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MULTI-OBJECTIVE ROBUST DECISION-MAKING APPROACH TO A JOINT PROBLEM UNDER DEEP UNCERTAINTY IN DEFENCE

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Abstract. Military systems typically operate within closed workforce structures and rely on long-term fleet planning, creating complex challenges in joint workforce planning and fleet management. These challenges are further compounded by deep uncertainty and competing objectives. Simulation models provide a powerful means of capturing such complexity and the interdependencies among system components and resources, and simulation–optimisation techniques have therefore been widely used to support strategic decision-making. However, many existing simulation–optimisation studies rely on best-estimate assumptions and do not adequately account for deep uncertainty. To address this limitation, this study explicitly considers deep uncertainty and derives robust strategies that perform satisfactorily across a wide range of plausible future conditions. Specifically, we analyse and compare two robustness frameworks developed for Decision-Making under Deep Uncertainty (DMDU): Multi-Objective Robust Decision-Making (MORDM) and Multi-Objective Robust Optimisation (MORO). The proposed approach integrates a simulation model with Exploratory Modeling and Analysis (EMA) to identify robust strategies governing recruitment, promotion, and fleet transition. Robustness is assessed using metrics derived from key objective functions, including workforce surplus cost and operational fleet availability. The methodology is demonstrated through a realistic case study motivated by the Royal Australian Navy's fleet modernisation program, which poses a joint workforce planning and fleet management problem under deep uncertainty. The results indicate that strategies identified using the MORO framework exhibit greater robustness across plausible future conditions than those obtained using MORDM, albeit at approximately an order-of-magnitude higher computational cost. Overall, the findings provide military decision-makers with insights into robustness–cost trade-offs and guidance on selecting an appropriate robustness framework for complex defence planning problems.

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1. Introduction

Military systems typically operate in closed workforce structures, where recruitment is largely internal and career progression follows a strict hierarchical pathway requiring sequential advancement. Workforce planning aims to ensure that personnel with appropriate skills are available for specific tasks at the required time [54,60].

Keywords. Multi-objective robust decision-making, multi-objective robust optimization, military, fleet management, workforce planning, deep uncertainty.

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In parallel, fleet management involves decisions related to asset size, composition, renewal, and the timing of commissioning and decommissioning [42].

These two domains are inherently interdependent, giving rise to a multi-objective decision problem characterised by competing priorities [10, 55]. Workforce planning typically seeks to minimise personnel-related costs through controlled recruitment and retention policies, whereas fleet management may prioritise asset expansion or modernisation to meet evolving mission requirements. The introduction of new assets alters workforce requirements in both scale and skill composition, creating a delicate trade-off between cost efficiency and operational readiness. Decision-makers must therefore balance budgetary constraints while maintaining sufficient operational fleet availability.

Given this complexity, model-based analytical approaches are essential for supporting planning and decision-making [29, 47]. Human cognition is limited in its ability to account for feedback loops, time delays, and non-linear interactions within complex systems [48]. Simulation models help overcome these limitations by representing dynamic system behaviour and enabling the exploration of multiple interacting factors [33, 49]. However, standalone simulation models and conventional what-if analyses remain insufficient because they rely on fixed parameter estimates and fail to adequately capture deep uncertainty.

Deep uncertainty arises in situations where decision-makers cannot agree on the appropriate system model, the probability distributions of key parameters, or the valuation of alternative outcomes [57]. As noted by Marchau *et al.* [34], such uncertainties are often overlooked due to practical constraints, including limited resources, competing stakeholder interests, and political pressures. In military settings, such as the Australian Navy's nuclear submarine acquisition program, uncertainties in workforce separation rates and vessel delivery schedules exemplify parameters that cannot be reliably inferred from historical data, yet exert substantial influence on long-term planning and operational readiness.

Conventional probabilistic decision-making frameworks are ill-suited to address such conditions [41,46]. Ignoring deep uncertainty may offer short-term convenience but can lead to significant long-term consequences. Moreover, ad hoc approaches to uncertainty treatment, such as restricting sensitivity analysis to a small subset of parameters, have raised concerns regarding their adequacy for informing robust decisions [61].

There exist two broad decision-making paradigms [59].

1. *Predict-then-Act*. Traditional decision-analytic methods largely follow this paradigm, seeking optimal strategies based on predictions derived from probabilistic representations of uncertainty [41]. These approaches typically rely on a single best-estimate system model and associated probability distributions for uncertain inputs. While effective in some contexts, they often struggle to achieve stakeholder consensus when predictions are highly contested.
2. *Seek Robust Solutions*. This paradigm, also referred to as *explore and adapt*, focuses on identifying strategies that perform satisfactorily across a wide range of plausible futures. Rather than predicting a single most likely outcome, these approaches aim to uncover vulnerabilities and minimise regret should initial assumptions prove incorrect.

Most existing studies addressing workforce planning and/or fleet management adopt the first paradigm. In contrast, this study follows the second paradigm by explicitly accounting for deep uncertainty.

Over the past decade, several frameworks and tools have been developed to support Decision-Making under Deep Uncertainty (DMDU) [28, 34]. Among these, Multi-Objective Robust Decision-Making (MORDM) and Multi-Objective Robust Optimisation (MORO) are two prominent frameworks for identifying robust strategies in problems involving multiple, often conflicting, objectives under deep uncertainty. Their primary distinction lies in the optimisation focus: MORDM seeks Pareto-optimal solutions by directly optimising objective functions, whereas MORO identifies robust Pareto-optimal solutions by optimising robustness metrics derived from those objectives [5]. In both approaches, simulation models are evaluated over large ensembles of scenarios sampled from the uncertainty space, enabling vulnerability analysis and trade-off analysis across objectives. Compared with conventional scenario planning methods, Exploratory Modeling and Analysis (EMA)facilitates reasoning over a broader and more diverse set of internally consistent futures [34].

This study presents a comparative analysis of MORDM and MORO applied to a joint military fleet management and workforce planning problem under deep uncertainty. The analysis focuses on identifying robust strategies, conducting vulnerability and trade off analyses, and systematically evaluating the relative performance of the two frameworks, an aspect that has not yet been examined in the context of integrated military planning.

The main contributions of this study are summarised as follows:

- Unified simulation-based problem formulation: This study formulates and applies a unified, simulation-based decision framework that integrates workforce planning and fleet management in a military context. Rather than proposing a new optimisation model, the contribution lies in explicitly capturing the interdependencies between these domains to avoid sub-optimal decisions that may arise when they are analysed in isolation.
- Explicit treatment of deep uncertainty: The proposed approach explicitly models deep uncertainty, enabling the identification of robust strategies that perform satisfactorily across a wide range of plausible future conditions, beyond what can be achieved using conventional probabilistic assumptions.
- Vulnerability analysis via scenario discovery: The study employs scenario discovery to systematically identify critical uncertain parameters and their associated ranges that lead to vulnerable outcomes, moving beyond traditional sensitivity analysis.
- Comparative assessment of robustness frameworks: By systematically comparing MORDM and MORO in a military planning context, the study highlights their respective strengths and limitations and provides practical guidance on selecting an appropriate robustness framework for complex defence decision problems.

The remainder of the manuscript is organised as follows. Section 2 reviews the relevant literature. Section 3 describes the problem setting and simulation model. Section 4 details the DMDU frameworks employed. Section 5 presents and discusses the results, and Section 6 concludes the paper.

2. Literature review

This section presents a state-of-the-art review of the current literature to position the novelty and contributions of this study. Section 2.1 reviews prior work on joint workforce planning and fleet management in military systems. Section 2.2 examines how uncertainty, and in particular deep uncertainty, has been treated in military decision-making. Section 2.3 provides an overview of comparative studies on DMDU frameworks and tools. Table 1 summarizes representative studies in this area.

2.1. Joint workforce planning and fleet management in military systems

As shown in Table 1, workforce planning and fleet management have been studied extensively in the literature. For example, Turan *et al.* [54] formulated MOO problems integrating military workforce planning, asset management, and fleet management, and provided a comprehensive review of related studies. According to their review and Table 1, most applications remain focused on non-military contexts. Existing research typically addresses these dimensions individually or in pairs, formulates the problem as either single- or multi-objective, and applies methods such as SP, SOP, goal programming, MIP, or RO.

Joint military workforce planning problems have also been considered by Turan *et al.* [55, 56], Horn *et al.* [21], and Akl *et al.* [1, 2]. Motivated by the Australian Navy's fleet modernisation plans, Turan *et al.* [55, 56] developed integrated models for strategic facility location and workforce planning, and for workforce planning with fleet renewal, respectively. While these studies use SOP, the former adopts a multi-objective formulation whereas the latter focuses on a single-objective problem. Other military applications, such as Horn *et al.* [21], and Akl *et al.* [1, 2], similarly concentrate on single-objective formulations, limiting their ability to capture trade-offs inherent in real-world decision-making.

In contrast to prior work that addresses workforce planning and fleet management separately or relies predominantly on single-objective formulations, this study adopts a unified multi-objective formulation that explicitly captures the interdependencies and trade-offs inherent in joint military workforce and fleet planning.

TABLE 1. The state-of-the-art literature on fleet management and/or workforce planning.

