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Intelligent Wargaming Approach to Increase Course of Action Effectiveness in Military Operations

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In this study, an intelligent wargaming approach is proposed to evaluate the effectiveness of a military operation plan in terms of operational success and survivability of the assets. The proposed application is developed based on classical military decision making and planning (MDMP) workflow for ease of implementation into the real-world applications. Contributions of this study are threefold; a) developing an intelligent wargaming approach to accelerate the course of action (COA) analysis step in the MDMP which leads creating more candidate COAs for a military operation, b) generating effective tactics against the opposite forces to increase operational success, and c) developing an efficient, visual wargame-based MDMP framework for future systems that require a small team of operators to supervise a network of automated agents. Several example engagement scenarios are performed to evaluate the system capabilities and results are given. Moreover, fleet composition issue for automated agents is investigated and the fleet composer algorithm with hyperparameter tuning architecture is proposed.

I. Introduction

With increase in the use of unmanned vehicles for complex tasks including intelligence, surveillance and reconnaissance operations, recent applications tend to shift towards the cooperation among a heterogeneous fleet of unmanned vehicles for executing these operations with high mission success rates [1]. Cooperation between heterogeneous agents for completing the complex tasks bring the need for multi-domain operational capability where artificial intelligence (AI) assisted war-game strategies play important role [2]. Specific goals such as using AI to discover tactics, which might improve the operational benefits via existing military capabilities, or might suggest effective concepts of use for new military capabilities are under consideration. AI decision-making have recently focused on open games, where all game states are visible to all players, or closed games, where restricted flexibility to wargaming exist. However, modeling decision-making strategies at both tactical and strategic levels requires novel algorithms that can operate within dynamic environments with changing rules, uncertainties, individual biases and randomness [3].

Wargaming is an important part of the MDMP, which is the armies' doctrinal approach to create operation plans, to predict counter-actions of the opposite forces and to evaluate the effectiveness of the proposed operation plan, since it offers a safe and vicarious reflection of some of the situational and decision-making dynamics associated with armed conflict. Although, there is no single definition for the term 'war-gaming', the commonly accepted one dated back to the beginning of 19^{th} century, which defines it as a simulation of a military operation, by whatever means, using specific rules, data, methods and procedures [4]. Therefore, it is important to give a clear statement about wargaming before to proceed with the definition and importance of MDMP. The MDMP starts with the receipt of a mission from higher headquarters. Then, mission analysis is performed by utilizing intelligence from other sources. In the next step, it processes commander's intents, operational requirements and available resources to develop course of actions (COAs) which include task organization plans. After development of the COA, COA analysis, which is focused on action, reaction, counteraction, and the adjudication process, is performed through wargaming to refine the COAs and potential decision points.

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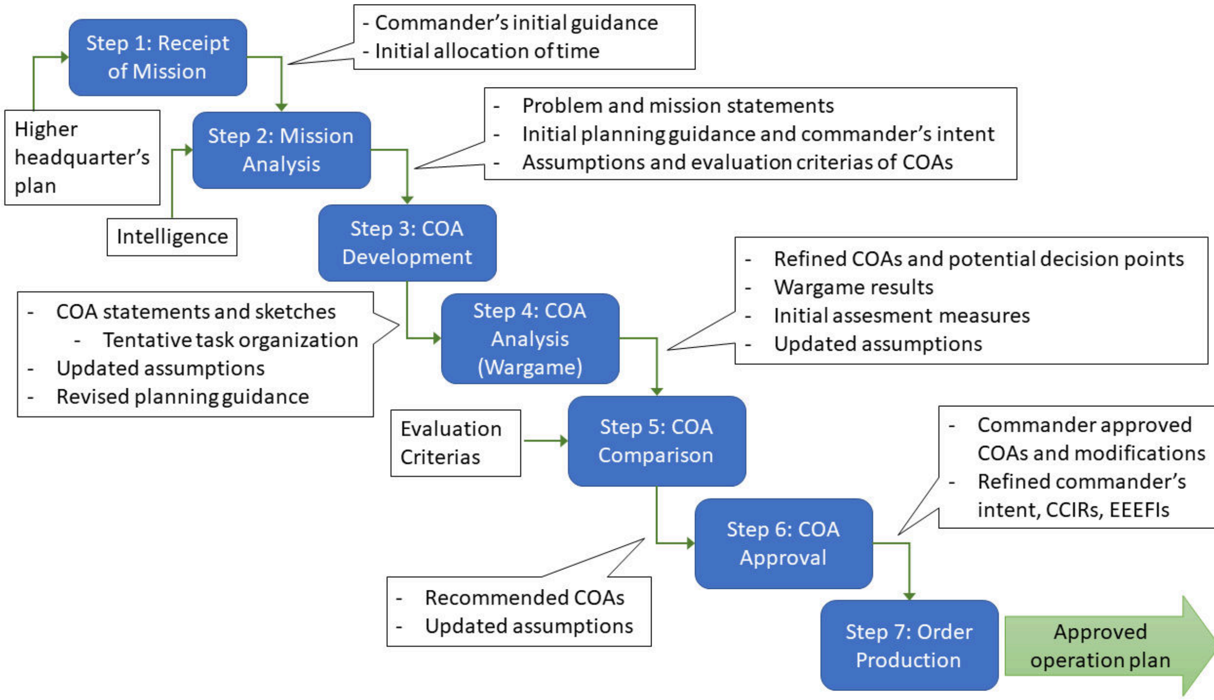

