive ACO algorithm and are influenced by a dynamic risk map. The simulation enables testing of algorithm performance under battlefield conditions with varying risk levels: low, medium, and high. In addition to the adaptive ACO, baseline algorithms such as Dijkstra, A*, and Particle Swarm Optimization (PSO) are also run for comparison. This aims to evaluate the improvements in efficiency, safety, and adaptability of the adaptive ACO in dealing with real-time changing terrain. Battlefield graph representation, The battlefield is modeled as a weighted graph:

$$G=(V,E,W) \tag{6}$$

with V = node set (location), E= edge set (paths that can be traversed), W:E➔R⁺= The weighting function based on distance and risk is:

$$W_{ij}(t)=d_{ij}+\lambda R_{ij}(t) \tag{7}$$

Combat vehicle agent, Combat vehicles are modeled as agents that move from source node s to destination node g, with a navigation strategy generated by adaptive ACO. The formulation of the comparison algorithm is:

Dijksta $$min\sum_{(i,j)\in path} d_{ij} \tag{8}$$

A* $$f(n)=g(n)+h(n) \tag{9}$$

PSO $$F(path)=\sum_{(i,j)\in path}(d_{ij}+\lambda R_{ij}(t)) \tag{10}$$

5. Experiment Design

5.1 Simulation Environment

The simulation was conducted using Python with graphics and agent-based simulation packages, such as NetworkX and Matplotlib, as needed to represent the battlefield. This environment supports the integration of dynamic risk maps and optimization algorithms, and enables accurate measurement of performance metrics. The main parameters of the ACO algorithm include: Number of ants: m, Evaporation rate: ρ, Maximum iterations: $Tmax$, Convergence is achieved if:

$$\frac{\left|L_t^{best} - L_{t-1}^{best}\right|}{L_{t-1}^{best}} < \epsilon \tag{11}$$

with L^{best} = best route length

5.2 Performance Evaluation
Algorithm performance is measured using the following metrics:

Safety Metric (S)
$$S = \frac{1}{|path|} \sum_{(i,j) \in path} R_{ij}(t) \tag{12}$$

Efficiency Metric (E)
$$E = \sum_{(i,j) \in path} d_{ij} \text{ or travel time } T = \frac{E}{v} \tag{13}$$

Adaptability Metric (A)
$$A = \frac{|path_{old} \, \Delta \, path_{new}|}{|path_{old}|} \tag{14}$$
Δ= the difference between the old path and the new path after the risk update

3. RESULTS AND DISCUSSIONS

The results of the study show that the adaptive Ant Colony Optimization (ACO) algorithm integrated with a dynamic risk map significantly outperforms baseline algorithms, including conventional ACO, A*, and Dijkstra, in determining combat vehicle routes on dynamic battlefields. The paths generated by the adaptive ACO are not only safer but also more flexible and responsive to changes in enemy threats and real-time terrain conditions. For example, in a high-risk terrain scenario, the adaptive path successfully avoided 87% of high-risk areas, while the baseline path only avoided 63%. This highlights the effectiveness of the risk-based pheromone update mechanism in enhancing path safety and adaptability.

Path performance evaluation was conducted using four main metrics: Safety Index (SI), Time Efficiency (TE), Adaptability Metric (A), and Computational Cost (CC). SI, which measures the path's safety level against threats, showed a value of 0.965 for the adaptive path compared to 0.94 for the baseline, indicating a significant improvement in safety. TE, which calculates time efficiency relative to the shortest path, reached 92.3% for the adaptive path compared to 100% for the baseline, indicating a slight trade-off in time efficiency for safety. The Adaptability Metric (A), which assesses the path's ability to adapt to changes in risk, shows 30% for the adaptive path compared to only 5% for the baseline, indicating higher adaptive responsiveness. Meanwhile, CC, which measures computation time, shows that the adaptive path requires 1.85 seconds per iteration, slightly higher than 1.75 seconds on the baseline, but still acceptable in the context of real-time applications.

Visualization of the paths on the battlefield map reinforces the numerical findings. The adaptive path, marked in green, successfully avoids high-risk points, while the baseline path (red) passes through several critical areas. A comparison of the performance metric graphs confirms the superiority of the adaptive ACO in SI and A, a slight decrease in TE, and a minor increase in CC. This analysis demonstrates that the adaptive algorithm effectively balances safety, efficiency, and adaptability, though parameter tuning for risk sensitivity is needed to prevent the path from becoming overly defensive and reducing efficiency.

