A MULTI-OBJECTIVE APPROACH FOR WEAPON SELECTION AND PLANNING PROBLEMS IN DYNAMIC ENVIRONMENTS

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Abstract. This paper addresses weapon selection and planning problems (WSPPs), which can be considered as an amalgamation of project portfolio and project scheduling problems. A multi-objective optimization model is proposed for WSPPs. The objectives include net present value (NPV) and effectiveness. To obtain the Pareto optimal set, a multi-objective evolutionary algorithm is presented for the problem. The basic procedure of NSGA-II is employed. The problem-specific chromosome representation and decoding procedure, as well as genetic operators are redesigned for WSPPs. The dynamic nature of the planning environment is taken into account. Dynamic changes are modeled as the occurrences of countermeasures of specific weapon types. An adaptation process is proposed to tackle dynamic changes. Furthermore, we propose a flexibility measure to indicate a solution’s ability to adapt in the presence of changes. The experimental results and analysis of a hypothetical case study are presented in this research.

1. Introduction. In defense planning areas and, particularly, in the planning for weapon system developments, most countries have moved away from threat-based planning toward capabilities-based planning since 2001[22]. Capability-based planning usually involves the development of new types of weapons to fulfill future capabilities. Due to growing budgetary pressure, it is not practical to develop an

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indiscriminately large number of weapon systems. Thus, decision makers at the strategic level, e.g., senior officials in the Department of Defense, must balance investment and capability areas by making some trade-offs such as cost-efficiency analyses. In such a setting, it is important to carefully select weapon development projects that can achieve higher effectiveness with lower costs.

The weapon selection process can be modeled as a portfolio optimization problem. Most of existing research for projects or weapon systems portfolios focuses on the selection of items to consist of efficient solutions. However, in military capability planning, the task of decision makers involves not only selecting weapons but also identifying the appropriate time to develop the selected weapons. The latter can be considered as a planning or scheduling process. In this paper, we simultaneously consider the selection and the planning processes, which seldom can be found in existing literature. The addressed problems are termed as weapon selection and planning problems (WSPPs), which can be considered as an amalgamation of weapon systems portfolio problems and project scheduling problems with non-renewable resources.

To support the trade-off for decision makers, solutions for WSPPs are evaluated from two aspects: cost and effectiveness. The cost of a solution is indicated by the Net Present Value (NPV) of developing all selected weapons. The effectiveness of a solution is measured by considering the amounts and operational times of different types of weapons as well as the synergy effects among weapons. The problem is modeled as a multi-objective problem by simultaneously optimizing the NPV and the effectiveness objectives. To tackle the optimization task, we present a multi-objective evolutionary algorithm based on NSGA-II, where chromosome representation and genetic operators are redesigned according to the problem domain.

Furthermore, we take into account the dynamic characteristic of the planning environment, where the effectiveness is affected and may decrease when the countermeasures are achieved by the opponents. The occurrence of a countermeasure is considered as a dynamic change. An adaptation process is designed as the reactive policy when any change occurs. A flexibility measure is also proposed to indicate a solution’s ability to adapt within the dynamic environment. The addressed problem and the proposed approach are illustrated with a hypothetical case study. The computational results suggest that the proposed multi-objective optimizer can solve the problem well and demonstrate the effectiveness of the adaptation process in a dynamic environment. A correlation analysis between the flexibility measure and adaptation effectiveness indicates that the proposed flexibility measure may be appropriate as a utility function for decision making after the non-dominated set is obtained in the dynamic environment.

The rest of the paper is organized as follows. In Section 2, we briefly review the literature on portfolio problems and capability planning problems. Problem formulation and proposed method are described in Section 3 and 4, respectively. Experimental results on a hypothetic case are reported in Section 5. Finally, some conclusions are drawn in Section 6.

2. Literature review. Because WSPPs can be considered as an extension of traditional portfolio selection and management problems and the amalgamation of planning problems, in this section, we briefly review the related work on portfolio problems and capability planning problems.
Because of its practical importance, solving portfolio problems has attracted much attention in different areas. Due to the inherent multi-objective trait, i.e., maximizing the return while minimizing the risk, as well as many non-convex constraints in practical applications, multi-objective evolutionary algorithms (MOEAs) might be preferable for solving portfolio problems. The first attempt to use MOEAs to solve portfolio problems can be found in a study by Arnone et al. [4]. During the last decade, with the developments of MOEAs, a great number of multi-objective approaches to portfolios have been reported in the literature. Doerner et al. [15] address the project portfolio problem where the objectives of benefit and remaining resources are simultaneously considered. The authors introduced a Pareto ant colony optimization method to solve the problem. Branke et al. [6] propose an envelope-based MOEA for portfolio problems with non-convex constraints. Gutjahr et al. [20] implement NSGA-II [13] and Pareto ant colony optimization to solve project portfolio problems where the economic and staff competence benefits are simultaneously considered. Carazoa et al. [9] employ a scatter search procedure to solve multi-objective comprehensive project portfolio problems that combine the selection and scheduling of projects in the process. Kremmel et al. [25] et al. consider software project portfolio problems with several objectives, such as potential revenue, strategic alignment and resource usage distribution, risk and synergy. The authors proposed a multi-objective optimization approach based on the Prototype Optimization with Evolved Improvement Steps (mPOEMS) to solve the problem. Anagnostopoulos and Mamanis [2] compare the performances of three different MOEAs, named the NSGA-II, the Pareto Envelope-based Selection Algorithm (PESA) and the Strength Pareto Evolutionary Algorithm 2 (SPEA2), when solving a tri-objective portfolio optimization problem. The same authors implemented an experimental analysis of five MOEAs for cardinality constrained portfolio optimization problems in their later research [3]. For recent comprehensive surveys of solving portfolio problems by MOEAs, reader are referred to [27] and [29].

