An Evolutionary Multi-objective Approach for Dynamic Mission Planning

Lam Thu Bui and Zbigniew Michalewicz

Abstract— **In this paper, we propose a computational approach for adaptation in mission planning, an important process in the chain of command and control. In this area, it has been highly regarded that military missions are often dynamic and uncertain. This characteristic comes from the nature of battlefields where the factors of enemies and terrains are not easy to be determined. Hence, it is necessary to generate plans that can adapt quickly to the changes during the missions, while avoiding paying a high cost. In addressing such an adaptation process, the issue of multi-objectivity can not be avoided. Our approach 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 an evolutionary multi-objective mechanism to adapt 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

In dynamic mission planning the selected plan is usually already in-use when the 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 other words, the existence of *multi-objectivity* within this adaption process is apparent. Given the importance of this issue, however there seems a lack of dedicated research to develop computational approaches dealing with it in the area of military mission planning. Here we will address this issue of tackling adaptation within the context of multi-objectivity.

We propose a special class of resource constrained project scheduling (RCPS) problems 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 objectives: *keeping the mission execution within its time-line* while *maintaining the less cost of adjusting*? 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. To address multi-objectivity during the adaptation process, it is then mathematically formulated as a multi-objective planning problem. Two objectives are proposed including the execution time, and the cost of operating capabilities. The execution time variation is selected as the change factor.

We adapt the current plan in a reactive-style. For a 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 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. An evolutionary multi-objective approach is designed for obtaining trade-off solutions. A case study was given based on a military scenario. We implement three techniques of adaptation 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 overview of mission planning, project scheduling, and evolutionary multi-objective optimization is presented in Sections 2, 3, and 4. The problem formulation and proposed method are introduced in Section 5. A case study is presented in Section 6. The last section is devoted to the conclusion of the work and lessons learnt.

II. MILITARY MISSION PLANNING

A. Overview of planning process

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*

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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 [7], [22].

Here, we focus on the planning process at the operational level. The 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.

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 or failure of capabilities, makes the task of mission planning more complex [22], [27], [18] 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.

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. 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 caused by the change. This adaptation must ensure meeting the timeline 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.

B. Computational approaches for the mission planning problem

To date, a large number of efforts has been paid on applying computational approaches to deal with mission planning. An excellent review of computational approaches can be found at [7]. The computational techniques range from a formal method of Petri Net [28], decision theoretic method using Markov decision processes [2] to heuristics techniques such as tabu search [5], and evolutionary algorithms [26]. Moreover, mission planning problems can be formulated as a resource constrained project scheduling problem, a popular class of NP-hard problems, the use of heuristics and evolutionary algorithms should be the favorite choice.

Further, the multi-objectivity ia also addressed when introducing computational approaches to mission planning. In [26], the authors proposed a hierarchical planning system where the objectives can be the mission execution time, the cost of assets or the accuracy of executing tasks. Meanwhile, in [5] the reliability was taken into account as as an objective together with the execution time. An interesting overview has been given in [9].

As stated in the above section, mission planning is a continuous and adaptive process. It constantly revises the plan over time to deal with changes. However, the issue of adaptation has been neglected in the area of computational decision support for mission planning. Most of the works focuses on addressing the aspect of robustness under uncertainties. In other words, they concentrated on the methodology of pro-activeness only. For examples, in [5], the authors used reliability as an additional objective to obtain a set of trade-off solutions; depending on the awareness of the decision makers, a solution is selected with an acceptable reliability with a hope that this solution can cope well with uncertainties. With a different view, the authors of [26] proposed to obtain a set of trade-off solutions, whenever a change happens, this set will be reviewed in order to select the best suitable one. For these approaches, the changes usually assumed happening with some bounds or with some anticipation. However, these assumptions might not always be satisfied; and further the changes over time might not be incremental. It can be the case that, once a change happened, all existing alternatives become infeasible. Hence there is a need to have a re-active adaptation mechanism for this case.

III. Multi-objective Optimization Concepts

Real-world problems often have multiple conflicting objectives. We would like to have a good quality car, but also want to spend less money on buying it, for instance. A solution to a MOP (Multi Objective Problem) is called a Pareto optimal solution if "there exists no other feasible solution which would decrease some criterion without causing a simultaneous increase in at least one other criterion" [11].

