Adaptation, Learning, and Optimization 26

Kyle Robert Harrison · Saber Elsayed · Ivan Leonidovich Garanovich · Terence Weir · Sharon G. Boswell · Ruhul Amin Sarker *Editors*

Evolutionary and Memetic Computing for Project Portfolio Selection and Scheduling

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Preface

Many organizations face the challenge of selecting and scheduling a subset of available projects subject to various resource and operational constraints. Formally, this problem is known as the project portfolio selection and scheduling problem (PPSSP). It is well known that the PPSSP is an NP-hard problem, thus, there is no known polynomial algorithm for it. Despite the complexity associated with solving the PPSSP, many traditional approaches to this problem make use of exact solvers. While exact solvers provide definitive optimal solutions, they quickly become prohibitively expensive in terms of computation time when the problem size is increased. In contrast, evolutionary and memetic computing afford the capability for autonomous heuristic approaches and expert knowledge to be combined, thereby they provide an efficient means for high-quality approximation solutions to be attained. As such, these approaches can provide near real-time decision support information for portfolio design that can be used to augment and improve existing human-centric strategic decision-making processes.

This edited book provides the reader with a broad overview of the PPSSP, its associated challenges, and approaches to addressing the problem using evolutionary and memetic computing. Contributions were welcomed from distinguished researchers and industry practitioners that highlight the state of the art and recent trends in memetic computing and evolutionary computation for the PPSSP in any domain. Each chapter published in this book has been peer-reviewed by a minimum of two experts in the field. We gratefully acknowledge the reviewers, listed below, for their valuable feedback and constructive comments on the contributed chapters, which have greatly improved this book.

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July 2021

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Contents

Evolutionary and Memetic Computing for Project Portfolio Selection and Scheduling: An Introduction

Kyle Robert Harrison, Ivan L. Garanovich, Terence Weir, Sharon G. Boswell, Saber M. Elsayed, and Ruhul Amin Sarker

Abstract The problem of selecting and scheduling a subset of projects is a complex task faced by many organizations. This problem is referred to as the project portfolio selection and scheduling problem (PPSSP). In nearly all cases, a budgetary constraint limits the number of projects that can be selected. Furthermore, complex operational constraints are often present as well. Hence, the selection of the optimal set of projects is a challenging task, which is further complicated by the necessity also to determine the scheduling of their implementation. In many cases, intelligent techniques inspired by evolutionary processes are employed to address such problems. This introductory chapter provides a short overview of the PPSSP and the relevant solution methodologies, providing context for the remainder of this book. A brief description of each contributed chapter is also provided.

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1 Introduction

Many people tend to assume that the term "portfolio" refers to a financial portfolio. This is likely a result of the seminal 1952 study of Markowitz [9], along with the fact that this domain is the most likely to be encountered by a layperson. In simple terms, a portfolio just represents a collection of things and can be encountered in any number of different application areas. For example, (i) in financial markets, a portfolio can represent a collection of financial investments, such as stocks, commodities, cash, and cash equivalents, (ii) in a corporate environment, it can represent a collection of products, services, and/or achievements of the company, and (iii) in any organization dealing with multiple projects, it can represent a collection of projects that share one or more resources.

Portfolio optimization is the process of selecting the best portfolio out of the set of all potential portfolios being considered, according to some objective(s). In a financial context, used for demonstration purposes, the primary goal is to select a subset of investment options (i.e., allocate the available assets to options) that provides the maximal expected return and does not violate the asset limitation. In some cases, additional objectives like minimizing the risk of return and minimizing the variance of returns are also considered. That means the optimization problem can be either single- or multi-objective. Once the investment decision is made, the investments may continue for years or can be revised depending on changes in the market conditions, assets, and/or the investment strategy.

A financial portfolio optimization strategy usually applies the concept of diversification, which means investing in a wide variety of asset types and classes. Diversification across asset classes is basically a risk-mitigation strategy. Here, the risk is defined as the chance that the investor will lose money on an investment or would not see the returns that are expected. However, investors also measure risk through volatility, which refers to the likelihood that an asset's price will change significantly. To deal with risk in the optimization process, additional constraints are usually imposed on the investment amount for each risk group (for example, high, medium, and low risk options). As discussed earlier, risk minimization can be considered as an objective. Analogous scenarios and problem descriptions arise in other domains.