Study	Workforce planning	Fleet management	Uncertainty considered	Robustness consideration	Single/Multi-objective (SO/MO)	Solution approach[a]	Military
Heuser *et al.* [19]	✓				SO	MIP	
Evans and Bae [12]	✓			✓	SO	SOP	✓
Bastian *et al.* [6]	✓		✓	✓	SO	SP + RO	✓
Horn *et al.* [21]	✓				SO	MLP	✓
Akl *et al.* [1]	✓		✓	✓	SO	SOP	
Akl *et al.* [2]	✓		✓		SO	SOP	
Berk *et al.* [8]	✓		✓	✓	SO	RO	
Restrepo *et al.* [44]	✓				SO	SP	
Tohidi *et al.* [50]	✓		✓		SO	RO+SP	
Francas *et al.* [13]	✓		✓		SO	SP	
Turan *et al.* [52]	✓		✓		SO	SOP	
Mirzapour Al-E-Hashem *et al.* [38]	✓		✓	✓	MO	MORO	
Ji *et al.* [22]	✓		✓		MO	MOO	
Li *et al.* [32]	✓				MO	Multi-Goal programming	
Caballini and Paolucci [9]	✓		✓		MO	MIP	
Mehdizadeh *et al.* [37]	✓				MO	Sub-population genetic algorithm	
Chavez *et al.* [10]	✓		✓	✓	MO	SP	
Ansaripoor *et al.* [3]		✓	✓		SO	SP	
Morch *et al.* [40]		✓	✓		SO	SP	
Turan *et al.* [53]		✓	✓		SO	SOP	✓
Hoffenson *et al.* [20]		✓			MO	MOO	✓
Siddiqui and Verma [45]		✓			MO	MIP	
Eskandarpour *et al.* [11]		✓			MO	Multi-directional local search	
Karatas [25]		✓	✓		MO	MILP	
Rabbani *et al.* [43]		✓			MO	MIP	
Turan *et al.* [55]	✓	✓			MO	SOP	✓
Turan *et al.* [54]	✓	✓	✓		MO	SO	✓
Turan *et al.* [56]	✓	✓	✓	✓	SO	SO	✓
This study	✓	✓	✓	✓	MO	MORDM	✓

Notes. [a]Abbreviations: MIP = Mixed Integer Programming; SOP = Simulation Optimization; SP = Stochastic Programming; RO = Robust Optimization; MOO = Multi-Objective Optimization; MILP = Mixed Integer Linear Programming; MORO = Multi-Objective Robust Optimization; MORDM = Multi-Objective Robust Decision-Making.

2.2. Deep uncertainty in military planning

Previous research has acknowledged the presence of uncertainty in workforce planning and fleet management problems [54]. However, as shown in Table 1, most studies address uncertainty using probabilistic approaches such as stochastic programming or scenario-based simulation. For example, Akl *et al.* [2] employed a chance-constrained SOP framework assuming known probability distributions, while Jnitova *et al.* [23] reported widespread use of probabilistic and scenario-based methods across defense workforce planning models. Such approaches are widely recognised as inadequate for addressing deep uncertainty, where probability distributions are unknown or contested [31, 58].

Studies such as Turan *et al.* [54] modelled uncertainty in workforce separation rates and operating cost growth using probability distributions but did not investigate deep uncertainty or vulnerability. Similarly, Turan *et al.*

[56] conducted sensitivity analysis across alternative scenarios but did not perform scenario discovery or explicitly quantify robustness. Importantly, neither study considered uncertainty in vessel acquisition schedules, which can critically affect long-term workforce and fleet performance.

Some non-military studies have applied RO to workforce planning problems [8, 38, 50], while Bastian *et al.* [6] addressed readiness and manning in the US Army cyber branch using RO. Although RO accommodates deep uncertainty by avoiding reliance on probability distributions, these studies do not conduct vulnerability analysis or identify critical uncertainty ranges.

Unlike existing studies that rely on probabilistic uncertainty modelling or limited sensitivity analysis, this work explicitly treats workforce separation rates and vessel acquisition schedules as deeply uncertain parameters and employs scenario discovery to identify vulnerabilities and critical uncertainty ranges in joint military workforce and fleet planning.

2.3. Comparative studies of DMDU frameworks and tools

A wide range of frameworks has been proposed to support decision-making under deep uncertainty, including Robust Decision-Making, MORDM, Adaptive Policy-Making, Dynamic Adaptive Policy Pathways, Real Options Analysis, Info-Gap Decision Theory [7], and Decision Scaling [28, 34]. Most applications of these frameworks have focused on environmental and socio-technical systems [30].

Comparative studies remain limited. Kwakkel and Haasnoot [28] highlighted the lack of systematic understanding of similarities and complementarities among DMDU frameworks. Subsequent work by Moallemi *et al.* [39] and Bartholomew and Kwakkel [5] compared selected frameworks, including MORDM and MORO, demonstrating that each is suited to different decision contexts and analytical goals. However, these comparisons have largely been conducted outside the military domain.

Building on prior comparative studies focused primarily on non-military applications, this research provides one of the first systematic comparisons of MORDM and MORO in a complex military planning context involving joint workforce and fleet management under deep uncertainty.

3. Problem description and formulation

This section describes the problem under investigation and its formulation within a simulation-based decision framework. The study focuses on a joint military workforce planning and fleet management problem under deep uncertainty, where decision-makers must determine recruitment levels, promotion and transition policies, and workforce allocation over time while accommodating planned fleet acquisitions and decommissioning. The overarching aim is to balance two competing objectives: maintaining a sufficient level of operational fleet availability and controlling workforce-related costs.

We conduct a comparative analysis of MORDM and MORO applied to a hypothetical case study inspired by the Australian Navy's plan to acquire eight nuclear-powered submarines by the mid-2050s [4]. The formulation introduced in this section provides a unified representation of the decision context and objectives, which is then used consistently by both frameworks to evaluate alternative strategies and their robustness across plausible future conditions.

The remainder of this section is organised as follows. Section 3.1 presents a brief overview of the system dynamics simulation model used to represent workforce flows and personnel states over the planning horizon. Section 3.2 introduces the objective functions, decision variables, uncertain parameters, and robustness metrics used to evaluate alternative strategies within the simulation-based framework. Together, these subsections provide the formal basis for applying and comparing the two robustness frameworks in the subsequent analysis.

3.1. Simulation model

The system dynamics simulation model focusing on workforce planning is implemented in AnyLogic 8 software. The model focuses on two main naval workforce types, namely, officers and sailors. Both workforce types consist of four ranks, ranging from the 1st to the 4th (Fig. 1). For ranks 1 through 3 in both workforces, there

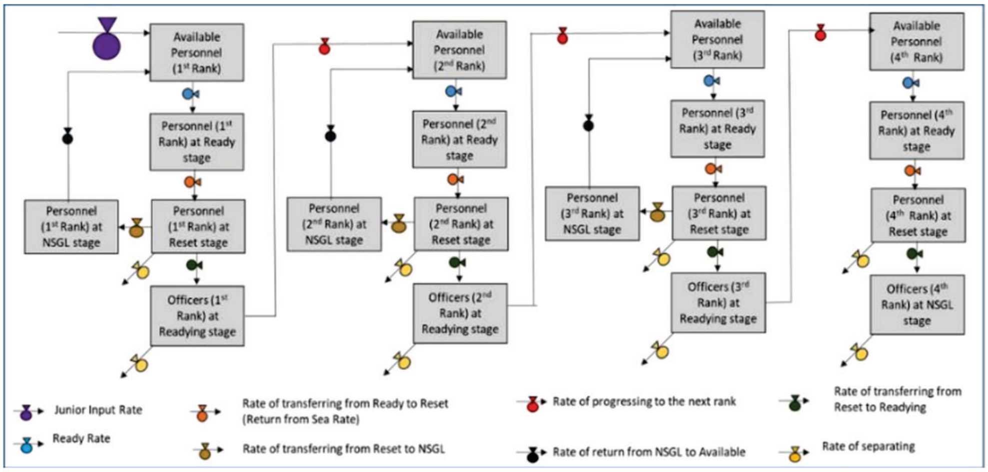


FIGURE 1. A structure of personnel flow in the developed simulation model [51].

are five possible status options: available, ready, reset, readying, and Non-Sea-Going Liability (NSGL). For rank 4 in both workforce types, the readying status does not exist; therefore, only four status options are considered. Each individual in the simulation is assigned to exactly one rank and one status at any given time.

In this study, the term *relationships* refers to the causal and logical linkages embedded within the simulation model that connect decision variables, uncertain parameters, and system outcomes. These relationships capture how recruitment policies, promotion and transition rules, workforce separation rates, and fleet transition schedules jointly influence personnel availability and fleet operability over time. They are operationalised through the workforce flow structure and transition rules represented in the simulation model.

We add the junior input rate to increase the available personnel for rank 1, as shown in Figure 1. The readiness rate at any given time t depends on the crew required to operate a platform. The ready stock denotes the cumulative number of personnel in the ready stage at time t, calculated by aggregating the readiness rate. Likewise, the reset stock indicates the cumulative number of personnel in the reset stage at time t, computed by aggregating the transition rate from the ready to reset stages.

When personnel transition into the reset stage, except for those in rank 4, they follow one of three paths: (i) they leave the Navy, (ii) they undergo a period in the reset stage before progressing to the readying stage, or (iii) they spend time in the reset stage before transitioning to the NSGL stock, as illustrated in Figure 1. Likewise, individuals in rank 4 have two options upon entering the reset stage: (i) they depart from the Navy, or (ii) they undergo a period in the reset stage before transitioning to the NSGL stage. For further details about the simulation model, interested readers can refer to Turan *et al.* [51].

