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# MULTI-OBJECTIVE DECISION MAKING IN MULTI-PERIOD ACQUISITION PLANNING UNDER DEEP UNCERTAINTY

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## ABSTRACT

Acquisition planning involves decisions to be made regarding the number of assets to be acquired initially and the type and timing of replacement and upgrade actions to maintain performance measures efficiently. Acquisition planning is challenging for high-valued assets because of considerable uncertainties in their long-term life cycle. This article proposes an approach to determine which acquisition strategy—i.e. what initial number of assets, what number of new acquisitions, and in what time throughout a long-term planning period—can robustly fulfil multiple performance objectives in the face of plausible future scenarios. The article incorporates robust optimization for the treatment of uncertainty inside the simulation multi-objective optimization process where the robustness of different acquisition strategies in future scenarios is analyzed by running many simulations. A fleet management system is used as an illustrative hypothetical example. The results show an adaptation map of robust acquisition strategies over the life cycle of the fleet.

## 1 INTRODUCTION

### 1.1 Background

The acquisition planning of high-valued assets is a strategy-focused planning framework that requires many years to develop and execute. The acquisition planning of high-valued assets (e.g. power generators, heavy equipment, fleet of aircraft) requires the selection of the number and types of assets to add to or to withdraw from the overall capacity in order to deal efficiently with existing and future requirements and conditions. In addition, decisions regarding the timing and the type of the replacement and upgrade actions must also be considered. In a realistic situation, organizational resources such that asset acquisitions are limited at any point of time due to the associated high initial investment costs and budget constraints (Shafi et al. 2017). Thus, in order to achieve a competitive advantage, an applicable planning process for high-valued assets is required to satisfy strategic goals set by decision makers within financial and time constraints.

The life cycle of high-valued assets is usually assumed to be greater than 30 years. The long lifetime and the uncertainty in future strategic, operational, and tactical conditions increase the importance of good acquisition planning. The development of a good plan is a challenging task that requires the accommodation of several time-dependent constraints and objectives that vary over the entire planning horizon and the useful lives of the assets in question. In addition, decisions regarding acquiring high-valued assets are almost irreversible and includes a risk of opportunity loss due to the high cost involved. To alleviate the aforementioned difficulties in the asset planning, we present a decision support tool that systematically: (i) addresses changing uncertainties that exist in long-term planning, and (ii) takes into account multiple objectives to identify the number and the timing of acquisitions.

### 1.2 Problem

The article is framed in the context of an acquisition planning problem for a fleet of a number of submarines, that undergo licensing, maintenance, and operation. Each of these activities requires a number of resources: crews are needed for licensing and operation and manpower (available in wharfs and docks) is needed for maintenance. If a resource is not available, a submarine has to wait (e.g. waiting for licensing if crew are not available) and the total waiting time over the whole investigation period is accumulated. A planning problem is then to determine what initial number of submarines and crews (as resources) and what number and scheduling for the acquisition of new submarines can result in high fleet's performance. We frame this acquisition planning problem as a *dynamic* problem whose behavior is governed by several feedback loops and delays. The performance of fleet is assessed based on the availability of submarines for operation over time and their total waiting time for maintenance and for licensing. This is considered a *multi-objective optimization* problem where solution alternatives are suggested in a search process against multiple performance objectives. The problem is also investigated under deep uncertainty where the system and environment characteristic are unknown and cannot be parametrized with probability distributions.

### 1.3 Aim

Based on the framed problem, we want to determine an appropriate acquisition strategy—i.e. what initial number of submarines and crews, what number of new acquisitions and in what time throughout the operation—which can *robustly* maximize the availability of submarines while minimizing the waiting time for licensing and maintenance over time and in the face of many future scenarios. We also want to analyze how different acquisition strategies influence the performance of the fleet over the life cycle. To achieve this aim: we search for Pareto optimal solutions using metaheuristic multi-objective evolutionary algorithms (Maier et al. 2014). We extend the use of multi-objective evolutionary algorithms and link it to robust optimization (Bai et al. 1997; Ben-Tal and Nemirovski 1998) to find Pareto optimality in many future scenarios.