In this introductory chapter, a brief discussion of the various general aspects of the PPSSP is presented, along with an overview of different solution methodologies. A brief summary of the contributed chapters is also presented.

2 Problem Formulation

In project portfolio optimization, the basic problem is to select a subset of projects, from a defined list, in order to maximize some measure of return or any other suitable objective measure, while satisfying the budget constraint. Project portfolio optimization is usually used as a planning tool by organizations that need to allocate funding to different projects and execute them as part of their organizational function. For example, this problem arises in such areas as:

- Public and Social projects [1],
- Software/IT [8],
- R&D and Production [10],
- Construction and Infrastructure [12],
- Investment [13], and
- Defense [4, 5, 7, 16].

Depending on the type of organization, the projects can be of different types and have differing characteristics. For example, the projects can be a mix of:

- small to large projects based on the budget, resources, and other technical requirements,
- short to long projects based on their duration of completion, and
- early to late start projects depending on their requirement within the organization.

When the start time of projects must also be decided during the optimization process, the problem becomes a combined resource allocation and scheduling problem known as the project portfolio selection and scheduling problem (PPSSP). In such problems, there may be a subset of the projects that must be selected, i.e., they are mandatory. The most straightforward approach to deal with mandatory projects is to exclude them from the optimization process and adjust the resources accordingly. Other common conditional relations that may arise between various projects are:

- precedence relationships: projects that cannot be executed until other specific projects have been completed,
- alternative projects: projects that serve the same purpose, such that only one should be executed,
- mutually exclusive projects: projects that cannot be executed simultaneously,
- mutually inclusive projects: projects that must be executed simultaneously or jointly,
- priority: some projects may have a higher priority compared to others, and
- project grouping: the projects may be divided into groups, and different budget limits and/or conditions may be applied to different groups.

The problem may then be formulated to have one or more objectives, depending on the goal of the organization. In the literature, the problem is defined in many different ways (considering a subset of the constraints and conditions discussed above). Additionally, uncertainty in data, missing data, and changing data with time are a few of the practical issues that should be considered. As a result, there are a variety of approaches, such as mathematical modeling with exact algorithms, and heuristics and evolutionary algorithms. In the next section, a brief discussion of solution methodologies is given.

3 Solution Methodologies

Just as there are many different formulations of portfolio optimization problems, there are various different optimization techniques that can be employed to address them. This section gives a brief introduction to three broad classes of optimization approaches that are commonly applied to PPSSPs.

3.1 Mathematical Optimization

In simple terms, the primary objective of an optimization problem is to find the set of input values that realize the maximum or minimum of some objective function, while adhering to a set of constraints. Clearly, there is an inherent mathematical underpinning to optimization. It should come as no surprise that many optimization approaches rely directly on mathematical modeling to aid in the decision making process. The use of mathematical derivation techniques to find the (feasible) optimum of an objective function is referred to as *conventional optimization*. These approaches leverage mathematical properties, such as gradient information, to derive an optimal solution for an optimization problem [14].

When addressing a problem using conventional optimization, it is important to consider the characteristics of the decision variables, objective function, and constraints. For example, the decision variables might be continuous or discrete, the objective function can be linear or non-linear, and the constraints may be convex or non-convex. It is well known that different problem characteristics require different optimization approaches with drastically different complexities. As an example, solving a linear program with real variables can be done in polynomial time, whereas solving an integer linear program is NP-hard—this implies that there is no known polynomial-time algorithm to provide solutions to integer linear problems, in general [6].

One of the most common approaches to address integer programs, using conventional optimization, is known as *branch and bound*. Branch and bound is a technique to recursively enumerate a search space by partitioning candidate solutions into subsets, referred to as *branches*. The best known upper and lower *bounds* for the objective value are maintained and used to discard branches that are incapable of improving on the (current) bound. This pruning strategy leads to a reduction in the number of solutions that must be enumerated, which can significantly lower the time needed to arrive at an optimal solution. However, given that solving integer linear programs is known to be NP-hard, branch and bound is still computationally infeasible for many real-world problems. One approach to mitigate the high computational burden is to introduce a relaxation (i.e., a simplification) of the model. The relaxed model can be used to identify feasible solutions much more rapidly, but these solutions are often sub-optimal with respect to the original (non-relaxed) model [15].

