Project Portfolio Selection with Defense Capability Options

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ABSTRACT

This paper proposes a novel formulation of the project portfolio selection and scheduling problem inspired by the Future Defense Force Design process in the context of the Australian Defence Force capability development. The core objective of the problem is to maximize the total capability portfolio value attained by the selection and scheduling of a set of capability projects, grouped in various subsets referred to as capability options, while adhering to budgetary, scheduling, and operational constraints. To provide initial solutions to the proposed model, a custom heuristic is developed and used to seed an initial population for a Genetic Algorithm.

CCS CONCEPTS

• **Computing methodologies → Search methodologies**; • **Applied computing → Decision analysis**.

KEYWORDS

Project Portfolio Selection, Future Defense Force Design, Heuristics

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1 INTRODUCTION

In the Australian Defence Force (ADF), Future Defense Force Design (FDFD) is a planning task that assists with critical defense capability investment decisions. The main deliverable of the FDFD process is the selection of a portfolio of defense capability projects from a large number of strategic investment or divestment options, each of which has an effect on the future capabilities provided by the ADF. In this context, a capability refers to the ability to achieve an operational effect. The portfolio of projects can consist of both investment and divestment projects, i.e., new projects that deliver additional or replacement capabilities at a cost and existing projects that are cancelled or amended, releasing funds for other use. The primary objective is to maximize the total portfolio value while satisfying budgetary, scheduling, and operational constraints.

Previous studies have examined this problem using a largely traditional formulation of the project portfolio selection and scheduling problem (PPSSP) [1, 2, 4], whereby the primary selection is done at the project level. The value of the portfolio is then dictated by the sum of the values associated with each of the selected projects. Many of the existing approaches in the literature have made use of exact solvers [1], representing a disconnect between the nature and scale of problems faced in real-world defense applications and the scholarly literature.

Due to the extremely complex nature of the modern FDFD process, which needs to capture and address numerous strategic, operational, and tactical inter-dependencies between various defense capabilities and capability projects, a new approach to the PPSSP is required to meet this challenge in a practical way. This paper examines this new model and proposes a custom heuristic to provide initial feasible solutions, which are subsequently used to seed an initial population for a Genetic Algorithm (GA).

2 PROBLEM FORMULATION

In the proposed problem, the primary unit of selection is the capability option (CO), which is a group of projects that provide an operational capability. A CO can only be selected as a whole unit such that all the constituent projects must be selected if the CO is implemented. The COs are also grouped into families, such that one CO must be selected from each family. The value is used as a proxy for the delivery of the capabilities of a CO as a whole, and it is determined by the earliest time period in which all individual projects in the CO can reach an initial level of their operating capability. Note that, a project can appear in multiple COs, but its cost should only be counted once. However, the net effect of a project on multiple COs is still realized. Thus, there is an inherent benefit to selecting projects that belong to multiple COs.

While it is clear that this problem bears resemblance to existing binary selection problems in the literature, no single existing problem formulation adequately addresses all aspects. Specifically, the proposed problem considers selection at the CO level, with potentially overlapping sets of projects, and encompasses both investments and divestments. Hence, existing heuristics are not appropriate and must be adapted for use on this problem formulation.

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3 SOLUTION APPROACH

To address this problem formulation, a custom heuristic is used to generate a feasible solution, which is subsequently refined using a GA. The heuristic process, inspired by some heuristics for similar problems [3, 5], works as follows. First, divestment COs are selected to release funds. Next, investment COs are greedily selected while adhering to the released funds and the yearly budget deviation allowance. Finally, a local search refinement process is used to improve the solution. Note that, there are a number of possibilities for each step and special care must be taken to ensure feasibility.

In more detail, the proposed heuristic technique to generate a feasible solution can be summarized as:

(1) Determine the initial divestment COs using a divestment selection strategy for each divestment family:
   - Select the CO that releases the most funds.
   - Select the CO with the largest ratio of funds released to value lost.
   - Randomly select a CO.
(2) For each family where no investment selection has been made:
   (a) Calculate the value-to-cost ratio for all COs.
   (b) Select the CO with the highest value-to-cost ratio that also leads to a feasible solution. Alternatively, select the project with the highest value, irrespective of its cost.
(3) Repeat Step 2 until a CO has been selected from each investment family.
(4) Perform a swapping local search for refinement until no further improvements can be made.

Note that, this process will always construct a feasible solution given that the selection in Step 2 requires feasibility. The heuristic process is repeated and returns the portfolio with the best fitness. Specifically, the process is run once for each combination of divestment and investment selection strategies, with the exception of the random divestment selection strategy, which is run 100 times. With slight modifications, it is expected that this heuristic will also be applicable to similar problems in the literature.

The GA used a discrete representation, where a value of i at index f represents that CO with index i was selected for family f, and employed the half-uniform crossover (HUX) with a rate of 90% and (integer) polynomial mutation with a rate of 10%. Each run had a population size of 100 and was terminated when 100 iterations had passed with no improvement to the fitness. The best heuristic solution was provided as a seed to the initial population, the remainder of which was initialized randomly. For all GA experiments, results are reported as the average over 30 independent executions.

4 RESULTS

To validate the solution process, an exhaustive solver was implemented to determine exact solutions. Due to the time complexity associated with exhaustively searching all possible solutions, only small instances can be reasonably addressed. A set of small-scale problem instances containing 8 families, either 50 or 100 projects, a divestment proportion of 25%, 33%, or 50%, and no yearly budget deviation were generated. For each configuration above, 30 problem instances were generated and solved using both the heuristic approach and the seeded GA. In all scenarios, the heuristic approach attained a minimum average of 73% of the fitness associated with the exact solution while the GA attained a minimum of 99%.

To test the heuristic and GA on larger instances, 108 problems were generated by varying the number of families ({25,50,100}), the total number of projects ({100, 250, 500, 1000}), the proportion of divestment-oriented families ({25%, 33%, 50%}), and the yearly budget deviation allowance ({$0, $500, $1,000}). When averaged across all problem instances, the fitness of the heuristic approach was 76.7% of the average fitness attained by the GA. That is, on average, the GA was able to improve the fitness of the heuristic solution by 23.3% across a wide variety of problem characteristics.

To ascertain the effect of the heuristic seeding process on the performance of the GA, experiments were repeated with purely random initialization. On average, solution quality was improved by 10.2% when the GA was seeded with a heuristic solution. In contrast, for 19 of the 108 problems, seeded initialization led to a decrease in fitness of 4.2%, on average. The standard deviation associated with the seeded GA was drastically decreased for 100 of the 108 problems, indicating improved stability as a result of seeded initialization. A two-tailed, paired Wilcoxon signed-rank test indicated that the improvement from seeded initialization was statistically significant with a p-value of 4.35e-11.

5 CONCLUSIONS

This paper examined a preliminary model for the selection of a portfolio of projects in the context of FDFD in the ADF, whereby the projects are arranged into families, each consisting of possibly overlapping subsets of projects, referred to as COs. A custom, greedy heuristic was developed and used to provide seeded solutions to a GA. Results indicated that the heuristic solution attained at least 73% of the optimal fitness on small instances while the GA attained at least 99%. For larger problem instances, the GA was able to provide an average improvement of 23.3% over the best heuristic solution, thereby providing preliminary evidence that the use of evolutionary solvers is warranted for this problem. The proposed PPSSP formulation and the solution approaches provide a practical and efficient way to manage complex inter-dependencies that exist in modern defense capability investment portfolios.

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