A Computational Framework for Adaptation in Military Mission Planning

Lam Thu Bui and Zbigniew Michalewicz

***Abstract*— Military missions are highly dynamic and uncertain. This characteristic comes from the nature of battlefields where such factors as enemies and terrains are not easy to be determined. Hence disruption of missions is likely to occur whenever happening a change. This requires generating plans that can adapt quickly to changes during execution of missions, while paying a less cost.**

In this paper, we propose a computational approach for adaptation of mission plans dealing with any possible disruption caused by changes. It first mathematically models the dynamic planning problem with two criteria: the mission execution time and the cost of operations. Based on this quantification, we introduce a computational framework, which has an evolutionary mechanism for adapting the current solution to new situations resulted from changes. We carried out a case study on this newly proposed approach. A modified military scenario of a mission was used for testing. The obtained results strongly support our proposal in finding adaptive solution dealing with the changes.

I. Introduction

Mission planning is one of the core elements in military command and control. It is aimed at providing a solution that implements the commander's intent, establishes activities, time or conditions for the operation, allocates capabilities, and coordinates subordinates. This is a complicated process that involves both aspects of *science* dealing with measurable factors such as capabilities, techniques and procedures and *art* where the intuition of the commanders about the relationships between friendly forces, enemies and environment as well as the effects of the operation on the solders [5].

Further, it should be noted that dynamics and uncertainties are unavoidable factors for military missions. The presence of these factors, such as delaying in mission execution, failure of capabilities, or uncertain intuition of commanders on the relationship between operations of the mission, makes mission planning more complex given that it is already a difficult one [5], [7], [4]. This brings up to the planning process a large number of what-if scenarios that usually go beyond handling ability of human planners. Hence, to avoid any possible disruption of the mission's execution, there is a need for finding a robust and responsive mechanism in support planning staff. It becomes the motivation for us to propose a computational approach in this paper.

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There is a fact that in dynamic mission planning the selected plan is usually already in-use when a change happens. Rescheduling the whole plan is not possible in this case or might pay a high cost (or a high rate of casualties and failures). Therefore, it is important to adapt the plan to new conditions after the change. This adaptation must ensure meeting the time-line of the mission while keeping the cost of adjusting at a minimal level.

In this paper, we formulate a special class of resource constrained project scheduling (RCPS) with taking into account dynamic factors and call it as Adaptive Mission Planning Problem (AMPP). For this problem, commanders and their military staff are expected to prepare adaptive plans to deal with any changes that might happen during execution of the mission. The question is that given the current being-used plan, how to generate the new adaptation policy that can satisfy both criteria: *keeping the mission execution within its time-line* while *maintaining the less cost of alteration*? Since the above-mentioned complexity of the problem, there is no easy answer for this question.

The problem is first analyzed within a context of a military mission planning process in order to capture all important aspects of the process. The main objective is to minimize the execution time of the mission under a limit on available capabilities. It is then mathematically formulated as a multi-objective planning problem. Two objectives are proposed including the execution time of the plan, and the cost of operating capabilities. Also, three types of changes are proposed to the problem including the execution time variation, the failure of capabilities, and the change of the task-relationship network.

A general framework with a stepwise structure is introduced to support the planning staff. For the adaptation component, we adapt the current plan in a reactive-style using an evolutionary algorithm. For any task, which is already executed or in progress, it will not be scheduled again. In this way, the rescheduling process will be smaller and simpler over time since the number of tasks to be scheduled decreases. To assist the decision making, we use the second objective as the an additional indication to select a new adapted plan. A set of plans are obtained trading-off between time and cost of re-allocating the capabilities.

A case study was given based on a military scenario. The performance of the proposed approach was analyzed and discussed. Also three adaptive approaches are proposed including randomly initializing, using the last population, and the non-dominated solutions only from the last population.

The remainder of the paper is organized as follows: an

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overview of mission planning in Sections 2. The problem formulation and proposed methodology are introduced in Section 3. A case study is presented in Section 4. The last section is devoted to the conclusion of the work and lessons learnt.

II. Military Mission Planning

A. Overview of planning process

Mission planing is a decision making process in which the commander's intent is materialized. It is a vital element in military command and control aiming at providing a solution that implements the commander's intent, establishes activities, time or conditions for the operation, allocates resources, assigns tasks and coordinates subordinates. This is a complicated process that involves both aspects: (1) *Science* that deals with measurable factors such as capabilities, techniques and procedures, and it is closely related to the analytic decision making; and (2) *Art* where the intuition of the commanders about the relationships between friendly forces, enemies and environment as well as the effects of the operation on the solders are the focus and it can be considered as a kind of the intuitive decision making. Mission planning is usually done for a matter of urgency or within a short time frame of a planning horizon [5].