### 1.4 Literature Review

The problem investigated in this article shares similarities with traditional optimization problems known as portfolio selection and fleet mix planning. The portfolio selection problem is the process of finding a subset of all projects (assets) to be executed in such a way to maximize the fulfilment of objective(s) within limited resources. Similarly, the fleet mix planning is the process of determining a combination of assets best suited to meet the current and future requirements while satisfying various resource constraints. In general, the portfolio problem is used to answer long-term strategic questions. On the other hand, the fleet mix planning focuses on finding solutions to short-term operational questions. In this section, we briefly review the related works. We also position our study with respect to the existing literature and point out our contributions.

For the acquisition planning of high-value assets in the defence domain, decision makers are interested in not only what type of assets to acquire but also when to acquire these assets. This timing matters because there are long delays in the system (e.g. time taken to recruit people and to train them and time taken to buy new investments and to introduce them to service) and therefore investments need to be taken into consideration ahead. The process is related to the long-term/multi-period planning problems which can be modelled as multi-period portfolio optimization. In this context, Shafi et al. (2017) studied the multi-objective, multi-period asset planning problem in defence. They modelled the problem as a portfolio selection problem with two objectives; i.e., minimize the cost and minimize the risk (or maximizes the effectiveness). They chose to model uncertainty in a limited set of possible future scenarios and used multi-objective evolutionary algorithms (MOEAs) as a solution method. Another recent study in a similar context by Xiong et al. (2017) addressed asset (weapon) selection and planning issues, and modelled the problem as a combination of project portfolio selection and project scheduling problems. The resulting multi-objective problem (with cost minimization and effectiveness maximization) was solved with a MOEA algorithm based on Non-Dominated Sorting Genetic Algorithm (NSGA-II). They handled the uncertainty/dynamic characteristic of planning environment by an adaptation procedure. Yang et al. (2011) investigated military asset investment as a portfolio selection problem. They used two heuristic methods, namely Genetic Algorithm (GA) and Tabu Search (TS) to find efficient solutions without including uncertainty in their model. Greiner et al. (2003) modelled the military asset selection problem as a single deterministic objective and single period 0-1 knapsack (portfolio) optimization model under a limited budget. The objective of their model was the maximization of benefits (priorities) which was obtained by an Analytic Hierarchy Process (AHP). They provided an illustrative example of a realistic application for an air force.

Our proposed approach to multi-objective, multi-period acquisition planning also has some common characteristics with fleet-mix and size-management problems. For example, Mazurek and Wesolkowski (2009) studied a multi-objective stochastic fleet-size estimation problem. They found expected optimal fleet size with regard to several objectives, namely minimizing fleet cost, total task duration time, and the risk that a solution would not be able to accomplish possible future scenarios. They used Monte-Carlo simulation to generate possible future demands that fleet would encounter and used a MOEA algorithm based on NSGA-II to solve the optimization problem. Yang et al. (2014) studied the fleet-routing problem in addition to fleet-sizing decisions. They modelled the problem as a single objective cost minimization in a deterministic setting. They solved the resulting mixed-integer programming model via the well-known Bender-Decomposition algorithm (Benders 1962). A similar fleet-sizing, renewal and routing problem but in a stochastic (under uncertainty) setting was studied by Pantuso et al. (2015) in non-defence context. They modelled the market (cost) related parameters as scenario dependent discrete random variables and minimized expected total cost over a 10-year planning horizon. Shafi et al. (2011) took into account the effect of uncertainty on fleet size and mix in the military logistic framework. They used Monte-Carlo simulation to generate possible future scenarios to handle uncertainty and an evolutionary rule-based approach was developed to solve the multi-objective problem. Baker et al. (2007) presented a fleet sizing and mixing problem in the military logistics setting. They integrated uncertainty with a scenario-based approach and utilized an evolutionary heuristic as solution approach. We refer to Hoff et al. (2010) and Pantuso et al. (2014) for more detailed discussions (literature review) on fleet composition and routing problems. We also refer the work of Wojtaszek and Wesolkowski (2012) for classification of fleet mix problems from defence perspective.

