26th International Congress on Modelling and Simulation, Adelaide, SA, Australia, 30 Nov–4 Dec 2025
mssanz.org.au/modsim2025

Multi-objective and multi-stage optimisation for force structure design

M.-T. Nguyen[a], **I. Widjaja**[b] **& A. Coutts**[a]

[a]*Human & Decision Sciences Division, Defence Science and Technology Group, Australia*
[b]*Melbourne eResearch Group, University of Melbourne, Australia*
Email: Minh-Tuan.Nguyen@defence.gov.au

Abstract: Defence Science & Technology Group (DSTG) have proposed an integrated approach to analyse Defence capabilities for strategic planning purposes, such as capability options assessment and force structure design. In previous study[1], we developed a Bayesian Reasoning Value Model (BRVM). It is a Bayesian network (BN) model to establish a qualitative and quantitative representation of the interactions among the force structure components (Defence element, force package, operational effect and mission) and calculate standard values of uncertain capabilities (such as mission success, operation/force effectiveness). We formulated a hybrid decision model where a multi-criteria decision making (MCDM) framework was designed to combine the influence of multiple BN models built from different scenarios/missions. We then used the hybrid decision model to evaluate and prioritise potential Defence capability options.

In this study, we integrate BN, multi-objective evolutionary algorithms (MOEA) and multi-stage optimisation (MSO) to present an interactive analysis tool for evaluating and optimising the operational impact of different capability/force options using decision makers (DMs) preferences. MOEA manages the combinatorial nature of the number of contributing capabilities/forces available and helps the DMs to avoid any arbitrary selection of sub-optimum options. Due to the computational complexity of the nonlinear multi-objective function of our BRVM, it is difficult to search for the optimal solutions with a single-run optimisation formulation. MSO method can help us to decompose a design into stages with small numbers of objectives and constraints. The output of one stage is then used as an input for the next stage, stimulating the involvement of stakeholders in a decision-making process and leading to widely supported decisions.

To facilitate our integrated approach, a new feature 'option design' was implemented into our Bayesian Evaluation Support Tool (BEST)[2]. Its graphical user interface is designed to include a very large number of BN nodes and to fully incorporate the selection flexibility (required constraints, limited objectives, etc.) into the optimisation procedure. Its interactive analysis tool is a web based application 'packaged' with software allowing the required calculations and optimal search to be completely automated and results to be captured in both tabular and graphical forms.

The proposed methodology provides modelling and data collection structures that assist in making explicit the force structures, scenario parameters, and DMs' preferences, as well as providing a tool for automating/documenting some of the time-consuming evaluation and design processes.

Keywords: *Bayesian network; BN; Pareto optimisation; multi-objective evolutionary algorithms; MOEA; multi-stage optimisation; MSO; decision support tool*

[1] https://www.mssanz.org.au/modsim2021/papers/M8/nguyen.pdf (accessed on September 29, 2025).
[2] BEST is jointly developed by DSTG and University of Melbourne (UoM) for creating BN model structures and capturing the required data to generate model parameters. Various built-in analyses (what-if, sensitivity, optimisation design/strategy exploration, cause-effect tracing, etc.) are available in our single web-based tool. Public version can be accessed through the UoM server https://best-staging.dst.eresearch.unimelb.edu.au (accessed on September 29, 2025).

1 Introduction

Defence Science & Technology Group have used various methodologies (e.g. Bayesian network (BN), multi-criteria decision-making (MCDM), Monte-Carlo simulation with parallel computing, optimisation, etc.) to analyse Defence capabilities and concepts for supporting strategic planning, evaluation, and force design. By working with Force Design Division, Vice Chief of the Defence Force Executive, we developed a Bayesian reasoning value model (BRVM) [Nguyen et al.] and a tool for managing and analysing data collected from subject matter experts (SMEs) (Nguyen et al. 2022).