It is quite common in military domain that each level in mission planning is corresponding to a level of conflict: *strategic*, *operational*, and *tactical*, although the borders between these three is not always clear. The *strategic level* of a conflict involves determining national or alliance security objectives and developing and using national resources to accomplish those objectives. It establishes strategic military objectives, sequences the objectives, defines limits and assesses risks for the use of military and other instruments of power, developing strategic plans to achieve the objectives, and providing armed forces and other capabilities in accordance with strategic plans. Meanwhile, the *operational level* is designated for campaigns and major operations in order to accomplish strategic objectives within theaters or areas of operations. Linking between tactics and strategies is done by establishing operational objectives needed to accomplish the strategic objectives, sequencing events to achieve the operational objectives, and initiating actions and applying resources to bring about and sustain those events. Lastly, the *tactical level* involves situations that battles and engagements are planned and executed to accomplish military objectives assigned to tactical units. The focus of this level is on the ordered arrangement and manoeuvre of combat elements in relation to each other and to the enemy in order to achieve combat objectives established by the operational level commander. In other words, the context of tactical operations is defined at the strategic and operational levels [1], [5].

Here, we focus on the planning process at the operational level. Planners at this level need to follow the Operational Art (OA) of using military forces. According to OA, the issues to be done at this level includes (1) identifying the military conditions or end-state that constitute the strategic objectives, (2) deciding the operational objectives that must be achieved to reach the desired end-state, (3) ordering a sequence of actions that lead to fulfilment of the operational objectives, and (4) applying the military resources (capabilities) allocated to sustain the desired sequence of actions. From this point onwards, we use the term mission planning to indicate planning at the operational level, otherwise stated.

There is no doubt that the planning process is based on a particular military doctrine. However, the main steps are almost similar among militaries. We will take the JMAP framework from Australian Defence Forces (ADF) [7] as an example

- **Step 0** Initialization: including obtaining mission information (basically called intelligence preparation of the battle-space - IPB)
- **Step 1** Mission Analysis: Determining the objectives, available capabilities and other constraints for the mission. Also forming the commanders planning guidance for the next step.
- **Step 2** Course of action (COA) Development: Developing the course of actions (ways to achieve the objectives with regards to the constraints)
- **Step 3** COA Analysis: Comparing and analyzing COAs to obtain an optimal plan.
- **Step 4** Decision & Execution: Deciding on the plan and executing it

Note that this is a repetitive process. Step 0 will be used to update information for all other steps. Once updated, the steps will be restarted for further analysis. If the time is long enough and the urgency is less, we will have a deliberate planning (DP) process. It is used to produce plans for contingencies and for later execution. When we need a plan for an immediate action or in a very short time with a high urgency, we will have a crisis action planning (or immediate planning) process (CAP). These two types of planning are highly interrelated with each other. DP produces the plans, while CAP uses these plans and adapt them to the current situations. In other words, CAP provides situation awareness.

For OA, it is also essential to define several key concepts. Firstly, it is *end-state*. A state is a behaviour of a system at a particular time step. End-state can be considered the final behaviour of the system when the system stops operating. For JMAP, end-state is defined as the set of conditions which will achieve the strategic objective. The national end-state is the set of desired conditions, incorporating the elements of national power, that will achieve the national objectives. The military end-state is the set of desired conditions beyond which the use of military forces is no longer required to achieve the national objectives. The military end-state for mission planned at the operational level is defined by the command at the strategic level. This needs to be done in Step 1.

Second concept is *centre of gravity* (COG). It is the point of gravitational attraction of an object. For JMAP, COG is considered as the key characteristic, capability, or locality from which a military force derives its freedom of action, strength or will to fight. Another one is *critical vulnerability* (CV). That is a characteristic or key element of a force that if it is destroyed, captured, or neutralized will significantly reduce the fighting capability of the force and its COG. Also, it needs to mention *decisive point* (DP). JMAP defines a DP as a major event that is a precondition to the successful disruption or negation of COG. A DP can be defined either in a time or geographical space. A mission plan might have many DPs. The line of DPs forms a path to attack or defeat enemies and to achieve the end-state. We also call it as the *line of operations* - (LOP). Determining LOP is the most important component of the operational level planning. The sequence of operations needs to be done in order to achieve the end-state. Each operation or (action or task) is defined to take care one DP.

