A STRATEGIC SIMULATION TOOL FOR CAPABILITY-BASED JOINT FORCE STRUCTURE ANALYSIS

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Abstract: This paper describes a stochastic discrete event simulation model for scheduling of joint military force structures. The model employs capability-based methods to link scenario requirements to force structure assets. Assignment of assets to scenarios is designed to attempt to mimic the decisions of a military scheduler. Force structure performance is evaluated based on how well and how often scenario capability requirements are met. The model output permits options analysis, capability gap analysis, determination of optimal force structure composition, and evaluation of force structure performance in the face of changing requirements and policies (such as readiness and sustainment, operations tempo, and personnel tempo constraints).

1 INTRODUCTION

Determining the size and composition of a future military force structure[1] is a problem that can be approached from many different directions, and is often driven by nation-specific policies, processes, and objectives. It is also a question of the depth and breadth of exploration required; depth in terms of the level of fidelity that is used to model the force structure, and breadth across military services.

In practice, quantitative evaluation of force structures range from "back-of-the-envelope" type calculations (e.g., with two bases, two ships are required at each so that one is always available when one is in maintenance) or subject matter expert (SME) opinion, to detailed theatre level combat modelling (e.g., Bulut, 2001, Gallagher and Kelly, 1991) or campaign analysis (Taylor and Lane, 2004). Low fidelity models are easy to generate, but tend to rely on broad-ranging assumptions and are subject to significant criticism regarding objectivity. Ideally, high fidelity models would be used to determine the performance of the total force against high-fidelity models are very data intensive and/or use physics-based approaches that are time-various threats across multiple scenarios (Farr et al., 1994). While they are significantly less subjective, consuming to evaluate and difficult to extrapolate for future capability. Taking a moderated approach, medium fidelity models focus on resource allocation (how many are needed) rather than resource effectiveness (how likely the mission can be accomplished). This is a specialized application of general scheduling and routing problems, for which many customized models have been developed.

[1] "Force structure" is a term used to designate the set of assets within a military unit and the inter-dependence between these assets, as well as their home base. For example, a naval force structure could include all the ships and crews, as well as the infrastructure supporting them.

Service-specific scheduling models abound. Logistic problems such as sealift (Salmeron et al., 2009), airlift (Wu et al., 2009, Wesolkowski and Billyard, 2008, Baker et al., 2002) – to name but a few, or a combined mobility problem (Mattock et al., 1995) are well developed, but difficult to expand for use across services. If not focused on airlift, air force structure models tend to be driven by maintenance requirements and facilities (Mattila et al., 2008). Army force structure analysis is highly separated between personnel-driven models (Klerman et al., 2008) and vehicle fleet mixes (Whitacre et al., 2008, Abbass et al., 2007, Walmsley and Hearn, 2004, Brown et al., 1991). Naval deployment scheduling applications are common (Zadeh, 2009, Horn et al., 2007, Dugan, 2007, and others). Five naval fleet planning applications (Gauthier et al., 2008, Fildes, 2006, Greer et al., 2005, Crary et al., 2002, Cortez and

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Kaiser, 1991) exhibit properties that may be useful if applied to joint force structure scheduling. Only two references (Davis, 2002, Farr et al., 1994) were found that attempt to tackle joint force structure problems. The first leaves much of the methodology undefined, and the second is a deterministic model that does not optimize over a range of requirements.

Selection of a force structure must balance strategic policies and objectives, while maintaining realism at the operational and tactical levels – and still provide answers in a timely fashion. To achieve a measure of balance among these conflicting drivers, Defence R&D Canada's Centre for Operational Research and Analysis (DRDC CORA) has developed a strategic level simulation tool, known as Tyche. Tyche takes a moderate-fidelity approach to joint force structure analysis that utilizes capability-based planning. The next section describes the Tyche model, including novel features and modelling limitations. Section 3 provides a sample joint force structure case study. Conclusions are given in Section 4.