Fig. 1 Summary of military decision making process. (Reproduced from [7])

Within the MDMP, COA analysis is often referred to as wargaming which links COA development to COA comparison and approval [5]. In the comparison step, each of the COAs is evaluated according to defined criterion such as simplicity, maneuvering, fires, civil control and mass which are given weights within a decision matrix for assessment. Moreover, selected COA from the comparison step is to have minimum risk, maximum security and flexibility. Then, COA approval process is completed according to the results from COA comparison and, in the last step, orders are produced and shared with the related units [6]. From the general point of view, overall MDMP process is given in Figure 1.

In this study, it is proposed to develop intelligence, surveillance, and reconnaissance (ISR) and suppression of enemy air defense (SEAD) operation plans that are supported by upper AI and assistive, decentralized decision-making strategies within a war-game to evaluate generated COAs in terms of probability of success, survivability of the assets and operational efficiency. This process is developed on the classical MDMP scheme for ease of implementation into the real-world applications and it is able to provide fast evaluation and objective comparison of the COAs before or during the operation. The process begins with receiving the mission analysis results from the second step of the MDMP. In the COA development step, initial task assignment process is performed by utilizing the CBBA algorithm which is able to solve assignment problems with decentralized communication structure, heterogeneous fleet and online replanning requirement. After creating several operation plans (i.e. COAs), they are fed into the wargaming process to evaluate their effectiveness. After that, these COAs are compared with each other in terms of success probability, survivability and cost and the most effective one is sent for approval step. General overview of the focused framework is given in Figure 2.

Contributions of this study are three folds; a) developing an intelligent wargaming approach to accelerate the course of action analysis step in the MDMP which leads creating more candidate COAs for a military operation, b) generating effective tactics against the opposite forces to increase operational success and c) developing an efficient, visual and robust war-game based MDMP framework for future systems that require a small team of operators to supervise a network of automated agents. Remaining of this study is structured as follows; In Section II, related studies from the literature are to be investigated. Section III defines the problem statement and Section IV gives the required background to approach the solution against the problem. In Section V, the methodology followed during the creation of this work is to be given and Section VI demonstrates the results of the simulation studies. Finally, Section VII is to conclude the article.

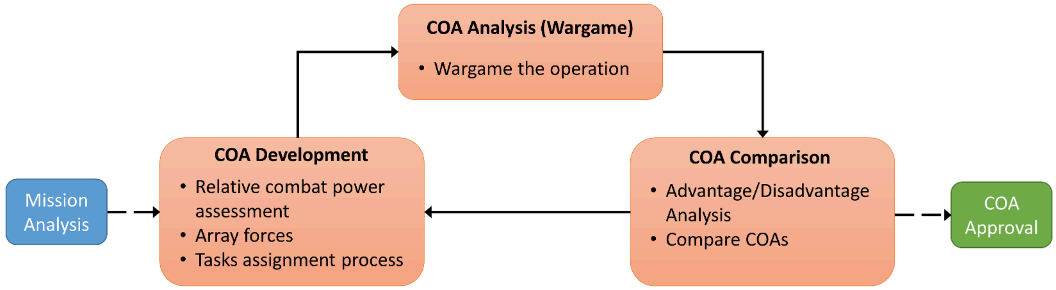

Fig. 2 Framework for COA generation.