Data collected from SMEs' interviews and wargaming workshops have been used to create our BRVM structure, which represents the interactions among the force structure components (Defence element, force package, operational effect and mission) using BN modelling approach. BN defines these dependencies via conditional probability tables (CPTs) which are called model parameters. We develop an extension of ACE (Application for Conditional probability Elicitation) method proposed in Hassall et al. 2019. Our elicitation method utilises the extra data captured on 'best' and 'worst' scenario probabilities, then distributes the contributing effects into other cases, which is more intuitive and easy to explain to SMEs (Nguyen and Coutts 2022). Our previous study[3] described a hybrid decision model where MCDM framework was designed to combine the influence of multiple BN models built from different scenarios/missions. We then used the hybrid decision model to evaluate and prioritise Defence capability options.

Recently, we collaborated with the University of Melbourne (UoM) and developed the Bayesian Evaluation Support Tool (BEST)[4] for creating model structures and capturing the required data to generate model parameters. BEST automates data collection by organising the data, facilitating data generation and distributing to multiple subject matter experts (SMEs) via email to provide timely responses. Various built-in analyses (what-if, sensitivity, optimisation design/strategy exploration, cause-effect tracing, etc.) are available in our single web-based application.

In this study, we integrate BN, multi-objective evolutionary algorithms (MOEA) and multi-stage optimisation (MSO) to present an interactive analysis tool for evaluating and optimising the operational impact of different capability/force options using decision makers (DMs) preferences. MOEA manages the combinatorial nature of the number of contributing capabilities/forces available and helps the DMs to avoid any arbitrary selection of sub-optimum options. Due to the interactions among the force structure components and the complexity of our BRVM, it is not easy to define an aspirational goal and hence the multiple objectives at once. MSO method can help us to decompose a design into stages with small numbers of objectives and constraints. The output of one stage is then used as an input for the next stage. It will stimulate the involvement of stakeholders in a decision-making process and lead to widely supported decisions.We explain the methodology using an illustrative and unofficial BRVM.

In order to facilitate our integrated approach, we implemented a new feature 'option design' into BEST. Its graphical user interface is designed to include a very large number of BN nodes and to fully incorporate the selection flexibility (required constraints, limited objectives, etc.) into the optimisation procedure. Its interactive analysis tool is packaged with SMILE library (Structural Modelling, Inference, and Learning Engine) (Druzdzel 1999) and MOEA framework (Hadka 2014) and run in a back-end server. It thus allows the required calculations and optimal search to be completely automated and results to be captured in both tabular and graphical forms which are then presented to the front-end users.

The proposed approach using BRVM with multi-objective and multi-stage optimisation is a continuation of our study on the BN modelling (Nguyen and Cao 2017, 2019; Nguyen et al. 2021; Zuparic et al. 2022) and the development of its accompanied decision support tool (Nguyen 2020; Nguyen et al. 2022). The approach presented here represents a much larger-scale problem with few hundred BN nodes and links and many objectives involving multiple DMs, each with a different set of priorities.

2 Defence capability/force options – Decision problem

The purpose of an evaluation framework is to explore/design capability options at the desired levels of operational effectiveness to accomplish the required mission. The measurement of each capability option is determined by force structure/allocation that provides operational effects for achieving various conditions and leading to required mission success. It is therefore desirable to develop a model to support upcoming decisions for assessing force structure options using DMs' preferences that optimise operational requirements.

Let DC $\stackrel{\text{def}}{=} \{DC_l \mid l = 1, \dots, L\}$, OE $\stackrel{\text{def}}{=} \{OE_p \mid p = 1, \dots, P\}$, and FP $\stackrel{\text{def}}{=} \{FP_q \mid q = 1, \dots, Q\}$ be the set of decisive conditions (DCs), operational effects (OEs) and force packages (FPs), respectively. FP represents a grouping of related

[3] `https://www.mssanz.org.au/modsim2021/papers/M8/nguyen.pdf` (accessed on September 29, 2025).