Using this definition of optimality, we usually find several trade-off solutions (called the *Pareto optimal set*, or *Pareto* *optimal front* (POF) for the plot of the vectors of decision variables corresponding to these solutions) that will be further explained later in this section. In that sense, the search for an optimal solution has fundamentally changed from what we see in single-objective optimization.

Here, the dominance concept need to be considered in evaluating individuals of a population. An individual x_1 is said to dominate x_2 if x_1 is better than x_2 when measured on all objectives. If x_1 does not dominate x_2 and x_2 also does not dominate x_1, they are said to be non-dominated. In general, if an individual in a population is not dominated by any other individual in the population, it is called a non-dominated individual. All non-dominated individuals in a population form the non-dominated set or the Pareto front.

IV. Resource constrained project scheduling problems

1) Overview: In this section, we summarize the main development of research on project scheduling in general. There are usually more than one type of resources (machine, people, money,etc). Traditionally, this problem is considered in a situation that there is a scarcity of resources when scheduling and it is usually referred to as *resource constraint project scheduling problem* - RCPS. For this problem, tasks are characterized by several aspects such as task duration, and required resources. Tasks can be involved in several execution modes and are constrained by a precedence graph. Only one mode is performed at a time. Algorithms for RCPS are expected to find an optimal schedule that minimizes the processing time (called the makespan). In general, this is a NP-hard problem [6]. Further, there are more practical approaches that can be transformed in the form of a RCPS such as production sequencing, timetabling, and flight scheduling.

In general, RCPS is a mixed integer programming problem. Therefore, conventional linear programming, such as the simplex method, is not really suitable. Researchers have actively developed a number of approaches. Broadly speaking, these approaches can be classified into two categories: exact and approximate methods. For exact methods, the final solution will the optimal one for RCPS. Some typical approaches are branch and bound [14], Lagrangean relaxation [15], and dynamic programming [10]. However, exact methods usually face an issue of scalability (the number of tasks $<= 60$, according to [3]). Therefore, approximation methods are preferred instead, such Heuristic/ meta-heuristic techniques as priority-based, truncated branch and bound, sampling techniques, local search techniques, tabu search, simulated annealing, scatter search, and evolutionary algorithms [19], [17], [20]. For stochastic project scheduling problems, several approaches have been proposed such as dynamic PERT networks [4], or MDP-based Q-learning [2].

Further, it has been surprising that although RCPS inherently possesses a feature of multi-objectivity, the literature of RCPS is dominated by work considered only single objectives [21], [24]. There exist a number of possible objectives for RCPS such as time, cost, resource balancing, robustness [1], [24], [5]. These objectives might conflict with each other to different degrees.

2) Adaptation in solving RCPS: Adaptation is a process of adjusting to the new conditions. This is one of the main topics in the literature of RCPS in dealing with the effect of uncertainties during the execution phase of a solution. Under the presence of uncertainties, changes might happen over time. Whenever there is a change, the current solution might become infeasible regarding constraints. It is essential to adapt the current solution against the effect of the change. There has been a considerable number of works on this topic [16], [23], [29]. In general there are three classes of methods tackling this adaptation issue:

- **Reactive**: In these methods, a pre-optimized solution is used as a baseline for scheduling. Whenever a change happens, this baseline solution is revised or repair to adapt with the new conditions. However, this baseline is obtained without any anticipation about the uncertainties. This repairing or revising process is usually repetitive and is considered as a local search process.
- **Proactive**: This class of adaptive methods takes into account some assumptions (anticipation) about the uncertainties such as the bound or level of changes, or the probabilistic distribution of changes in order to find the most suitable solution. The proactive solution usually obtained via a sensitivity analysis (mostly using the Monte Carlo simulation). This is usually considered as the robustness analysis process.
- **No-baseline**: In these methods there is no baseline solution in advance. The new search process will be carried out to find the new solution adapting with the new conditions (it is similar to the re-initialization process).

Also, the use of multi-objectivity is also considered as a tool for adaptation. Some examples can be described here. In [8], the authors used the set of trade-off solutions in a proactive manner with risk as an additional objective; also in this manner, [26] proposed to use the obtained tradeoff solutions as the alternatives when the change happens. In [25], a reactive adaptation technique was proposed. The authors defined two objectives : one is the make-span, while the second is the magnitude of derivation from the baseline schedule, after every change (they called it as reliability), a set of trade-off solutions is obtained, one will be selected subject to the DM's preference towards the reliability.