B. Mission planning problem

Determining COG, CV, and especially DPs is a challenge. It relies very much on the experience and knowledge of the staff and commanders. Further, given that these concepts are defined, finding LOPs is also a big deal. The scope of the problem triggers a large possibilities of LOPs. The limitation of capabilities, synchronization of operations (the precedence relationship between operations), and time make it very difficult to arrange the sequences of tasks to achieves all DPs. From a computational point of view, it is valuable to quantify these concepts. Given the limitation of capabilities, precedence, and time , there is a need to schedule the tasks to obtain the optimal sequence.

Note that a task is defined as a tactical operation (or action) that a military force must do for achieving a DP. From the previous analysis, we can see that modeling tasks is a very important component. Quantitatively, a task usually has

- *A set of pre-conditions*: Defining operational conditions for a task that need to be achieved before commencing it. It might be derived from the defined relationship between tasks.
- *A set of effects*: it is usually defined by the DP.
- *A duration for execution*: A task can not be executed without a time limit in order to synchronize with other tasks.
- *A set of required capabilities*: This might be equipment, weapon, vehicles or troops

Based on this definition, the planning problem can be transformed as follows

Parameters

- A set of tasks (a decomposition of the mission)
- A set of synchronization constraints for tasks.
- A limit on the capabilities available for the mission

Objective

- Military end-state (that can be expressed as a set of conditions)

Outcome

- Plans that offer different lines of operations

C. Dynamics and uncertainties

Dynamics and uncertainties are unavoidable factors for military missions. This is the nature of wars where enemies as well as environmental aspects are highly unpredictable. That is the reason for introducing the concept of the crisis action planning. One of important requirements from the US Army is that the planning process needs to be continuous and adaptive to any changes. The presence of these factors, such as delaying in mission execution, failure of capabilities, or uncertain intuition of commanders on the relationship between operations of the mission, makes the task of mission planning more complex [5], [7], [4] with a large number of what-if scenarios that usually goes beyond the handling ability of human planners. Hence, there is a need for finding a robust and responsive mechanism in support planning staff.

There are many aspects that might be changed during the mission. Here, we describe three most typical ones to demonstrate the concept including the *execution time of tasks*, *the availability of capabilities*, and *the relative relationship of tasks*. During the mission, there is no guarantee that a task will be completed in time. That might be cause of the fatigue of the troops, equipment, logistics, or new reinforcement of the enemies. Because of the limitation on the capabilities, if a task is late, there will be no return of the capabilities to do other tasks that are scheduled at the time. The question is how to adapt the current plan to deal with this change? It should be aware that any changes of the plan can cause a huge cost in terms of logistics and safety. Further, there will be that at some points, the disruption of capabilities might happen. This might be troop wounded or equipment damaged. There is a need to adjust the plan to deal with this disruption. Finally, during the mission, the importance of a task might change due to the reinforcement or changes of enemies. This might affect the relationship between tasks. Some tasks might be better to be executed before others. The staff and commanders have to figure out how to deal with this without causing too much cost.

Also, the selected plan is usually in use when happening a change. Rescheduling the whole mission is not possible in this case or might pay a high cost (or a high rate of casualties and failures). It is important to adapt the plan to the new conditions causing by the change. This adaptation must ensure meeting the time-line of the mission while keeping the cost of adjusting at a minimal level. This means the existence of multi-objectivity within this adaption process is apparent.

III. Methodology

We start with formulating the mission planning problem under the presence of dynamics and uncertainties. Since dealing with the matter of adaptation for mission planning, we call it as the *Adaptive Mission Planning Problem* (AMPP).

A. Mathematical formulation of AMPP

The problem formulation is described as follows:

- **Inputs:**

- A set V of N tasks: $V = V_1, V_2, ..., V_N$, these are non-pre-emptive. Each V_i will have:
  - A duration d_i
  - A vector rr_i of required capabilities by tasks: $rr_i = \{rr_{ij}\}$ with $j = 1, ..., M$ (M is the number of capability types)
- A network G of tasks where nodes and arcs represent the tasks and the precedence relations respectively: $G = (V, E)$. $Pred(j)$ defines a set of direct predecessors, while $Succ(j)$ is the set of direct successors of task j. A dummy node 0 represents the starting point (central base)
- A matrix c of operational costs $c = \{c_{i,j,k}\},\ i = 0, .., N;\ j = 0, ..., N$, and $k = 1, ..., M$. Here $c_{i,j,k}$ is the cost to move a capability type k from task i to task j. $c_{i,0,k} = 0 \forall i, k$ - no cost imposed on the return of items to the base
- A set R of M capabilities $R = \{R_1, R_2, ..., R_M\}$