3.2. Decision objectives, uncertainty, and robustness metrics

This decision problem is formulated as a bi-objective problem reflecting two competing planning goals. The first objective aims to maximize average operational fleet availability over the planning horizon, capturing the ability of the Navy to sustain required operational capability during fleet transition. The second objective aims to minimise total workforce surplus cost, representing the financial impact of overstaffing relative to fleet requirements. These objectives are evaluated through simulation and form the basis for defining robustness metrics under deep uncertainty.

The configuration of this collaborative problem is depicted in Figure 2.

To formally describe the simulation-based decision framework, we introduce notation for the decision variables, uncertain parameters, and key simulation outputs used to define the objectives and robustness metrics.

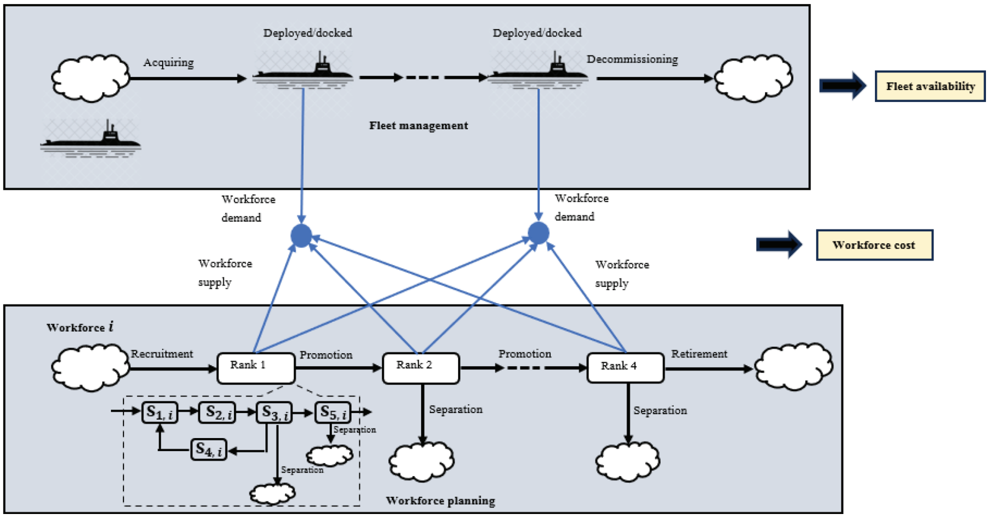


FIGURE 2. The holistic view of the problem addressing workforce planning and fleet management.

This notation supports the transparent description of the simulation-based decisional process and does not represent a standalone analytical optimisation model. It is important to note that a strategy $\omega \in \Omega$ is formulated using decision variables. Further, the decision variables define a strategy by controlling recruitment levels and personnel transitions over time, and directly influence both fleet availability and workforce surplus cost through the simulation model.

Sets and indices:

- I: The set of workforce types with index $i \in I$.
- J_i: The set of distinct ranks for workforce type $i \in I$ with index $j \in J_i$.
- K: The set of fleets, indexed by $k \in K$.
- V_k: The set of vessels in fleet $k \in K$, indexed by $v \in V_k$.
- $\mathbf{S}_{j,i}$: The set of statuses of personnel at rank $j \in J_i$ for workforce type $i \in I$.
- t: Discrete time index over the planning horizon; *i.e.*, $t \in \{0, 1, \ldots, T\}$, where T denotes the length of the planning horizon.
- Ω: A set of all feasible strategies with a strategy $\omega \in \Omega$.

Here, t is explicitly introduced as a discrete time index to emphasise the temporal structure of the simulation-based formulation, as all decision variables, system states, and objective functions are evaluated dynamically over the planning horizon $t = 0, 1, \ldots, T$.

Decision variables:

- $\beta_{i,t,1}$: The count of new recruits at rank 1 for each workforce type $i \in I$ at each time t.
- $x_{j,i}^{s \to s'}$: The maximum movement of personnel from rank $j \in J_i$ transitioning from status $s \in \mathbf{S}_{j,i}$ to the status $s' \in \mathbf{S}_{j,i} \cup \mathbf{S}_{j+1,i}$ at any given time.
- $y_{j,i}^{s \to s'}$: The minimum duration for personnel at rank $j \in J_i$ to stay in status $s \in \mathbf{S}_{j,i}$ before transitioning to status $s' \in \mathbf{S}_{j,i} \cup \mathbf{S}_{j+1,i}$ within the same or higher rank.

Parameters:

- T: The length of the planning period.

$d^v_{j,i}$: The required amount of personnel at rank $j \in J_i$ for workforce type $i \in I$ to crew vessel $v \in V_k$ for fleet $k \in K$.
$c_{j,i,t}$: The salary of personnel at rank $j \in J_i$ for workforce type $i \in I$ at time t.
t^{dec}_v: The decommissioning date of each vessel $v \in V_k$ for fleet $k \in K$.
t^{acq}_v: The acquisition date of each vessel $v \in V_k$ for fleet $k \in K$.
$w_{j,i,0}$: The initial amount of personnel at rank $j \in J_i$ for workforce type $i \in I$.

Uncertain model parameters and their bounds:

$r^i_{j,s}$: The separation ratio or fraction (*i.e.*, the proportion of crew turnover) of personnel at rank $j \in J_i$ for workforce type $i \in I$ at status $s \in \mathbf{S}_{j,i}$ for each time period. $r^i_{j,s} \in [\underline{b}^s_i, \bar{b}^s_i] \subset [0,1]$, where $\underline{b}^s_i$ and $\bar{b}^s_i$ denote the lower and upper bound, respectively.
σ^{acq}_v: The deviation of the acquisition date from its planned acquisition date t^{acq}_v for each vessel $v \in V_k$.

Collected values of important simulation outcomes:
To assess objective functions and consequently the robustness metrics, we gather the following parameter values during each computational experiment.

$\gamma_{v,t}$: The number of operational vessels $v \in V_k$ for $k \in K$ at time t.
$\alpha_{i,j,t}$: The surplus at rank $j \in J_i$ for workforce type $i \in I$ at time t.

3.2.1. Assumptions and simplifications

To reflect the hierarchical and closed structure of the military workforce, we establish several assumptions.

1. At the outset, all personnel in each workforce type and rank, denoted as $w_{j,i,0}$ (for all $i \in I$ and $j \in J_i$), are in the available status.
2. Individuals are prohibited from transitioning between workforce types during their careers due to minimal transfer amounts between these types in comparison to the overall workforce size.
3. Recruitment only occurs at rank 1 for each workforce type.
4. Career advancements occur gradually, following the hierarchical rank chain structure.
5. Workforce outsourcing is not allowed for any workforce type and any rank.

Furthermore, we introduce the following assumptions for the sake of simplicity and the specific focus of this paper.

(i) Throughout the planning horizon, the salary of personnel at rank $j \in J_i$, $c_{j,i,t}$, remains constant.
(ii) The separation fraction for each time period of rank $j \in J_i$ for workforce type $i \in I$ at status $s \in \mathbf{S}_{j,i}$ remains constant.
(iii) The recruitment amount for rank 1 for each workforce type $i \in I$ remains constant over time.

3.2.2. Objective functions

In a military context, maintaining the maximum number of operational vessels throughout fleet transitions is essential to ensure their prompt deployment when needed [53]. Maximising the availability of the operational fleet involves timely maintenance of the vessels, acquiring new vessels as necessary, and retiring old vessels to prevent unnecessary costs and idleness of the workforce.

Figure 2 illustrates how fleet management, in particular, fleet transition, and workforce planning interplay to impact operational fleet availability. Workforce planning, encompassing recruitment and promotion, is responsible for providing the necessary personnel to operate the fleet's vessels. Simultaneously, fleet transition dictates the retirement timing and the acquisition of vessels, shaping the fleet's size and composition throughout the planning period. This, in turn, determines the crewing requirements for these vessels. The capability gap emerges when vessels become unavailable due to a mismatch between the personnel supplied by the workforce planning and the demands generated by fleet transition. Thus, maximizing operational fleet availability also minimizes the capability gap.

Consequently, the operational fleet availability stands as an intermediary challenge bridging workforce planning and fleet transition, underscoring the essential need for a holistic approach in addressing workforce planning and fleet management. Notably, operational fleet availability and workforce cost are interconnected and not mutually exclusive, representing conflicting objectives in this context. Below, we introduce objectives of our bi-objective optimisation problem.

Objective 1: maximize the average operational fleet availability F_A

$$\max_{\omega \in \Omega} \; F_A, \tag{1}$$

where

$$F_A = \frac{1}{T} \sum_{t=1}^{T} \sum_{k \in K} \sum_{v \in V_k} \mathcal{A}_{v,t}, \tag{2}$$

and $\mathcal{A}_{v,t} = \begin{cases} 1, & \text{If vessel } v \in V_k \text{ for } k \in K \text{ is operational available at time } t \\ 0, & \text{Otherwise.} \end{cases}$

Within the realm of military expenditures, workforce, capital, and sustainment costs stand out as primary contributors [16, 17, 54]. Workforce cost predominantly encompasses personnel salaries over a given planning horizon, while capital cost is associated with vessel acquisition expenses (Fig. 2). On the other hand, sustainment cost is tied to the operational and maintenance outlays for the fleet of vessels. As we consider the acquisition of eight vessels and operational and maintenance costs are assumed constant for the purpose of this study, capital cost and sustainment cost are independent of the choice of the strategy. Consequently, our study is focused on the minimization of the workforce cost arising from the workforce surplus.