II. Related Works

Wargame simulations are used as decision making tools in different fields from business to military [8], from conflict scenarios to surveillance or crisis drills, search and rescue missions in the military perspective [9]. In Filho et al. [10], the position of UAVs in a beyond visual range combat has optimized using the war game approach. The effectiveness of tactical formation of a friendly swarm team was investigated considering enemy uncertainties in a war game. Chen et al. [11] proposed an emergency rescue wargame model based the decision trees in a urban flooding situation. In the model, while the enemy task is limited to road water accumulation, the friendly team consists of emergency vehicles trying to prevent this flooding. Su et al. proposed geographic information system (GIS) based flood wargame assistance platform in order to prevent from flooding in Taiwan [12]. A different approach to the use of wargame-based strategies is crisis drills which Song et al. stated that the wargaming is an efficient way for crisis drill with low cost and in a convenient manner [13].

An effective wargaming strategy depends on the accurate and optimal distribution/allocation of the assets to subordinate commanders for accomplishing their missions [7]. Numerous methods have been developed for enabling the agents to distribute the tasks amongst themselves from task list of a known operation. Main idea of these approaches is not only increasing the mission effectiveness, but also decreasing the operational costs and risks. Centralized task allocation, which requires communication link between agents and a central server, generates an allocation plan for the entire fleet. Since the centralized systems are able to reduce the burden of processing requirements on the ground, they are effective for making the agents smaller and cheaper to build. Moreover, it has been investigated that using the heuristic methods such as genetic algorithms [14–16] and particle swarm optimization methods [17–19] in the centralized task allocation systems provides better performance in terms of computational time [20]. On the other hand, due to the structure of the centralized task allocation, a persistent communication should be maintained between the agents and the operation base to provide cooperation which requires sending/receiving operational updates. This requirement about the communication system directly affects the fleet capability and robustness of the fleets.

In the contrast of the centralized applications, performance and robustness of the fleet could be improved by utilizing decentralized methods in which agent-to-agent communication is required to obtain consensus on a given task set. This type of communication topology increases robustness of the fleet in the presence agent loss, communication loss and real-time updates on the task list, i.e. adding and removing tasks [21]. In this manner, decentralized planning methods that eliminate the need for a central base have been investigated in the literature. Most of these methods assume perfect communication with infinite bandwidth for ensuring that agents have the same situational awareness before the planning. However, this can be easily violated in real world scenarios including search and rescue missions where the agents have limited range of communication or communication channel with limited bandwidth [22]. In the presence of inconsistencies in situational awareness, decentralized task allocation algorithms can be augmented by utilizing consensus-based algorithms such as Consensus-Based Bundle Algorithm (CBBA) in order to converge on a consistent solution [23–25]. There are not only consensus algorithms which can be integrated into decentralized frameworks but also Partially Observable Markov Decision Process (POMDP) based approaches exist in the literature [26]. Although consensus algorithms guarantee convergence on information, i.e. reaching to a consensus, this may take a significant amount of time and often requires transmitting large amounts of data which might result in high latency in low-bandwidth environments and increment in the processing time to find an optimal task assignment solution for the unmanned fleet [27]. There are also several reports about an intermediate hierarchical architecture, i.e. an hybrid architecture, between the centralized and the decentralized architectures which is used for to benefit from the advantages of two methods [28].

Even though numerous attempts try to address the task allocation problem for unmanned heterogeneous fleets, and all of the previously mentioned studies examined the ability of underlying automation (in the form of planning and control algorithms) to allocate a network of heterogeneous unmanned vehicles (UxVs), there is a crucial need for integrating an enhanced/upper AI-generated guidance and assistive decision-making support into the MDMP which generates the COAs [29]. Several preliminary attempts such as the Defense Advanced Research Projects Agency's (DARPA) Broad Agency Announcement (BAA) for the Collaborative Operations in a Denied Environment (CODE) Program and BAA for Distributed Battlespace Management (DBM) are proposed to improve human–automation collaboration and decisions to assist battle managers and pilots via executing a series of automated and autonomous actions [30]. However, such frameworks with different task allocation methods might be brittle and unable to respond to sudden events. Such systems can be mitigated by human operators who are bringing their knowledge-based reasoning and experience [31].

Therefore, it is obvious that both task planner, and operator framework within a platform should be carefully constructed. One of the most important platforms for modelling and analyzing such a framework is wargames, which are used to execute decisions on future force assets, military capabilities, and to prepare for numerous operations. Wargames are able to be executed in numerous different ways, ranging from seminar war-games, through manual board games to complex computer-assisted war-games [32], where the computer judges the consequences of engagements [33].