2 THE SIMULATION MODEL

Tyche is a stochastic simulation model that schedules the deployment of assets within a force structure to address a set of missions. The assignment of assets to missions is based on a set of predefined rules that attempt to reproduce the decisions made by a military scheduler. Scheduling assignment is capability-based; meaning each mission requires a set of capabilities for success, and each asset type provides a set of capabilities that may or may not overlap with the required mission capabilities. The force structure measure of performance (MOP) is evaluated based on how well and how often the missions' capability requirements are met.

When it was originally developed in 2004, Tyche was designed to model naval force structures. It was later adapted to accommodate joint asset types; however, a number of assumptions within the program affect the range of detailed joint military applications. These limitations will be discussed in the following subsections, and are slated for future development.

Tyche is divided into three interconnected environments: a data entry environment where the data required to perform simulations are entered; a run environment where the specifics of the desired simulations are entered; and a data exploration environment where the MOP and run output can be visualized and further investigated. The function of these three environments is described.

2.1 Data Structure

There are five fundamental data structures employed within the Tyche model to build a simulation: capabilities, asset types, bases/theatres, scenarios, and force structures.

2.1.1 Capabilities

While capabilities simply refer to any ability to perform a task, they provide a flexible way to link mission requirements to force structures. Most force structure analysis models are either platform-based (meaning requirements are defined in terms of the number and type of platforms for mission success) or physics-based (specifying physical characteristics, such as dimensional capacity for air or sea lift). Tyche is unique in that the user can define capabilities to suit the simulation model requirements. Typical capabilities used for military simulations simulation include command and control (C2), surveillance, firing, jamming, transportation, etc. Quality and quantity factors are associated with each capability. Quality is a scale on (0,1] for relative comparison; quantity is a positive integer ($\in \boldsymbol{Z}$). This permits objective comparison of often subjective evaluations (e.g., the higher C2 capability of a destroyer compared to a frigate is modelled model by a higher numerical quality), as well as encompassing the physical characteristics in a single, broader definition of capability (e.g., lane meters of sea lift is associated to a numerical quantity).

2.1.2 Asset Types

Asset types are defined to allow for modelling of equipment, personnel, weapons, modules, etc., and include both dynamic and static assets (static assets cannot travel to theatre on their own, such as maritime helicopters). Various levels of fidelity in the modelling of assets are possible, which positions the tool well to cross between coarse strategic-level studies and more detailed operational-level analysis. One limitation that the user must bear in mind when defining asset types is the timescale within Tyche. The smallest unit of time is one day, and simulations are intended to run over multiple years (an assumption that was suitable for naval applications). A user-selectable timescale is planned for future versions of the software to accommodate force structures that commonly operate on smaller timescales.

Tyche also allows for modelling of external assets; those that could be chartered or assumed available (based on a given probability) from another source. This allows for simple modelling of assets about which little knowledge is available.

The concept of “level” is introduced as a key element in the modelling of assets. Levels are used to model the different states or working conditions of the assets such as the readiness states, breakdowns, maintenance, training, and leave. In essence, the levels allow the modelling of variations of the capability supplied by the assets under user-defined circumstances. An asset type’s levels are prioritized, so that critical tasks can override (or bump) less important tasks. Associated with each prioritization instruction between two given levels are a bump time, a bump penalty, and rescheduling instructions for the bumped level.

In addition, levels are characterized by type, a set of capability supply and demand, and the optional inclusion of constraints with regards to the possible asset assignment. Level types include random (e.g., to model unforeseen breakdowns), scheduled (e.g., to model maintenance periods), on-demand (e.g., to model mission assignment), and follow-on (e.g., to model a quality of life break following a long mission assignment). The set of capability supply and demand associated with the asset type is specific to each level. For example, a user may model levels of readiness with different degrees of capability and response time associated with each. Synergistic effects can also be captured; as when two assets are assigned together to produce a higher level capability of either alone (e.g., a helicopter embarked on a frigate to increase the effectiveness of the frigate’s surveillance capability).

The association of capability demand to assets leads to the ability to model multi-layer and co-dependent capability demand chains. An asset may demand capability, just as a scenario would. This is common with static assets requiring transportation into theatre. Co-dependent demand arises when a demanded asset requires capability supplied by the asset requiring it. For example, a helicopter requires transportation to theatre which can be provided by a frigate, and in reverse the frigate requires a helicopter to provide surveillance.