[4] Public version can be accessed through the UoM server `https://best-staging.dst.eresearch.unimelb.edu.au` (contact authors for login details).

lower level capabilities (known as Defence elements, e.g. air combat FP brings together Classic F/A-18, Super Hornet F/A-18F, Growler E/A-18G, Hawk aircraft and combat control team). Each capability is assigned a level of operational readiness and depends on the availability of trained personnel, the availability of major platforms, combat systems and supplies, and the standard of collective training (Gaidow et al. 2006). A process for converting armed force resources into fighting power is called OEs (Millett et al. 1986). These OEs will contribute and establish the required DCs[5] that allows commanders to gain a marked advantage over an opponent or contribute materially to achieve mission objectives (e.g. secure environment maintained, interim governance provided, key infrastructure restored, etc.) (NATO 2010). The dependencies among model components are summarised in Figure 1.

Our decision problem is to find force structures that maximise all operational requirements. Let U_{ij} be the utility function of DC_i accomplishment or OE_i achievement or FP_i effectiveness when capability/force option j is selected (i.e. fully funded). Note that capability option is an investment portfolio on multiple FPs. The mathematical optimisation is written as follows:

$$\begin{aligned} &\text{Maximise} \quad U_{ij}, \\ &\quad \forall i \in [1, \dots, N],\ N = \max\{L, P, Q\}; \\ &\quad \forall j \in [1, \dots, M]. \end{aligned} \tag{1}$$

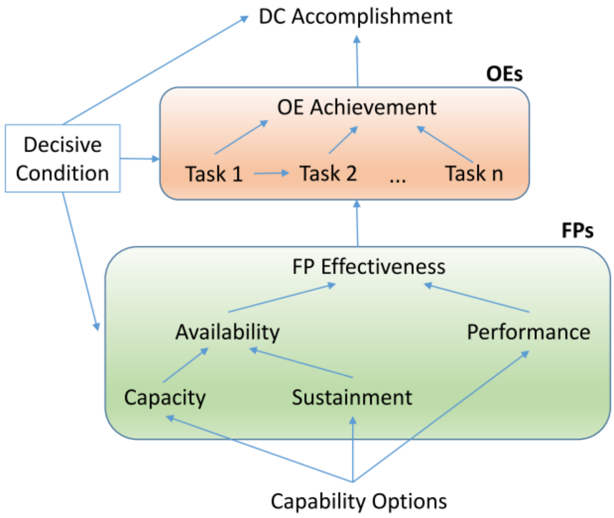

Figure 1. Dependencies between model components

3 Defining objective functions – BRVM

In order to define and evaluate a capability/force option utility value function, U_{ij}, we first build a BN for the force structure (FP – OE – DC) model (hence named BRVM). U_{ij} is then obtained by inferring from this BN.

The BN is a graphical model for conceptualising and quantifying uncertainty about the causal relationships between variables and consists of

- a list of nodes representing random variables $\mathrm{X} \overset{\text{def}}{=} \{X_1, X_2, \dots, X_k\}$
- a list of directed links expressing causal probabilistic relationships between the variables
- conditional probability tables (CPTs) $\{P(X_i|\Pi_i)\}$ detailing the strength of causal relationship between the nodes, where $\Pi_i \subseteq \mathrm{X} \setminus \{X_i\}$ is the parent node set of X_i.

Using Bayes' theorem, we calculate the joint probability distribution in the BN by the multiplication of the conditional probabilities of all the nodes (Pearl 1988).

$$p(X_1, X_2, \dots, X_k) = \prod_{i=1}^{k} p(X_i|\Pi_i). \tag{2}$$

We establish the BN model through three steps: (1) build the network structure – set up the network nodes and links; (2) determine the network parameters – populate the CPTs; and (3) carry out probability propagation – network inference, i.e. calculating the probability of each node given evidences.

