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Constructive wargaming simulation as a critical component of the tactical swarm configuration optimization

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Abstract

The importance of effective operational planning as a decision-support tool is steadily increasing across various domains. There is significant potential in combining operational insights with high-level human reasoning. These insights, which are derived through modeling and simulation, are critical to enhancing operational effectiveness. Constructive wargaming offers a vital advantage in military planning by optimizing activity options and improving operational efficiency and readiness in a rapidly changing security environment. It could be employed to plan complex operations, conduct military training, or develop doctrines and standards. This paper presents a simplified example and approach to determining the optimal swarm configuration, explicitly focusing on the number of Unmanned Ground Vehicles (UGVs) required for particular tactical tasks. This example may inspire additional scenarios or be integrated into wargaming simulations as a tool to enhance the effectiveness of swarm behavior.

Keywords: maneuver optimization, modeling and simulation, wargaming, terrain analysis, off-road navigation

1. Introduction

Scientific and technological progress is advancing at an unprecedented pace, opening up new dimensions of possibilities and process quality that were previously unimaginable. This fact has been significantly helped by the dynamic development of artificial intelligence (AI) and related domains for over ten years. AI represents considerable application potential in the military, particularly in mobility and maneuverability. The critical influence of AI on the domination of the 21st-century battlefield, a fact that was predicted as early as the 1980s, is a testament to its relevance in military mobility and maneuverability. The potential of AI in the military field is immense, offering new strategies and technologies that significantly enhance the effectiveness of military operations.

However, the pace of AI implementation, even in modern armies, was very conservative until recently, and only the deteriorating security situation escalating with the conflict in Ukraine caused its significant acceleration. With NATO starting to deal more seriously with areas such as AI and autonomous weapon systems as early as 2013, it was not until 2018 that "official" changes in the setting of the "lines of effort" came to ensure NATO's operational effectiveness in confronting potential adversaries on the future battlefield.

The given topical area (issue) and solution could be approached in many ways, for example, through methods from the field of operations research (consisting of solving the optimization of a system of operational-tactical analyses, composing the concept of a model of a complex operational-tactical task), or using "reinforcement learning" (for which, however, it is necessary to have an appropriate data training set or system/model for evaluating the quality/effectiveness of variant steps of sub-elements of the organizational structure). However, one of the other ways of effective solution is to implement the principle of "constructive wargaming" in filling a multidimensional tree of potential tactical configurations and applying other optimization algorithms. [1,2,3,4,5,6,7,8,9,10,11]

By "constructive wargaming", we mean a process that allows you to simulate (primarily using computer technologies), analyze, and evaluate various variants of the activities of friendly units (or the enemy) in a complex operational environment. It is usually a complex SW tool that provides:

- Simulated environment: allows you to create a credible model of the operating environment that includes terrain, climatic and geographical conditions, and other subregions. It is primarily based on math-physics principles.
- Unit and resource modeling: realistic simulation of units and their interaction to represent real-world capabilities and limitations.
- Scenarios and Scenarios of Action (COAs): Creates scenarios that include different COAs and allows for their detailed evaluation.

In this paper, we introduce a simplified example using an optimization approach.

2. State of the art analyses

During the problem analyses and related research evaluations, several publications were dedicated to the problem mentioned. Except for the papers previously written by authors [13,14,15,16,18,19,20], several relevant documents oriented to path/maneuver optimization were found inspiring the presented solution:

- "Graphs over Time: Densification Laws, Shrinking Diameters and Possible Explanations": Jure Leskovec, Jon Kleinberg, Christos Faloutsos, ACM Transactions on Knowledge Discovery from Data, 2007, this paper discusses how graphs evolve, including how densification and diameter shrinking occur in dynamic networks. Understanding how movement and control over regions change over time needs to be applied to military strategy.

- "A Knowledge Graph-Based Approach to Operational Coordination Recognition in Wargame," Part of the book series 2022, Chenye Song, Ludi Wang, Yi Du, Xiao Xu, Shengming Guo. This study proposed a novel framework based on knowledge graph to predict operational coordinations. There was constructed a novel large scale knowledge graph that consists of 29313 nodes and 191542 edges from Wargame Competition dataset. The embedding method jointly considers information from node attributes, local situations and global structure, and then combine the three parts with a self-attention mechanism.