3.2 Evolutionary Computation

Evolutionary computation (EC) refers to an optimization paradigm that draws inspiration from the principles of Darwinian evolution. More specifically, EC techniques are stochastic, meta-heuristic search procedures that are characterized by three prominent features. Firstly, EC approaches are population-based search processes whereby the search simultaneously "evolves" a collection of candidate solutions. This is in contrast to conventional optimization approaches, which typically operate by performing an iterative improvement of a single solution. Secondly, EC approaches provide a mechanism to share and/or recombine information between individuals in the population. The exchange of genetic material is performed through genetic operators, such as mutation and crossover, which are used to produce new individuals for (possible) insertion into the population. Finally, EC approaches adopt a survival-of-the-fittest paradigm. A selection bias is employed in favor of better-fit individuals, thus providing an inherent pressure towards improving the overall suitability of the population as a whole.

Approaches from the field of EC are widely used to address optimization problems that are too challenging for conventional optimization. Notably, evolutionary approaches do not require a complete enumeration of the search space, thus they can be efficiently applied to problems that are computationally infeasible for conventional optimization. However, EC approaches do not provide any guarantee on the quality of the solutions they generate. Rather, they are used to find high-quality approximate solutions in significantly less time than conventional approaches. As a further benefit of EC approaches, in most cases only the fitness function is problem-specific, thereby providing a flexible approach that can be easily adapted to new problems [3]. Nonetheless, each of the components of an evolutionary approach can be carefully selected to craft a tailor-made optimizer for a particular problem [2].

3.3 Memetic Computing

Memetic computing refers to a computational paradigm that facilitates the sharing of information between different computational processes, i.e., the hybridization of two or more optimization approaches. Often, this manifests as the combination of a population-based meta-heuristic, such as an EC approach, with a local search process [11]. This hybrid algorithm is referred to as a memetic algorithm (MA). In many cases, the local search component is heavily inspired by the particular problem at hand and often draws inspiration from heuristic techniques employed in conventional optimization. Therefore, one can view memetic algorithms (MAs) as a hybridization of EC and conventional optimization approaches, such that they leverage the diverse, rapid search process of the former and the rigorous mathematical derivations of the latter.

4 Summary of Chapters

This edited volume consists of seven chapters and presents recent trends in project portfolio selection and scheduling, focusing on the evolutionary and memetic computing approaches used to address such problems. An outline of the chapters is provided in Table 1, while a brief summary of each chapter follows.

Chapter "Evolutionary Approaches for Project Portfolio Optimization: An Overview" presents a survey on the use of evolutionary approaches to address project portfolio optimization problems. The review focuses on three fundamental aspects, namely the application areas, the novelties found in their mathematical models, and the evolutionary approaches employed to solve the models.

Chapter "An Introduction to Evolutionary and Memetic Algorithms for Parameter Optimization" presents an introduction to the ideas and formulations of evolutionary algorithms (EAs). The chapter features a discussion of the advantages and disadvantages of EAs in comparison to conventional (mathematical) optimization methods. Finally, the chapter provides a brief introduction to memetic algorithms as an extension of EAs.

Chapter "An Overall Characterization of the Project Portfolio Optimization Problem and an Approach Based on Evolutionary Algorithms to Address It" provides a characterization of the project portfolio selection problem and proposes a formal problem statement that considers such features. It is argued that previously published approaches to project portfolio selection problem do not adequately address the entire complexity. In addition, the chapter provides insight into plausible components that evolutionary approaches should adopt to address the generalized problem.

Table 1 Summary of contributed chapters

Chapter	Chapter title	Domain
2	Evolutionary approaches for project portfolio optimization: an overview	General problems
3	An introduction to evolutionary and memetic algorithms for parameter optimization	General methodologies
4	An overall characterization of the project portfolio optimization problem and an approach based on evolutionary algorithms to address it	Social projects
5	A new model for project portfolio selection and scheduling with defence capability options	Defense projects
6	Analysis of new approaches used in portfolio optimization: a systematic literature review	Investment projects
7	A temporal knapsack approach to defence portfolio selection	Defense projects
8	A decision support system for planning portfolios of supply chain improvement projects in the semiconductor industry	Manufacturing projects

Chapter "A New Model for the Project Portfolio Selection and Scheduling Problem with Defence Capability Options" examines a real-world use case of the PPSSP in the defense sector. The chapter develops a new model to address the PPSSP in the context of the Australian Defence Force (ADF) capability development process. A custom-built heuristic approach is developed, with evolutionary approaches used to further refine the heuristic solutions.