Intelligent wargames have been questioned whether they are valuable for facilitating the military decision making since the preliminary studies about the topic [34]. Roles of these systems during the decision making process have been also discussed under four main disciplines, which are sensing, situational-awareness, plan generation and learning [35, 36]. After those discussions, progress in AI discipline and with the developing technology, it was reported that the application of artificial intelligence to the armies' MDMP has great potential to support the command center ability to plan for battlespaces that are becoming both hyper-competitive and more complex so that Schwartz et al. approached to the problem with genetic algorithms (GAs) within assistive AI architecture [37]. Boron et al. approached to the integration of AI-based wargaming to the decision making process, and they used reinforcement learning (RL) within the different combat scenarios for assessing the performance of their algorithms [38]. Xin et al. considered the uncertainties that are usually neglected in previous studies, so that they proposed a solution titled as hybrid-intelligence multi-branch wargaming which accounts uncertainties via fusion of RL-based AI methods and human intelligence [39]. Recently, Tarraf et al. proposed a wargaming framework where the rules and engagement statistics used in a commercial tabletop wargame to enable remotely operated and fully autonomous combat agents and agents with AI/ML-enabled situational awareness [40]. Goecks et al. discuss the past and current efforts on how games and simulators, together with the AI algorithms, have been adapted to simulate certain aspects of military missions and how they might impact the future battlefield. Moreover, they investigate how advances in virtual reality (VR) and visual augmentation (VA) systems provide new frontiers in human interfaces with gaming platforms and their military [41].

III. Problem Statement

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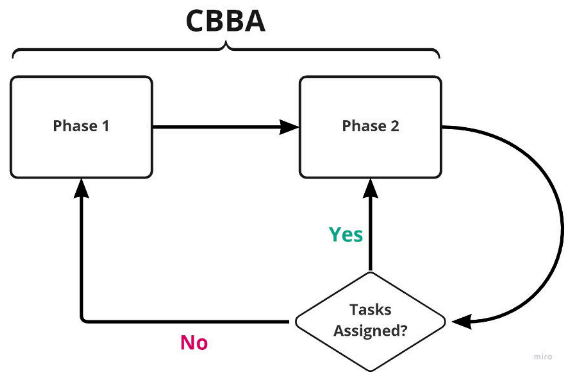

Fig. 3 Inner cycle of CBBA for each agent

IV. Background

After defining the problem, mission requirements, assumptions and evaluation criterias in the Step-2 of the MDMP, it is important to assign blue team military units to suitable red team tasks. This is accomplished by utilising consensus-based bundle algorithm (CBBA) [27] which supports decentralised, heterogeneous fleets and dynamic environments. In this section, details of the CBBA algorithm is given and described.

A. Consensus-Based Bundle Algorithm (CBBA)

CBBA is a decentralised market-based protocol that provides provably good approximate solutions for multi-agent multi-task allocation problems over networks of heterogeneous agents and addresses the task allocation to coordinate a heterogeneous fleet of the autonomous vehicles via using the decentralised communication approach [27]. This type of communication topology eliminates the need for a central base, and it increases robustness of the fleet in the presence of agent loss, communication loss and real-time updates on the task list, i.e., adding and removing tasks. CBBA is made up of iterations that alternate between two phases: the first phase, a bundle construction phase in which each vehicle generates an ordered bundle of jobs greedily, and the second phase, a consensus phase in which conflicting assignments are found and resolved by local communication among neighbouring agents. Figure 3 demonstrates the inner cycle of CBBA, the chosen task allocation planner as follows.

1. Phase 1: The Bundle Construction

An agent internally builds up a single bundle containing all the tasks it plans to complete and updates it as the assignment process progresses during the first phase. Each agent continually adds to its bundle until it is incapable of adding any other tasks. Two lists of tasks are carried by the agents: the bundle b_i and a path p_i. The bundle contains all tasks that an agent is going to complete and is grouped in the order tasks were added, and the path, but it contains an ordered sequence of tasks that agent i is going to execute.

$$c_{ij}[b_i] = \begin{cases} 0, & \text{if } j \in b_i \\ max_{n \leq |p_i|} R_i^{p_i \theta_n [j]} - R_i^{p_i}, & \text{otherwise} \end{cases} \tag{1}$$

where || denotes the cardinality of the list, and h_n denotes the operation that inserts the second list right after the nth element of the final list. A new task is inserted into the current path at all possible locations to find the highest increase in reward. Each agent carries five vectors: a winning bid list y_i, a winning agent list z_i, an agent update time s_i, a bundle b_i and the corresponding path p_i. The winning agent list z_i stores the agent currently assigned to each task such that when $z_{ij} = k$ agent i believes that agent k is assigned to task j. An agent needs to know not only if it is outbid on a task it selects but who is assigned to each task as well; this enables better assignments based on more sophisticated conflict resolution rules.