Using BEST[6], we can both build the BRVM and visualise it directly BEST supports SMILE (Druzdzel 1999) special node type 'submodel' for modularity in large and complex networks. The built network can be also exported to file and displayed in other BN packages/tools, e.g. GeNIe[7]. All FP and OE nodes in the typical FP–OE–DC network[8] shown in Figure 2 are 'submodel' types:

- *FP sub-model* produces probability to effectively achieve its assigned roles under various threats.
- *OE sub-model* produces probability to successfully conduct relevant operational tasks and create superior effects that contribute to achieving DC objectives.

[5]DCs represent key phases or sections of a higher level mission and as such have their own set of objectives and requirements for specific OEs.
[6]For capturing the required data to generate model parameters, BEST automates data collection by organising the data and allocate subsections of the model to match participants' expertise, facilitating data generation and distributing to multiple SMEs via email to provide timely responses. It is critical for eliciting data from different SMEs in large, complex and multi-domain Defence problems.
[7]`http://support.bayesfusion.com/docs/` (accessed on September 29, 2025).
[8]The BN evaluation framework presented here do not represent an agreed or endorsed position by Defence.

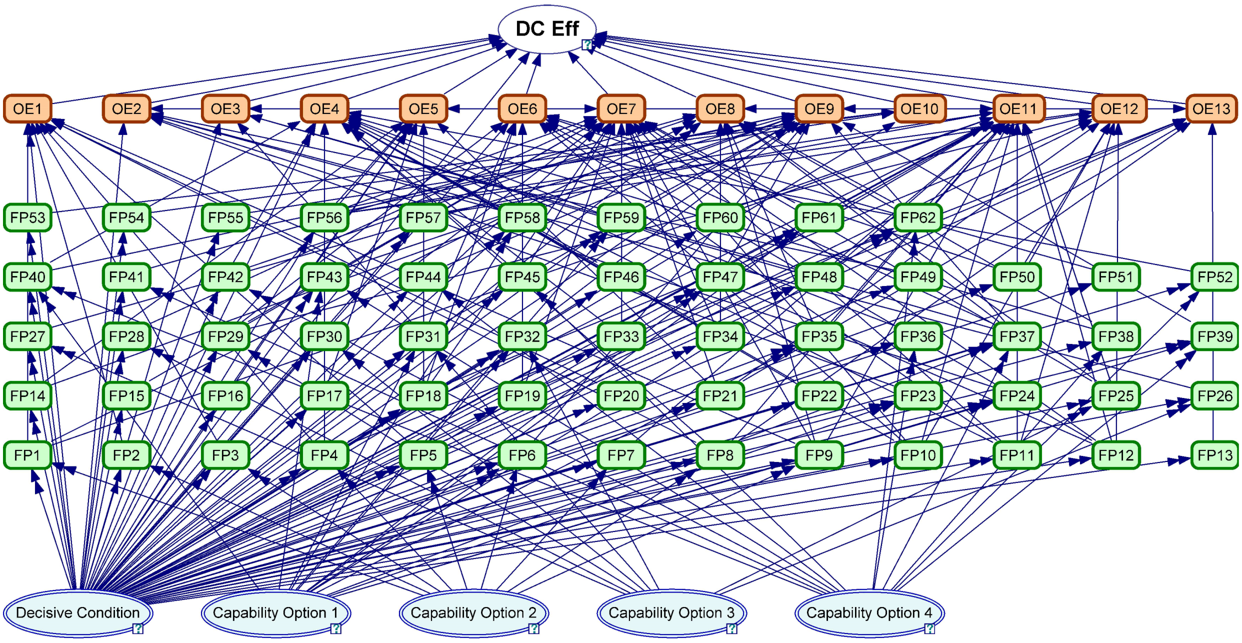

Figure 2. An illustrative example for modelling the force structure (FP–OE–DC) using BN

The capability/force option value functions are then defined by the expected utility functions (von Neumann and Morgenstern 1953)

$$U_{ij} \stackrel{\text{def}}{=} \sum_{k=1}^{S_i} p_{ij}^k U_{ij}^k, \; \forall i \in [1, \dots, N]; \; \forall j \in [1, \dots, M] \tag{3}$$

where

- $\{p_{ij}^k \mid \sum_{k=1}^{s} p_{ij}^k = 1\}$: posterior probability distribution for BN node i for Option j
- U_{ij}^k: utility value of Node i for Option j in State k, $k \in [1, \dots, S_i]$
- S_i: number of states/outcomes for the BN node i

In the next section, we will compare the capability/force options and search for optimum ones across multiple possible changes under various scenarios and constraints.