Objective 2: Minimize the total workforce cost over the planning horizon, denoted by C_T

$$\min_{\omega \in \Omega} \; C_T, \tag{3}$$

where

$$C_T = \sum_{t=1}^{T} \sum_{i \in I} \sum_{j \in J_i} c_{i,j,t} \alpha_{i,j,t}, \tag{4}$$

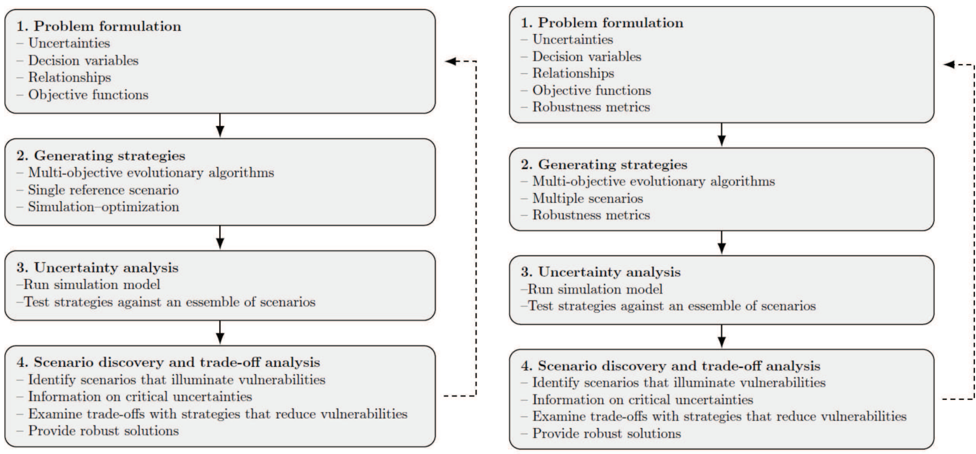
and T denotes the final period of the planning horizon.

3.2.3. Robustness metrics

As previously mentioned, it is essential to establish robustness metrics to aid in identifying robust optimal strategies and to evaluate strategy performance under conditions of deep uncertainty. We define the following robustness metrics based on the objective functions. Following a unified framework proposed by McPhail *et al.* [36], we employ descriptive statistics (specifically, the 10th percentile worst-case scenarios) in defining these robustness metrics. Below, we outline the robustness metrics derived from the aforementioned objective functions.

Robustness metric 1: the 10th percentile average operational fleet availability F_A^{10p}.
When identifying robust optimal strategies, maximizing this value is crucial. A higher value indicates better robustness when assessing strategy performance under conditions of deep uncertainty.

Robustness metric 2: the 90th percentile total workforce cost C_T^{90p}.
When seeking robust optimal strategies, minimizing this value is necessary. A lower value indicates better robustness when evaluating the performance of strategies under conditions of deep uncertainty.



(a) MORDM (b) MORO

FIGURE 3. Two robust decision-making frameworks (adapted from Bartholomew and Kwakkel [5]).

4. Simulation-based application of MORDM and MORO

This section describes how the simulation based decision framework introduced in Section 3 is combined with MORDM and MORO. It also explains how strategies are generated, evaluated, and compared under deep uncertainty using exploratory modeling and analysis.

The remainder of this section is organised as follows. Section 4 outlines the overall simulation-based workflow adopted in this study. Section 4.1 describes the application of MORDM, including strategy generation and vulnerability analysis. Section 4.2 presents the MORO approach, focusing on robustness metric optimisation and subsequent evaluation. Together, these subsections define the analytical procedure used to compare the two frameworks.

4.1. Multi-objective robust decision-making

MORDM, as proposed by Kasprzyk *et al.* [26], integrates multi-objective evolutionary algorithms with the robust decision-making framework introduced by Lempert [31]. This framework offers a structured approach to aid in selecting a preferred solution from the multitude of strategies produced by multi-objective evolutionary algorithms. Multi-objective evolutionary algorithms capture decision alternatives (strategies) that entail significant trade-offs among conflicting objectives [15]. Figure 3 presents overview of the simulation-based decision frameworks, showing the relationships between decision variables, uncertain parameters, simulation dynamics, and performance outcomes. In particular, Figure 3a shows the steps involved in MORDM framework.

It should also be noted that Steps (3) and (4) (uncertainty analysis, including scenario discovery and trade-off analysis) in Figure 3 represent common elements of the simulation-based workflow and are identical for both MORDM and MORO; they correspond to the instantiation of the simulation model and the evaluation of candidate strategies across scenarios.

Once the problem is effectively formulated, and strategies are discovered through a multi-objective evolutionary algorithm, the next step involves a rigorous performance evaluation of these strategies by stress testing over many scenarios. Scenarios encompass the deeply uncertain parameters of the problem. In essence, these scenarios should reflect the entire spectrum of relevant uncertainties. To construct this set of scenarios, one approach recommended by Kasprzyk *et al.* [26] is to employ Latin Hypercube Sampling across the uncertainty space (*i.e.*, space spanned by the deeply uncertain parameters). This method guarantees that every member of the uncertainty set receives adequate representation across the sampled scenarios, thereby enhancing the comprehensiveness of the analysis [35].

Following the evaluation of each candidate strategy across a wide range of scenarios, the next phase entails comprehensive data analysis. The main aim of this analysis is to evaluate the robustness of these candidate strategies, with specific attention to understanding the influence of various deeply uncertain factors, either individually or in combination, on this robustness [18]. The findings of this analysis are communicated through interactive visualizations, enabling decision-makers to delve into the robustness of strategies. These visual aids are instrumental in clarifying the intricate trade-offs among different objectives, thereby fostering a more thorough comprehension of the decision landscape.

MORDM is inherently iterative. If decision strategies' trade-offs or their robustness are deemed unsatisfactory, the process repeats on a subsequent iteration. As this framework incorporates a multi-objective evolutionary algorithm for generating strategies, refinements primarily occur at the problem formulation step [5]. This enables the incorporation of new insights, which may help adjusting the uncertainty space, modifying decision variables, or refining the objective functions, thereby improving the overall decision-making process.

4.2. Multi-objective robust optimisation

The solutions derived from optimisation with a reference scenario may exhibit poor performance in alternative scenarios [5]. Considering the cost of robustness, it is improbable that a solution optimal in any specific scenario would also be highly robust across numerous scenarios. As the primary goal of facilitating DMDU is to identify robust strategies that provide satisfactory performance across multiple conflicting objectives, MORO incorporates robustness into the search phase for candidate solutions [5].

MORO differs from MORDM in its treatment of uncertainties. In MORO, the optimisation process focuses on optimising a set of robustness metrics derived from the objective functions, as illustrated in Figure 3b.

Managing the runtime complexity in the search phase of MORO can present challenges when assessing the robustness of candidate solutions across numerous scenarios. To tackle this issue, Bartholomew and Kwakkel [5] have introduced a structured approach that integrates MORO into the robust decision-making framework. This approach involves discovering robust optimal solutions with a few scenarios and subsequently conducting uncertainty analysis, scenario discovery, and trade-off analysis. These steps facilitate comprehensive testing of each solution against a diverse array of scenarios. Following Bartholomew and Kwakkel [5], we find the robust optimal solutions by utilizing a few scenarios in the search phase followed by uncertainty analysis, scenario discovery, and trade-off analysis.

5. Analysis of the results

In this section, we present, discuss, and compare the results obtained from MORDM and MORO. First, Section 5.1 provides an overview of the real-world case study explored in this work, focusing on the submarine acquisition and decommissioning schedules. The results from MORDM are discussed in Section 5.2, while the results from MORO are discussed in Section 5.3. A comparative analysis of the results between the two frameworks is provided in Section 5.4.

5.1. Real-world case study

Currently, the Royal Australian Navy operates a fleet of six Collins-class diesel submarines (hereafter referred to as the existing fleet). The case study examines the transition from this existing fleet to a future fleet that includes eight nuclear-powered submarines (hereafter referred to as the new fleet), planned to be fully operational by the mid-2050s, as introduced in Section 3. This transition reflects a long-term strategic modernisation effort and introduces significant planning challenges related to workforce capacity and fleet availability.

Figure 4 illustrates the assumed commissioning schedule for the new vessels and the decommissioning schedule for the existing fleet. Under the adopted assumptions, the first new submarine is commissioned in 2031, followed by two additional vessels at two-year intervals. The fourth vessel is introduced in 2038, followed by the fifth in

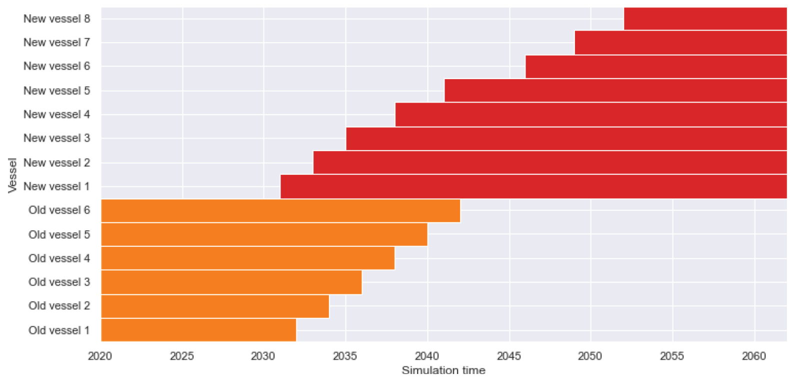


FIGURE 4. Commissioning schedule of new vessels and decommissioning schedule of existing vessels over the planning horizon.

2041. The remaining three vessels are then commissioned at three-year intervals starting in 2046, resulting in a total of eight new vessels by the mid-2050s.