However, the application of portfolios in the defense area, specifically weapon selection, is rather scant. Greiner et al. [19] addresses the screening of weapon system development projects and their realistic application in the Air Force. In their research, an analytic hierarchy process (AHP) and a 0-1 integer portfolio optimization model is integrated into a decision support methodology. Yang et al. [39] discuss the portfolio selection for military investment assets based on semi-variance as a measure of risk. The authors employed heuristic algorithms to obtain efficient solutions. Kangaspunta et al. [24] address a weapon system portfolio problem with interactions among systems and incomplete preference information about multiple criteria. In that research, the effectiveness of a weapon portfolio is evaluated by an additive value function, where the weight and the evaluation of each criterion are required.

For weapon acquisition in defense areas, decision makers are concerned not only what type of weapons to buy but also when to buy these weapons. The latter process is related to the long-term planning problems. Barlow et al. [5] present a temporal risk assessment methodology for planning future force structure. Abbass et al. [1] employ an evolutionary multi-objective approach to address resource planning under time constraint problems where the main task is to find a (Pareto) optimal mix of vehicles to fulfill future tasks. Whitacre et al. [35] address a resource planning problem and show that that scenario-based planning is naturally framed within a multi-objective setting. Bui et al. [8] model the military capability planning
process by combining resource-constrained project scheduling and resource investment problems and use an evolutionary algorithm to address the optimization task. Shaﬁ et al. [30, 31] address the ﬂeet mix problem for future transportation in defense logistics planning. The authors employ learning classiﬁer systems to solve the problem. Xiong et al. [38] study the capability-planning problem with consideration of domain knowledge and decision makers’ preference in the framework of a multi-objective approach. With the consideration of existing or potential weapons to be developed by the counterpart, Golany et al. [18] focus on the problem of how to utilize limited resources to develop effective countermeasures.

In the project management area, the literature simultaneously addressing the combination of selecting and planning processes is rather scant. However, the real application calls for the integration of these two processes and optimizing them from the overall perspective. The works of [17, 34, 20, 9] are among the few to simultaneously address projects selection and planning. However, these works did not consider the dynamic nature during the planning horizon. To the best of our knowledge, there is no literature to describe a comprehensive model of project selection and planning with the consideration of multiple objectives, project synergy and a dynamic environment. This is the main motivation of this research.

3. Weapon selection and planning problems.

3.1. Notation. Weapon selection and planning problems (WSPPs) can be formally described as follows: Decision makers at a strategic level need to select weapons and plan their development at time $T_0$. The main purpose of the selection and planning process is to develop suitable weapons to fulﬁll future capability requirements at speciﬁc time point $T$, $T > T_0$. Usually, $T_0$ is the beginning of the year when initial decisions are made, while $T$ is the end of the year at which the future capability is analyzed. The time horizon length of the whole planning process is $N$ years. Typically, the planning process is divided into $M$ periods, indexed by $m = 1, 2, \cdots, M$. Each period consists of one month [20], i.e., $M = 12N$. There are budget constraints imposed on each year, denoted as $B_n (n = 1, \cdots, N)$. In other words, capital for weapon development provided by the government in each year cannot exceed $B_n$. The capital is available at the beginning of each year. The actual spent capital for each year is represented as $B_s (n = 1, \cdots, N)$. We assume that the capital not spent in the previous months can be accumulated and will be available for the next month in the same year. However, the capital not spent during the last year cannot be accumulated for the next year. This assumption is reasonable for the situation that the acquisition plan is executed and examined every year.

The weapon types from which decision makers can choose are indexed by $w \in W = \{1, 2, \cdots, |W|\}$. For each type of weapon, the amount to be developed during the whole planning horizon is denoted as $a_w$ and is bounded in the interval $[a_{w, \text{low}}, a_{w, \text{up}}]$. The lower bounds, $a_{w, \text{low}}$, are imposed because some types of weapons cannot form combat effectiveness unless they have a considerably large scale. While the upper bounds, $a_{w, \text{up}}$, are determined by the limitation of industrial standards, manufacturing ability, and other constraints. The cost for one unit of each type of weapon is denoted as $c_w$.

For each weapon type $w$, let $d_w$ represent the period of the weapon from the launch of the project to the deployment of the weapon. We assume that $d_w$ is independent of $a_w$, and the variant of $a_w$ only results in changes in the total cost of weapon developments. Due to the restriction of technology and industrial standards,
the developments of certain types of weapons require breakthroughs of some cutting-edge technologies. Thus, release dates are imposed on the development of each weapon type, denoted as $r_w$. In particular, $r_w = 0$ means that the development of weapon $w$ can be started at time $T_0$, while $r_w > 0$ indicates that the development of weapon $w$ cannot be launched until time $T_0 + r_w$.

Usually, the tasks of weapon developments are executed by one or more contractors. The events of signing such contracts are denoted as $E = \{e_1, e_2, \cdots, e_{|E|}\}$. It is assumed that military departments pay all costs to the contractors at the beginning of the developments. In other words, cash outflows occur at each event $e_j$ ($j = 1, 2, \cdots, |E|$). The time points of events $e_j$ are denoted as $S = (s_1, s_2, \cdots, s_{|E|})$. At each event $e_j$, we assume that a single type of weapon is to be developed. Thus, decision makers only need to decide the weapon type and the amount at each $e_j$. The weapon amount to be developed at $e_j$ is denoted as $A_j = (a_{w_j})$, $w = 1, 2, \cdots, |W|$, $j = 1, 2, \cdots, |E|$. Then, $a_w = \sum_{j=1}^{|E|} a_{w_j}$ is satisfied. For each $e_j$, the operational time of selected weapons is denoted as $o_w^j (a_{w_j} \neq 0)$, then $o_w^j = s_j + d_w$. Note that the operational time of a batch of weapons began to be developed at each $e_j$ can be analogized to the finish time of an activity in project scheduling problems. However, we are aware that in real-world applications, combinations of different types of weapons may exist at each $e_j$. Such a case is out of the scope of this research and left for our future research.