4 BEST 'Option design' – force design with MOEA & MSO

We develop interactive features in our analysis tool, BEST, which allows end-users to easily perform inferences over the BN as well as visualisation and comparison of results. The tool organises the nodes based on the cause-and-effect relationships, i.e., BN nodes are classified into criteria or options. This makes the user-interaction more intuitive and user-friendly. Let us now consider a top-down analysis where a strategy is given (e.g., a confidence for at least 70% success in a required mission), and the analysis tool will then suggest various options including where the effectiveness level of FPs has to be lifted up to achieve it.

In our illustrative example, we only allow more investment into the FPs such that its effectiveness is increased by δ amount where $\delta \in \{20\%, 40\%, 60\%, 80\%, 100\%\}$ (FP disinvestment can be modelled by allowing δ takes negative values[9]). With the large number of FPs, the problem with evaluating all force options and using brute-force search algorithms is that its computational complexities grow exponentially (e.g. we need $5^{20} \approx 95$ trillion evaluations for 20 FPs and the actual size of our problem is in order of a few hundred FPs).

To overcome this problem, we have turned to multi-objective optimisation using evolutionary algorithms (Qu et al. 2018; Zhou et al. 2011), which has become a popular and useful field of research and application in the last two decades.

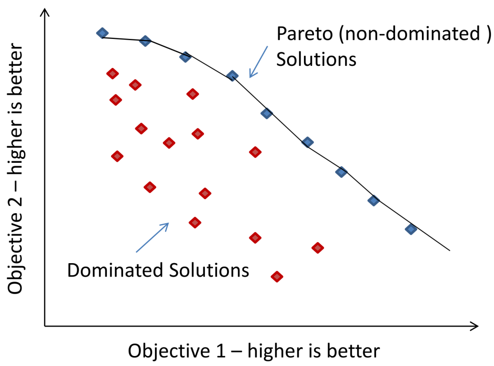

Figure 3. Pareto optimality

[9] Search direction in BEST allows users to select any one from three options: negative, both, or positive.

4.1 Multi-objective optimisation

Multi-objective optimisation attempts to solve this problem by using the concept of Pareto optimality to find non dominated solutions. A solution is said to be non-dominated when there is no other solution in the space which is better with regards to all decision variables. The set of non-dominated solutions, or Pareto front, makes up a hypersurface along which improvement in one objective requires a sacrifice in another (Figure 3). Once this front has been found, the DM can use it to explore the relationship between the objectives so that intelligent decisions can be made.

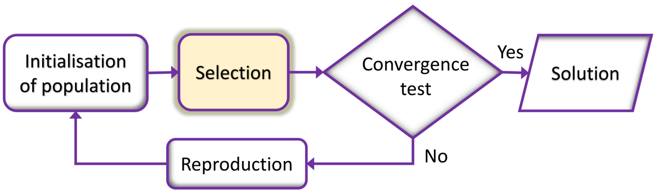

Figure 4. Evolutionary algorithms (EA) framework

In the force option problem, the multi-objective optimisation is written as follows

$$\begin{aligned} \text{Maximise} \quad & U_{ij} \\ \text{subject to} \quad & p(X_1, X_2, \ldots, X_k) = \prod_{i=1}^{k} p(X_i|\Pi_i), \\ & u_i - \epsilon \leq U_{ij} \leq u_i, \text{ and } C_j \leq c, \\ & \forall i \in [1, \ldots, N];\ \forall j \in [1, \ldots, M] \end{aligned}$$

where U_{ij} is the utility/value function of BRVM observed (objective) nodes i for force option j to be maximised [see Equation (3)]; C_j is the total number of BRVM decision (variable) nodes to be changed under Option j, and the feasible/search region is defined by the BN model, BRVM [Equation (2)], with a limited effectiveness[10] in $[u_i - \epsilon, u_i]$ and a restricted number of changes c (if required).