A distinction between capability supply and capability demand is in the number of associated attributes. Capability supplies have only an assigned quantity and quality which specify the number and the degree to which the capability is provided. On the other hand, in addition to a quantity, capability demands have two quality values specified: the required and marginal quality levels. The required quality determines the degree of desired quality for satisfactory performance, and the marginal quality provides the degree needed for minimum performance standards. The quantity determines the number of requested capabilities to support a single asset type at the level being defined. In addition to the quality and quantity, the capability demand also requires a weight, which is used to quantify the importance of this capability demand with regard to other capability demands. Finally, a capability demand can be deemed “essential”. If an essential capability demand cannot be satisfied at the required quality with a capability supply from another asset, then this asset will not be able to go to this level. For example, for a ship to leave a port, it needs to be manned by a crew. If there is no crew available, then the ship will stay alongside. Thus, the crew provides a capability that is essential to the ship when it is requested to leave the port.

Constraints on maximum or minimum duration or on the number of occurrences of one or more levels over a given period of time can also be imposed to mimic scheduling limitations such as maximum time used (e.g., annual flight hours for aircraft), or frequency of usage in long-term high-intensity missions to maintain personnel tempo.

2.1.3 Bases and Theatres

Bases are locations where assets are stationed when not assigned to a mission and theatres are locations where missions occur. Neither is given physical coordinates, merely relative distances to one another. No units of distance are specified, allowing the user to determine a physical route for travel that is compatible with the speed unit that will be associated with the assets using these locations. For example, two bases could be used to represent a single location from which air and sea assets depart. An over-land great circle arc distance would be used for the distance that air assets travel, while an over-water distance (often much larger, when taking into account land mass detours) would be used for the sea assets.

In this formulation, a simple model of one home base for each asset, which then travels to a single theatre for a scenario, is used. Waypoints for intermediate activities (such as resupply), and forward stationing of assets, are more complex behaviours that are under consideration to better model aspects of joint force operation.

2.1.4 Scenarios

Scenarios represent missions (or a group of missions) to which assets are assigned. A scenario is defined in terms of phases, which represent the variation of capability demand required over time (e.g., pre-crisis a scenario might require more diplomatic and economic intervention and a show of force, while later phases may demand combat capabilities and non-combatant evacuation). Each scenario also has a number of possible theatres, each having a probability of assignment. Each phase can be independent, or linked to one or more other phases. Consequently, activities of varying capability demand, duration, and location can be modelled.

In terms of associated attributes, the phases of a scenario show many similarities with the levels of an asset. There are three types of phases: scheduled, random, or follow-on. As with the level, a scheduled phase requires a start date and frequency that set the precise dates the phase will occur. For the random phases, only the frequency must be specified; a Poisson distribution is used to determine the occurrence of these scenarios (see Section 2.2.1).

The main difference between levels and phases is the absence of the timing constraints and capability supply for the latter, as well as the appearance of more complex scoring criteria. The scoring criteria determine how to select assets for the phase, by means of a cost function for various choices of assets and selecting the best additive score of all the possibilities.[2] The cost function will be defined in Section 2.2.2.

2.1.5 Force Structures

A force structure stores all the assets from the different asset types that would be used for a given simulation run, including possible external assets. The term "fleet" was used but the assets are not limited to naval types. Assets are defined by specifying type, home base, and a scheduling offset. The offset is a number that specifies the number of days by which the start date of the scheduled levels of the asset will be shifted with respect to other assets of the same type. Currently, many force structures can be defined, but each must be run individually. The possibility of incorporating the model inside an optimization routine is under consideration, so as to determine the optimal force structure to meet a set of requirements.

[2] The reader might wonder why scoring criteria are required for the phases, but not for the levels. In fact, Tyche employs hard coded scoring criteria for the levels. The capability and conflict criterion, with constant weights, scales, and thresholds, are used to assign assets to meet the level's capability demands.

2.2 Simulation Procedure

At its core, Tyche is a discrete-event scheduling program. For every iteration, the force structure data are initialized, a list of events is generated where each event requires assets to be assigned, and the "best" available assets are then assigned to these events. Data is then output in the form of an operational schedule for each iteration. Data for reinitializing the random number generator are also output to allow for continuation of simulation runs at a subsequent time (this can be useful in the event of computer issues).