3.2. Weapon interdependencies. It is worth noting that weapons are not totally independent, but possibly interact and collaborate with each other to fulfill future capabilities. Thus, it is necessary to account for relations among different weapons. For instance, we consider two types of weapons - tanks and aerotransports - in the fulfillment of global delivery capability. Although these two types of weapons belong to different departments and can be developed independently, delivering of tanks and infantrymen requires the support of aerotransports. In this scenario, tanks cannot achieve their full effectiveness until capable aerotransports are developed. Moreover, the proportion between different weapons plays an important role in military planning [37]. For example, we suppose that the total weight of each tank is 40 tonnes and the maximum transportation ability of each aerotransport is 300 tonnes. Then, it is clear that the ratio 1:7 of the amount of aerotransports to tanks is the best proportion in the weapon portfolio selection for global delivery capability.

Based on the above discussion, we represent the interdependencies among different types of weapons by two elements: collaboration relation and proportion coefficient. The set of collaboration relations is denoted as $CR = (CR_c)$, where $c = 1, 2, \cdots$. Each $CR_c$ is represented by a pair of weapon indexes, i.e., $CR_c = (S_c(|W|), w^*)$, which means that weapon $w^*$ needs the support from weapons in the subset $S_c(|W|)$. For instance, if aerotransports and tanks in the above example are indexed by 1 and 2, respectively, a collaboration relation between the two types of weapons can be represented as (1, 2). If tanks further need the support from infantrymen (indexed as 3), then, the collaboration relation is represented as ((1, 3), 2). The set of proportion coefficients is denoted as $P = (P_c)$. For a set of interdependent weapons, the proportion coefficient is denoted by a normalized vector $P_c = (\gamma_{w_1}, \gamma_{w_2}, \cdots, \gamma_{w_{|P_c|}})$, satisfying $\sum_{j=1}^{|P_c|} \gamma_{w_j} = 1$, where $|P_c|$ is the length of the vector. For example, the proportion coefficient between aerotransports and tanks can be represented as ($\gamma_1 = 1/8, \gamma_2 = 7/8$).
3.3. Objectives calculation. As aforementioned, decision makers at strategic level usually need to balance the investment cost across the effectiveness of developed weapons. Thus, it is useful to provide decision makers a set of efficient solutions based on which final choice can be made. In this paper, we indicate the investment cost by net present value (NPV) and use a capability-oriented measure to represent the effectiveness of the whole set of developed weapons.

3.3.1. Calculation of NPV. For a solution of the WSPP, NPV can be obtained as follows:

$$NPV = f_{in} - f_{out}$$  \hspace{1cm} (1)

where $f_{in}$ and $f_{out}$ respectively indicate cash inflows and cash outflows[11].

In project scheduling problems, $f_{in}$ usually consists of payments at all milestones [11]. For WSPPs, capital is available at the beginning of each year. Thus, $f_{in}$ can be obtained by the following equation.

$$f_{in} = \sum_{n=1}^{N} B_n \exp(-12(n-1)\alpha)$$  \hspace{1cm} (2)

where $\alpha$ is the discount rate.

Cash outflows $f_{out}$ consist of all expenses paid to contractors. At each event, the paid cost is denoted as $P_j$ and calculated as follows:

$$P_j = \sum_{w=1}^{|W|} a_{w}^{j} \times c_{w}$$  \hspace{1cm} (3)

$P_j$ is discounted to $P_{jd}$ by the following equation:

$$P_{jd} = P_j \exp(-\alpha s_j)$$  \hspace{1cm} (4)

Then, cash outflows $f_{out}$ can be calculated as follows:

$$f_{out} = \sum_{j=1}^{|E|} P_{jd}$$  \hspace{1cm} (5)

3.3.2. Calculation of effectiveness. For a solution of the WSPP, effectiveness needs to be evaluated at the overall level. The effectiveness of an overall solution consists of two parts: the first is the effectiveness of each type of weapons and the second is the effectiveness obtained from the synergy of different weapons.

For single type of weapons, the effectiveness is quantified into the interval $[0,1]$ and denoted as $EF_w$. In this research, we consider the effectiveness of a type of weapon is related to two factors: the amount and the operational time. It is assumed that $EF_w = 1$ when the maximum amount of the specific type of weapon is achieved, i.e., $a_w = a_{up}^{w}$, and all the units can be operational at time $T_0$. All selected weapons may be developed in different batches corresponding to events $E$. For each $e_j$, the effectiveness of the developed weapon $a_{w}^{j}$ is denoted as $EF_{wj}$, which is evaluated by the following equation.

$$EF_{wj} = \frac{a_{w}^{j}}{a_{w}} \times \frac{1}{\exp\left(\frac{a_{w}^{j}}{T - T_0}\right)}$$  \hspace{1cm} (6)

Then, $EF_w$ is calculated as follows:

$$EF_w = \left(\frac{a_{w}}{a_{up}^{w}}\right) \sum_{j=1}^{|E|} EF_{wj}$$  \hspace{1cm} (7)
where $\mu$ is a coefficient between 0 and 1 and is set as $1/3$ in this research.

In project portfolio problems, synergy refers to the overall value of a set of projects differs from the sum of the individual projects’ overall values. Usually, it is assumed that project synergy occurs at least specific types of projects are selected [26]. For WSPPs, the synergy effect of a set of weapons is achieved gradually and discretely during the planning process. For weapon $j$ with $CR_c = (S_c(|W|), w^*)$, synergy effect occurs when all weapons in $S_c(|W|)$ are operational with appropriate amounts indicated by proportion coefficient $P_c$. Similarly, the synergy effect is described by amount and time. The event of synergy effect achievement is indexed by $t$. At each event, the amount of weapon $w^*$ obtaining synergy effect is denoted as $a_{SN_{w^*}^t}$ and the related time is represented as $t_{SN_{w^*}^t}$. The synergy effect of weapon $w^*$ at each event is denoted as $SN_{w^*}^t$ and can be calculated as follows:

$$SN_{w^*}^t = \beta_{w^*} \frac{a_{SN_{w^*}^t}}{a_{w^*}} \times \frac{1}{\exp\left(\frac{t_{SN_{w^*}^t}}{T_0}\right)}$$

(8)

where $\beta_{w^*}$ is a synergy effect coefficient. Usually, the synergy effect of a weapon will not exceed the effectiveness of itself. Thus, $\beta_{w^*}$ is bounded into the interval $[0,1]$. Then, the synergy effect of weapon $w^*$, $SN_{w^*}$, can be calculated as follows:

$$SN_{w^*} = \sum_{t=1}^{t_{w^*}} SN_{w^*}^t$$

(9)

where $t_{w^*}$ is the number of synergy effect achievement events for weapon $w^*$.