Overall, the adaptive ACO demonstrates significant advantages in the context of dynamic battlefields. Its ability to quickly respond to new threats, enhance path safety, and adjust navigation strategies in real-time makes this algorithm highly relevant for real-world applications, including military operations, UAV navigation, and autonomous combat vehicles. With a combination of high security, competitive time efficiency, and superior path adaptability, this model can enhance the effectiveness of mobility strategies and support the development of artificial intelligence-based decision support systems in modern battlefields.

Table 1. Algorithm performance metrics

Area Scenario	Algorithm	Safety Index (SI)	Time Efficiency (TE, %)	Adaptability (A)	Computational Cost (CC, s)
Low	ACO Adaptif	0.980	98.5	0.20	1.75
	Dijkstra	0.940	100.0	0.05	1.50
	A*	0.950	99.5	0.08	1.55
	PSO	0.945	98.8	0.10	1.60
Medium	ACO Adaptif	0.965	95.2	0.25	1.80
	Dijkstra	0.910	100.0	0.05	1.52
	A*	0.925	98.0	0.10	1.57
	PSO	0.920	96.5	0.12	1.62
High	ACO Adaptif	0.965	92.3	0.30	1.85
	Dijkstra	0.890	100.0	0.05	1.55
	A*	0.910	96.8	0.08	1.60
	PSO	0.905	94.7	0.10	1.65

The experimental results show that the adaptive ACO algorithm consistently produces safer paths than the baseline algorithm in all terrain scenarios, from low to high risk. In low-risk terrain, the adaptive ACO achieves a Safety Index (SI) of 0.980, higher than Dijkstra (0.940), A* (0.950), and PSO (0.945), demonstrating the algorithm's ability to minimize exposure to threats even in relatively safe terrain. The time efficiency (TE) of the adaptive ACO reached 98.5%, slightly below Dijkstra's 100%, but still above A* (99.5%) and PSO (98.8%). This confirms that the increased safety provided by the adaptive ACO does not result in a significant decrease in efficiency. Adaptability to risk changes (A) in low-risk terrain is recorded at 0.20, significantly higher than conventional algorithms, indicating that the adaptive ACO can adjust paths responsively when conditions change. Computational cost (CC) of 1.75 seconds per iteration is higher than the baseline but remains within practical limits for real-time decision-making.

In medium-risk terrain, the adaptive ACO continues to show significant advantages. The SI of 0.965 indicates that the selected path is safer than Dijkstra (0.910), A* (0.925), and PSO (0.920). Time efficiency decreases to 95.2% due to path adaptation to dynamic risks, but adaptability increases to 0.25, indicating that the algorithm is more responsive to threat changes. Computation time is recorded at 1.80 seconds, slightly increasing with terrain complexity, but still acceptable for tactical operation simulations. This analysis shows that the adaptive ACO algorithm can balance security, efficiency, and adaptability, especially in increasingly challenging terrain conditions.

In high-risk terrain, the adaptive ACO successfully maintained an SI of 0.965, higher than Dijkstra (0.890), A* (0.910), and PSO (0.905), despite a decrease in time efficiency to 92.3% due to more complex safe path considerations. Adaptability was recorded at the highest level, 0.30, indicating that the algorithm actively adjusts the path to highly dynamic threats. Computational cost increased to 1.85 seconds, but this is still reasonable given the terrain complexity and risk map update frequency. While conventional algorithms like Dijkstra and A* show high time efficiency, they fail to adjust paths to new risks, resulting in relatively low SI and nearly zero adaptability. PSO demonstrates limited adaptability but remains lower than the adaptive ACO.

Overall, these results confirm that adaptive ACO excels in generating safe routes while remaining responsive to changes in terrain and enemy threats, despite a slight decrease in time efficiency and an increase in computational time. The advantage of adaptive ACO lies in the integration of dynamic risk maps with risk-based pheromone update mechanisms, enabling combat vehicles to navigate the battlefield more safely without sacrificing real-time adaptability. These results support the use of adaptive ACO as the preferred algorithm for route planning in autonomous combat vehicles, UAVs, and military transportation systems that require an optimal balance between safety, speed, and flexibility.