- "Graph-based subterranean exploration path planning using aerial and legged robots", Tung Dang, Marco Tranzatto, Shehryar Khattak, Frank Mascarich, Kostas Alexis, Marco Hutter, The Journal of Field Robotics 2020. This paper contributes a novel graph-based subterranean exploration path planning method attuned to key topological properties of subterranean settings, such as large-scale tunnel-like networks and complex multibranched topologies. Designed for aerial and legged robots, the proposed method is structured around a bifurcated local- and global-planner architecture.

- "Generalized multi-commodity network flows: case studies in space logistics and complex infrastructure systems", 2013 DSpace@MIT, Ishimatsu, Takuto. Past space logistics studies have mainly focused on a "vehicle" perspective such as propulsive feasibility, cargo capacity constraints, and manifesting strategies, with the arbitrarily predetermined logistics network. This thesis aims to develop a comprehensive graph-theoretic modeling framework to quantitatively evaluate and optimize space exploration logistics from a "network" perspective. In an attempt to create such a modeling framework, a novel network flow model referred to as the generalized multi-commodity network flow (GMCNF) model was developed.

- "Percolation processes and wireless network resilience", 2008 IEEE Zhenning Kong; Edmund M. Yeh. In networks carrying traffic load, the failure of one node results in a redistribution of the load onto other nearby nodes. If these nodes fail due to excessive load, this process results in cascading failure. The paper analyzes this cascading failures problem in large-scale wireless networks and shows that it is equivalent to a degree-dependent site percolation on random geometric graphs. Analytic conditions for cascades were reached in this model.

Even though we found many similarities or inspirations, the approach introduced in this paper was not found within the searched documents.

3. Approach to the solution

There are many incrementally rising complexity levels of the operational problems, and this paper discusses the approach to the particular simplified case, which is defined as follows:

In the operations area, we search the optimal number (N) of UGVs to deliver the asset to a number (M) of destination points. The UGVs randomly operate in the destination area and could supply the destination points (in this case, all vehicles are tasked to supply all destination points simultaneously). Tactical conditions will cause technical failures of vehicles, which is probabilistic, meaning that the UGV swarm plan has to be continuously updated. Destination points have to be redistributed to the functional vehicle path plan. The optimal number of UGVs is evaluated by the objective function Pf_{UGV}(UGVcount, $ATPL_i$) in the context of the average total 'tactical' path length (ATPL), what is the result of the cooperative TSP with constraints to supply all destination points (Vn)

$$OMC = min \rightarrow Pf_{UGV}(1..UGVcount, ATPL_{1..UGVcount}) \quad (1)$$

where:

i – index

OMC – Optimal Mission Configuration.

$ATPL_i$ — Average total tactical path length is calculated from all particular solutions based on the cooperative Traveling Salesman Problem with constraints.

Pf_{UGV} – Objective function expressing the weighted compromise between the tactical length and the UGV count.

UGVcount – Particular number of UGVs employed in the supply distribution.

Remark: In this case, we simplify the problem to avoid an increase in exponential complexity. We count only one type of supply and one type of UGVs that could manage the delivery process.

For this particular case, we developed the following conceptual architecture:

1. Operations area selection and other conditions, such as tactical criteria integrated into the tactical path length, observation area selection, etc.
2. Destination points selection: In this case, the points are retaken from the solution of the minimum observation points to cover the selected area by observation/fire.
3. Selection of the UGV number and its positions. The UGV count rises from 1 to N, and its positions is randomly distributed over the operations area.
4. Construction of the 'tactical' maneuverability graph for each UGV to all nodes (destination points), integrating the geo-tactical cost of maneuver in each weighted connection. As indicated, the nodes represent destination points (observation position) and initial UGV location.
5. Statistic data generation - simulation of the wide scope of position options described in part 3 and followed by part 4 for a particular count of UGVs (1..N), where N practically should be limited to an available time for a solution because each N increase exponentially increases the solution time. Usually, when function Pf_{UGV} starts with an increasing trend, the simulation stops, and the result is searched within the available results.
6. The final result is the number of UGVs (N) corresponding with the minimum of the function Pf_{UGV}(N, ATPLN).

The conceptual architecture was further developed into the software application (C++) to automate all steps and demonstrate the results described further.