2.2.1 Event Generation

The list of events is generated at the start of every iteration, and updated as the clock progresses in the simulation. An event occurs every time a scenario phase begins or an asset changes level. To build the list of events, Tyche first selects a random date, which is the initial date at which the simulation starts. All scheduled events are created in relation to this date (where day 0 is the first day of the calendar year). Random phases and levels are determined from a Poisson distribution with a frequency of occurrence per year of λ. For an iteration of n years, the number of events (N) is determined by selecting a random number, r uniformly distributed on [0,1], and applying Eq. (1).

$$N = i \text{ with } i \in \boldsymbol{Z} \mid e^{(-\lambda n)\sum_{j=0}^{i-1}\frac{(\lambda n)^j}{j!}} < r \leq e^{(-\lambda n)\sum_{j=0}^{i}\frac{(\lambda * n)^j}{j!}} \tag{1}$$

Note that the sum over the integer j from 0 to i-1 is set to 0 in the case i=0. The start date of each random event is then selected from the set of days inside the time window using a uniform distribution.

The duration of events that cross the number of years simulated are reduced to fit completely inside the time window. Events that are too short to have any assets assigned (based on minimum preparation and travel time) are removed from the simulation. As a result, the first and last year of all simulation iterations are not counted in the statistics generation (see Section 2.3.1) to eliminate this burn-in effect.

There are times during the simulation run when the event list can be modified. While follow-on phases are generated immediately after their preceding phase, follow-on levels are only added to the event list when the asset goes to the level that precedes the follow-on level. In addition, rescheduling of an asset from one event to another (bumping) alters the event list. Based on the rescheduling rules selected with the bumped event, it may be added again later in the event list.

Once a list of events for the iteration has been built, Tyche will assign assets to each event in a chronological order. The flow chart in Figure 1 illustrates how Tyche processes each Nth event in the event list.

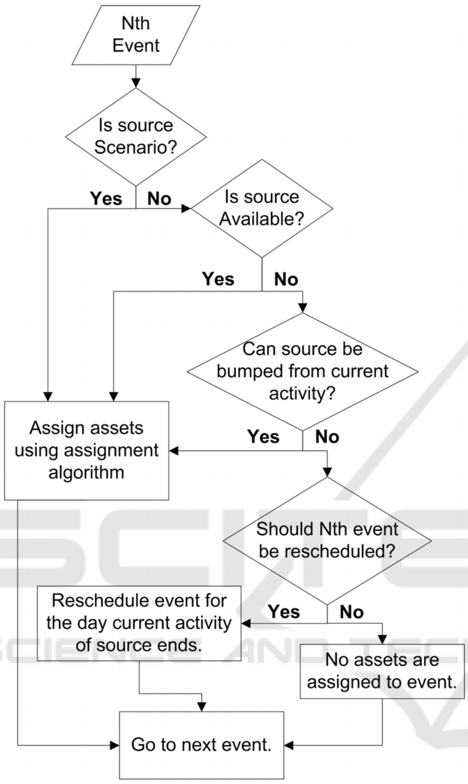

Figure 1: Event logic flow chart.

2.2.2 Asset Scoring Criteria

The method by which assets are selected for assignment is based on an additive cost function. While this is a myopic policy for meeting a single requirement by selecting from a list of assets based on information that is known now and actionable now (MP:R-AL/KNAN) (Wu et al., 2009), it provides a great deal of flexibility to mimic the decisions made by a military scheduler. Additional model development is planned to include optimization of asset assignment over the entire requirements list (events) at a given point in time and implementing a rolling time-horizon policy for forecasted demand.

The cost function is calculated for a set of assets using four scoring criteria that are described in Table 1; each criterion is defined separately for every scenario phase (for events with an asset source, levels use a predefined subset of these criteria). The first set of assets computed that has the highest score based on the scoring criteria is assigned to the mission. In the case of a tied score, the first computed with the score is selected – hence, entry order is important.

Table 1: Scoring criteria composition.