The above literature review reveals that, even though both portfolio optimization and fleet planning problems are studied in the defence literature, the combination of these two problems has not been investigated to the best of our knowledge. Our work is indented to fill this gap in the literature to answer both short (e.g., workforce/crew planning) and long-term (e.g. asset acquisition planning) questions in the planning stage. Further, previous studies either ignored uncertainty (as in the deterministic case) or modelled it by the limited number of future realizations (as in scenario analysis or Monte Carlo simulation). In this article, we relax such restrictive assumptions on uncertainty and model the problem under deep uncertainty—where no information about the probability distribution of uncertain factors exists. The integrated modelling of strategic and operational decisions under deep uncertainty increase the complexity of the problem. Thus, we propose a robust optimization approach to address these issues.

## 2 METHOD

We take a multi-method approach, using long-term planning and decision-making frameworks, to address different aspects of the framed acquisition planning problem. The frameworks that we use are rooted in an emerging area of literature for modelling under uncertainty called exploratory modelling (Bankes 1993). Exploratory modelling assists planning and decision making by systematically investigating the influence of different parametric (input data) and non-parametric (model structure) uncertainties on the performance of different decisions through performing many computational experiments with a simulation model(s) (Kwakkel et al. 2016). This approach results in *robust* insights about different decision options—insights which are insensitive to potential changes or errors in the forecast of the future. This is the opposite of traditional way of planning where an optimal decision for one certain condition of system and environment is sought (Bankes 1993; Bankes et al. 2001).

The planning and decision-making frameworks which adopt the use of exploratory modelling (Walker et al. 2013) can help to address our planning problem in different aspects, for example by: proposing measures to assess the robustness of acquisition strategies, generating scenarios for dealing with future uncertainties, enumerating solutions (i.e. acquisition strategies), and identifying conditions where solutions need to be adapted over time. Herman et al. (2015) and Kwakkel (2017) have proposed a taxonomy for these planning and decision-making frameworks which distinguishes the different ways that they can handle each aspect:

- Definition of robustness: robustness of solutions can be evaluated based on different measures (McPhail et al. 2018). Examples are regret measures showing the difference between performance of a single solution with the performance of best possible solution, satisficing measures showing the fulfilment of minimum performance thresholds, and descriptive statistics (such as mean). We use descriptive statistics ($10^{th}$ percentile worst case scenarios) to measure robustness, We assume that optimal solutions under these extreme conditions will perform robustly well in the remaining circumstances (Kasprzyk et al. 2013).
- Generation of scenarios: future scenarios for analyzing the performance of different solutions can be pre-specified (by experts), generated in an exploration process (e.g. Monte Carlo simulation), or generated through an optimization search process (e.g. worst-case discovery). We an exploration process using the Exploratory Modelling Workbench (Kwakkel 2017) to generate a matrix of future scenarios.
- Generation of solutions: solutions can be pre-specified, identified in an exploration process, identified in an optimization search process, or identified in an iterative stress-and-test (vulnerability analysis) process. We use multi-objective robust optimization (Kwakkel et al. 2015) to enumerate solutions and to assess the performance of solutions over scenarios at the same time.
- Adaption of solutions (vulnerability analysis): it evaluates the impact of the uncertainty space on the robust performance of different solutions. It can be performed differently, for example using a subspace partitioning technique called scenario discovery (Lempert et al. 2008; Bryant and Lempert 2010) and adaptation tipping points (Kwadijk et al. 2010). We adopt the concepts of adaptation tipping points and adaptation pathways (Haasnoot et al. 2013) to show when and how to adapt acquisition strategies as new conditions emerge over time and to provide a roadmap for decision makers.

## 3 APPLICATION

We use a fleet management system dynamics model as the simulation engine for the exploratory process. The model simulates the performance of a fleet (e.g. availability, waiting time, and cost) under different acquisition and maintenance strategies. The model is a resource-based model and considers the availability and usage of different resources (e.g. crews, manpower, docks) for performing different activities (e.g. maintenance, operation). The model has a modular structure and uses a combined discrete event and system dynamics approach. The model is implemented in AnyLogic 8 and is run as a Java applet. We consider the investigation period of 9 years with a weekly time-step for simulation. We use the Exploratory Modelling Workbench for performing computational experiments using this simulation model and for implementing multi-objective robust optimization. The workbench is an open-source Python library for exploratory modelling and analysis (Kwakkel 2017).