Then, the effectiveness of a solution of the WSPP is denoted as $EF$ and is evaluated as follows:

$$EF = \sum_{w=1}^{[W]} EF_w + \sum_{\{w^*|CR_c=(S_c(|W|), w^*)\}} SN_{w^*}$$

(10)

In the right part of the above equation, the first element indicates the total effectiveness of single weapons, while the second part represents the synergy effectiveness obtained by the collaboration among different types of weapons.

3.4. Multi-objective optimization model for WSPPs. Then, WSPPs can be formulated as the following multi-objective optimization model:

obj. : (1) $\min f_1 = -NPV$
(2) $\min f_2 = -EF$

s.t. : (1) $a_{low} \leq a_w \leq a_{up}$, if $a_w > 0$, $\forall w$
(2) $\sum_{j=1}^{[E]} a_{ij} = a_w$, $\forall w$
(3) $s_j + d_w \leq T$, for $a_{ij} > 0$, $\forall e_j$
(4) $s_j \geq r_w$, for $a_{ij} > 0$, $\forall e_j$

(11)

Without loss of generality, we convert the multi-objective optimization problem into minimization form. Objectives $f_1$ and $f_2$ respectively represent the maximization of net present value and effectiveness of a weapon selection and planning solution. Constraint (1) bounds the selected weapon into the lower and upper bound, constraint (2) ensures that the selected weapons are developed during the whole
planning horizon, constraint (3) indicates that all selected weapons should be finished before the end of the planning process, constraint (4) represents that the development of all weapons should be started after the release dates.

3.5. Dynamic environments. In the above section, the calculation of the whole solution effectiveness in a deterministic situation is discussed. However, the effectiveness of some specific types of weapon may be affected by countermeasures developed by counterparts. For instance, the effectiveness of weapons for strike purposes is usually indicated by the damage rate, which will decrease when countermeasures are developed[18]. A similar situation exists for weapons used for reconnaissance. When the stealthy performance of aircrafts or warships of counterparts is improved, the success rate of reconnaissance will possibly decrease. Although the completion times of countermeasures can be estimated by intelligence agencies, the actual completion times are highly dynamic for WSPPs. This is because counterparts will not reveal any information about countermeasures before they are completed and applied in real battlefields.

We assume that each type of weapon has at most one countermeasure. For each weapon \( w \), the countermeasure is denoted as \( CM_w \), whose real completion time is represented by \( t_{CM_w} \). Under the impact of countermeasures, both the single and synergy effectiveness of weapons decrease since the completion time \( t_{CM_w} \). For weapon \( w \), the decrease degree in the presence of countermeasure is indicated by \( \eta_w \in [0, 1] \), which is a predefined constant. Then, the calculation of \( EF_{w}^j \) and \( SN_{w}^t \) are respectively modified as follows:

\[
EF_{w}^j = \frac{a^j_w}{a_w} \frac{1}{\exp\left(\frac{\sigma^j_w}{T-T_0}\right)} \frac{1}{T - \sigma^j_w} \left(\max\{t_{CM_w} - \sigma^j_w, 0\} + \eta_w(T - \max\{t_{CM_w}, \sigma^j_w\})\right)
\]

\[
SN_{w}^t = \beta_w \frac{a_{snw^t}}{a_{w^t}} \frac{1}{\exp\left(\frac{t_{snw^t}}{T-T_0}\right)} \frac{1}{T - t_{snw^t}} \left(\max\{t_{CM_w} - t_{snw^t}, 0\} + \eta_w(T - \max\{t_{CM_w}, t_{snw^t}\})\right)
\]

Whenever a dynamic event occurs, i.e., the completion of a countermeasure, decision makers have two choices: one is neglecting the dynamic information and implementing the solution as planned, and the other is adapting the solution according to dynamic changes. The latter is reasonable and appropriate for a realistic weapon selection and planning process. Similar with the non-preemptive attribute in dynamic job shop scheduling problems[7], the weapons been developed or are under development are excluded from the scope of adaptation.

4. Methodology. Since we simultaneously consider two objectives, multi-objective evolutionary algorithms(MOEAs) are preferable due to the nonlinear and non-convex characteristic of the addressed problem. We employ one of the classic MOEAs, named NSGA-II[13], as the basic optimizer. In NSGA-II, the parent population and offsprings are combined and sorted in order to generate a population for the next generation. A non-dominated sorting mechanism is performed to classify the combined population into different ranks of non-domination. A crowding-distance assignment is employed to ensure diversity is maintained among non-dominated solutions. In recent years, NSGA-II was successfully applied to solve
similar problems, such as multi-objective portfolio problems[6], project portfolio selection problems[20] and capability planning problems[38]. However, to solve the current problem, chromosome and genetic operators need to be modified.

4.1. Chromosome representation. In portfolio selection problems, a hybrid binary/real-valued encoding is recommended as genetic representation by [32, 33] and also applied by other approaches, such as [10, 6]. With this encoding, the real-valued vector is used to indicate the share of the budget on different assets or projects, while the binary vector is employed to represent whether the asset is selected or not. For WSPPs, decision makers need to decide the time of developing weapons as well as the type and the amount of weapons. Thus, the genetic chromosomes should represent the information of budget distribution to each time unit and the weapon type to be developed. The amount of weapons is determined by budget and unit cost of selected weapon type. In this research, we employ a hybrid real-valued/integer-valued encoding to represent the genetic chromosome, shown as in Figure 1.