Chapter "Analysis of New Approaches Used in Portfolio Optimization: A Systematic Literature Review" presents a systematic literature review of recent approaches used in portfolio optimization. This review examines and analyzes the solution methodologies, software implementation framework, model constraints, and technical analysis from a variety of studies, largely focusing on investment applications. This chapter also discusses the gaps identified in the literature and provides suggestions for future research.

Chapter "A Temporal Knapsack Approach to Defence Portfolio Selection" examines a second application of portfolio optimization in the defense sector. In this chapter, a set of candidate projects was first determined through wargaming and cost modeling. The "value" associated with each project was dictated by the year in which it commences, thereby incorporating a temporal aspect. This problem is formulated as a mixed-integer linear program (MILP), which resembles a temporal knapsack problem, and a methodology to solve it using Microsoft Excel™ is discussed.

The final chapter, Chap. "A Decision Support System for Planning Portfolios of Supply Chain Improvement Projects in the Semiconductor Industry", provides an example of the portfolio selection process in the manufacturing domain. This chapter describes the development of an integer programming model based on a multi-attribute portfolio value model. A discussion on how the model developed was used to build a decision system that would aid decision makers during committee meetings is given. Observations and insights from a real-world case study are presented.

5 Guide for Readers

This section provides a guide for readers to assist with navigating this book depending on the background and/or intentions of the reader.

For those not familiar with the field of EC and EAs, in general, we recommend to begin by reading Chap. "An Introduction to Evolutionary and Memetic Algorithms for Parameter Optimization". For those wanting an overview of the state-of-the-art in PPSSP literature, we recommend reading Chaps. "Evolutionary Approaches for Project Portfolio Optimization: An Overview", "An Overall Characterization of the Project Portfolio Optimization Problem and an Approach Based on Evolutionary Algorithms to Address It", and "Analysis of New Approaches Used in Portfolio Optimization: A Systematic Literature Review". For readers interested in chapters detailing the use of EC for portfolio selection and/or scheduling, we recommend Chaps. "Evolutionary Approaches for Project Portfolio Optimization: An Overview", "An Overall Characterization of the Project Portfolio Optimization Problem and an Approach Based on Evolutionary Algorithms to Address It", and "A New Model for the Project Portfolio Selection and Scheduling Problem with Defence Capability Options". For readers interested in the use of conventional optimization techniques, we recommend reading Chaps. "A Temporal Knapsack Approach to Defence Portfolio Selection" and "A Decision Support System for Planning Portfolios of Supply Chain Improvement Projects in the Semiconductor Industry".

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Evolutionary Approaches for Project Portfolio Optimization: An Overview

Ruhul Amin Sarker, Kyle Robert Harrison, and Saber M. Elsayed

Abstract This chapter presents a brief review of evolutionary approaches to address project portfolio optimization problems. This review focuses on three key aspects. Firstly, the problem descriptions are reviewed by grouping them into six broad application areas. Secondly, the key novelties found in their respective mathematical models are discussed. Finally, the evolutionary approaches for solving these models are reviewed. Key findings are also presented in tabular form for ease of reference and comparison.

1 Introduction

In project management, a project is defined as a set of activities (or tasks) that usually require different amounts of time and resources, must be accomplished in a specific order, and must achieve a combined goal [2]. A project portfolio is then a set of projects that share one or more common resources. A project portfolio decision problem is an upper level project selection process that is to select a set of projects from a long list of competing projects based on one or more objectives, goals, or criteria while satisfying one or more constraints [2, 19, 39, 40]. This problem is known as a project portfolio optimization problem or a project portfolio selection problem. There are a few steps in solving an optimization problem that includes problem identification, problem definition, mathematical representation of the problem (also known as formulating a mathematical model), solving the model (solution approach), result interpretation, and implementation [36]. This chapter aims to present a brief

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review of project portfolio optimization problems and approaches to solving such problems using evolutionary and memetic algorithms. In this context, discussions are focused on the problem definitions, mathematical models, and solution approaches from different publications in the literature. It is noted that some of the aforementioned practical steps, such as problem identification and implementation, are outside the scope of this review.