### 3.1 Definition of Robustness

For each acquisition strategy, there is a distribution of fleet performance in terms of three objectives—waiting time for maintenance, waiting time for licensing, and the availability of submarines—across possible future scenarios. While the availability of submarine has a negative correlation with waiting time, the relationship between waiting time for maintenance and waiting time for licensing is unknown as they rely on two different types of resources (i.e. crew and manpower). We define robustness in the most 10% extreme scenarios in the fulfilment of these objectives (Kasprzyk et al. 2013). The following descriptive statistics are used as robustness metrics (see (1) and (2)):

$$90^{th}\ percentile\ o_i\ if\ minimisation \tag{1}$$
$$10^{th}\ percentile\ o_i\ if\ maximisation \tag{2}$$

where $o$ is one decision objective, $i$ refers to waiting time for licensing, waiting time for maintenance, and the availability of submarines. We search for solutions which (robustly) minimize waiting time for licensing and maintenance in the worst top 10% (i.e. $90^{th}$ percentile) while maximizing availability of submarines in the worst bottom 10% (i.e. $10^{th}$ percentile).

### 3.2 Generation of Scenarios

Scenarios are generated in response to the presence of uncertainties in the future. Exogenous factors within systems, in the system's environment, and in stakeholder expectations form the uncertainty space. We assume that the uncertainty space is dynamic over time in response to future events, such as the outbreak of a sudden conflict which can increase the baseline value for the duration of the licensing activity. We adopt a time-dependent approach towards the delineation of the uncertainty space (Schaffner et al. 2013). With this approach, we assume that the dynamics and transition logic—how the value of parameters changes over the investigation period—of the uncertainty space can be articulated based on qualitative stories/narratives obtained from stakeholders. Each of these stories—called an *era*—specifies a certain demarcation of the uncertainty space over the whole investigation period. As one example era in this article, we assume that uncertainty in the duration of any licensing activities grows as the prediction time horizon increases. This growing range of uncertainty—as a *transition logic*—is opposite to the range of other uncertainty factors, such as available industry manpower where their range of variation remains static over time. To capture the dynamics of the uncertainty space within this era, we partition the whole uncertainty space of the relevant licensing parameters into three different episodes over time with 25%, 50% and 75% ranges of variation compared to the baseline value (see Table 1). Each episode is called an *epoch*. The partitioning of the uncertainty space should comply with specified transition logics and be according to the qualitative stories/narratives of eras informed by stakeholders. Table 1 shows the demarcation of the uncertainty space for model input parameters over 9 years investigation period.

Table 1: The demarcation of the uncertainty space over the investigation period.

| Uncertain parameter name | Description | Epoch 1 | Epoch 2 | Epoch 3 |
|---|---|---|---|---|
| Expected Licensing Intermediate Maintenance Duration | The expected duration for Intermediate Maintenance licensing | 3–5 | 2–6 | 1–7 |
| Expected Licensing Intermediate Docking Duration | The expected duration for Intermediate Docking licensing | 4–8 | 3–9 | 1–11 |
| Expected Licensing Midcycle Docking Duration | The expected duration for Midcycle Docking licensing | 6–10 | 4–12 | 2–14 |

| | | | | |
|---|---|---|---|---|
| Expected Licensing Full-cycle Docking Duration | The expected duration for Full-cycle Docking licensing | 12–20 | 8–24 | 4–28 |
| Time Taken Trainee Crew | Time taken for trainees to become crew. This parameter is an input to the pipeline delay function. | 13–39 | | |
| Wastage Fraction per Week | The fraction of crew separated from the crew pool | 0.001–0.003 | | |
| Industry Manpower Available Dock 1 | The maximum manpower available at a particular dock | 200–600 | | |
| Industry Manpower Available Dock 2 | | 125–375 | | |
| Industry Manpower Available Dock 3 | | 150–450 | | |

An ensemble of future scenarios can be generated by sampling from uncertainty spaces—related to constructed epochs—and by running the simulation model using the sampled set of parameters as the model input. The horizontal concatenation of scenarios over epochs and their vertical concatenation over eras form an array of scenarios over which the robustness of solutions needs to be tested (see (3)).

$$X = \begin{bmatrix} x_{11} & \cdots & x_{m1} \\ \vdots & \ddots & \vdots \\ x_{1n} & \cdots & x_{mn} \end{bmatrix} \tag{3}$$

where $X$ is the array of scenarios, $n$ is number of eras, $m$ is number of epochs in each era, and $x_{mn}$ represents scenarios generated by sampling from the uncertainty space related to epoch $m$ in era $n$. In practice, scenarios are simultaneously generated with solutions in the next section in a many objective robust optimization process.