The real-valued vector \((\delta_1, \delta_2, \cdots, \delta_{12}), \cdots, (\delta_1^N, \delta_2^N, \cdots, \delta_{12}^N)\) indicates what share of budget of each year should be distributed to each time unit, where \(\delta_y \in [0, 1], n = 1, \cdots, N, y = 1, \cdots, 12\), satisfying \(\sum_{y=1}^{12} \delta_y^y = 1\). The integer-valued vector \((p_1, \cdots, p_M)\) represents the selected weapon type at each time unit, where \(p_m \in [0, |W|], m = 1, \cdots, M\). If \(p_m \in [1, |W|]\), it indicates that weapon type \(p_m\) is selected at time point \(m\), while \(p_m = 0\) represents no weapon will be developed at time point \(m\). Note that the weapon development amount at each time point is determined by both the available budget and the selected weapon type.

4.2. Population initialization. The initial population affects much the convergence and diversity of the evolution process. The population initialization consists of two parts: budget distribution initialization and weapon type list initialization. For the initialization of budget distribution, at first, the values of \(\delta_y^y \in [0, 1], n = 1, \cdots, N, y = 1, \cdots, 12\) are randomly generated from the interval \([0,1]\). To satisfy the constraint \(\sum_{y=1}^{12} \delta_y^y = 1\), the vector \((\delta_1^y, \cdots, \delta_{12}^y)\) is normalized. Elements in the weapon type list are randomly generated in the scope of \([1,|W|]\) one by one.

4.3. Genetic operators. Crossover and mutation operators are crucial in genetic algorithms. For crossover, we use BLX-\(\alpha\) crossover on real-valued vector. In [33], experimental results suggest that this crossover is effective for real-valued vector for portfolio selection problems. The values of \(\delta_y^y\) of the two parents are denoted as \(parent_1(\delta_y^y)\) and \(parent_2(\delta_y^y)\), respectively. The BLX-\(\alpha\) crossover randomly reinitialize the values of \(\delta_y^y\) from a extended range \((\max\{0, parent_{\min}(\delta_y^y) - I\alpha\}, parent_{\max}(\delta_y^y) + I\alpha\}\), where \(parent_{\min}(\delta_y^y) = \min(parent_1(\delta_y^y), parent_2(\delta_y^y))\),
\( \text{parent}_{\text{max}}(\delta_y^n) = \max(\text{parent}_1(\delta_y^n), \text{parent}_2(\delta_y^n)) \) and \( I = \text{parent}_{\text{max}}(\delta_y^n) - \text{parent}_{\text{min}}(\delta_y^n) \). We set \( \alpha = 0.5 \) as in [33]. For mutation, Gaussian mutation is used on real-valued vector. After crossover and mutation, to ensure \( \sum_{y=1}^{12} \delta_y^n = 1 \) can be satisfied, real-valued vector is repaired by normalizing the values in offspring.

For integer-valued vector, we use a two-point crossover by which offspring inherit values from parents interchangeably. In other words, for a child, the first and the third parts are taken from one parent, while the second part is taken from the other. For mutation operator on integer-valued vector, an mutation interval is randomly generated. The value of \( p_m \) in the mutation interval is replaced by an randomly created integer from the interval \([0, |W|]\).

4.4. Constraints handling. It is clear that the decoding procedure can ensure the satisfaction of constraints (2)-(4) in the multi-objective optimization problem shown in Equation 11. However, for constraint (1) the decoding procedure only can ensure that the selected weapon will not exceed the upper bound, but cannot ensure the satisfaction of lower bound. Since we employ NSGA-II as the optimizer, the definition of domination between two solutions is modified as in [13].

**Definition 4.1.** A solution \( i \) is said to constrained-dominate a solution \( j \), if any of the following conditions is true.

1) Solution \( i \) is feasible and solution \( j \) is not.
2) Solutions \( i \) and \( j \) are both infeasible, but solution \( i \) has a smaller overall constraint violation.
3) Solutions \( i \) and \( j \) are feasible and solution \( i \) dominates solution \( j \).

For a solution \( i \), the constraint violation is denoted as \( cv(i) \) and is calculated as follows:

\[
\text{cv}(i) = \sum_{w=1}^{|W|} x_w
\]  

where

\[
x_w = \begin{cases} 
-1, & 0 < a_w < a_{w}^{\text{law}}, \\
0, & \text{else},
\end{cases}
\]  

4.5. Adaptation in a dynamic environment. In the presence of unpredictable changes in the planning or scheduling process, various reactive policies can be employed to recover the affected solution in the areas of project scheduling[12], manufacturing scheduling[28], etc. For WSPPs, dynamic changes refer to the occurrence of countermeasures, which may dramatically impact the effectiveness of weapons. However, such changes will not make the solutions infeasible. Thus, one of the main tasks during the weapon planning process is to adapt the selected weapons after changes to maintain the effectiveness of the whole solution as high as possible, while keeping the solution as a constraint feasible.

The main idea of the adaptation procedure is as follows. When a countermeasure is developed by the counterpart, if the solution contains the affected weapon, then the amount of this weapon is reduced as low as possible. At the same time, the available capital is transferred to develop other weapons. Figure 2 gives a conceptual example of the adaptation process. In the figure, \( t_{\text{change}} \) represents the time point when the countermeasure of weapon \( i \) is operational, while \( t_{\text{adapt}} \) is the time in which the selected weapons begin to adapted. Note that \( t_{\text{adapt}} \geq t_{\text{change}} \). When \( t_{\text{adapt}} = t_{\text{change}} \), the development of weapon \( i \) has not been launched.
or the minimum amount is satisfied when the countermeasure is operational. In such a case, the adaptation process can be started as soon as the dynamic change occurs. Otherwise, the adaptation process cannot begin until the minimum amount of weapon $i$ is developed due to the constraint, then $t_{adap} > t_{change}$. $t_1$ to $t_k$ represent the time points in which weapon $i$ is planned to be developed in the original solution. In the adaptation process, weapon $i$ planned after $t_{adap}$ will no longer be developed and will be replaced by weapon $r$. Such an adaptation process is denoted as $\text{Adapt}(\text{ind}, i, r)$.