It is quite interesting from these works that they used multi-objectivity purely for proposing alternatives for the selection after the change. There have not been any work, especially for the reactive style, that exploit the characteristics of multi-objectivity to facilitate the search in the adaptation process. One of such characteristics is that the multi-objective approaches usually offer a set of tradeoff solutions. This set of solution can provide not only the alternative use, but the tendency of the search over time. The question is how can we exploit this tendency to facilitate the adaptation process? This becomes the focal point of the research reported in this paper.

V. 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 durations 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: $m_{it} = \{m_{ijt}\}, j = 0, ..., R_i$

$$m_{ijt} = \begin{cases} 1 & l_{ijt}! = lc_{ijt} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

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

$$I_i \notin Succ(I_j) \forall i, j | I_i \leq I_j \quad (2)$$

  - Time constraint

$$ts_i + d_i \leq ts_j \quad (3)$$

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

$$r_{it} \leq R_i \quad (4)$$

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

$$f_1 = ts_{\overline{N}} \quad (5)$$

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

$$f_2 = \sum_{t=1 \to T} \sum_{j=1 \to M} \sum_{k=1 \to R_j} m_{jkt} \times C_{lc_{jkt}, l_{jkt}, j} \quad (6)$$

- **Outputs:**
  A schedule ts based on the obtained index I $ts = \{ts_1, ts_2, ..., ts_N\}$

B. Dynamic factor

- **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 3 is rewritten as follows

$$ts_i + d'_i(t) <= ts_j \quad (7)$$

C. 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 number of task in $V'(t)$

D. An evolutionary multi-objective approach for AMPP

The use of an additional objective for AMPP is to facilitate the adaptation process. Hence, 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. 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 [13] 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.

E. 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 [25] 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

$$P(t) = P1(t-1) + P'(t) \tag{8}$$

  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

$$P(t) = \overline{P(t-1)'} + P'(t) \tag{9}$$

  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.

VI. 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)

TABLE I

PROPERTIES OF TASKS

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

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 in Table I

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.

B. Parameter settings

From the problem description, we can see that the chromosome size is obviously 30. We used a population size

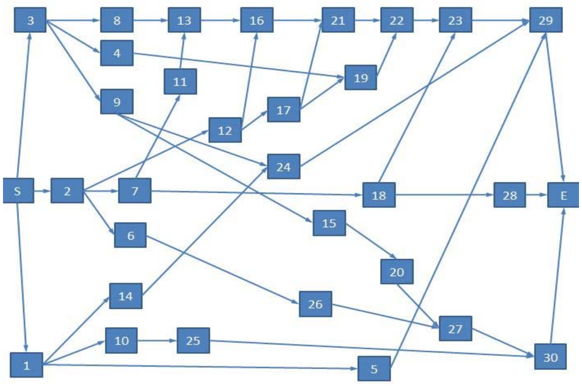

Fig. 1. Precedence network of tasks.

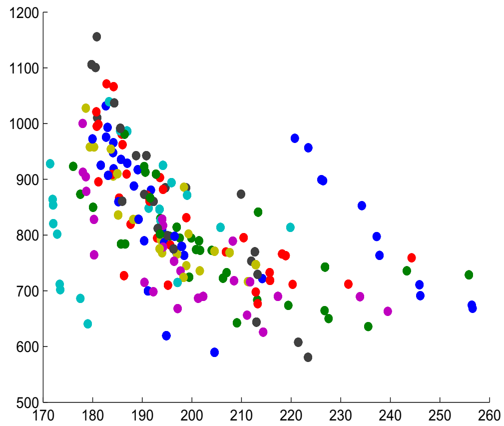

Fig. 2. Sets of non-dominated solutions over all 30 runs

of 40. The crossover and mutation rates were 0.9 and 1/30 respectively. The size of the centroid set was 10 and the results were recorded after the tenth change. There is no particular reason for selecting these parameters values, except they were set after a number of trials and they gave the most reliable performance. 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, the changes happened at time slots 1, 3, 7, and 10 (a snapshot of schedules was given in Figures 3 and 4: the baseline schedule, the adapted schedule after the first change). At time zero, the baseline plan (Figure 3) 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 (Figure 4). The process continued until the last change. 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.

A visualization of the non-dominated solutions obtained from all runs was given in Figure 2. 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. The above analysis has shown this matter.

Our implementation allowed the original solutions being reconsidered after every change. If they are still feasible, they will be included for consideration, and they might be excluded during evolution process if they become dominated.