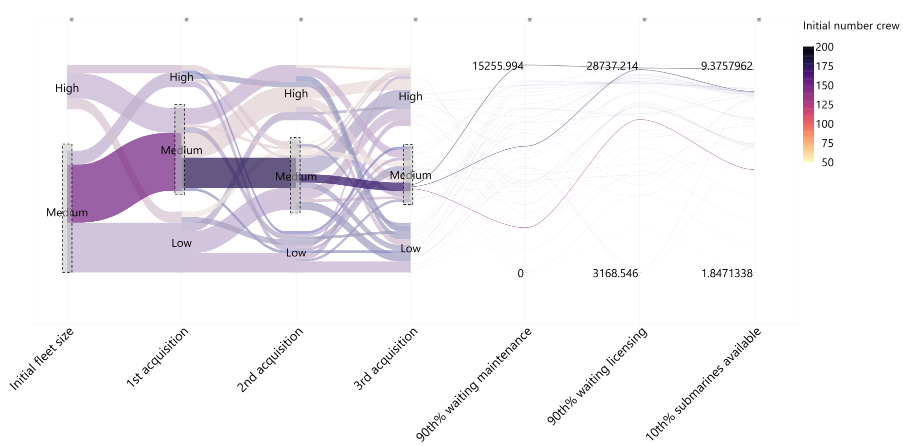
### 3.3 Generation of Solutions

We use multi-objective evolutionary optimization to generate solutions, i.e. acquisition strategies which fulfil multiple objective. We also use robust optimization to include the treatment of uncertainty inside the simulation optimization process where the robustness of solutions is analyzed by running many simulations. This multi-objective robust optimization approach searches over the solution space and calculates the robustness of the performance of each solution over the generated array of scenarios. We use an established multi-objective evolutionary optimization technique called epsilon Non-Dominated Sorting Genetic Algorithm II (NSGA2) implemented in the Exploratory Modelling Workbench for enumerating alternative solutions in the face of future scenarios. The results are Pareto optimal solutions which can make a trade-off between the fulfilments of objectives and also remain valid in different future scenarios. In our application, the solution space is created by ranges that we assumed for the initial number of submarines and initial crews and the number and the scheduling (week) of new acquisitions in each epoch (see Table 2). The multi-objective robust optimization algorithm finds Pareto optimal solutions by searching through this solution space. In the current test analysis, we assume that the initial number of submarines is reset at the beginning of each epoch. We also assume that an initial acquisition of submarines happens at the beginning of each epoch and three more possible new acquisitions can happen over the first 60 weeks of each epoch of three years duration. This assumption helps us to limit the solution space and to make the optimization process faster by searching within a narrower area. This initial assumption can be relaxed and the solution space can be set widely depending on the availability of computational power and the preference of decision makers in a real case study.

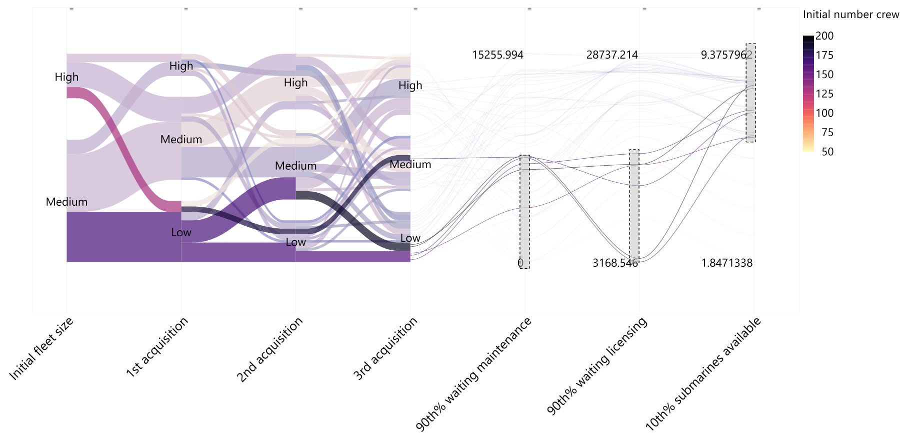
Table 2: The boundary of the solution space.