- **Parameters:**
  - A vector of start time ts: $ts = \{ts_i\}$, with $i = 1, ..., N$
  - For each R_i at time t, a vector of locations for each item of a capability type l_{it} is defined to indicate where the item is located (or the task index). A zero value means the item is at the central base): $l_{it} = \{l_{ijt}\}, j = 0, ..., |R_i|$
  - For each R_i at time t, a vector of previous locations for each item of a capability type lc_{it} is defined to indicate where the item was from (or the task index). A zero value means the item is at the central base): $lc_{it} = \{lc_{ijt}\}, j = 0, ..., |R_i|$
  - For each R_i at time t, a vector of locations for each item of a capability type m_{it} is defined to indicate if the item was moved or not: $m_{it} = \{m_{ijt}\}, j = 0, ..., |R_i|$

$$m_{ijt} = \begin{cases} 1 & l_{ijt}! = lc_{ijt} \\ 0 & \text{otherwises} \end{cases} \tag{1}$$

  - A vector $r_t = r_{it}, i = 1, ..., M$ presents the current amount of resources being used at time t
  - Indices of the tasks: $I = \{I_1, I_2, ..., I_N\}$ (a schedule)
- **Constraints:**
  - Precedence constraint

$$I_i \notin Succ(I_j) \forall i, j | I_i \leq I_j \tag{2}$$

  - Time constraint

$$ts_i + d_i \leq ts_j \tag{3}$$

    $\forall j$, and $\forall i \in Prec(j)$
  - Capability constraint

$$r_{it} \leq |R_i| \tag{4}$$

    $\forall i$ and t
- **Objective functions:**
  - Makespan (f1): Minimization of the start time of the last task to be scheduled)

$$f_1 = ts_{\overline{N}} \tag{5}$$

    where $\overline{N}$ is the last task to be scheduled
  - Cost of resource operations (f2)

$$f_2 = \sum_{t=1 \to T} \sum_{j=1 \to M} \sum_{k=1 \to |R_j|} m_{jkt} \times c_{lc_{jkt}, l_{jkt}, j} \tag{6}$$

- **Outputs:**
  A schedule ts based on the obtained index I $ts = \{ts_1, ts_2, ..., ts_N\}$
- **Dynamic factors**
  - **Duration**: Dynamic duration of a task V_i is defined as $d'_i(t)$. It is reasonable to consider this change following a probabilistic distribution that usually is $N(d_i, \delta)$, where N is the normal distribution with the mean as the pre-defined duration d_i. Constraint Eq. 3 is rewritten as follows

$$ts_i + d'_i(t) <= ts_j \tag{7}$$

  - **Availability of capabilities**: we use a sign function to indicate the availability of capabilities:

$$l'_{ijt} = sign(t) * l_{ijt} \tag{8}$$

    where $sign(t)$ is the sign function returning either +1 or -1, a negative value means unavailable but at the location $|l_{ij}|$. Note that the number of capabilities that change their status usually follows the Poisson distribution.
  - **Precedence network**: The dynamic function representing this change is defined as reversing the relationship between two tasks on network G.
    - A function $rev(i, j)(t)$ is defined for this change defining reverse precedence between two task i and j.
    - $i, j \in V'(t)$ where $V'(t)$ is the set of un-executed tasks
- **Parameters after a change**
  Structures of l_{it}, lc_{it}, m_{it} and r_t remain unchanged. The only change is applied to the indices in which $I = I_1, I_2, ..., I_{N'}$ with N' is the numbers of tasks in $V'(t)$

B. A general framework

In this section, we propose a step-wise framework to support the staff during their planning process. The steps are described as follows:

- **Step 1**: Obtain a set of trade-off plans and select one for execution. This needs a multi-object algorithm to carry the task.
- **Step 2**: Execute the plan
- **Step 3**: Update planning information. If tasks are done, Go to Step 8
- **Step 4**: Process changing information. If no change, Go to Step 2

- **Step 5**: Check the current plan
- **Step 6**: Trigger the adaptation procedure that also needs a multi-objective mechanism.
- **Step 7**: Decide a new solution for execution and Go to Step 2
- **Step 8**: Complete the mission

In summary, for Step 3, it is the time for obtaining information from environment. If all tasks are done, the mission is completed. Also, if there is no information about any change or disruption, all the next steps will be discarded. In case of occurring a change, the staff needs to check the current plan for any possible infeasibility. If it is still feasible, there is no need to adjust the plan. Conversely, the adaptation procedure (that will be detailed in the next subsection) will be used to generate new set of plans. The loop is continued until the mission is completed.