To ensure continuity of operational capability and maintain Australia's maritime sovereignty during the transition period, no decommissioning of the existing fleet is assumed prior to 2032. From 2032 onward, the six Collins-class submarines are decommissioned sequentially at two-year intervals.

To capture the full dynamics of this fleet transition and its interaction with workforce planning, the simulation model is executed over the period from 2020 to 2062, using quarterly time steps.

5.2. Multi-objective robust decision-making

As discussed in Section 4, the initial stage of MORDM involves problem formulation, including the identification of decision variables, deeply uncertain parameters, system relationships, and objective functions, as detailed in Section 3. The subsequent step focuses on specifying the simulation input parameters and defining realistic ranges for the decision variables and deeply uncertain parameters.[1] The identified relationships are then instantiated within the simulation model, as described in Section 3.

The workforce is categorised into two types, Sailors and Officers, each comprising four ranks. For both workforce types, ranks 1 to 3 include five possible status options, while rank 4 includes four status options, as outlined in Section 3.

The simulation input parameters and their baseline values are summarized in Table 2. The decision variables and their corresponding bounds are summarized in Table 3. The deeply uncertain parameters, their bounds, and reference values are summarized in Table 4.

Following Step 2 of MORDM (recall Fig. 3a), we identified Pareto optimal solutions, representing candidate strategies, using a reference scenario. This reference scenario is defined by the reference values reported in Table 4, which represent best-estimate values for each deeply uncertain parameter. The ϵ-NSGAII algorithm was implemented within the EMA workbench [5] to optimise the objective functions of average operational fleet availability and total workforce cost, as defined in Section 3.2. The algorithm employs auto-adaptive operator selection and adaptive population sizing. To ensure convergence, the number of function evaluations was set to 750 000, with convergence behaviour illustrated in Figure S1 of the supplementary materials.

The search phase identified 28 Pareto optimal solutions, each corresponding to a distinct strategy and objective-function trade-off. The complete set of Pareto optimal solutions is provided in the supplementary file. The search phase required approximately 24 CPU hours using 10 parallel workers on a standard desktop computer with 12 cores operating at 2.70 GHz. The parallel coordinate plots in Figure 5 illustrate the resulting

[1]These data are derived and estimated from `https://www.anao.gov.au/sites/default/files/ANAO_Report_2014-2015_17.pdf`.

TABLE 2. The input parameters in the simulation model.

Input parameter	Description	Value
$w_{1,S,0}$	The initial amount of rank 1 Sailors	100
$w_{2,S,0}$	The initial amount of rank 2 Sailors	160
$w_{3,S,0}$	The initial amount of rank 3 Sailors	100
$w_{4,S,0}$	The initial amount of rank 4 Sailors	40
$c_{1,S}$	The quarterly salary of a rank 1 Sailor	\$14 000
$c_{2,S}$	The quarterly salary of a rank 2 Sailor	\$16 000
$c_{3,S}$	The quarterly salary of a rank 3 Sailor	\$20 000
$c_{4,S}$	The quarterly salary of a rank 4 Sailor	\$25 000
$w_{1,O,0}$	The initial amount of rank 1 Officers	40
$w_{2,O,0}$	The initial amount of rank 2 Officers	60
$w_{3,O,0}$	The initial amount of rank 3 Officers	60
$w_{4,O,0}$	The initial amount of rank 4 Officers	40
$c_{1,O}$	The quarterly salary of a rank 1 Officer	\$19 000
$c_{2,O}$	The quarterly salary of a rank 2 Officer	\$25 000
$c_{3,O}$	The quarterly salary of a rank 3 Officer	\$32 000
$c_{4,O}$	The quarterly salary of a rank 4 Officer	\$44 000

objective-function values. The axis corresponding to total workforce cost is inverted to facilitate interpretation of the trade-off: strategies achieving higher average operational fleet availability are generally associated with higher total workforce cost.

Next, in line with Step 3 of MORDM (recall Fig. 3a), we assess each strategy against 20 000 scenarios drawn from the uncertainty space outlined in Table 4. These scenarios are generated through Latin Hypercube sampling within the EMA workbench. Robustness metrics, specifically the 10th percentile average operational fleet availability and 90th percentile total workforce cost, are employed to quantify the robustness of the strategies. As mentioned earlier, higher 10th percentile average operational fleet availability signifies greater robustness for a strategy, while lower 90th percentile total workforce cost indicates higher robustness. The values of these robustness metrics are presented in Figure 6. The axis corresponding to 90th percentile total workforce cost is inverted for clarity in interpreting the results, with the most robust solution depicted as a straight line at the top.

Following Step 4 of MORDM, we engage in scenario discovery to identify scenarios that reveal vulnerabilities. The impact of strategies on average operational fleet availability and total workforce cost, as depicted in Figures 5 and 6, highlights the significant influence of these strategies on the defined objectives. As a result, we exclude strategies from subsequent analysis, instead focusing on identifying critical uncertainties associated with undesirable performance regarding average operational fleet availability. To set a standard for success, we use a benchmark of 5 operational vessels available per quarter on average. If there are fewer than five vessels deployed over the long term, it suggests a failure to maintain the readiness needed to meet the Navy's force projection requirements in a strategic setting [24].

To identify the specific area within the uncertainty space linked to unsatisfactory performance (defined as having fewer than 5 operational vessels on average in each time period), we used the scenario discovery function in the EMA workbench. This involved employing the patient rule induction method [14]. This method identifies hyper-rectangular scenario boxes positioned on the trade-off curve, aiming to maximize coverage and density while minimizing interpretability. Coverage is defined as the ratio of decision-relevant inputs encompassed within the box to the total decision-relevant inputs, where a value of 1 signifies the inclusion of all decision-relevant inputs [47]. Conversely, density is calculated as the ratio of decision-relevant inputs to the total inputs within the box, with a value of 1 indicating that all points in the box are decision-relevant inputs. Interpretability is defined as the number of parameter space axes along which the box is constrained in size.

TABLE 3. Decision variables.

Decision variable	Description	Bounds
$\beta_{S,t}$	The number of recruits for Sailors at each time t	[14, 83]
$\beta_{O,t}$	The number of recruits for Officers at each time t	[6, 13]
$x_{1,S}^{s\to s'}$	The highest amount of rank 1 Sailors who transition from status s to status s'^{a}	[0, 40]
$x_{2,S}^{s\to s'}$	The highest amount of rank 2 Sailors who transition from status s to status s'	[4, 40]
$x_{3,S}^{s\to s'}$	The highest amount of rank 3 Sailors who transition from status s to status s'	[8, 40]
$x_{4,S}^{s\to s'}$	The highest amount of rank 4 Sailors who transition from status s to status s'	[12, 40]
$y_{1,S}^{s\to s'}$	The minimum duration required for Sailors of rank 1 to stay in status s before transitioning to status s'	[8, 28]
$y_{2,S}^{s\to s'}$	The minimum duration required for Sailors of rank 2 to stay in status s before transitioning to status s'	[10, 28]
$y_{3,S}^{s\to s'}$	The minimum duration required for Sailors of rank 3 to stay in status s before transitioning to status s'	[12, 28]
$y_{4,S}^{s\to s'}$	The minimum duration required for Sailors of rank 4 to stay in status s before transitioning to status s'	[14, 28]
$x_{1,O}^{s\to s'}$	The highest amount of rank 1 Officers who transition from status s to status s'	[0, 20]
$x_{2,O}^{s\to s'}$	The highest amount of rank 2 Officers who transition from status s to status s'	[2, 20]
$x_{3,O}^{s\to s'}$	The highest amount of rank 3 Officers who transition from status s to status s'	[4, 20]
$x_{4,O}^{s\to s'}$	The highest amount of rank 4 Officers who transition from status s to status s'	[6, 20]
$y_{1,O}^{s\to s'}$	The minimum duration required for Officers of rank 1 to stay in status s before transitioning to status s'	[4, 28]
$y_{2,O}^{s\to s'}$	The minimum duration required for Officers of rank 2 to stay in status s before transitioning to status s'	[6, 28]
$y_{3,O}^{s\to s'}$	The minimum duration required for Officers of rank 3 to stay in status s before transitioning to status s'	[8, 28]
$y_{4,O}^{s\to s'}$	The minimum duration required for Officers of rank 4 to stay in status s before transitioning to status s'	[10, 28]

Notes. [a]Ranks 1–4 Sailors and Officers can move from statues reset to NSGL, NSGL to available, reset to readying, and readying to available while rank 4 Sailors and Officers can move from statues reset to NSGL and reset to readying (see Fig. 1).

The ideal scenario box would have both coverage and density values of 1, while being constrained along one or two dimensions. Low coverage and density imply the inclusion of a few decision-relevant scenarios inside the box and more decision-irrelevant scenarios inside the box, respectively. After examining the trade-off curve provided in Figure S2 of the supplementary materials, we select a scenario box with a coverage of 0.62 and a density of 0.65 to inspect. The scenario box corresponding to this point is illustrated in Figure S3 of the supplementary materials. We present critical uncertain parameters, their corresponding critical ranges, and *qp*-values in Table 5. In the context of scenario discovery, the *qp*-value is a statistical measure used to assess the significance of a given

TABLE 4. Deeply uncertain parameters.