| Decision variable | Range of variation |
|---|---|
| Initial fleet size | 5–10 (submarine) |
| Initial number crews | 50–200 (crew) |
| 1st acquisition | 1–10 (submarine) |
| 2nd acquisition | 1–10 (submarine) |
| 3rd acquisition | 1–10 (submarine) |
| Week of 1st acquisition | 1–10 (week) |
| Week of 2nd acquisition | 11–30 (week) |
| Week of 3rd acquisition | 31–60 (week) |

Using the fleet management simulation model and the Exploratory Modelling Workbench, we perform 9000 experiments and represent generated Pareto optimal solutions for all epochs in a parallel coordinate plot (see Figure 1). The plot shows the state of decision variables and their performance over the robustness measures. The state of solutions in terms of initial submarine and the number of three subsequent acquisitions is shown with bars in three categorical values of low (0-3), medium (4-7), and high (8-10) number of acquisition. The size of each bar shows the frequency (percentage) of each category as a fraction of the entire data set. Decision makers can interact with the plot to gain more specific decision insights using a technique called brushing, which limits Pareto optimal solutions based on some criteria set on the solution space or on the expected performance of solutions. Brushing represents the selected solutions in color while keeping the remaining solutions in greyed-out in the background, which enables decision makers to compare the performance of different solutions and to trade-off among them based on pre-specified criteria. We can identify what performance would be expected for a certain acquisition strategy of submarines. As an example, in Figure 1 (a), medium acquisitions of submarines and a high initial number of crews lead to long waiting times but a high number of available submarines. We can also identify what kind of solutions result in certain robust performance. For example, in Figure 1 (b), it is observed that solutions which can maintain waiting time lower than a certain limit and the availability of submarines higher than a certain limit are characterized with medium-to-high initial crew sizes, the majority of them have medium initial number of submarines, and the size of subsequent acquisitions is low-to-medium.




(a)




(b)

Figure 1: (a) The performance of solutions with medium initial, first, second and third acquisition (b) Solutions which lead to certain performance of fleet.

## 3.4 Adaptation of Solutions

Generated Pareto optimal solutions vary between epochs and eras. Pathways (i.e. roadmap) for the adaptation of solutions over time should be specified. We use the concepts of adaptation tipping points and adaptation pathways (Kwadijk et al. 2010; Haasnoot et al. 2013) to show the adaptation of Pareto optimal solutions from one epoch to another over the investigation period. Adaptation tipping points happen at the end of each epoch and are aligned with the epochs' duration. The adaption pathways show what number of new submarines should be acquired and in what week (over the investigation period) to robustly maintain a given fleet performance. We use the same brushing technique we used to narrow down the number of solutions to those which could result in less than 10000 hours waiting for maintenance and 20000 hours waiting for licensing and more than six available submarines (see Figure 2).

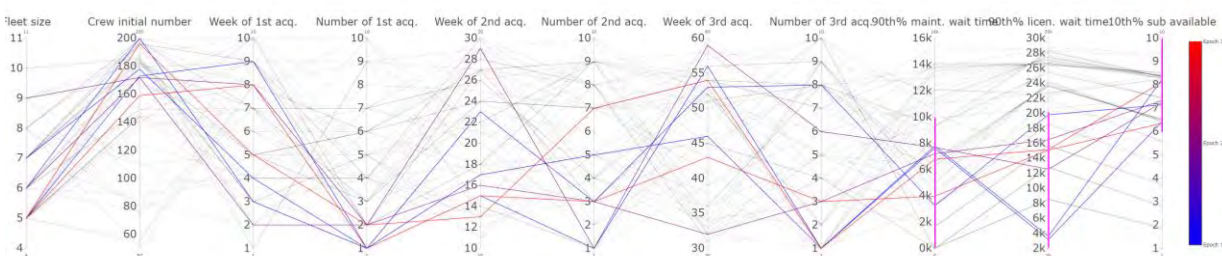



Figure 2: Solutions from different epochs which result in less than 10000 hours waiting for maintenance and 20000 hours waiting for licensing and more than six available submarines.