C. Adaptation procedure

1) An evolutionary multi-objective approach for adaptation: We need to design a multi-objective approach that can offer a set of trade-off solutions for the commanders and their staff to make the decision (as in Step 1 and Step 6 of the framework). Here, we propose to use a GA approach using dominance relations. The algorithm starts with a population being initialized by techniques proposed in the next section. This population will be evolved over time. During the evolution process, all good solutions are preserved.

To perform this task, we employ the non-dominated sorting mechanism as proposed in NSGA-II [3] where the parent population and offsprings are combined and sorted in order to generate a population for the next generation. Selection of solutions for producing offspring is also performed as in NSGA-II where a scheme of crowding tournament selection is used. However, the crossover and mutation operations are redesigned since the original operators for NSGA-II are not suitable for our problem.

- **Solution representation**:

Representation is an important issue to our problem. In our problem, a complete solution must contain information for the schedule of task execution. It contains an indirect representation of a schedule. The indices of this sequence indicate the order of scheduling, while the element at each index is the ID of a task in $V'(t)$ to be executed: $S = (I_1, I_2, ..., I_{N'})$

- **Schedule generation and evaluation**:

We simply select the serial sequence generation scheme (SSGS) as the scheme for our schedule generation. For this scheme, when a task is scheduled, it is necessary to check whether it will violate the precedence relation and resource constraint (introduced by the second component of the solution) or not. This shows an interaction between the two components of a solution.

Evaluation of a solution involves calculation of two objectives. The task list is to make the schedule and therefore the makespan. The cost objective will be determined by simulating the plan with regards to the current in-use plan.

- **Genetic operators**:

The crossover operator is crucial for the behavior of GAs. Two solutions are selected and their features are combined to generate two offspring. Similar mechanisms occur in biology, this operator allows children to inherit characteristics from their parents. However, from a search and optimization perspective, this operator provides exploitation ability to the algorithm in which offspring are generated in sub-spaces around parents.

We apply a two-point crossover strategy (partial mapping) to our algorithm with a constraint on the precedence feasibility. This means that for each crossover operation, we need to select two crossing points for each component. Also, mutation is another important operator. It randomly changes the values of one or more genes in the chromosomes according to a certain distribution. This bio-inspired operator helps to reintroduce some genetic materials lost during the evolutionary process and some variability to the population. In search/optimization, this operator strengthens the exploration ability of the algorithm. It might help the algorithm to search unexplored areas of the search space. The mutation operation works as follows two consecutive genes are swaped with a predefined probability, if the newly formed sequence of tasks is precedence feasible.

2) Starting a population after a change: The initial population is very important in such time-demanding scenarios as mission planning. A good initialization will give the search a quick convergence towards the optimal solution. For AMPP, a natural way should be to start with random initialization of the initial population as done in [6] for RCPS. This method is very straightforward to implement, but gives a slow convergence during the adaptation process since the population is started from scratch. An opposite view is also taken when adapting the current plan for AMPP that is to start the population from the last population obtained from the previous change. This helps to speed up the search if the new optima is somewhere close to the area of the old population. However, if the effect of the change is large, the old population becomes entirely infeasible, this method turns to be the random one. We also implemented it with three others adjusting from adaption for RCPS with a single objective:

- **The last population** - *LP*: For this approach, we use the last population obtained from the previous adaption period $P(t-1)$ (dealing with change at change $t-1$) as the initial population $P(t)$ to deal with the change t. Any solution that is infeasible with regard to the new conditions caused by the change will be randomly re-initialized. So, if P(t-1) is the last population with size N, then P(t) is defined as

$$P(t) = P1(t-1) + P'(t) \quad (9)$$

where $P1(t-1)$ is the set of $\overline{N1}$ solutions that are feasible under the new conditions caused by the change and $P'(t)$ is the set of $N - \overline{N1}$ newly randomly initialized.