2. Phase 2: Conflict Resolution

In CBBA, the agents make bids on tasks based on their currently assigned task set. If an agent is outbid on a task, then the score values for all the following tasks are no longer valid. Therefore, when an agent is outbid, it must release

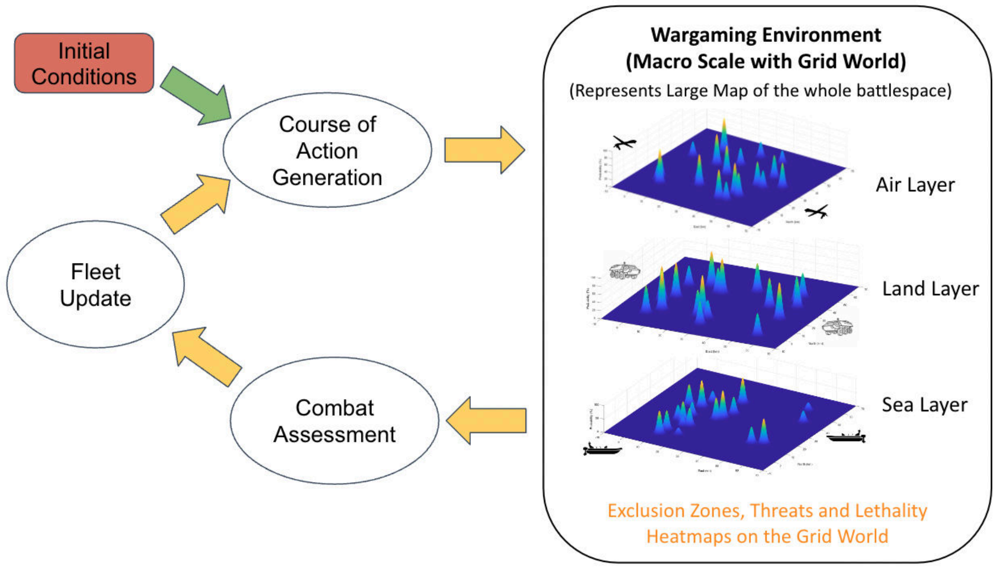

Fig. 4 General view of the simulation environment.

all the tasks added after the outbid task. When agent i receives a message from another agent, k, z_i and s_i are used to determine which agent's information is the most up-to-date for each task. There are three possible actions agent i can take on task j according to the communication table proposed by Choi et. al [27]. Using this lookup table, an agent determines whether it should update, reset or leave the bid. Agents compare their knowledge on task j between the receiver i and the sender k along with when each agent last received communication from the agent they believe is assigned to task j. Agents alternate between the two phases until they converge on a conflict-free solution.

- Update: $$y_{ij} = y_{kj}, z_{ij} = z_{kj} \tag{2}$$
- Reset: $$y_{ij} = 0, z_{ij} = \emptyset \tag{3}$$
- Leave: $$y_{ij} = y_{ij}, z_{ij} = z_{ij} \tag{4}$$

V. Methodology

A. Simulation Environment

In order to create the modular architecture which would be supportable, extensible and easily modifiable, it is decided to split intelligent mission planner into the four sub-groups. Engine module includes the main engine script which contains the critical methods such as task allocation, pathfinding, strategy, engagement, and some other important methods to step forward during the simulation. Task allocation method inside the Engine script uses the Consensus-Based Bundling Algorithm (CBBA) which is also within the Engine module. Environment module includes a World object inside the script which is giving the boundaries for the simulation environment and also the grid representation of this environment with the task, terrain, enemy presence costs attached. Models contain necessary information about the agents and tasks used during the simulations. In order to create heterogeneous agents, UAV, UGV, USV and close air-defense (CAD) agent objects are individually created, and Team object is created for setting the enemy team and following the moves done by the teams. View module is responsible for the representation of the results in a visual perspective. Summary of the modular architecture of intelligent mission planner is given in Figure 4.

B. Lethality Heatmap Generation

In the simulation environment, lethality heatmaps are generated on air, ground and sea layers to model the firepower of the opposite forces in a given area. These heatmaps are generated based on kernel density estimation (KDE) algorithm which is used to estimate danger level (i.e. effectiveness level of an opposite force unit) of a given point on the map with respect to the opposite force location. In this study, it is assumed that the lethality distribution of the military units according to the range is modeled as Quartic or Epanechnikov functions as given in Eq. 5.