The filtered solutions are represented in an adaption pathways map in Figure 3. The adaption pathways map shows acquisition planning strategies in each epoch with lines where week (in horizontal axis) and the number (in vertical axis) of new acquisitions are marked by flags over time. The number of new crews joining the fleet at the beginning of each epoch is also marked inside the flag. The concatenation of acquisition planning strategies in epochs creates alternative pathways among which decision makers can choose. For example, one potential pathway (Pathway I) with a robust performance needs 178, 172, and 186 crews at the beginning of each epoch. It also needs to acquire initially seven submarines, and then one submarine in week 4, one submarine in week 15, one submarine in week 56, six submarines in week 156, two submarines in week 164, three submarines in week 172, three submarines in week 188, five submarines in week 312, two submarines in week 317, seven submarines in week 325, and one submarines in week 366. In the worst 10% of scenarios, the availability of submarine under this pathway would be 6.42 (in average). This implies that decision makers should take this pathway if this minimum number of available submarines can fulfil the operational requirement for the fleet. Otherwise, other pathways should be chosen. Moreover, this pathway leads to 7636 and 16476 hours (accumulation for all submarine over nine year period) waiting time for maintenance and licensing in the worst 10% of scenario. This informs decision makers that waiting for licensing is the bottleneck in the operation and availability of submarines. Therefore, provision of further resources (i.e. crews) for licensing activity can shorten the waiting time and increase the performance of the fleet under this pathway. Several other alternative pathways can be investigated in the same manner. Their implication of their performance over time can inform the adoption of appropriate acquisition strategy.

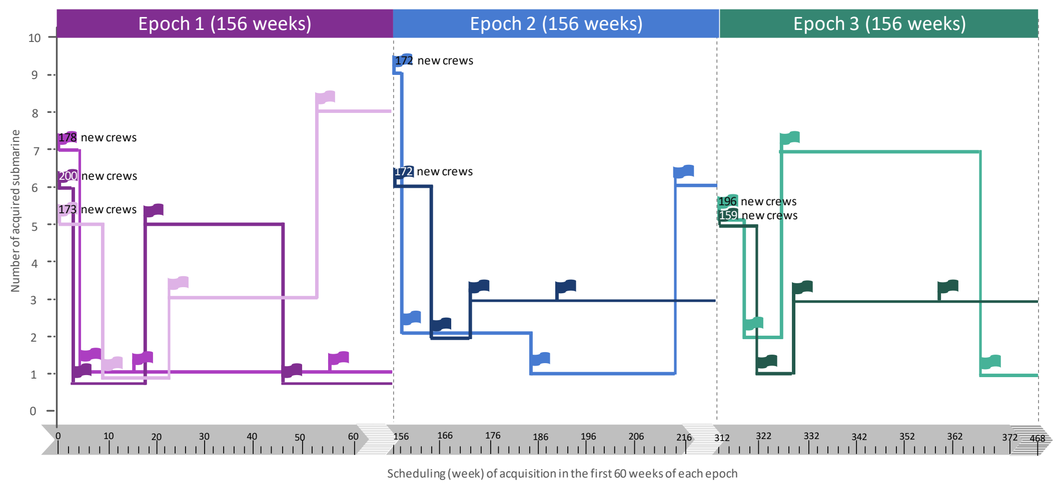



Figure 3: Adaption pathways map.