To identify suitable articles for this review, a search of the Scopus[1] database was conducted for articles containing “Project Portfolio”, “Project Portfolio + Optimization”, and “Project Portfolio + Optimization + Evolutionary” in the title, keywords, or abstract. Note that the search automatically accounts for both the American and British spellings of optimization/optimisation. As of 24 March 2021, the searches returned 8461, 898, and 43 documents, respectively. From the 43 papers returned via the query “Project Portfolio + Optimization + Evolutionary”, manual filtering identified 31 suitable articles for this review. The 12 articles not included either did not have full text available or were deemed to be irrelevant.

Additionally, other relevant articles from our earlier work and other sources were also included in this review. It is believed that these articles are adequately representative of the primary focus areas of this book. To the best of the authors’ knowledge, articles from predatory publication venues were not included in this review.

From the literature review, the articles on project portfolio optimization can be categorized into the following broad areas:

- Public and Social projects,
- Software/Information Technology (IT),
- Research and Development R&D and Production,
- Construction and Infrastructure,
- Investment, and
- Defense.

The problem context and the definition of the above projects will be discussed in the next section. All these problems were modeled as constrained optimization with either single or multiple objectives, and the developed models were solved using evolutionary algorithms and other approaches. The mathematical models of the problems and approaches for solving the models will be reviewed in the later sections.

2 Problem Description

Most project portfolio problems are defined as project selection problems, such that a set of projects must be selected from a long list of projects. In some cases, the scheduling of the projects is also considered where the start time of each selected project must also be decided. These problems are known as project portfolio selection

[1] Available at: https://www.scopus.com/search/form.uri.

and scheduling problems (PPSSPs). This section discusses the various high-level problem descriptions, grouped by application domain, found in the literature.

2.1 Public and Social Projects

Projects in the public and social domains are those that receive public funding, generally from a government organization. Quantifying their performance is usually subjective and often based on multiple criteria or objectives. Cruz-Reyes et al. [8] considered multiple groups of independent projects in which each group represents a number of projects from a given geographical region. The central decisions were the selection of projects and a budget allocation process, which were based on the available budget along with an upper and lower limit on the number of projects for each geographical region. Portfolio quality was determined by taking the union of project benefits (social return) across the entire portfolio. Similar problem descriptions can also be found in later works, such as Cruz-Reyes et al. [9–12], Martíez-Vega et al. [31], and Balderas et al. [3]. However, these studies considered different objectives and proposed alternative approaches for decision-making, which will be discussed in a later section. The study of Fernandez and Navarro [16] included priorities among the regions and introduced fuzziness in funding requirements as part of their problem definition. Note that, neither the practical details of the social projects nor their full data were presented in these studies.

Fernandez et al. [15] considered similar regional social projects selection with priority on the selection criteria. Although this included a stationary one-cycle budget, year-wise budget allocation for multiple years is an interesting feature of this problem description. Martínez-Vega et al. [32] described the problem with a multiple-year budget allocation such that a selected project may or may not receive funding in a given year and the available resources may vary from year to year. This time-varying resource allocation problem is termed as dynamic allocation of resources.

Zhang et al. [43] introduced a PPSSP whereby the project selection as well as the project start time must be decided simultaneously. Zhang et al. [43] also considered fuzzy resource constraints to deal with uncertainty. Blecic et al. [4] presented a PPSSP with interdependencies in continuous time. These interdependencies can broadly be categorized as benefit, resource, and technical interdependencies.