- **the set of non-dominated solutions from the last population**- *NDLP*: Instead of using all individuals in the last population, we propose to use the non-dominated only. This will help to focus on the area of the best solutions only. The rest of the population will be randomly initialized to ensure diversity of the population at some degrees. P(t) is defined as

$$P(t) = \overline{P(t-1)'} + P'(t) \qquad (10)$$

where $\overline{P(t-1)}$ is the set of $\overline{N'}$ non-dominated solutions that are feasible under the new conditions caused by the change and $P'(t)$ is the set of $N - \overline{N'}$ newly randomly initialized.
- **Randomly initialized population** - *RI*: This approach simply creates P(t) by randomly initialization without caring any information in the past.

IV. A Case Study

A. Test scenarios

We deign a military mission to validate our proposal. Note that this mission is aimed at providing an educational test only; it does not imply any particular military. For this mission, the military is to face a major peacekeeping operation of protecting a troubling Pacific Island. The strategic objective for this mission is to protect the newly installed government. The end state for this mission is the defeat of the insurgents. The main available capabilities for this mission include (exclude the landing facilities that are already provided conveniently):

- 12 Light Mortar Batteries (C1)
- 13 Infantry Companies (C2)
- 4 C130s (C3)
- 12 Apache helicopters (C4)

After analyzing the mission, the commanders and staff concluded that the mission will have 30 tactical tasks including setting up bases/checkpoints, conducting surveillance by some special troops taken from infantry companies and by helicopters, securing the government, diplomatic missions, and foreigners, protecting some key infrastructures, attacking insurgent sites, and regular patrolling either in the cities or countryside. The precedence relationship between tasks is given in Figure 1. The requirements for these tasks are listed as follows

Further, during the mission, the time delay in executing tasks is unavoidable. The intelligence source at that island is not highly reliable that cause the estimation of insurgents less accurate. Further, because of tropical weather, the failure of capabilities are highly expected with a small rate. However, the current logistic supports at the island can help to quickly repair or reinforce the capabilities. Also, the precedence of the tasks is quite relative because of unreliable intelligence information. So changes of the precedence relationship is expected. So, we will have three scenarios being equivalent with three types of change.

Task ID	Duration	C1	C2	C3	C4
1	18	4	0	0	0
2	14	10	0	0	0
3	16	0	0	0	3
4	23	3	0	0	0
5	18	0	0	0	8
6	15	4	0	0	0
7	19	0	1	0	0
8	12	6	0	0	0
9	17	0	0	0	1
10	19	0	5	0	0
11	22	0	7	0	0
12	16	4	0	0	0
13	23	0	8	0	0
14	19	3	0	0	0
15	10	0	0	0	5
16	16	0	0	0	8
17	15	0	0	0	7
18	23	0	1	0	0
19	17	0	10	0	0
20	22	0	0	0	6
21	27	2	0	0	0
22	22	3	0	0	0
23	13	0	9	0	0
24	13	4	0	0	0
25	17	0	0	4	0
26	18	0	0	0	7
27	23	0	8	0	0
28	17	0	7	0	0
29	20	0	7	0	0
30	20	0	0	2	0

TABLE I
PROPERTIES OF TASKS

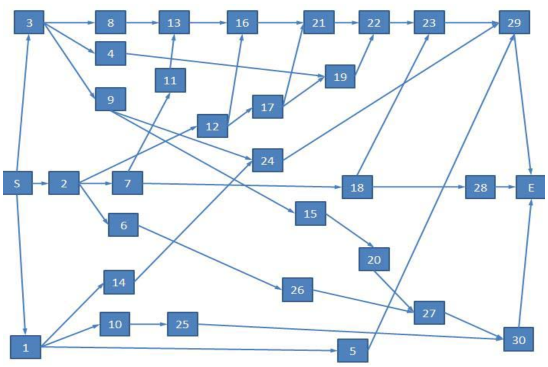

Fig. 1. Precedence network of tasks.

B. Parameter settings

From the problem description, we can see that the chromosome size is obviously 30. We used a population size of 40. The crossover and mutation rates were 0.9 and 1/30 respectively. The results were recorded after the tenth change. Each experiment was repeated for 30 times with different random seeds in the hope of eliminating the stochastic behavior caused by the random generator.