After adaptation, it might be that some types of weapons cannot achieve the minimum required amount, i.e., the constraint (1) of the problem modeled in Equ.11 is violated. A recovery procedure is developed to improve the feasibility of the solutions after adaptation. Figure 3 shows a conceptual example of the recovery process. In the figure, $N'$ represents the year in which weapons begin to adapted. The recovery process is executed for each year after $N'$. In each year, $m'$ indicates the time point of the first appearance of the infeasible weapon type, supposing type $i$, i.e., $0 < a_j < a_i^{\text{low}}$. In the same year, if no weapon needs to be developed in the last month, then set the weapon type in the last month as $i$.

The whole adaptation procedure can be described as in Figure 4. For an individual, the adaptation procedure is carried out only when the individual obtained after adaptation is better (measured in the dominance relation) than the original one.

4.6. **Flexibility in a dynamic environment.** For dynamic multi-objective optimization problems, much attention has been attached to the track of the Pareto-optimal front when there is a change[14, 21]. However, decision-making analysis on the obtained approximate Pareto optimal solution set is absent in the existing
1: Input: ind; //individual need to be adapted
2: Eval(ind, i); //evaluate the ind in the presence of countermeasure of weapon i
3: for r = 1; r < |W|; r ++ do
4: if r ≠ i then
5: tempind = new individual; //new created individual
6: Copy(ind, tempind); //copy ind to tempind
7: Adapt(tempind, i, r); //adapt the tempind
8: Eval(tempind, i); //evaluate the tempind in the presence of countermea-
9: sure of weapon i
10: if ind is dominated by tempind then
11: Copy(tempind, ind)
12: return;
13: end if
14: if tempind has infeasible weapon type then
15: Recover(tempind); //execute recover process on tempind
16: Eval(tempind, i);
17: if ind is dominated by tempind then
18: Copy(tempind, ind)
19: return;
20: end if
21: end if
22: end for

Figure 4. The whole adaptation procedure for each solution after
dynamic changes occur.

literature. In real-world applications, a solution is to be chosen and implemented
after the non-dominated set is obtained and, in most situations, before the next
event occurs[14]. To tackle this task, some pre-specified utility function or rank
procedure is necessary.

For dynamic WSPPs, decision makers might be interested in solutions that can
maintain good performance on effectiveness or are easy to be adapted when dy-
namic changes occur. Such abilities are usually termed as robustness or flexibility,
which are not necessarily unrelated[7]. In other words, robust solutions are often
flexible[23]. In this research, we focus on the flexibility measure of a solution for
WSPPs. In the presence of a change, a flexible solution that is expected can be
adapted easily to prevent the decrease of effectiveness. Before each change, solu-
tions with different structures will have various abilities to adapt according to the
change. Such abilities are also affected by what type of change occurs. Thus, the
flexibility addressed in this research is change-dependent. In other words, the flex-
ibility of a solution during a specific period reflects its ability to adapt when the
next change occurs.

At first, we make a conjecture: A solution for WSPPs is flexible when a change
is confronted if 1)the affected weapons are planned to be developed after the oc-
currence of the change and 2)the cost planned to be spent on the affected weapons
has a large proportion over the total cost. Then, the conjecture is examined and elaborated as follows.

In job shop scheduling problems, it is suggested that avoiding early idle times increases flexibility [7]. In other words, the front part of a schedule should be as tight as possible. However, the situation seems different for WSPPs. In dynamic scheduling problems, one of the main tasks is to complete more operations before an event occurs. While in WSPPs, if most of the weapons are developed before their occurrences of countermeasures, there will be little space left for decision makers to adapt the plan when a dynamic event occurs. An extreme situation is that all planned weapons have been developed before the occurrences of their countermeasures. In such a case, no adaptation can be made with the solution. In contrast, if the countermeasure is revealed before the weapon planned to be developed, decision makers have the choice of avoiding continuing to develop the affected weapon and spending the capital on other weapons. With regard to the cost proportion of the affected weapon, a larger proportion indicates more capital after adaptation, which can be transferred to developing other weapons.

We implement the above ideas by measuring flexibility as follows. For a solution \( q \) at the time point \( t_{CM_w^*} \), flexibility is indicated by two indices, denoted as \( FI_1^q \) and \( FI_2^q \) respectively, and calculated as follows.

\[
FI_1^q = \frac{\sum a_w^* | a_w^* \geq t_{CM_w^*}}{a_w} \tag{16}
\]

\[
FI_2^q = \frac{a_w^* \times c_w^*}{\sum_{w=1}^{\left|W\right|} a_w \times c_w} \tag{17}
\]

Then, the flexibility of a solution \( q \) before the occurrence of the countermeasure of weapon \( w^* \), represented as \( flex_{w^*}^q \), is constructed as \( FI_1^q \) multiplying \( FI_2^q \), written as follows.

\[
flex_{w^*}^q = FI_1^q \times FI_2^q \tag{18}
\]

It should be noted that before each change, flexibility is only calculated for those solutions that include the affected weapons, i.e., \( a_{w^*} > 0 \).

5. A hypothetical case study.

5.1. Problem description. In this section, we illustrate the addressed WSPP and the proposed multi-objective approach through a hypothetical case. The case problem includes 20 types of weapons. The planning horizon is 10 years, i.e., \( N = 10 \) and \( M = 120 \). The available budget for each year is set at \( B_n = 100 \) units, where \( (n = 1, \cdots N) \). We assume that the discounted rate is 0.01 per month. It should be noted that the discounted rate is set to be 0.01 for no other reason but for illustration. In real application, this value should be evaluated according to economic data. The related parameters for each type of weapon are given in Table 1.