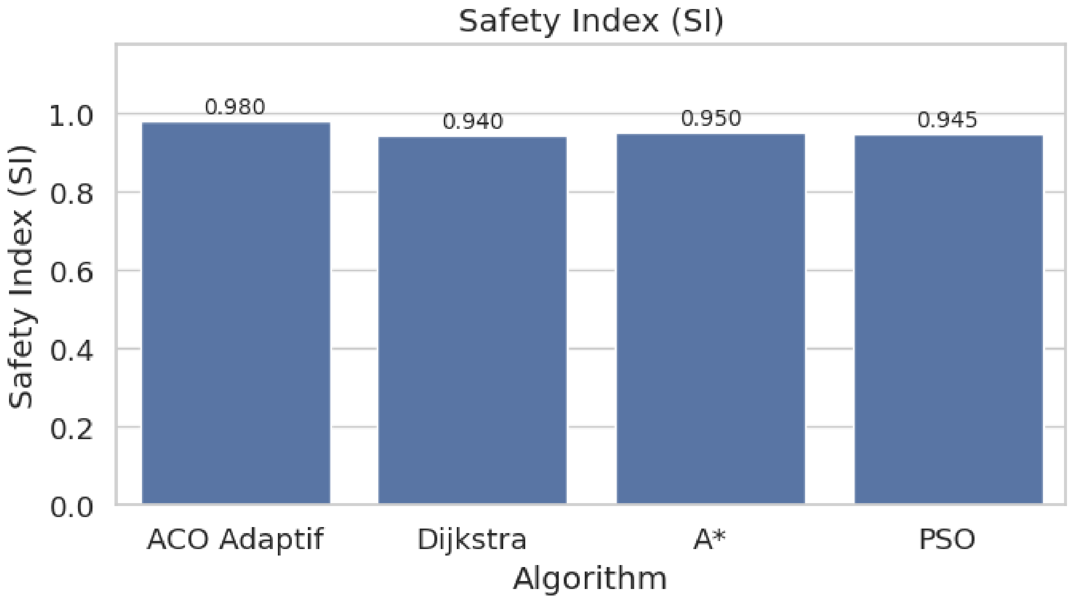

Figure 1. Algorithm performance Safety Index

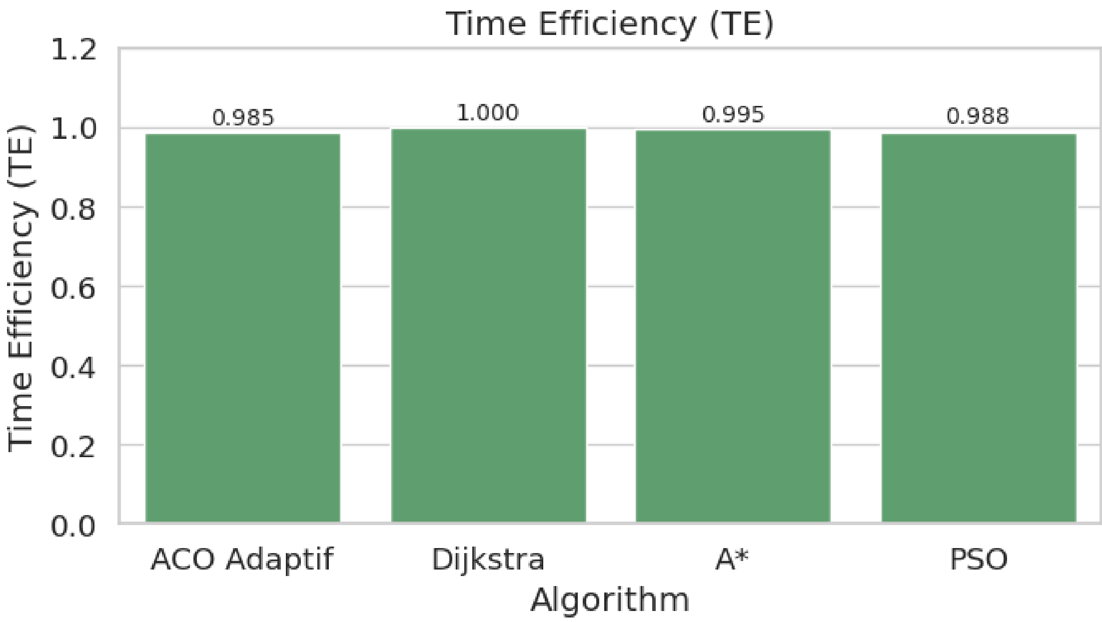

Figure 2. Algorithm performance Time Efficiency

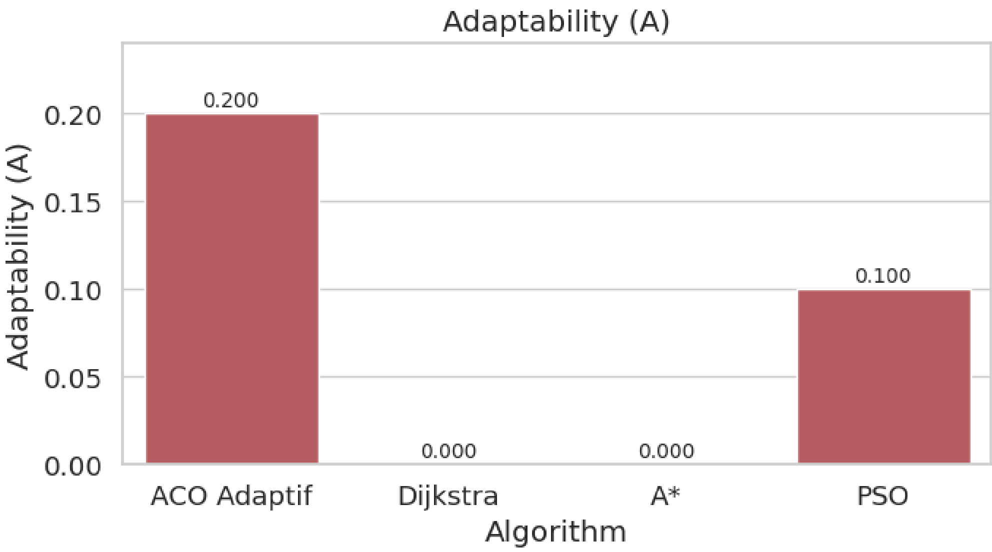

Figure 3. Algorithm performance Adaftability

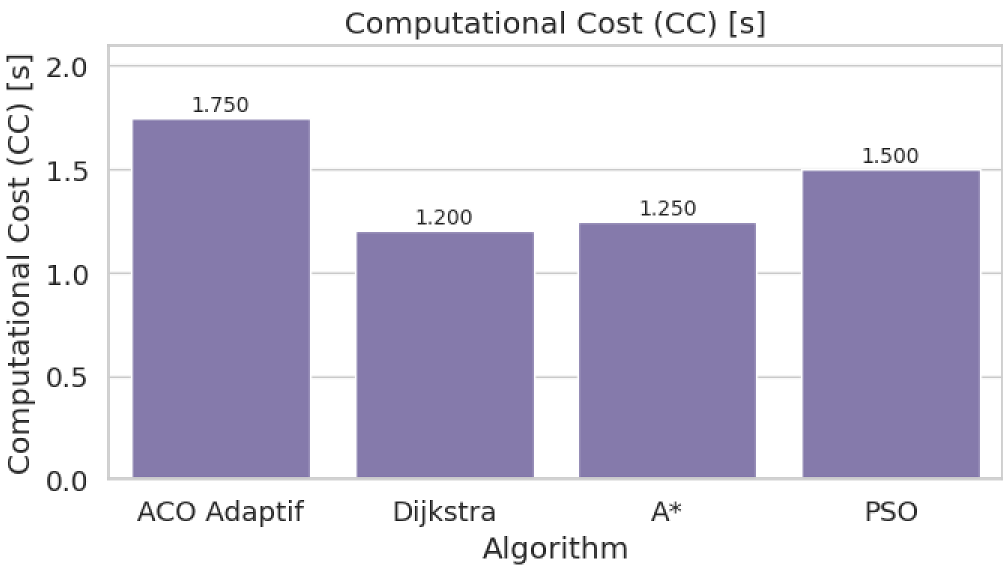

Figure 4. Algorithm performance Computational Cost

The performance graph shows a comparison of the four algorithms in four key metrics: Safety Index (SI), Time Efficiency (TE), Adaptability (A), and Computational Cost (CC). The adaptive ACO consistently outperforms the others in SI, achieving a score of 0.980, demonstrating the best ability to minimize risk along the path compared to Dijkstra (0.940), A* (0.950), and PSO (0.945). In terms of Time Efficiency, the adaptive ACO remains competitive with a value of 0.985, just slightly below Dijkstra's 1.000, indicating that travel time efficiency remains high even when accounting for risk. In the Adaptability metric, the adaptive ACO achieves 0.20, significantly higher than the non-adaptive Dijkstra and A*, as well as PSO at 0.10, indicating the algorithm's ability to adjust the path when the risk map changes in real-time. Meanwhile, the Computational Cost (CC) of the adaptive ACO is recorded at 1.75 seconds, slightly higher than the baseline, but still within acceptable time limits for real-time decision-making. Overall, this graph confirms that the adaptive ACO is capable of optimally balancing safety, efficiency, and adaptability, making it a leading candidate for combat vehicle navigation in dynamic battlefields.