4.2 MOEA using non-dominated sorting genetic algorithm (NSGA)

The aim of MOEA is to find multiple non-dominated points *as close* to the Pareto-optimal front *as possible*, with a *wide trade-off* among objectives. It is heuristic based, so may not be guaranteed in finding Pareto-optimal points, but it has essential operators to constantly improve the evolving non-dominated points similar to the way most natural and artificial evolving systems continuously improve their solutions.

Figure 4 is the outline of a simple EA that begins with an initialisation process, where the initial search population is generated. It next enters a loop of selecting parent individuals from the search population, applying a recombination operator (such as crossover and mutation in genetic algorithms) to generate offspring, and finally updating the search population with these offspring using a replacement strategy. This loop is repeated until some termination conditions[11] are met, usually after a fixed number of objective function evaluations (NFE). Upon termination, the EA reports the set of optimal solutions discovered during search.

The NSGA-II (Deb et al. 2002) and NSGA-III (Deb and Jain 2014) are the most popularly used MOEA frameworks as it has the following features:

- It uses an elitist principle whereby the population is classified into different non-domination classes and its priority is carried to the next generation in order of their classes
- NSGA-II uses an explicit diversity preserving mechanism using crowding distance which is related to the density of solutions around each solution – The less dense are preferred. NSGA-III introduces improvements in diversity preservation and efficiency by supplying and adaptively updating a number of well-spread reference points, allowing for a more accurate approximation of the Pareto front.
- It emphasises the non-dominated solutions.

A MOEA framework (Hadka 2014) with the NSGA-III option using the default values setting and the termination condition of running for 50,000 NFEs or 'no improvement' after 10 consecutive generations (by comparing the Euclidean distance between any two solutions) has been deployed in the tool for finding the 'best' force options.

4.3 Interactive force design with MSO and numerical experiments

MOEA manages the combinatorial nature of the number of contributing capabilities/forces available and helps the DMs to avoid any arbitrary selection of sub-optimum options. Due to the interactions among the force structure components and the complexity of our BRVM, it is not easy to define an aspirational goal and hence the multiple objectives at once. MSO method can help us to decompose a design into stages with small numbers of objectives and constraints. The output of one stage is then used as an input for the next stage. It will stimulate the involvement

[10]By default, $\epsilon \overset{\text{def}}{=} 5\% u_i$ in BEST

[11]Three termination conditions: a maximum number of objective function evaluations , a searching time limit, and a maximum number of unchanged solutions ('no improvement') can be set from 'Configure' menu in BEST .

of stakeholders in a decision-making process and lead to widely supported decisions. This iterative and interactive design is an exploration effort to investigate and understand possible strategies/options before making decisions. At each stage, relevant stakeholder preferences and objectives can be captured, revised and combined with the output of the previous stage.

A graphical user interface is designed to include a very large number of capability/force options and to fully incorporate the selection flexibility (required constraints, limited objectives, etc.) into the optimisation procedure. This allows us to define the population members currently being evaluated (restricted by pre-selecting some of its options, if wanted) and also manage the number of objectives to be optimised. Constraints on various results can also be introduced.

Optimising effectiveness: a typical force option design can be conducted in various searches. For example[12], we consider the BRVM with its baseline or current force assessment[13] (i.e. without any extra capability investment) of `'dcs'` at 55%, `'oe1'` at 48%, `'oe10'` at 33%, `'oe3'` at 53%, and `'oe4'` at 60%. We may want to know which capability options we can achieve the best effectiveness for all above components (modelled as BN nodes). BEST 'option design' analysis (solving problem in Section 4.1 with MOEA framework) will produce a table of three 'optimal' candidate options, captured in Figure 5. For brevity, the level of FPs (option detail shown in BEST) is not included here as there are more than 80 FPs to be invested.