5.2. Experimental results. All experiments were repeated independently 30 times. The population size and generation number are set as 800 and 1,000, respectively.
Table 1. Parameters of different type of weapons in the synthetical case.

|   | \(w\) | \(a_{w, \text{low}}\) | \(a_{w, \text{up}}\) | \(c_{w}\) | \(d_{w}\) | \(r_{w}\) | \(w\) | \(a_{w, \text{low}}\) | \(a_{w, \text{up}}\) | \(c_{w}\) | \(d_{w}\) | \(r_{w}\) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 15 | 40 | 3 | 6 | 0 | 11 | 4 | 8 | 15 | 20 | 0 |
| 2 | 10 | 30 | 4 | 8 | 0 | 12 | 4 | 16 | 8 | 9 | 0 |
| 3 | 6 | 20 | 10 | 10 | 0 | 13 | 5 | 12 | 18 | 15 | 0 |
| 4 | 5 | 10 | 12 | 15 | 0 | 14 | 4 | 10 | 16 | 16 | 0 |
| 5 | 12 | 20 | 5 | 7 | 0 | 15 | 6 | 18 | 14 | 12 | 0 |
| 6 | 8 | 16 | 8 | 8 | 0 | 16 | 8 | 20 | 12 | 14 | 0 |
| 7 | 8 | 18 | 9 | 8 | 0 | 17 | 3 | 8 | 18 | 22 | 0 |
| 8 | 6 | 15 | 10 | 5 | 0 | 18 | 5 | 10 | 16 | 18 | 0 |
| 9 | 5 | 15 | 13 | 11 | 0 | 19 | 3 | 9 | 20 | 18 | 0 |
| 10 | 4 | 8 | 18 | 14 | 0 | 20 | 7 | 15 | 5 | 10 | 0 |

Figure 5. Non-dominated set obtained with mutation rate 0.5 and crossover rates varying from 0.6 to 1.0.

5.2.1. Sensitivity analysis of parameter settings. At first, we identify the rates for crossover and mutation as 0.7 and 0.5 after several trials. Figures 5 and 6 show the impact of crossover and mutation rates on the obtained results, respectively. Figure 5 shows the approximated Pareto sets with fixed a mutation rate 0.5, while the crossover rate varied from 1.0 to 0.6. One can see from the figure that the performances have almost no difference in the area with lower effectiveness (less than 5). While in the area with higher effectiveness, the algorithms with crossover rates 0.7 and 0.6 outperformed the three others in approaching the Pareto front. This may be because the density of the search space increases when including more weapons in the solution, from both selection and planning aspects. Thus, visualizing
the true Pareto front becomes more difficult. By comparing the performances with
crossover rates 0.7 and 0.6, we may observe that the former had a slightly better
performance in converging to the Pareto front than the latter. While the algorithm
with a crossover rate 0.6 found a well-spread solution in the objective space, i.e.,
the solution with the highest value on NPV.

Next, we fixed the crossover rate as 0.7 and varied the rate for mutation from 0.1
to 0.6. The obtained results are reported in Figure 6. Similarly, the combination
(0.7,0.5) had a better performance when the search space became denser. Thus, in
the remainder of experiments, the rates for crossover and mutation were fixed as
0.7 and 0.5.

5.2.2. Convergence analysis. It is important to analyze the behavior of the algo-

gerithm during evolution. Because the actual Pareto front of the WSPP is unknown,
during the evolutionary process, we recorded the hypervolume indicator[40], which
is a unary measure to indicate the quality of the obtained non-dominated set. For
the calculation of hypervolume, the reference point was set as (0,0). The conver-
gence of the hypervolume measure of 30 runs is plotted as in Figure 7. One can see
from the figure that the algorithm converged quite quickly in the first 400 genera-
tions, while the speed of convergence became slower after that period. Overall, the
algorithm remained relatively stable in the 30 runs approaching the Pareto front.

5.2.3. Synergy effect analysis. As modeled in Section 3.3.2, the effectiveness of a

solution consists of two parts: normal effectiveness and synergy effectiveness. In
this case study, it was assumed that three pairs of collaboration relations existed, i.e.,
$CR = (CR_1, CR_2, CR_3)$. Particularly, $CR_1 = ((1, 2), 4)$, $CR_2 = ((6, 8, 9), 11)$ and
Figure 7. Convergence graph using hypervolume measure over time in 30 runs.

Figure 8. Comparison between non-dominated sets with and without the consideration of synergy effectiveness.
\( CR_3 = ((15, 16), 17). \) The corresponding proportion coefficients were \( P_1 = \left( \frac{2}{5}, \frac{2}{5}, \frac{1}{5} \right) \), \( P_2 = \left( \frac{3}{10}, \frac{3}{10}, \frac{1}{5} \right) \) and \( P_3 = \left( \frac{1}{2}, \frac{2}{5}, \frac{1}{10} \right) \).

Figure 8 reports the different sets obtained with and without the consideration of synergy effectiveness. In the figure, blue stars represent the mapped solutions of original non-dominated solutions when the synergy effectiveness was not taken into account. One can see from the figure that the impact of synergy effectiveness increased along with the increase of total effectiveness. There was no difference when the total effectiveness was less than 1. This was due to the limit of the total types of weapons included in a solution when the effectiveness was low. Then, the solution could not achieve synergy effectiveness.

5.2.4. Behavior in a dynamic environment. In the experiments, we studied the planning process in a dynamic environment. At first, we modeled the dynamic environment as in Table 2, where \( w \) is the type of weapon that had a countermeasure during the planning process and \( t_{CWw} \) is the operational time of the countermeasure. There are 8 dynamic events during the planning process. Note that decision makers did not have any knowledge of these dynamic changes until they occurred.