$$P_1(d) = \frac{15}{16}\left(1 - d^2\right)^2 \text{ for } |d| \leq 1 \tag{5a}$$

$$P_2(d) = \frac{3}{4}\left(1 - d^2\right) \text{ for } |d| \leq 1 \tag{5b}$$

where d is distance between the military unit and specified point on the map (i.e. center of the related hexagon). For the lethality calculation at $d = 0$, the maximum value of the distributions is scaled by 1. Example heatmap generation results for air, ground and sea layers are given in Figure 5. Here, lethality heatmap of the red team units are given for a) ground layer, b) Naval layer, and c) Air layer. On the ground layer, both UAV, UGV, USV and CAD units are effective threats against the blue forces in given letality areas. On the naval layer, USV is the main threat but UAV, UGV and CAD are also effective. On the air layer, in first look, there seems no threat for blue team because the UAV, UGV and USV of the red team are not effective against the air force of the blue team. However, if CAD asset presence exists in the area, it would be crucial threat against the blue and results would be fatal.

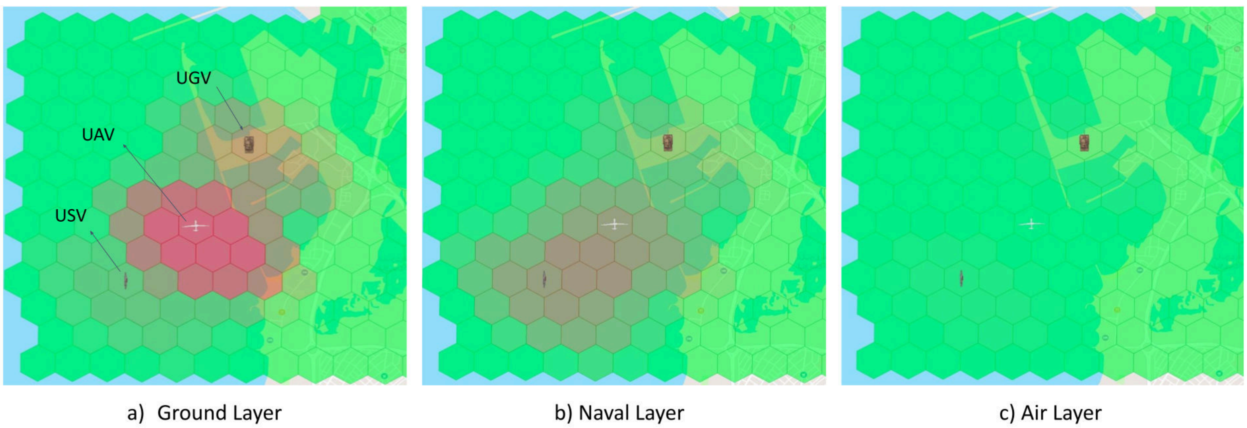

Fig. 5 Lethality heatmaps of the red team forces on a) ground, b) naval and c) air layers.

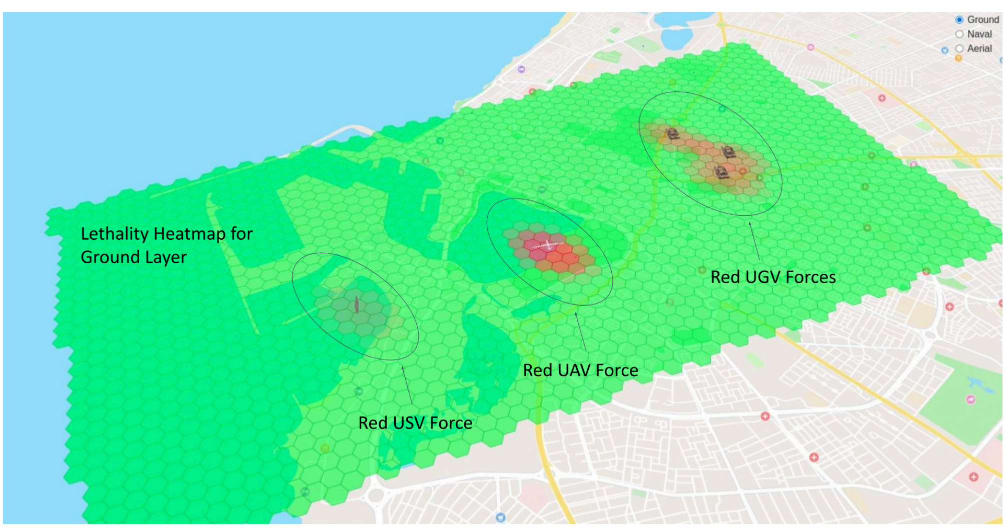

Fig. 6 Example Case: Lethality heatmap of the red team forces on the ground layer.