Observed node	Constraint	option 1	option 2	option 3
oe1		83.6830	83.3672	83.4730
oe10		94.5000	94.5000	94.5000
oe3		97.6440	97.6440	97.6440
oe4		80.3597	81.7530	81.2863
dcs		89.8517	89.7957	89.8145
No. of changes		84	86	86

Figure 5. 'Optimal' effectiveness achieved

Observed node	Constraint	option 1	option 2
oe1		83.4730	83.3672
oe10	70	68.7747	68.7747
oe3		97.3985	97.3985
oe4		81.2394	81.7060
oe5		88.7705	88.7705
dcs		90.2920	90.2643
No. of changes		86	86

Figure 6. 'Optimal' effectiveness with constraints

Limiting effectiveness and extra requirement: As an illustration, we determine `'oe5'` (currently at 52%) also needs to be optimum and we also want to search options that give us a reasonable accomplishment for `'oe10'` (e.g. around 70% which is much improved from its baseline at 33%). Figure 6 is the result of this illustrative design.

Observed node	Constraint	option 1	option 2	option 3	option 4	option 5	option 6
oe1		77.9696	79.2753	78.3427	79.2753	79.4851	78.3427
oe10	70	68.3975	68.3975	68.3975	68.3975	68.3975	68.3975
oe3		79.6229	92.3822	87.5786	69.8628	69.8628	86.3322
oe4		67.4902	67.4902	68.6943	67.4902	68.6943	68.6943
oe5		68.3623	60.0590	59.5014	68.3165	65.8326	64.9708
dcs	85	84.1853	84.5265	84.9722	83.7881	83.8985	84.9729
No. of changes		20	20	20	20	20	20

Figure 7. 'Optimal' effectiveness with limited changes

Limiting changes: Most of the force options in the above designs require many FPs to be at the high level (i.e. 50% increased in its operational effectiveness) and we may not be able to afford to fully fund them all. We, therefore, try to search options with a limited changes. Figure 7 is the result of force options allowed using up to 20 FPs[14] with a limited `'dcs'` effectiveness around 85%.

[12]Model parameters in BRVM presented here are fictitious and used for illustrative purposes only.
[13]Conducting a 'What-If' analysis in BEST with the current force structure will give us the baseline results.
[14]Note that the maturity of technologies may prevent FPs from achieving a higher level of its effectiveness in reality. One should deselect these FPs from the decision variable list (i.e. the level of these FPs are unchanged and kept at the current baseline option) and conduct again the process.

5 Conclusion

This paper illustrates an integration of BN and MOEA with MSO developed for evaluating the operational impact of different capability/force structures and selecting the 'best' option under various scenarios and constraints. The proposed methodology provides modelling and data collection structures that assist in making explicit the force structures, scenario parameters, and DMs' preferences, as well as providing a tool for automating/documenting some of the time-consuming evaluation and design processes.

Acknowledgments

The authors would like to acknowledge Force Design Division for supporting our project and providing SMEs in various workshops. Special thanks go to our colleagues in Human & Decision Sciences Division for their advice on mathematical modelling aspects of our proposed model and interactive analysis tool.

References

Deb, K., A. Pratap, S. Agarwal, and T. Meyarivan (2002). "A fast and elitist multiobjective genetic algorithm: NSGA-II". In: *IEEE Transactions on Evolutionary Computation* 6.2, pp. 182–197.

Deb, K. and H. Jain (2014). "An Evolutionary Many-Objective Optimization Algorithm Using Reference-Point-Based Nondominated Sorting Approach, Part I: Solving Problems With Box Constraints". In: *IEEE Transactions on Evolutionary Computation* 18.4, pp. 577–601. DOI: 10.1109/TEVC.2013.2281535.