C. Results and discussion

We start discussion with an analysis on the behaviour of the proposed approach on the test scenarios. We look at the results after 10 changes from a run and take these results for analysis. We take the results obtained by LP as an example demonstrating how the adaption process happened by our proposed framework. The changes happened at time slots 1, 3, 7, 10, 13, 14, 17, 18, 19, and 22. At time zero, the baseline plan indicated that task 2 was only one that needed to be executed first and it was followed by tasks 1 and 3 at time 14. The objective values of the plan were (224 and 719.339). Note that tasks 1 and 2 can not be scheduled at the same time since both required 14 units of C1 while the maximum of C1 is 12. After a change at time 1 (note that task 2 was in-progress), it found 6 new adaptive plans. The plan with objective values of (179.553 and 1065.609) was selected. With this plan, task 3 was scheduled at time 1 and 5 tasks were kept the original starting time unchanged. The process continued until the change number 10. Again, we obtained 8 plans trading-off on time and cost. Note that at this time tasks 2 and 3 were already completed and tasks 1, 4, 7, and 12 were in-progress. So their time was not affected by the adaptation process.

For the second type, the first change was at time 4 when only task 2 was in-progress (it started at time 0) and task 3 was about to start. After the change, we adapted the plan with the remaining tasks (including task 3). We obtained 11 new plans, assumed the plan with objective values of (194 and 1034.598) for execution. With this plan, tasks 1, 10, and 25 were kept for their original starting-times and the rest was adjusted with new starting-times. Finally, after the tenth change, we obtained new 5 plans for adaptation process and these plans can be submitted to the decision makers.

In the case of the third type, after the fist change (at time 4), we obtained 5 trade-off solutions. The process continued with quite similar manner as the above two. However, here the new adapted plan kept the same starting-times for none task (except task 2 that was already in-progress at time 0). These results clearly show the nature of the change that this type can cause a large difference in terms of feasibility before and after a change.

A visualization of the non-dominated solutions obtained from all runs was given in Figure 2 with different colors. It shows us quite diverse sets of non-dominated solutions spreading over two objectives. It is important to have this diversity since we need to offer the decision makers alternatives for adapting against the change. Based on the capacity to afford the cost, the decision makers will select the final plan for the adaptation process. The above analysis has shown this matter.

D. Comparison of starting methods

We now discuss the relative performance methods (LP, NDLP, and RI). We compare them using the non-dominated plans obtained after the last change (after change No 10) of all 30 runs. Here we use the measure of the 'set coverage' - SC [2] to access the performance of these approaches. SC is determined between two sets A and B (SC(A,B)) by counting the number of solutions in B that are dominated by a solution in A: $SC(A,B) = \frac{|b \in B | \exists a \in A : a \preceq b|}{|B|}$ where $a \preceq b$ indicates a dominates b. Obviously SC(A,B) is not necessary to be equal SC(B,A).

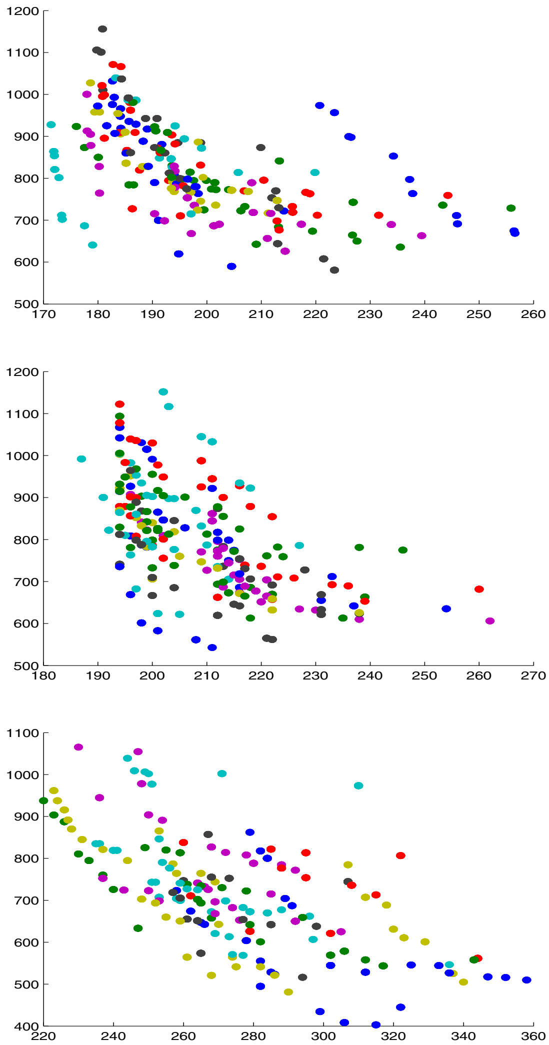

Fig. 2. Sets of non-dominated solutions over all 30 runs

The mean values and standard errors from 30 runs are reported in Table II for all methods. It seems that using the last population (LP) is a reasonable way to deal with changes. However, with changes that make a significant effect (ie. make the whole population severely infeasible), LP might not be able to offer a good start the adaptation process. That is why in comparison to RI, LP was better than RI for types 1 and 2, but it was worse for the third type. As indicated above, for the third type, a single change might cause all current population becomes infeasible, and if so the use of LP does not make much sense. Obviously, RI seems to be the unstable one as it was inferior to LP in almost all cases. This is expected since the initial population is randomly re-initialized without any past information. Meanwhile, LP and