Another example from the simulation environment is given in Figure 6. For ease of visualization, no CAD units are inserted into the environment. Here, lethality heatmap of the UAV, UGV and USV are given for the ground layer. In this case, it is shown that the lethality of the UAV and UGV are relatively high when compared to the USV on the ground layer on which the USV has a limited range and effectiveness. This is directly modeled by utilising the effectiveness table of the military units given in Table 1. This table gives information about damage effectiveness of each type of assets to different layers.

Table 1 Damage effectiveness table for each type of assets.

	UGV	UAV	USV	CAD
Land	0.5	1	0.25	0.25
Air	0.05	0.05	0.05	1
Sea	0.25	0.5	0.5	0.25

C. Combat Model

Combat modeling abstracts and simplifies the combat entities, their behaviors, activities, and interrelations to answer defense-related research questions. There is no general model that answers all questions, and even if such a model could be constructed it would become more complex than the reality, as it not only includes real systems but also imagined ones. Combat models can be either stochastic or deterministic. Intuitively, a stochastic model assumes uncertain or probabilistic inputs regarding a situation and makes an indefinite prediction of the results. A deterministic model states exactly what will happen, as if there were no uncertainty. More formally, a stochastic model requires the terminology of the theory of probability for its description, whereas a deterministic model does not.

$$F = H_P \cdot L \cdot P_H \cdot P_D \cdot P_T \cdot P_W \cdot E_L \tag{6}$$

where $F, H_P, L, P_H, P_D, P_T, P_W, E_L$ are total firepower, firepower health, lethality, hit probability, detection probability, targeting system reliability, weapon reliability and layer effectiveness, respectively. Here, it is also important to model damage matrix of the military units which defines their effectiveness against the enemy forces in an engagement. In simulation environments, a damage matrix is assumed as given in Table 1. By using these definitions, survivability of each asset is modeled as given in Eq. 7 and 8.

$$F_k = F_{k-1} - F_{o_k} \tag{7}$$

$$M_k = M_{k-1} - F_{o_k} \tag{8}$$

where F_k, M_k are firepower and mobility of the related team at time k. F_{o_k} is firepower of the opposite force at time k.

D. Evaluation Metrics and Combat Assessment

Effective assessment incorporates both quantitative (observation-based) and qualitative (opinion-based) indicators. Human judgement is integral to assessment. A key aspect of any assessment is the degree to which it relies on human judgement and the degree to which it relies on direct observation and mathematical rigour. Rigour offsets the inevitable bias, while human judgement focuses rigour and processes on intangibles that are often key to success. Verbal definitions are straightforward to state, but in order to educate the overall system in a intelligent manner, it is crucial to represent these sentences into the mathematical indicators. The transition from verbal to mathematical definition of the metrics is an open-ended procedure, and it can be manually selected in a way that captures optimal decisions [42].

In order to asses the mobility and firepower capabilities of the red and blue teams, several combat assessment metrics are developed as given in Eq. 9 and 10.

$$\bar{F}_x = \frac{\sum F_{x_t}}{n_{x_t}} \tag{9}$$

$$\bar{M}_x = \frac{\sum M_{x_t}}{n_{x_t}} \tag{10}$$

where subscript $x \in \{b, r\}$ denotes for blue and red teams, $t \in \{air, ground, sea\}$ defines the level of assets, F, M are firepower and mobility of the military units after engagement, $\bar{}$ shows mean value, n is total number of alive assets after the engagement.

E. Fleet Composition

Composition of the adequate fleet is closely related with the scoring function of CBBA given as following.

$$J_j(a_j, t_j) = e^{-\lambda . t_j} R_j(a_j) \tag{11}$$

This function gives the score an agent receives from task j when it arrives at the task at time t_j. Score is composed of two parts that the first is the nominal reward for the task, $R_j(a_j)$ which is a function of a_j, the index of the agent assigned to task j, and the second is the discount function, which is a function of the arrival time for task j, t_j. λ is a discount factor that accounts for the decrease in target value with time. This factor is included in the objective function to better represent the real-world problems in which the value of visiting a target decreases proportional to the time in which it is visited [43].

Since the discount factor is changing the effect of arrival time for tasks, it needs to be tuned according to the size of the world. Therefore, following architecture, visually seen on Figure 7 is to be proposed to overcome to choose the optimal discount factor and the fleet configuration.