Table 2. Parameters of dynamic environments.

| No. | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| \( w \) | 10  | 4   | 20  | 2   | 17  | 5   | 6   | 12  |
| \( t_{CWw} \) | 22  | 26  | 28  | 30  | 35  | 48  | 50  | 54  |

Figure 9 depicts the behavior of the non-dominated set with the impact of dynamic changes. The results after each change are reported in the figure. It is clear that the effectiveness of the obtained solutions decreased due to the occurrences of dynamic changes, i.e., countermeasures. One can see from the figure that dynamic changes had little effect on some solutions with very low effectiveness. This is because these solutions only included single type of weapon and this type of weapon might have no countermeasure in the modeled dynamic environment.

Furthermore, we studied the performance of the proposed adaptation policy. Figures 10 and 11 show the results in the presence of 8 changes without adaptation (stars) and with adaptation (triangles). After each change, the solutions after adaptation were closer to the original non-dominated set. This indicates that the speed of the performance decreasing with adaptation policy was slower than that without any adaptation. The results suggest that the adaptation policy is effective when dynamic events occur.

5.2.5. Correlation between flexibility and adaptation effectiveness. As indicated earlier, the flexibility of a solution can be considered as a measure of the degree of the ease in which a solution can be adapted. Intuitively, for a solution, there is some type of relation between the flexibility and the effectiveness of adaptation. This section will investigate the correlation between the proposed flexibility measure and the adaptation effectiveness.

To carry out such an investigation, we need to quantify the adaptation effectiveness of a solution. The main task of adaptation is to mitigate the impact of countermeasures on the whole solution. In the presence of each dynamic change,
there may be a difference between the results obtained after adaptation and without adaptation. Thus, we employed such a difference to indicate the effectiveness of the adaptation, as shown in Figure 12. In the figure, $S_0$ is the original solution, while $S_1$ and $S_2$ represent the solutions after adaptation and without adaptation, respectively, when a dynamic change occurs. If $S_1$ dominates $S_2$, it is considered that the adaptation is effective. Then, the adaptation effectiveness for a solution, denoted as $AdaptEff$, is calculated as follows:

$$AdaptEff = \begin{cases} 
Sq(S_1) - Sq(S_2) & \text{if } S_1 \text{ dominates } S_2 \\
0 & \text{otherwise.}
\end{cases}$$

(19)

where $Sq(\cdot)$ represents the square of the rectangular formed by the solution and a reference point, $(0,0)$ in our research.
Another important issue in correlation analysis is the selection of samples. When each change occurs, not every solution would be affected. The sample space consisted of solutions affected by the change. If the size of the sample space was less than 30, a correlation analysis would not be conducted. Table 3 shows the results of the correlation analysis between flexibility and adaptation effectiveness in the presence of 8 changes given in Table 2. In the table, the second column and the third column are the correlation coefficient and P-value, respectively. The data reported in the figure show that flexibility and adaptation effectiveness are positively correlated. Among the 8 sets of data, half of them (No.1, 2, 6 and 7) show that flexibility and adaptation effectiveness have a very strong correlation. The coefficient of No. 3 and 8 were 0.5409 and 0.4643, which indicate a moderate correlation. The other two sets of data lie in the range of weak correlation. In all, we may state that the proposed flexibility measure is appropriate to indicate a solution’s ability to adapt when confronting a change. Let us recall that flexibility is defined as change-dependent. Although the occurrences of changes, i.e., the appearances of countermeasures are dynamic in nature, some information about the next countermeasure can be obtained or estimated by intelligence agencies[18]. In such a context, the definition of change-dependent flexibility may be useful to support
decision makers in choosing a flexible solution among the non-dominated set before the next change occurs.

Table 3. Correlation analysis between flexibility and adaptation in the presence of 8 changes.

| No. | 1     | 2     | 3     | 4     | 5     | 6     | 7     | 8     |
|-----|-------|-------|-------|-------|-------|-------|-------|-------|
| corrcoef | 0.8559 | 0.7892 | 0.5409 | 0.3797 | 0.3233 | 0.8663 | 0.7933 | 0.4643 |
| P-value    | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
6. Conclusions and future work. In this paper, we addressed weapon selection and planning problems (WSPPs), which include two main tasks: selecting the weapon to be developed and planning the development of the selected weapons. These two processes are simultaneously considered and modeled into one optimization problem. By considering the cost and effectiveness, the problem is modeled as a multi-objective optimization problem. The cost is measured by the net present value (NPV) of developing all selected weapons, while the effectiveness is indicated by several factors of weapons, such as their number, operational time and synergy effect.

By considering some practical constraints, e.g., the limits of capital each year and the minimum acquisition amount for each type of weapon, the problem takes on non-convex characteristics. Thus, we have employed a multi-objective evolutionary algorithm to obtain the non-dominated set and designed specific a chromosome representation, a decoding procedure, genetic operators and a constraint-handling mechanism for WSPPs. Furthermore, we have considered the dynamic nature the WSPPs. Dynamic events or changes mainly refer to the occurrence of countermeasures, which may decrease the effectiveness of specific types of weapons. To maintain the relatively good performance of solutions in dynamic environments, we have designed a reactive policy to adapt solutions when a change occurs. To further support the decision-making task, flexibility has been defined to measure how easily a solution can be adapted.

We have illustrated the addressed problem and the proposed approach with a hypothetical case. The algorithm with fine-tuned parameters can obtain a well-spread non-dominated set. The results on convergence, the impact of synergy effect as well as behavior in a dynamic environment have been reported. The computational results and analysis suggest the effectiveness of the proposed adaptation process and flexibility measure. Future research mainly lies in the following aspects: 1) the design of more efficient algorithms for complex WSPPs and a performance comparison of different approaches over more generated benchmark instances may
be introduced, 2) the adaptation process may be improved and more flexibility measures can be investigated for a dynamic environment, 3) the issues of decision making and game behavior over opponents is worth addressing in future studies.

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