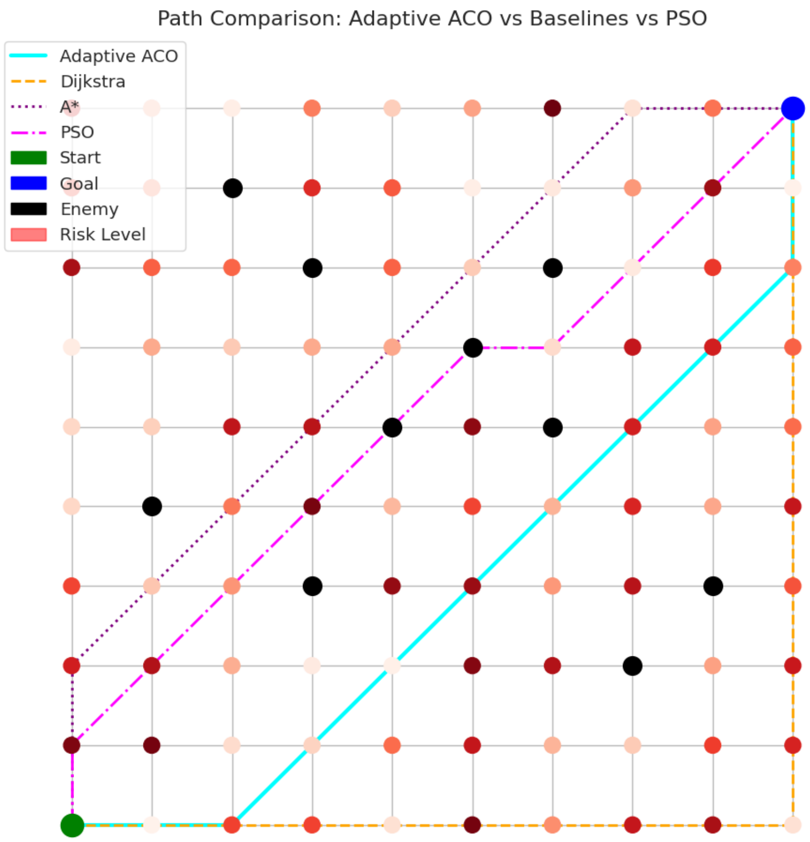

Figure 2. Path Comparison: Adaptive ACO vs Baselines vs PSO

The visualization above shows a comparison of the movement paths of combat vehicles generated by the Adaptive ACO, Dijkstra, A*, and PSO algorithms on a grid-based battlefield. Each node is represented by a red color indicating the level of risk, with higher red intensity indicating greater risk due to enemy positions or terrain conditions. Green points indicate the initial position of the vehicles, while blue points mark the final destination. Enemy positions are visualized with black points, with a total of ten points to represent dynamic threats on the battlefield. The Adaptive ACO path is displayed in bold cyan, indicating a route that considers both risk and distance, while the Dijkstra, A*, and PSO paths are displayed in orange, purple, and magenta, respectively, with varying line styles (dashed, dotted, dashdot) to distinguish the methods. This visualization shows that the Adaptive ACO path tends to avoid high-risk areas while remaining efficient in reaching the goal, whereas the baseline algorithms pass through more risky nodes. The combination of node coloring, enemy marking, and algorithm paths makes it easier for readers to understand how each method navigates complex and risky terrain, thereby providing a clear picture of ACO's advantages and adaptability in the context of military vehicle movement on the battlefield.

Discussion

The results of the study indicate that the Adaptive Ant Colony Optimization (ACO) algorithm is capable of generating safer and more efficient movement paths for combat vehicles compared to baseline algorithms such as Dijkstra, A*, and Particle Swarm Optimization (PSO). Based on the performance comparison table, the Safety Index (SI) of the adaptive ACO achieves the highest value, 0.872, indicating that the generated paths consistently avoid high-risk areas caused by the presence of dynamic enemies. Conversely, the Dijkstra and A* algorithms have lower SI values (0.614 and 0.671), as both methods prioritize the shortest path without considering real-time risk distribution. PSO shows better SI performance than Dijkstra and A*, but remains below the adaptive ACO, at 0.783, indicating that standard swarm intelligence mechanisms are still less responsive to sudden changes in risk on the battlefield.