Criteria	Description
Capability (mandatory)	Number of capability demands that are met at the required or marginal level.
Capability Excess (optional)	Sum of the quality of the capabilities supplied by the assigned assets that exceed the capability demand of the scenario phase.
Timeliness (optional)	Sum of the time delay for all capabilities provided after the desired response time.
Conflict (optional)	Sum of the penalties for every asset bumped to go to the scenario phase.

The cost function for a single asset is simply the weighted sum of the scores obtained for all selected scoring criteria. Weights for each criterion are subjectively established by the user and can be tailored to try to reproduce the asset selections made by a military scheduler. A tool is included in the software to allow the user to preview the ideal asset selections (assuming unlimited assets and no timeliness or scheduling conflict) to tune the weights before a simulation is run. Consider a scenario (*s*) with a set of capability demands *{D}*. An asset with a set of capability supply *{S}* will have the cost (*C*) components defined in Eqs. (2)-(5), with the subsequent scaling factors (*Sc*). The scaling factors are also weights that are subjectively established by the user, different from the cost component weights used in the overall cost function.

$$C_C = Sc_C\left(\sum_{D(R)} W_D + 0.5\sum_{D(M)} W_D\right) \tag{2}$$

$$C_{EC} = -Sc_{EC}\sum_{S\notin\{D\}} Q(\mathrm{S}) \tag{3}$$

$$C_T = -Sc_T\left(\frac{\sum_{S\notin\{D\}}\left[\left(T(S)-T_R\right)*\Theta\left(T(S)-T_R\right)\right]}{\sum_{S\in\{D\}} 1}\right) \tag{4}$$

$$C_{SC} = -Sc_{SC}\sum_{A:L_C(A)\neq L_D} \text{Bump Penalty}(L_D, L_C) \tag{5}$$

The capability score (Eq. 2) is obtained by summing over the capability demands that are met at the required level (*D(R)*) and over those met only at the marginal level (*D(M)*). The arbitrary factor 0.5 multiplying the second sum indicates that the capability met at the required level provides a higher contribution to the capability score than those only met at the marginal level. Furthermore, since the capability score is obtained from the sum of the capability weights (*W(D)*, indicating the importance of the capability to the success of the scenario phase), capabilities with higher weights will contribute more to the score.

The excess capability score in Eq. (3) is obtained by summing over all the capability supplies (*S*) that are not requested by the capability demand ($\notin D$). This excess score prevents Tyche from sending too much capability (too many assets or too capable assets) to the scenario phase. Excess quality of a capability that is required by a scenario and provided by an asset is not taken into account (i.e., if two assets supply the same capability at different qualities, both greater than the required quality level, there is no penalty for selection of the one asset that exceeds the required level more than the other).

Eq. (4) defines the timeliness score, where T_R is the desired response time and $\Theta(T(S)-T_R)$ is the Heaviside step function. The timeliness score is obtained by computing the overall delay ($T(S)-T_R$) required to get all of the capability supplies (*S*) that are requested by the capability demand ($\in D$) into theatre. The summation is normalized by the number of supplied capabilities.

Finally, the conflict score is obtained by summing the penalties of all bumped assets in Eq. (5). The penalty given for bumping the asset is specified by the user in the asset type definition for bumping the asset from its current level (L_c) to the desired level (L_D). The sum is over all selected assets (*A*) for which the current level ($L_c(A)$) is not the default level. This conflict score favours the selection of available assets rather than bumping non-available ones.

The cost function for a group of assets is then the additive score for each individual asset; it is also a function of the order in which the assets are assigned. This will be discussed further in Section 2.2.3.

In addition, a threshold is also established for each scoring criteria. The threshold is used to reject poor groups of assets. In other words, if the best group of assets has an unacceptably low score component, it is possible to reject it and not send any assets at all. The threshold allows the user, for example, to prevent assets from being sent to a six-month mission to arrive only two days before the end of the mission. The effect of the thresholds (*Thr*) can be summarized as follows. If, for a given mission, the set of assets with the highest cost function is a set of *k* assets, $\sigma(A_1,\ldots,A_k)$, then the set of assets assigned to the mission, σ*, is given in Eq. (6).

$$\sigma^* = \begin{cases} 0 \text{ if } \exists \text{ Criterion } x \mid \dfrac{C_x}{Sc_x} < Sign(Sc_x) * Thr \\ \sigma(A_1,\ldots,A_k) \text{ otherwise} \end{cases} \tag{6}$$

Where “0” is the empty set of assets and “Sign” is a function that returns -1, 0, or 1 based on the value of the argument (<0,=0,>0).