TABLE II

THE VALUES OF SC OBTAINED AFTER ADAPTING AGAINST THE LAST CHANGE

	LP	NDLP	RI
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

D. Comparison of starting methods

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 [12] 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:

$$SC(A,B) = \frac{|b \in B | \exists a \in A : a \preceq b|}{|B|} \tag{10}$$

where $a \preceq b$ indicates a dominates b. Obviously SC(A,B) is not necessary to be equal SC(B,A).

The mean values and standard errors from 30 runs are reported in Table II for all methods . Clearly, it seems that the use of the last population (LP) is a reasonable way to deal with changes. In comparison to RI, LP was better than RI. The exploitation of the past information seemed to give a big support for adaptation process. Obviously, the method of RI was inferior to LP. This is expected since the initial population is randomly re-initialized without any past information. Meanwhile, LP and NDLP had a quite similar behaviour. Their SC values were very small (0.083-0.040). That is because for our test case, the set of obtained non-dominated solutions occupied almost all the last population

VII. CONCLUSION AND FUTURE WORK

In this paper, we proposed an evolutionary multi-objective approach for adaption in dynamic military mission planning

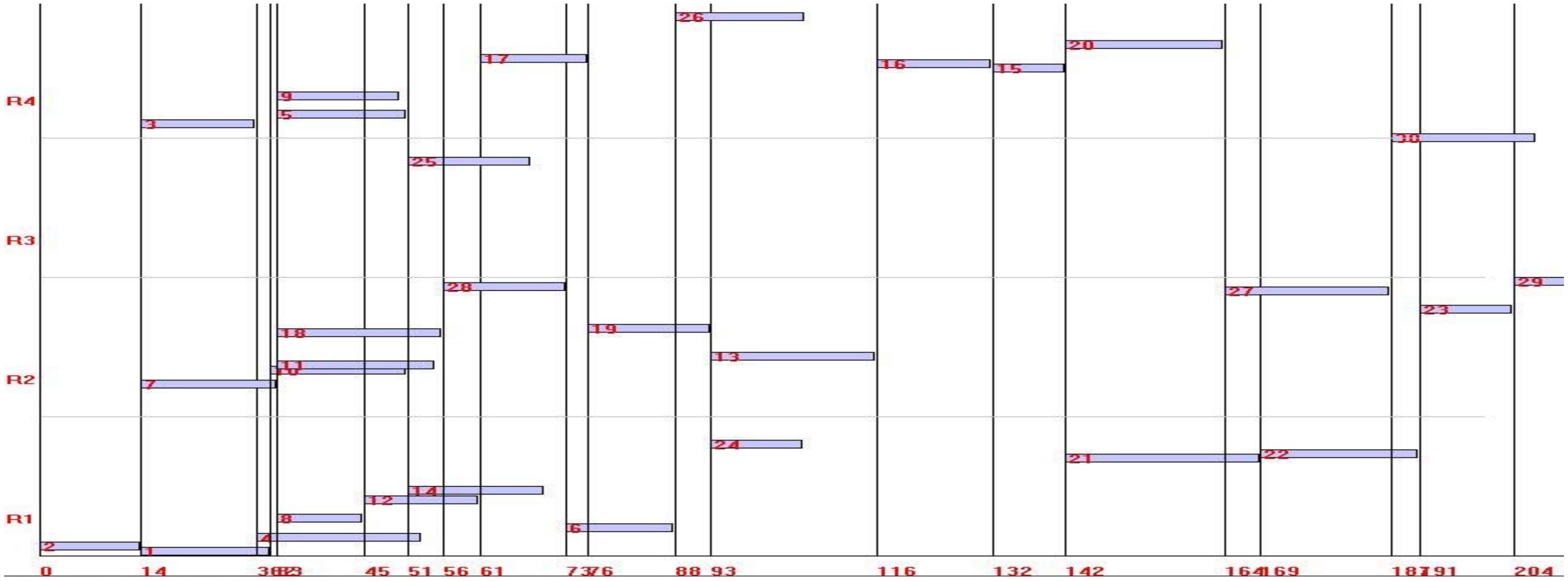

Fig. 3. The baseline schedule

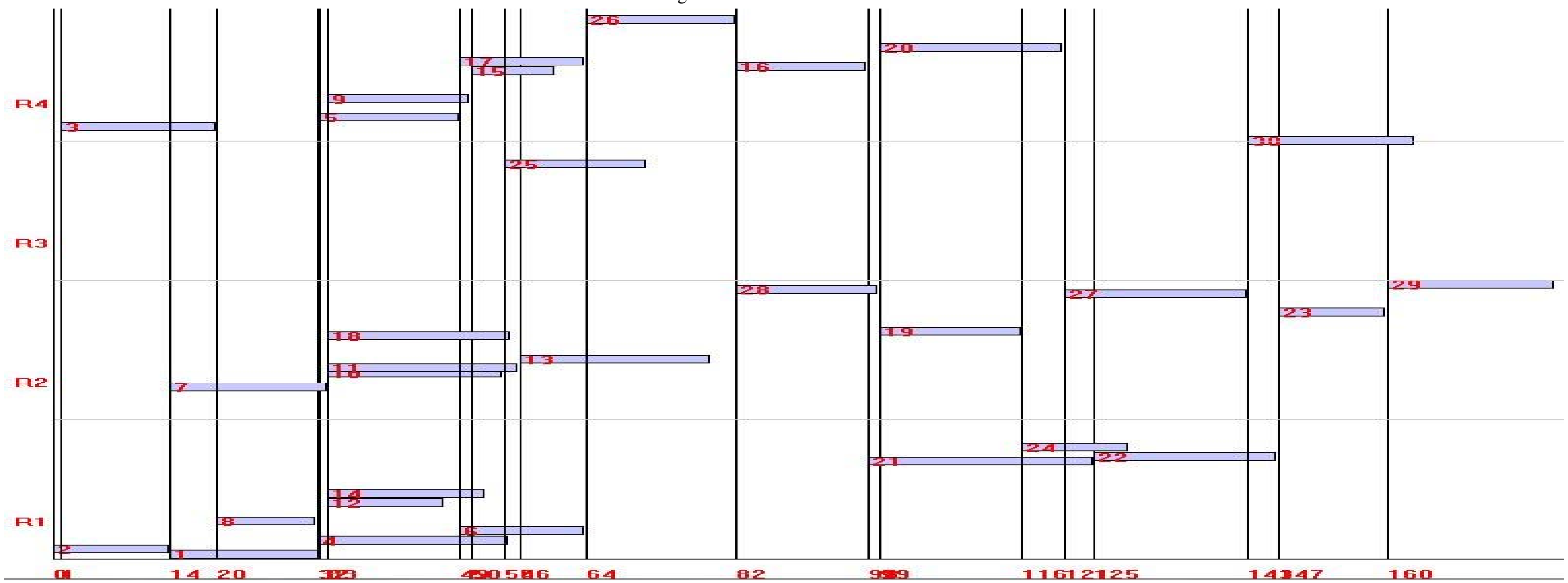

Fig. 4. The adapted schedule after the fist change obtained by LP

(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. The question is that given the current being-used plan, how to generate the new adaptation policy that can satisfy both objectives: *keeping the mission execution within its time-line* while *maintaining the less cost of adjusting*?