Deeply uncertain parameter	Description	Bound	Reference value
$s^S_{1,r}$	The quarterly separation fraction of rank 1 Sailors at reset status	[0.015, 0.05]	0.025
$s^S_{2,r}$	The quarterly separation fraction of rank 2 Sailors at reset status	[0.025, 0.06]	0.03
$s^S_{3,r}$	The quarterly separation fraction of rank 3 Sailors at reset status	[0.025, 0.06]	0.03
$s^S_{4,r}$	The quarterly separation fraction of rank 4 Sailors at reset status	[0.015, 0.05]	0.025
$s^S_{4,n}$	The quarterly separation fraction of rank 4 Sailors at NSGL status	[0.015, 0.05]	0.025
$s^S_{1,p}$	The quarterly separation fraction of rank 1 Sailors at readying status	[0.015, 0.05]	0.025
$s^S_{2,p}$	The quarterly separation fraction of rank 2 Sailors at readying status	[0.025, 0.06]	0.03
$s^S_{3,p}$	The quarterly separation fraction of rank 3 Sailors at readying status	[0.025, 0.06]	0.03
$s^O_{1,r}$	The quarterly separation fraction of rank 1 Officers at reset status	[0.01, 0.025]	0.0125
$s^O_{2,r}$	The quarterly separation fraction of rank 2 Officers at reset status	[0.015, 0.03]	0.015
$s^O_{3,r}$	The quarterly separation fraction of rank 3 Officers at reset status	[0.015, 0.03]	0.015
$s^O_{4,r}$	The quarterly separation fraction of rank 4 Officers at reset status	[0.01, 0.25]	0.0125
$s^O_{4,n}$	The quarterly separation fraction of rank 4 Officers at NSGL status	[0.01, 0.025]	0.0125
$s^O_{1,p}$	The quarterly separation fraction of rank 1 Officers at readying status	[0.01, 0.25]	0.0125
$s^O_{2,p}$	The quarterly separation fraction of rank 2 Officers at readying status	[0.015, 0.03]	0.015
$s^O_{3,p}$	The quarterly separation fraction of rank 3 Officers at readying status	[0.015, 0.03]	0.015
σ^{acq}_v	Deviation of acquisition time of each new vessel v in quarters	$[-1, 1]^a$	0

Notes. [a]This is an integer: −1 denotes 2 quarters early; 1 denotes 2 quarters late; 0 denotes on-time.

restriction on uncertain parameters with respect to an outcome of interest. It evaluates whether the observed concentration of satisfactory or unsatisfactory outcomes within a restricted region is unlikely to have occurred by chance. Smaller *qp*-values indicate stronger statistical support for the identified condition and, therefore, greater relevance of the corresponding uncertain parameter.

Referring to Table 5, the critical uncertainties identified are the quarterly separation fraction of rank 1 Officers at reset and readying statuses (*i.e.*, $s^O_{1,r}$ and $s^O_{1,p}$), as well as the quarterly separation fraction of rank 2 Officers at reset status (*i.e.*, $s^O_{2,r}$). The presence of zero or near zero *qp*-values for these uncertainties indicates their pronounced influence on average operational fleet availability. Factors related to the quarterly separation fraction of ranks 1 and 2 Officers at reset status exert the greatest impact on poor fleet availability. If these

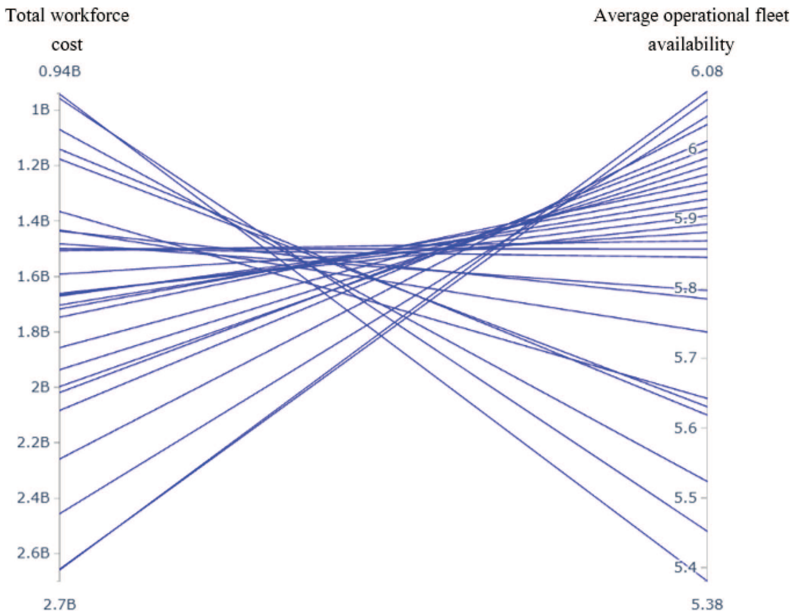


FIGURE 5. Parallel coordinate plots illustrate the values of objective functions for solutions identified during the search phase of MORDM. The total workforce cost is denoted in Australian dollars, while average operational fleet availability is expressed as the number of vessels per quarter. The axis corresponding to total workforce cost is inverted for ease of interpretation.

TABLE 5. Critical uncertain model parameters, along with their associated critical ranges and *qp*-values, for describing vulnerable outcomes. The definition of success, delineated by the threshold to classify computational experiments as decision-relevant (*i.e.*, vulnerable in our case), was established at an average of 5 available vessels per quarter.

Critical uncertainty	Critical range	*qp*-value
The quarterly separation fraction of rank 1 Officers at reset status ($s^O_{1,r}$)	[0.013, 0.025]	0
The quarterly separation fraction of rank 1 Officers at readying status ($s^O_{1,p}$)	[0.011, 0.025]	1.9×10^{-162}
The quarterly separation fraction of rank 2 Officers at reset status ($s^O_{2,r}$)	[0.021, 0.03]	0

critical uncertainties fall within the specified critical range outlined in Table 5, 65% of computational experiments yield undesirable outcome, based on our success criterion (averaging 5 operational vessels per quarter). From a decision-making standpoint, these uncertainties become pivotal parameters requiring careful monitoring to avoid undesirable outcomes. This insight presents an opportunity to enhance the strategy by implementing preventive or corrective measures, such as recruiting additional personnel for Officers, promoting personnel to rank 2, or adjusting salaries to retain ranks 1 and 2 Officers. Furthermore, it underscores the importance of closely monitoring these critical uncertainties during the implementation of an identified optimal strategy to detect any potential drift toward an undesirable state early on. Timely adjustments should be made to correct the course. Essentially, this information serves as an early warning, offering insight into when and why the system may underperform when employing this strategy.

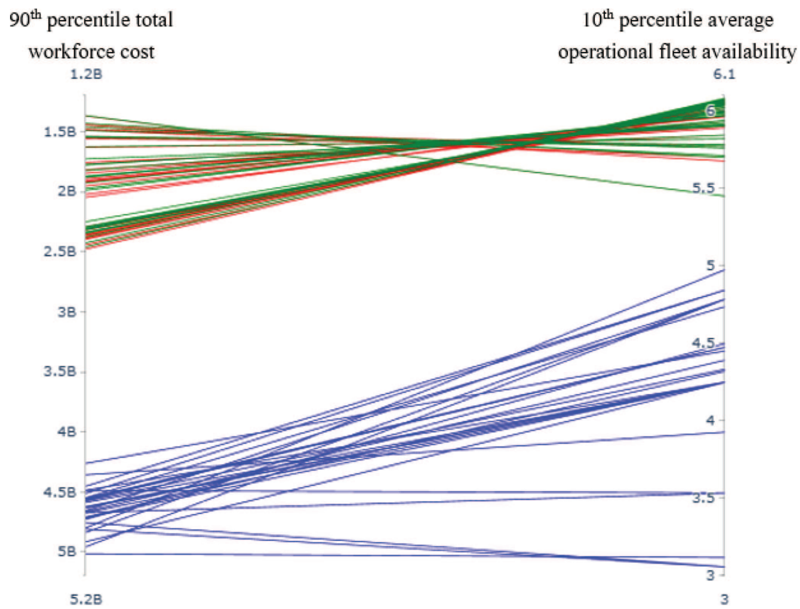


FIGURE 6. Parallel coordinate plots depict the values of robustness metrics resulting from the uncertainty analysis of solutions obtained during the search phase of MORDM (depicted in blue) and MORO (depicted in red). The values of robustness metrics for solutions identified during the search phase of MORO are represented in green. The axis corresponding to the 90th percentile total workforce cost is inverted for clarity in interpretation.

Figure 7 shows the relative impact of each deeply uncertain parameter on each outcome. We used feature scoring, a built-in function in the EMA workbench [27]. It shows that the quarterly separation fraction of rank 2 Officers at reset status (*i.e.*, $s^O_{2,r}$) and the quarterly separation fraction of rank 1 Officers at reset and readying statuses (*i.e.*, $s^O_{1,r}$ and $s^O_{1,p}$) exert the most significant influence on average operational fleet availability. This aligns well with the earlier scenario discovery results discussed. Furthermore, the findings highlight a notable impact of the quarterly separation fraction of rank 3 Sailors at reset and readying statuses (*i.e.*, $s^S_{3,r}$ and $s^S_{3,p}$) on average operational fleet availability.

The combined findings from scenario discovery and feature scoring indicate that, apart from the specific deeply uncertain parameters identified and discussed earlier, all other variables have a relatively insignificant effect on average operational fleet availability. Notably, the discrepancy between the scheduled acquisition dates of new vessels and their actual dates of acquisition (*i.e.*, σ^{acq}_v for $v = 1, 2, 3, \ldots, 8$) were found to have an insignificant impact on average operational fleet availability. This indicates that the strategies identified during the search phase (Step 2 of Fig. 3a) of MORDM effectively address uncertainties stemming from the deviation of commissioning dates of new vessels from their planned dates to a significant extent.