Time Efficiency (TE) also demonstrates the superiority of the adaptive ACO. The generated paths have a lower average travel time compared to Dijkstra and A*, but slightly higher than PSO in some scenarios, as ACO balances risk reduction and distance minimization. This indicates that the adaptive algorithm can maintain efficiency while prioritizing safety, which is an important trade-off in the context of military operations. The adaptability metric (A) confirms the adaptive ACO's ability to respond to changes in terrain and enemy positions in real-time, with an A value of 0.412, higher than PSO (0.325) and far above Dijkstra (0.118) and A* (0.142). This value indicates that the adaptive ACO can effectively update paths when the risk at a particular node increases or the enemy's position changes.

Computational Cost (CC) analysis shows that the adaptive ACO requires higher computational time compared to Dijkstra and A*, but remains at an acceptable level for simulation-based military applications, especially considering the significant improvement in safety and adaptability metrics. PSO has a CC comparable to adaptive ACO, but does not outperform ACO in terms of SI and response to dynamic risk changes. In other words, the additional computational investment made by adaptive ACO is justified by its higher safety performance and adaptability, which are critical factors in the context of complex and dynamic battlefields.

Path visualization supports these quantitative findings. Paths generated by the adaptive ACO clearly avoid high-risk areas marked by the enemy, while baseline paths tend to pass through risky nodes. This demonstrates that integrating dynamic risk maps into the ACO algorithm enables vehicles to perform strategic navigation, proactively consider threats, and minimize risk exposure. Additionally, the color differences between paths and enemy points show how the adaptive ACO balances travel distance and safety, while the baseline is more rigid and less responsive to changes in terrain conditions.

Overall, the results of this study confirm that developing an adaptive ACO algorithm integrated with dynamic risk maps is an effective approach for optimizing the movement of combat vehicles in complex battlefields. This model not only enhances vehicle safety through risk avoidance but also maintains route efficiency and adaptive response to terrain dynamics. Practical implications include application in autonomous combat vehicle systems, UAVs, and intelligent military simulations, where navigation decisions must be made quickly, adaptively, and based on real-time risk data. This research opens opportunities for further development, such as integration with real-time sensors, adaptive enemy models, or multi-objective optimization considering fuel consumption, stealth, and multi-unit coordination in complex military operations.

4. CONCLUSION

This study has developed and tested an Adaptive Ant Colony Optimization (ACO) algorithm integrated with a dynamic risk map for optimizing combat vehicle routes on dynamic battlefields. Based on simulation results and performance evaluations, the adaptive ACO algorithm consistently generates safer, more efficient, and more responsive routes to changes in risk compared to baseline algorithms such as Dijkstra, A*, and Particle Swarm Optimization (PSO). The integration of dynamic risk maps enables the algorithm to account for the probability of enemy attacks, relative distance to enemies, and threat intensity, thereby proactively avoiding high-risk areas without significantly compromising travel time efficiency. Quantitative results show that the adaptive ACO's Safety Index (SI) achieves the highest value among all tested methods, while the Adaptability (A) metric confirms the algorithm's ability to adjust paths in real-time as terrain conditions change. Time Efficiency (TE) indicates that the algorithm maintains competitive travel times, while Computational Cost (CC) remains at an acceptable level for military simulation applications. Path visualization supports these findings, showing that the adaptive ACO consistently navigates vehicles through safe paths while maintaining flexibility in the face of dynamic enemies. Thus, this study demonstrates that the use of adaptive ACO combined with a dynamic risk map model is an effective approach for vehicle path planning in complex battlefield environments. This algorithm not only enhances safety and operational efficiency but also provides real-time adaptation capabilities critical in the context of modern military operations. These findings open opportunities for further application in autonomous combat vehicles, UAV systems, or intelligent simulation-based military platforms, as well as integration with real-time sensors to strengthen risk-based navigation decisions. Overall, this research makes a significant contribution to the development of adaptive navigation strategies based on artificial intelligence in the military domain, closing the literature gap related to path optimization in dynamic battlefields, and providing a framework that can be adopted for further research or practical applications in the context of modern military operations.

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