3.1. Selection of areas of operations and criteria setting

The operations area, particular input, tactical, and maneuverability criteria must be set in advance for the optimization processing. This includes the operational weights for the movement and other tactical factors like restricted or dangerous areas, threat positions, destination points, etc.

In the operational context of the presented example, the destination points were considered as a tactical optimization task that search for the minimum observation point count and their locations because the observation ability of the enemy/destination area is always essential. Our previous work developed the solution described in [12], where the problem is defined as:

$$\bigcup_1^n V_n = \bigcup_1^m V_m\,;\, n \in N, m \in M;\; M \subset N, \min \rightarrow m \quad (2)$$

V_n — *point set,* $V_n \in D$*, visible from n, n* $\in N$*,*
V_m — *point set,* $V_m \in D$*, visible from m, m* $\in N$*,*
N — *point set of the source area,*
M — *point subset of the source area,*
n — *particular point from N,*
m — *particular point from M.*

The algorithm is based on iterative integration of the V_n and elimination of all M members, which creates a pure subset. A brief algorithm description is as follows:

1. *L = 1*
2. *Generate the visibility set V from n = first(N), n* $\in$ *N,*
3. *n = next(N), n* $\in$ *N,*
4. *Generate the visibility set T from n, n* $\in$ *N,*
5. *If T* $\subset$ *V continues by step 3,*
6. *If not 5, L = L+1, V = T* $\cup$ *V, continue by step 3*
7. *Return L*

The following figure presents the results of one particular case:

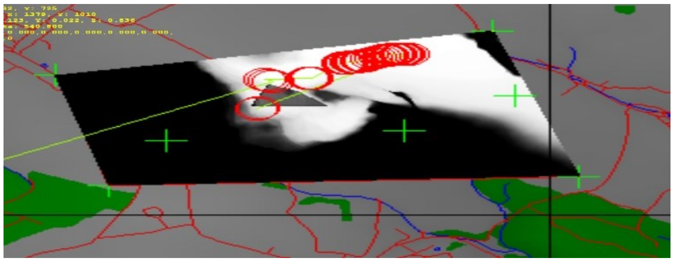


Figure 1: Visibility map (perceptual visibility of the destination area, <0,1> as <black, white> greyscale) and calculation results of the best observation points to watch the destination area – red circles

3.2. Selection of UGV count and its positions

For each simulation scenario, the initial selection of UGV positions is randomly distributed across the operations area (Monte Carlo approach). This expresses the dynamics of the operational environment, where we could expect the vehicles to be anywhere within the tactical task fulfillment (within the ground approachability of the operations area). For each scenario/configuration of the destinations point set, 100 random UGV position configurations were selected for the representative statistical data set for evaluation

3.3. Tactical maneuverability graph

As mentioned, each UGV could be characterized by a specific maneuvering and payload capability with different constraints. The user has to generate the multi-criteria table, impacting a selected transport cost within the operations area. The 'tactical' maneuverability graph calculation for each UGV is derived from the minimum tactical path from each vehicle to all destination points. The solution is based on the Dijkstra approach, searching the path in the model of 2048 x 2048 nodes connected with 8 x 20482 edges; each node represents the square 10x10m. Our optimized version uses specific weight limitation constraints for indexing the particular weight sums and achieves the solution relatively quickly. Even though the solution is computationally intensive, results are delivered within minutes for the several UGVs. The decisive impact on the calculation time is the number of destination points to visit. The following image shows an example of one version of the maneuverability graph example, where the level of the grey is the reciprocal cost/weight value (1 to 16).

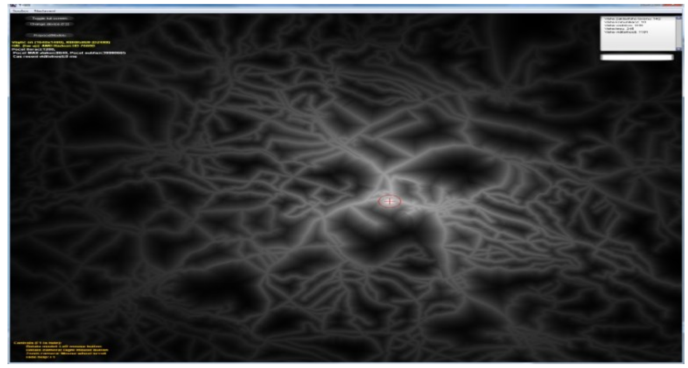


Figure 2: Tactical multi-criteria maneuverability graph after Dijkstra algorithm application to all nodes