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.

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 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 initialization techniques within the proposed evolutionary approach. The obtained results clearly showed the good performance of the proposed approach on dealing with the effects of changes.

For future work, we plan to investigate more complex instances of AMPP and with the use of a more complex simulation that allows us to present the factor of human in the loop.

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References

[1] B. Abbasi, S. Shadrokh, and J. Arkat. Bi-objective resource-constrained project scheduling with robustness and makespan criteria. *Applied Mathematics and Computation*, 180:146–152, 2006.

[2] D. Aberdeen, S. Thiébaux, and L. Zhang. Decision-theoretic military operations planning. In *Proc. ICAPS*, 2004.

[3] J. Alcaraz and C. Maroto. A robust genetic algorithm for resource allocation in project scheduling. *Annals of Operations Research*, 102(4):83–109, 2001.

[4] A. Azaron and R. Tavakkoli-Moghaddam. Multi-objective timecost trade-off in dynamic PERT networks using an interactive approach. *European Journal of Operational Research*, 180:11861200, 2007.

[5] L. Belfares, W. Klibi, N. Lo, and A. Guitouni. Multi-objective tabu search based algorithm for progressive resource allocation. *European Journal of Operational Research*, 177:1779–1799, 2007.

[6] J. Blazewicz, J.K. Lenstra, and A.H.G. Rinnooy Kan. Scheduling subject to resource constraints: Classification and complexity. *Discrete Applied Math*, 5:11–24, 1983.