5.3. Multi-objective robust optimisation

Similar to MORDM, the initial phase of problem formulation in MORO remains unchanged (recall Fig. 3b). However, MORO incorporates additional robustness metrics, as detailed in Section 3.2. The definitions of the decision variables and deeply uncertain parameters are provided in Tables 3 and 4, respectively.

Following the methodology described in Section 4, robust optimal strategies were identified using the ϵ-NSGAII algorithm within the EMA workbench. In contrast to MORDM, the second step in MORO focuses on optimising robustness metrics directly. During the search phase, the number of function evaluations was set

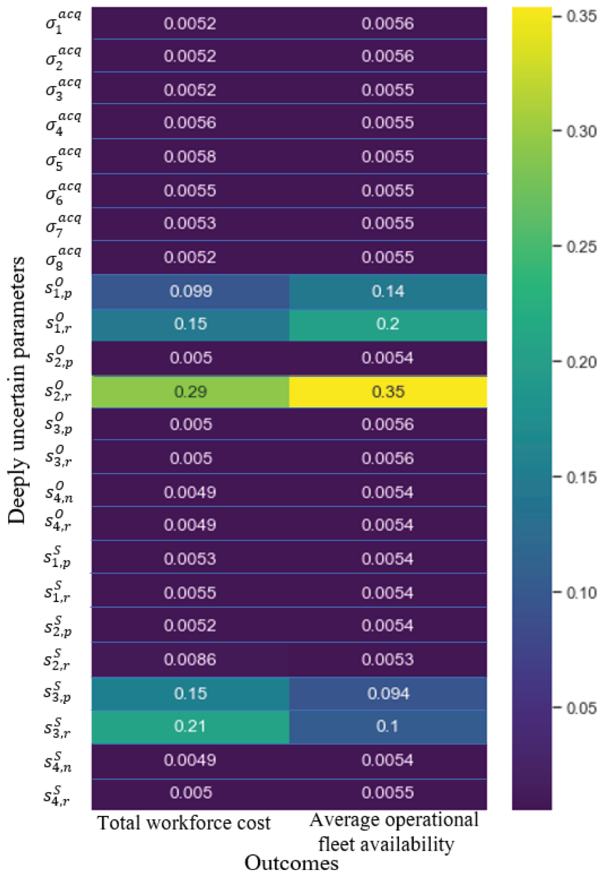


FIGURE 7. A feature scoring plot for computational experiments with obtained optimal strategies during the search phase of MORDM. This plot illustrates the relative impact of deeply uncertain parameters (on the y-axis) on the outcomes (on the x-axis). The color bar denotes the influence, with blue colors representing low influence and yellow colors indicating high influence. σ_v^{acq} for $v = 1, 2, \ldots, 8$: the deviation of the acquisition date from the scheduled date for eight new vessel; $s_{1,r}^O$–$s_{4,r}^O$: the quarterly separation fraction of ranks 1–4 Officers at reset status; $s_{1,r}^S$–$s_{4,r}^S$: the quarterly separation fraction of ranks 1–4 Sailors at reset status; $s_{1,p}^O$–$s_{3,p}^O$: the quarterly separation fraction of ranks 1–3 Officers at readying status; $s_{1,p}^S$–$s_{3,p}^S$: the quarterly separation fraction of ranks 1–3 Sailors at readying status; $s_{4,n}^O$: the quarterly separation fraction of ranks 4 Officers at NSGL status; $s_{4,n}^S$: the quarterly separation fraction of ranks 4 Sailors at NSGL status.

to 200 000 to ensure convergence, with convergence behaviour illustrated in Figure S4 of the supplementary materials. To identify robust optimal solutions, 25 scenarios were sampled from the uncertainty space defined in Table 4 using Latin Hypercube Sampling. These scenarios were used to evaluate candidate strategies during the search phase, with the limited number of scenarios selected primarily to reduce computational cost.

The search phase identified 29 robust Pareto optimal solutions, each corresponding to a distinct robust strategy and set of robustness-metric values. This phase required approximately 225 CPU hours using 10 parallel workers on a standard desktop computer with 12 cores operating at 2.70 GHz. The parallel coordinate plots shown in green in Figure 6 present the resulting robustness metrics. The axis corresponding to the 90th percentile total workforce cost is inverted to facilitate interpretation of the trade-off: strategies achieving lower 90th percentile workforce cost are generally associated with lower 10th percentile average operational fleet availability.

Because only 25 scenarios were used during the optimisation stage, the robustness of the resulting strategies was subsequently evaluated against a larger and more diverse set of scenarios. Accordingly, in Step 3 of MORO (recall Fig. 3b), each strategy was tested against the same set of 20 000 scenarios used in the preceding MORDM analysis. This ensures a fair and consistent comparison between the two frameworks. The parallel coordinate plots corresponding to this reevaluation are shown in red in Figure 6.

As shown by the red lines in Figure 6, the 10th percentile average operational fleet availability remains consistently above 5.4 vessels per quarter across all 29 robust strategies identified during the search phase. Moreover, none of the evaluated scenarios resulted in an average operational fleet availability falling below five vessels per quarter for any strategy, as shown in Figure 10a. Figure 10a illustrates the reevaluation of strategies identified using MORDM and MORO under the full set of scenarios in terms of average operational fleet availability. Consequently, scenario discovery aimed at identifying vulnerability-inducing scenarios was not conducted for MORO, in contrast to MORDM, where a threshold of 5 operational vessels per quarter on average was used to define success.

Nevertheless, we examined the relative influence of each input parameter on the outcomes using feature scoring, employing the built-in functionality of the EMA workbench. The results, presented in Figure 8, indicate that the quarterly separation fraction of rank 2 Sailors at reset status (*i.e.*, $s^S_{2,r}$), as well as the quarterly separation fraction of rank 1 Sailors at readying and reset statuses (*i.e.*, $s^S_{1,p}$ and $s^S_{1,r}$), have a significant impact on average operational fleet availability. When implementing any of the identified strategies, these parameters therefore emerge as critical uncertainties that warrant close monitoring to sustain higher levels of operational fleet availability.

Furthermore, Figure 8 indicates that, under a wide range of plausible conditions, deviations in the acquisition dates of the eight new vessels (*i.e.*, σ^{acq}_v for $v = 1, 2, \ldots, 8$) have a negligible effect on average operational fleet availability when the identified robust strategies are employed. However, these deviations have a noticeable impact on total workforce cost. Since total workforce cost includes salaries for surplus Officers and Sailors across different ranks, this finding suggests the presence of idle workforce resulting from changes in the commissioning schedule of new vessels.

5.4. Comparison of the results

The optimal strategies identified during the search phase in both MORDM and MORO are illustrated in Figure 9. The figure presents parallel coordinate plots of the decision variables for the (robust) Pareto-optimal solutions, where each line corresponds to a distinct strategy. Strategies obtained using MORDM are shown in blue, while those obtained using MORO are shown in red.

The decision variables shown in Figure 9 include recruitment rates for sailors and officers ($\beta_{S,t}$ and $\beta_{O,t}$), personnel transition limits between operational states (*e.g.*, from reset to NSGL, NSGL to available, reset to readying, and readying to available), and the minimum time requirements associated with these transitions across different ranks. Together, these variables govern how personnel are recruited, retained, and allocated across ranks and statuses over the planning horizon.

This depiction highlights that some decision variables exhibit similar patterns across strategies, such as the recruitment rates of officers and sailors ($\beta_{O,t}$ and $\beta_{S,t}$), while others display substantial variation. Notably, pronounced differences are observed in variables controlling transitions of senior personnel, such as the maximum number of rank 1 officers moving from NSGL to available ($x^{n \to a}_{1,O}$). These differences underscore the importance of balancing recruitment, promotion, and transition decisions to achieve favourable trade-offs among objectives or robustness metrics.

Robustness of the strategies identified by the two frameworks after reevaluation across a large set of scenarios is shown in Figure 6. The results indicate that strategies obtained from Step 2 of MORO are generally more

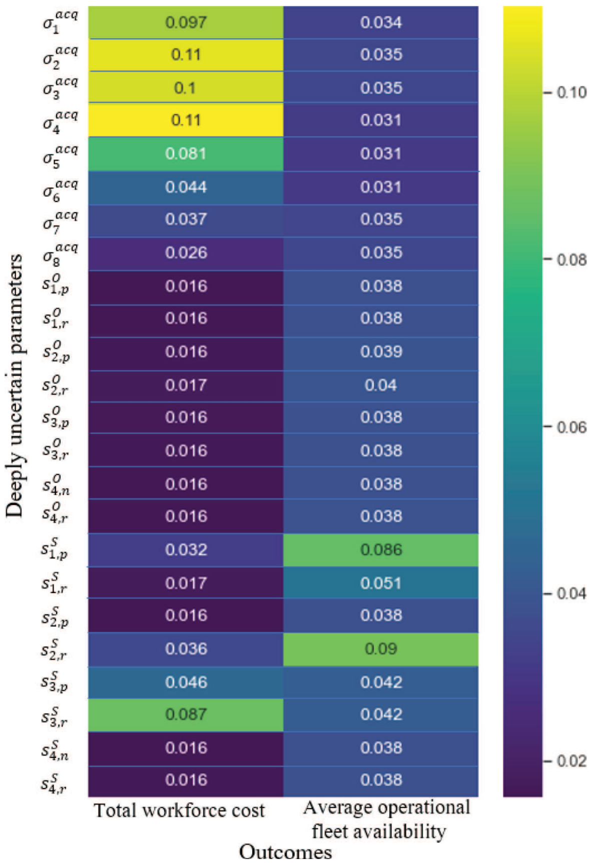


FIGURE 8. A feature scoring plot for computational experiments with obtained optimal strategies during the search phase of MORO. This plot illustrates the relative impact of deeply uncertain parameters (on the y-axis) on the outcomes (on the x-axis). The color bar denotes the influence, with blue colors representing low influence and yellow colors indicating high influence. σ_v^{acq} for $v = 1, 2, \ldots, 8$: the deviation of the acquisition date from the scheduled date for eight new vessel; $s_{1,r}^O$–$s_{4,r}^O$: the quarterly separation fraction of ranks 1–4 Officers at reset status; $s_{1,r}^S$–$s_{4,r}^S$: the quarterly separation fraction of ranks 1–4 Sailors at reset status; $s_{1,p}^O$–$s_{3,p}^O$: the quarterly separation fraction of ranks 1–3 Officers at readying status; $s_{1,p}^S$–$s_{3,p}^S$: the quarterly separation fraction of ranks 1–3 Sailors at readying status; $s_{4,n}^O$: the quarterly separation fraction of ranks 4 Officers at NSGL status; $s_{4,n}^S$: the quarterly separation fraction of ranks 4 Sailors at NSGL status.