Druzdzel, M. J. (1999). "SMILE: Structural Modeling, Inference, and Learning Engine and GeNIe: A Development Environment for Graphical Decision-theoretic Models". In: *Proceedings of the 16th National Conference on Artificial Intelligence, AAAI '99/IAAI '99*. Orlando, Florida, USA, pp. 902–903.

Gaidow, S., S. Boey, and R. Egudo (2006). "*A Review of the Capability Options Development & Analysis System and the Role of Risk Management*". (DSTO-GD-0473), Defence Science and Technology Organisation, Australia.

Hadka, D. (2014). *MOEA Framework User Guide: A Free and Open Source Java Framework for Multiobjective Optimization (Version 2.4).* http://www.moeaframework.org/.

Hassall, K. L., G. Dailey, J. Zawadzka, A. E. Milne, J. A. Harris, R. Corstanje, and A. P. Whitmore (2019). "Facilitating the elicitation of beliefs for use in Bayesian Belief modelling". In: *Environmental Modelling & Software* 122, p. 104539.

Millett, A. R., W. Murray, and K. H. Watman (1986). "The Effectiveness of Military Organizations". In: *International Security* 11.1, pp. 37–71.

NATO (2010). *Allied joint doctrine AJP-01(D)*. Ed. by Allied Joint Publication, North atlantic treaty organization.

von Neumann, J. and O. Morgenstern (1953). *Theory of Games and Economic Behavior*. 3rd. New York: Princeton University Press.

Nguyen, M.-T. (2020). "*B*ayesian network analysis tool for evaluating land combat vehicle system: a user's guide". (DST-GD-1069), Defence Science and Technology Group, Australia.

Nguyen, M.-T. and T. Cao (2017). "A hybrid decision making model for evaluating land combat vehicle system". In: *the 22nd International Congress on Modelling and Simulation, MODSIM2017*. Ed. by G. Syme, D. Hatton MacDonald, B. Fulton, and J. Piantadosi. Hobart, Australia, pp. 1399–1405.

– (2019). "A Multi-Method Approach to Evaluate Land Combat Vehicle System". In: *Int. J. Applied Decision Sciences* 12.4, pp. 337–360.

Nguyen, M.-T., A. Coutts, J. Knoll, M. Zuparic, J. Peacock, D. Bilusich, M. Galister, and K. Johns (2021). "An evaluation model and tool for Defence capability options". In: *the 24th International Congress on Modelling and Simulation, MODSIM2021*. Ed. by R. Vervoort, A. Voinov, J. Evans, and L. Marshall. Sydney, Australia, pp. 946–952.

Nguyen, M.-T. and A. Coutts (2022). "*Parameter generation in Bayesian reasoning value model for evaluating capability options*". (DSTG-TN-2239). Defence Science and Technology Group, Australia.

Nguyen, M.-T., A. Coutts, and M. Zuparic (2022). "*Bayesian network analysis tool suite for evaluating capability options: A user's guide*". (DSTG-GD-1178), Defence Science and Technology Group, Australia.

Pearl, J. (1988). *Probabilistic Reasoning in Intelligent Systems*. San Francisco: Morgan Kaufmann.

Qu, B., Y. Zhu, Y. Jiao, M. Wu, P. Suganthan, and J. Liang (2018). "A survey on multi-objective evolutionary algorithms for the solution of the environmental/economic dispatch problems". In: *Swarm and Evolutionary Computation* 38.1, pp. 1–11. DOI: https://doi.org/10.1016/j.swevo.2017.06.002.

Zhou, A., B.-Y. Qu, H. Li, S.-Z. Zhao, P. Suganthan, and Q. Zhang (2011). "Multiobjective evolutionary algorithms: A survey of the state of the art". In: *Swarm and Evolutionary Computation* 1.1, pp. 32–49.

Zuparic, M., A. Coutts, and J. Peacock (2022). "*Validation and analysis of the Bayesian reasoning value model*". (DSTG-TR-3917), Defence Science and Technology Group, Australia.