2.2 Software/IT Projects

Software/IT project selection is a company-level decision making process. Karimpour and Ruhe [26] indicated that inaccuracies due to uncertainty must be considered in defining the software project selection problem. Specifically, they claimed that there was uncertainty pertaining to both the market and the engineering capabilities of the development team. Chiang and Nune [7] considered the selection problem as an optimization problem where an optimal mix of the projects must be determined assuming discrete time-based resource constraints. They also assumed the option of resource divisibility and sharing, task duration variability, time-dependent returns, resource rotation, and learning effect. The project selection as well as the sequencing of the project with their start times are considered by Kremmel et al. [28, 29] and Xiao et al. [41]. In Kremmel et al. [28, 29], project size was determined by the source lines of code measure, with resources formulated as development time, i.e., person-months. The work of Xiao et al. [41] was noted as an extension of [29], with no significant difference in the problem considered. Given that these projects in these studies are scheduled over a planning horizon of multiple periods, they are considered selection and scheduling problems.

2.3 R&D and Production Projects

Projects from the R&D and Production sectors are reported together given that they have significant similarities and overlap in their problem descriptions. George and Farid [18] considered the selection of bio-pharmaceutical, therapeutic antibody projects with activity scheduling. In this study, the timeline was an important aspect associated with project selection. Another important aspect considered in their problem was whether activities were best conducted within the company, outsourced to a contracted researcher, or conducted with a partner company. Kostuik et al. [27] examined offshore exploration and production projects where production is a function of the volume of gas to be injected into each well. Medaglia et al. [33] presented an Research and Development (R&D) project selection problem with full or partial funding options subject to a limited budget. Their model allowed for posterior articulation of preferences and claimed to require the least amount of information from the decision maker. Ferníndez et al. [14] considered an R&D project selection problem in manufacturing for new product development that incorporated imperfect knowledge regarding project completion time and budget availability.

2.4 Construction and Infrastructure Projects

Abido and Elazouni [1] and Elazouni and Abido [13] presented multiple problems in the construction domain for coordinated scheduling of activities, whereby the start time for each project must be decided. In their study, the start time of a project is taken as the start time of the first activity. Note that, these problems consist only of the scheduling of activities, i.e., there was no selection aspect.

Iniestra and Gutiérrez [25] introduced a transportation infrastructure project selection problem with multiple selection criteria and a limited budget. This problem is similar to the public project selection problems discussed in Sect. 2.1. Chen et al. [6] described the alternative material supply plans to multiple construction projects, using a transshipment supply chain network, as the contractor's project portfolio. Again, there was no project selection aspect associated with this study.

2.5 Investment Projects

In an investment project selection problem, investors seek to maximize their return by selecting an optimal mix of investment options. In this domain, an investor can be either an individual or a corporation. An important consideration in these types of problems is the risk-reward trade-off, given that investments typically come with some associated risk [30]. Generally, an investor will seek to attain a portfolio that maximizes the expected return while minimizing the risk. In come cases, this can be considered as a multi-objective problem [5]. See [35] for a recent survey on investment stock portfolio selection.

Huang [24] proposed an investment selection problem, assuming a fixed investment amount, with both single- and multi-objective variants. The problem was considered as an abstracted 0/1 knapsack problem. Zhou et al. [45, 46] dealt with a similar problem, but also considered the uncertainty in the portfolio return. Furthermore, multi-term investments were also considered.

2.6 Defense Projects

Although defense projects are publicly funded, they are quite different from social projects in terms of their requirements and prioritization [38]. See [20] for an in-depth review of portfolio optimization in the defense sector. Shafi et al. [37] proposed a defense-oriented PPSSP that encompassed different project groupings that shared a common (central) funding source. This study accounted for many decision making conditions and preferences specific to the defense industry when selecting and scheduling the projects. Xiong et al. [42] described the selection of weapon development projects, similar to the R&D domain discussed in Sect. 2.3. However, Xiong et al. [42] considered both the selection and scheduling of projects, subject to temporal and budgetary constraints. In addition, the variation in performance of a weapon due to the action of counterparts was also considered. Zhou et al. [44] considered a simple weapon selection problem with a limited budget in multiple periods. Harrison et al. [22, 23] proposed a PPSSP inspired by the Future Force Design (FFD) process undertaken by the Australian Department of Defence (DoD). This study examined both the selection and scheduling of a portfolio of projects while adhering to various constraints that were characteristic of the problem faced by the DoD. Harrison et al. [22, 23] then extended their previous work to include grouping into five capability streams, namely Air, Information and Cyber, Land, Maritime, and Space.