robust, as evidenced by higher values of the 10th percentile average operational fleet availability and lower values of the 90th percentile total workforce cost.This difference arises primarily because MORO generates strategies by explicitly evaluating candidate solutions against 25 scenarios during the search phase, whereas MORDM relies on a single reference scenario representing best-estimate future conditions, as discussed in Section 4.

To quantify the number of robust strategies following the reevaluation against 20 000 scenarios, we utilize the percentage of computational experiments resulting in at least 5 vessels per quarter. A strategy is deemed robust if this percentage is at least 80%. Using this robustness measure, we find 6 out of 28 strategies in MORDM, and 29 out of 29 strategies in MORO, to be robust. Remarkably, none of the strategies identified during the search phase in MORO resulted in average operational fleet availability falling below 5 vessels per quarter under any

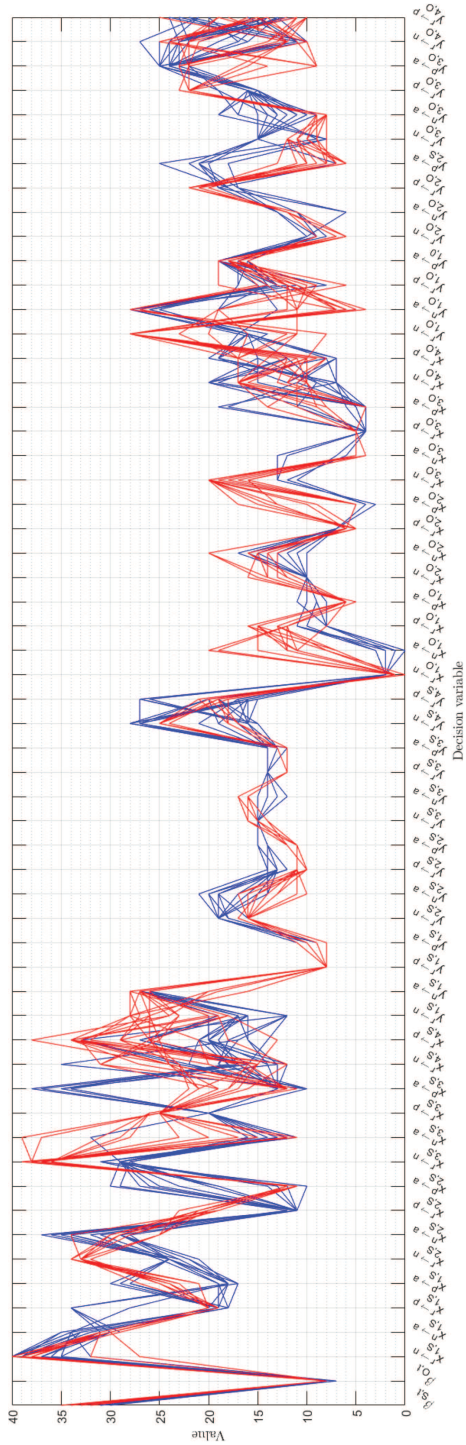


FIGURE 9. Parallel coordinate plots depicting the values of decision variables in the (robust) Pareto-optimal solutions identified during the search phase of MORDM (blue lines) and MORO (red lines). Each line represents a strategy.

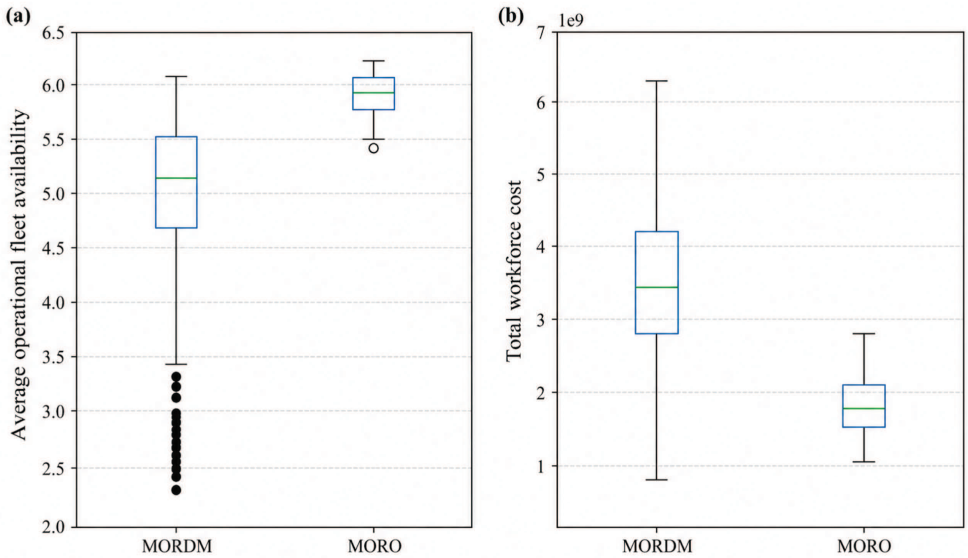


Figure 10. The box-plots show results after reevaluation of strategies identified from MORDM and MORO.

scenario as depicted in Figure 10. While only a few strategies identified during the search phase in MORDM could withstand different plausible future conditions characterized by scenarios, all strategies identified during the search phase in MORO demonstrate the ability to handle various plausible future conditions. This shows the importance of incorporating a few diverse scenarios and hence optimising robustness metrics during the search phase.

As mentioned in the preceding section, scenario discovery and feature scoring revealed most critical uncertain parameters that either lead to vulnerable outcomes or have varying degrees of influence on the outcomes within both frameworks. Given the pivotal role of these identified critical deeply uncertain parameters in generating unsatisfactory system performance, close monitoring is essential. This proactive approach enables the implementation of preventive and/or corrective measures to avert system failure.

In summary, the MORO framework entails higher computational costs compared to the MORDM framework. However, upon reevaluation against many diverse scenarios, strategies derived from the MORO framework demonstrate greater robustness against plausible futures. Therefore, if there is no urgency in discovering strategies and robustness is paramount under deep uncertainty, the MORO framework would be the preferable choice. Conversely, if relatively quick and robust decisions are required, the MORDM framework is more suitable. Within the MORDM framework, strategies can be iteratively redesigned to enhance robustness based on scenario discovery results, potentially faster than within the MORO framework. Consequently, the selection of the appropriate framework heavily relies on the specific decision problem and its requirements.

6. Conclusion and future research directions

We compare and contrast two distinct robustness frameworks, namely MORDM and MORO, within the context of a realistic case study from the Royal Australian Navy. This case study addresses a complex problem encompassing workforce planning and fleet management. Our findings offer decision-makers valuable insights into the computational costs associated with each framework and decision-making insights. This understanding aids decision-makers in selecting the most suitable framework for addressing decision problems under conditions of deep uncertainty.

Generation of strategies in MORDM is approximately nine times faster than that in MORO. However, the strategies discovered in MORO are more robust to the plausible future conditions than that in MORDM. That is, the strategies discovered from each framework can withstand different extent to which they handle the plausible future conditions. Embedding robustness requirement during the search phase of strategies increases the computational cost as well as robustness.

Scenario discovery identified critical deeply uncertain parameters associated with vulnerable outcomes, while feature scoring highlighted the relative influence of input parameters on the objective functions. This information can be leveraged to iteratively redesign strategies and enhance their robustness [24]. Therefore, if tactical or operational short-term decisions are required, MORDM is recommended, as it allows for iterative refinement of strategies to improve robustness.

In our current analysis, we make the assumption that the recruitment of Officers and Sailors remains independent of time, which could potentially limit the discovery of more optimal trade-off strategies. This also limits the dynamic adaptive decision-making. Additionally, in applying the two frameworks to our realistic case study, we only consider uncertainty related to the acquisition date, while other factors such as the number of vessels and decommissioning time of old vessels are not explicitly treated as decision variables. However, depending on the application, it is possible to treat the number of vessels and acquisition date as decision variables. Furthermore, decommissioning time for each old vessel could also be considered a decision variable.

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Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statement

This document contains the supplementary figures associated with this manuscript. The strategies identified during the search phase of MORDM and MORO are provided from Google drive at https://drive.google.com/drive/folders/12fjz_Mzoj57MJGVoFsGa0APv7MC3gkt4.

Supplementary material

The supplementary material is available from https://www.rairo-ro.org/10.1051/ro/2026068/olm.

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