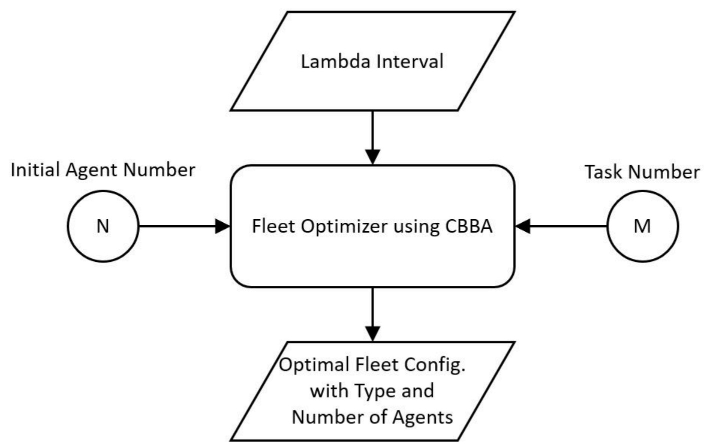

Fig. 7 Architecture of the fleet composer with λ search algorithm

VI. Simulation Studies

In simulation studies, asset types of the fleet are assumed to be heterogeneous and include unmanned aerial vehicles (UAVs), unmanned ground vehicles (UGVs) and unmanned surface vessels (USVs). As an unmanned aerial vehicle, a system with medium-high altitude long endurance capability, which is required for ISR missions, is modeled. For the unmanned ground vehicle, the performance of an average armored personnel carrier vehicle is modeled. It is assumed that this vehicle has the ability to move in any terrain. On the other hand, unmanned surfaces vessels for use in coastal areas are modeled similar to the lightweight high-performance rigid-hull inflatable boat (RHIB). The performance parameters of these agents are given in Table 2. Since the fuel and fuel consumption data of the vehicles in the task assignment algorithm are of primary importance in the distribution of tasks, these parameters are especially included in the table.

Table 2 Performance parameters of agents.

Parameters	UAV	UGV	USV
Cruise Speed (mph)	194	60	45
Range (miles)	1150	300	230
Fuel Capacity (lb)	4000	13200	175
Fuel mass flow rate (lb/s)	0.079	0.367	0.01

A. Results

Following results are obtained from initial simulation studies. In this scenario, proposed methodology is tested with different number of unmanned agents and tasks within $20x20$ grid-world environment where the heatmap is implemented. The scenario contains both the terrain and enemy presence effects where the main goal for the unmanned agents is to execute their tasks while avoiding from enemy presence areas introduced within the heatmap. In the first scenario, the blue team is initiated with 2 UAVs, and the red team, enemy includes one UGV and two UAVs within different regions of the grid-world. The result of the first scenario can be seen on Figure 8.

	Red Aerial	Red Ground	Red Naval	Blue Aerial	Blue Ground	Blue Naval
Health	0.529	0	0	0	0	0
Mobility	0.618	0	0	0	0	0

Blue Team: 2 UAVs,

Red Team: 2 UAVs, 1 UGV.

Fig. 8 The first scenario results

Clearly visible from the Figure 8, blue forces lost in the first scenario even with the optimal choice of λ. Since the remaining enemy presence consists aerial threat, the fleet configuration is updated in a way that to increase the number of UAV assets. Therefore, the second scenario is executed with 3 UAVs in the blue team and 2 UAVs, 1 UGV in enemy red team as previous scenario. The result visual can be seen on Figure 9.

	Red Aerial	Red Ground	Red Naval	Blue Aerial	Blue Ground	Blue Naval
Health	0	0	0	0.197	0	0
Mobility	0	0	0	0.127	0	0

Blue Team: 3 UAVs,

Red Team: 2 UAVs, 1 UGV.

Fig. 9 The second scenario results

As can be seen, in this scenario, the blue team is won the repeated scenario with its extra reinforcement.

VII. Conclusion

COA analysis is one of the fundamental steps of the MDMP workflow which is used to produce operation plans in military domain. Due to the operational risks and time constraints, it is important to evaluate the generated COAs with high accuracy in a limited time. In this study, an intelligent wargaming approach is proposed to accelerate the COA analysis in the MDMP. Simulation environment includes grid-world representation of the operation area, performance models of military units and combat model. Operational risks on the air, ground and sea levels are modelled as heat maps in the grid-world environment to represent the criticality level of the related location on the map. Moreover, in future studies, it is aimed to add uncertainty within battlefield that is related with the concept of fog-of-war, uncertainty in situational awareness faced by every component of wargame. Consistent and reliable communication between assets within the battlefield while completing the missions is another important aspect of this study, and it is also to be investigated as a future study. Evaluation of the COAs is performed based on combat assessment metrics. Current studies are focused on implementation of attack and defense tactics for military units to be selected and executed by the RL agent. Then, training of the RL agent will be completed by utilising the proximal policy optimization algorithm. After that, a comprehensive evaluation process will be performed to validate the effectiveness of the overall system.

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