[7] A. Boukhtouta, A. Bedrouni, J. Berger, F. Bouak, and A.Guitouni. A survey of military planning systems. In *The 9th ICCRTS Int. Command and Control Research and Technology Symposium*, Copenhagen, Denmark, 2004.

[8] Lam T. Bui, Michael Barlow, and Hussein A. Abbass. A Multiobjective Risk-based Framework for Mission Capability Planning. *New Math. and Natural Comp., World Scientific*, 5(2):459–485, 2009.

[9] L.T. Bui and S. Alam. *Multi-Objective Optimization in Computational Intelligence: Theory and Practice*. Infor. Sc. Publishing, 2008.

[10] J. A. Carruthers and Albert Battersby. Advances in critical path methods. *Operations research quarterly*, 17(4):359–380, 1966.

[11] C. A. C. Coello. Evolutionary multi-objective optimization: A historical view of the field. *IEEE Comp. Intel. Mag.*, 1(1):28–36, 2006.

[12] K. Deb. *Multi-objective optimization using evolutionary algorithms*. John Wiley & Sons, New York, 2001.

[13] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Trans. on Evolutionary Computation*, 6(2):182–197, 2002.

[14] E. Demeulemeester and W. Herroelen. A branch-and-bound procedure for the multiple resource-constrained project scheduling problem. *Management Science*, 38(12):1803 – 1818, 1992.

[15] A Drexl and A Kimms. Optimization guided lower and upper bounds for the resource investment problem. *Journal of Operations Reseach Society*, 52:340–351, 2001.

[16] W. Herroelen and R. Leus. Project scheduling under uncertainty: Survey and research potentials. *European journal of operational research*, 165(2):289–306, 2005.

[17] K. S. Hindi, H. Yang, and K. Fleszar. An evolutionary algorithm for resource-constrained project scheduling. *IEEE Trans. on Evol. Comp.*, 6(5):512–518, 2002.

[18] R.H. Kewley and M.J. Embrechts. Computational military tactical planning system. *IEEE Trans. on Systems, Man, and Cybernetics, Part C*, 32(2):161–171, 2002.

[19] R. Kolishch and S. Hartmann. Experimental investigation of heuristic for resource constrained project scheduling: An update. *European Journal of Operational Research*, 174:23–37, 2006.

[20] D. Merkle, M. Middendorf, and H. Schmeck. Ant colony optimization for resource-constrained project scheduling. *IEEE Trans. on Evolutionary Computation*, 6(4):333–346, 2002.

[21] R. Slowinski. *Advances in project Scheduling*, chapter Multiobjective project scheduling under multiple-category resource constraints. Elsevier, 1989.

[22] US Department of the Army. FM 5-0: Army Planning and Orders Production, 2005.

[23] S. Van de Vonder, E. Demeulemeester, and W. Herroelen. A classification of predictive-reactive project scheduling procedures. *Journal of Scheduling*, 10(3):195–207, 2007.

[24] Ana Viana and Jorge Pinho de Sousa. Using metaheuristics in multiobjective resource constrained project scheduling. *European Journal of Operational Research*, 120:359–374, 2000.

[25] S.D. Wu, R.H. Storer, and P.C. Chang. One-machine rescheduling heuristics with efficiency and stability as criteria. *Computers and Operations Research*, 20(1):1–14, 1993.

[26] F. Yu, F. Tu, and KR Pattipati. Integration of a Holonic Organizational Control Architecture and Multiobjective Evolutionary Algorithm for Flexible Distributed Scheduling. *IEEE Transactions on Systems, Man and Cybernetics, Part A*, 38(5):1001–1017, 2008.

[27] L. Zhang, L. Falzon, M. Davies, and I. Fuss. On relationships between key concepts of operational level planning. In *Proceedings of 5th International Command and Control Research and Technology Symposium*.

[28] Lin Zhang, Lars M. Kristensen, Chris Janczura, Guy Gallasch, and Jonathan Billington. A coloured petri net based tool for course of action development and analysis. In *CRPIT '02: Proceedings of the conference on Application and theory of petri nets*, pages 125–134. Australian Computer Society, Inc., 2002.

[29] G. Zhu, JF Bard, and G. Yu. Disruption management for resource-constrained project scheduling. *The Journal of the Operational Research Society*, 56(4):365–381, 2005.