Types		LP	NDLP	RI
1	LP	NA NA	0.083±0.037	0.389±0.073
	NDLP	0.040±0.015	NA NA	0.350±0.068
	RI	0.376±0.075	0.400±0.074	NA NA
2	LP	NA NA	0.021±0.012	0.532±0.068
	NDLP	0.010±0.006	NA NA	0.532±0.068
	RI	0.283±0.066	0.286±0.066	NA NA
3	LP	NA NA	0.014±0.010	0.235±0.062
	NDLP	0.014±0.010	NA NA	0.235±0.062
	RI	0.409±0.073	0.409±0.073	NA NA

TABLE II

THE VALUES OF SC OBTAINED AFTER ADAPTING AGAINST CHANGE NO. 10

Types		LP	NDLP	RI
1	LP	NA NA	0.056±0.005	0.391±0.008
	NDLP	0.036±0.002	NA NA	0.377±0.008
	RI	0.379±0.006	0.383±0.006	NA NA
2	LP	NA NA	0.035±0.002	0.470±0.008
	NDLP	0.028±0.002	NA NA	0.469±0.008
	RI	0.292±0.006	0.294±0.007	NA NA
3	LP	NA NA	0.007±0.001	0.246±0.006
	NDLP	0.007±0.001	NA NA	0.246±0.006
	RI	0.329±0.015	0.329±0.015	NA NA

TABLE III

AVERAGE VALUES OF SET-COVERAGE OBTAINED FROM ADAPTATION OVER A RANGE OF CHANGES

NDLP had a quite similar behaviour. That is because for our test cases, the set of obtained non-dominated solutions occupied almost all the last population, especially in the case of type 3, the last population was entirely filled by non-dominated solutions.

Further the results somewhat indicate the degree of difficulty of changing types. For types 1 and 2, changes did not make the sequence of tasks infeasible in terms of precedence constraints. The matter of adaptation is to find the alternatives that give a suitable cost of adjusting capabilities. However, for type 3, the sequence can also be infeasible with even a single flip of the precedence network. This is reflected via the obtained results. For type 3, the SC rates of LP and NDLP obtained against RI were less than that of types 1 and 2.

To get a more concrete support, we calculated the SC values of the non-dominated sets for several changes around the current being-considered change (change number 10). We started from the fifth change until the change No. 12. The average values of SC obtained after adapting to these changes were given in Table III. Again, LP and NDLP was consistently better than RI for all types of change, especially for the more difficult ones : types 2 and 3. Meanwhile RI had quite inconsistent behaviour over types of changes. The use of the past information certainly was a great help for searching under new conditions caused by changes.

V. CONCLUSION AND FUTURE WORK

In this paper, for the first time, we proposed an evolutionary multi-objective approach for adaption in dynamic military mission planning (at the operational level). We propose to investigate a special class of planning problems called Adaptive Mission Planning Problem (AMPP). For this problem, commanders and their military staff are expected to prepare adaptive plans to deal with any changes that might happen during execution of the mission. A step-wise framework was proposed for supporting the planning process.

The problem is first analyzed within a context of a military mission planning process in order to capture all important aspects of the process. The main objective is to minimize the execution time of the mission under a limit on available capabilities. To address the multi-objectivity during adaptation process, it is then mathematically formulated as a multi-objective planning problem. Two objectives are proposed including the execution time of the plan, and the cost of operating capabilities. Also, three types of changes are proposed to the problem including the execution time variation, the failure of capabilities, and the change of the precedence network.

We adapt the current plan in a reactive-style using an evolutionary algorithm. For any task, which is already executed or in progress, it will not be scheduled again. In this way, the rescheduling process will be smaller and simpler over time since the number of tasks to be scheduled decreases. To assist the decision making, we use the second objective as the an additional indication to select a new adapted plan. A set of plans are obtained trading-off between time and cost of re-allocating the capabilities. A case study based on a military mission was used to validate our approach. We also implement three other initialization techniques within the proposed evolutionary approach.

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