The solution to the mentioned (and in our case, 'simplified') problem is based on the TSP algorithm, and there are many potential approaches or algorithm classes like 'Lin Kernigen', Ant Colony Optimization, Nearest Neighbour, GRASP, and others. Because transformation to the 'Tactical Domain' (maneuverability graph containing just tactical coefficients coming from the multi-criteria evaluation) is relatively 'tricky', and thus it is disputable if the perfect mathematical (optimal) solution could perform in reality better than other close optimal solutions, we chose simplicity and initial demonstration just a 'nearest neighbor' adjusted to any number of UGVs. The algorithm searches for the 'total' shortest path of all vehicles visiting the destination points. Any vehicle has to visit the destination point just once. Thus, a situation could appear where only some vehicles are employed when some vehicle is too far, and other vehicles fulfill the task until this vehicle is acle to visit any target point and is left apart. The solution to the problem is illustrated in the following picture.

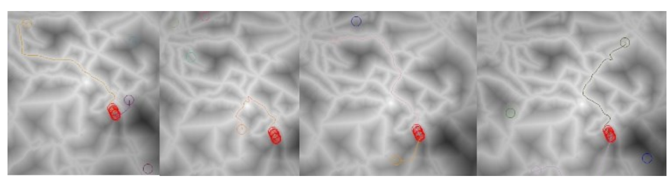
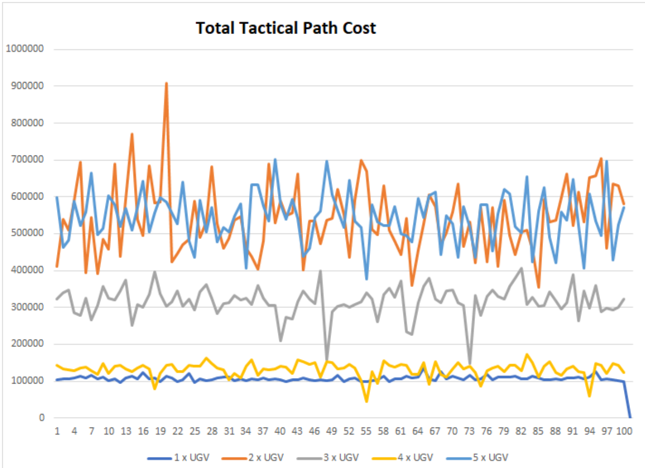


Figure 3: The solution result is shown in the figure, which includes four example scenarios with the random deployment of the three UGVs (colored circles – other than red) within the operations area and its optimal paths (corresponding color) to the destination point (red circles)

3.4. Selection of UGV count and its positions

The final evaluation is processed with simulated results. As mentioned in section 3.2, the algorithm incrementally raises the UGV count, simulates 100 random UGV positions, and solves the TSP to the destination points in the tactical graph with multiple UGVs. The goal is to find the optimal number of UGVs to perform a particular task (*supply the destination points; all vehicles provide all destination points simultaneously*). The solution searches for the minimum function $Pf_{UGV}(N, ATPL_N)$, where the corresponding N is the optimal number of UGVs. The particular simulation results are presented in graph 1.



Graph 1: Simulated results of the 100 iterations of the total tactical path cost in a particular scenario with multiple UGVs (1-5)

Based on the simulated results (see Graph 1), one vehicle appears optimal for the particular scenario regarding the tactical cost, summarizing the total complications. However, the situation could differ in another scenario.

4. Conclusion

In conclusion, the importance of effective operational planning in various areas (as a decision-support component) is constantly increasing. There is excellent potential in aggregating operational relations and findings into high-level human reasoning. These features are extracted by modeling and simulation methods and are essential to operational effectiveness. Constructive wargaming provides military planning a crucial advantage in optimizing activity variants and improving operational efficiency and readiness for a dynamically changing security environment. Generally, it is used to plan complex operations, conduct military training, or develop doctrines and standards.

This paper introduces an essential simplified example and approach to finding a solution for the swarm configuration or the optimal entity count. In this case, effective UGV counts converge to one to perform particular tactical tasks. This example could inspire additional scenarios or be applied within wargaming simulations as a tool, increasing the swarm behavior's effectiveness.

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