## 4 DISCUSSION AND CONCLUSIONS

We used a multi-method approach to identify Pareto optimal solutions. We divided the investigation period into epochs to identify only those solutions with robust performance over epochs. Considering epochs enabled us to have a more realistic picture of each solution performance and to look more closely into the variation of solution performances over the investigation period. Figure 4 shows this variation in terms of robustness measures with boxplots over three specified epochs. The boxplots show that the median of the availability of submarines in Pareto optimal solutions drops over time while the median of waiting for licensing increases. This can be related to the usage of resources and the backlog of submarines in the licensing activity which are increasing over time. We also used multi-objective robust optimization to identify Pareto optimal solutions and to provide a roadmap for adaptation of solutions over time in format of different pathways. Each pathway resulted in a different performance, and the desired pathway needed to be chosen interactively with decision makers and based on operational requirements and trade-off between different performance measures. Table 3 shows the comparison of three example pathways from the adaptation pathways roadmap. The table shows that waiting time for maintenance is less sensitive to the pathway that decision makers choose. This implies that switching between pathways cannot improve waiting time for maintenance significantly. However, the expansion of the initial uncertainty space (see Table 1), such as considering higher number of manpower as a required resource for the maintenance activity, can lead to the generation of new sets of solutions with an improved (lower) waiting time. Table 3 also shows that the performance of the fleet with respect to waiting time for licensing and availability of submarines is sensitive to the pathway that decision makers choose. For example, Pathway III has the best performance (among three pathways) in terms of availability of submarine whereas the worst performance for waiting for licensing (and vice versa for Pathway II). This implies that a trade-off between the fulfilment of these two performance measures would be possible to be achieved by switching between different pathways.

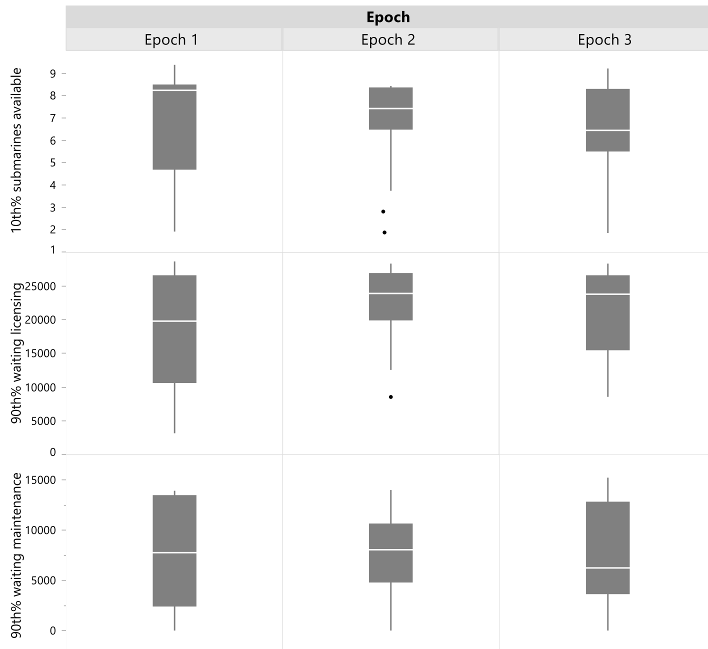



Figure 4: Variation of the performance of fleet over the investigation period in epochs.

Table 3: Comparison of three selected adaptation pathways.

| Pathway | (Week, Size) of acquisition | Initial number of crew (at the beginning each epoch) | 90% waiting time for maintenance | 90% waiting time for licensing | 10% availability of submarines |
|---|---|---|---|---|---|
| Pathway I | (0, 7), (4, 1), (15, 1), (56, 1), (156, 6), (164, 2), (172, 3), (188, 3), (312, 5), (317, 2), (325, 7), (366, 1) | 178, 172, 186 | 7636 (hour in total over period) | 16476 (hour in total over period) | 6.42 (average submarine) |
| Pathway II | (0, 6), (3, 1), (17, 5), (46, 1), (156, 9), (158, 2), (185, 1), (215, 6), (312, 5), (320, 1), (327, 3), (355, 3) | 200, 182, 159 | 7804 (hour in total over period) | 15089 (hour in total over period) | 6.36 (average submarine) |
| Pathway III | (0, 5), (9, 1), (23, 3), (53, 8), (156, 9), (158, 2), (185, 1), (215, 6), (312, 5), (317, 2), (325, 7), (366, 1) | 173, 182, 186 | 7684 (hour in total over period) | 19798 (hour in total over period) | 7.15 (average submarine) |

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