2.2.3 Asset Assignment Algorithm

The assignment problem consists of matching the capability demand with the capability supply in an optimal way, with the objective of maximizing the cost function. This problem is thus equivalent to finding an optimal matching on a bipartite weighted graph. This equivalence follows from the following definitions (Diestel, 2005):

- A graph is a set of nodes and a set of edges between nodes. For the assignment problem, the nodes are given by the set of capability supplies and capability demands while the edges are determined from the search domain;
- A weighted graph has a scalar value associated with every edge. For the assignment problem, the weight associated with the edge is computed using the capability and timeliness scoring criteria as described in Eqs. (2) and (4);
- A bipartite graph is a graph for which the set of nodes can be divided into two subsets such that there is no edge between nodes pertaining to the same group. For the assignment problem, the nodes can be divided into the set of capability demand and the set of capability supply. Since every edge is between a capability and a capability demand, the graph is bipartite;
- A matching on a graph is obtained by selecting a subset of edges such that no selected edge has a common node. The assignment of assets is done by matching each capability demand with one, and only one, capability supply. It thus corresponds to selecting a matching on the graph. Every asset for which at least one capability supply is adjacent to an edge pertaining to the matching belongs to the set of selected assets.

Only the capability score and timeliness score can be assigned as a weight associated with the edges. This is possible because these two scores are given as a sum over the capability demands that are matched. The excess and conflict score cannot be obtained through a distributed sum along the edges pertaining to the matching. Thus, if the excess and conflict score do not belong to the selected scoring criteria then the optimal matching corresponds directly to the highest weight matching, which is a well-known problem in graph theory (Diestel, 2005). In particular, the backtracking and backjumping algorithm has been applied successfully to this type of problem (Wolf, 2006). Because the weights for the excess and conflict scoring criteria are typically small, this algorithm should produce solutions that, while not optimal, are "good enough".

Because there are typically few asset types that can satisfy a given set of capabilities, the user can exploit this information to define a restricted search domain. An enumerated search is then performed to determine which assets to assign. Tailoring of the search domain adds a significant amount of flexibility for assignment selection, increasing the capability of the program. The enumerated search is guaranteed to select the best available asset when only one asset is required for a scenario. If more than one asset is required, it is possible that the highest ranked combination of available assets is not assigned, because the search is conducted on an asset-by-asset basis. The next asset that adds the most to the total score, based on the remaining capability demand, is assigned.

The selection of assets is also done in a multi-layered way. At each layer, assets are selected to meet the capability demands that were introduced at the previous layer. If, at some layer, the capability demands cannot be met, then the algorithm backtracks to the previous layer and selects a different group of assets. At each layer, after a group of assets has been selected, the algorithm checks for redundancy. If redundant assets are found, then the redundant asset is removed and replaced by the new asset that can provide the capability that the redundant asset was providing and the algorithm backjumps to the layer where the redundant asset was selected.

2.3 Output and MOP

The results of the Monte Carlo simulation are output so that operational schedules from individual iterations can be viewed in text or graphical format. This allows for detailed examination of asset assignment, scheduling conflicts, and mission timing. Upon completion of the simulation run, statistics are generated for asset usage, scenario assignments, and capability fulfillment. A capability-based risk measure is introduced to aggregate the results into a single MOP for force structure comparisons.

2.3.1 Statistical Information

Asset statistics collect information on the assignment of individual force structure assets in terms of average duration and standard deviation of the duration spent at a given level. While the user must reconstruct which levels correspond to which scenario phases, the data output is generalized for use across all military services.

Scenario statistics indicate the average frequency of occurrence of scenario phases and the percentage of time that particular combinations of assets (or no assets) are being sent.

Capability statistics are the primary indicator of the ability of a force structure to meet scenario demand. For each scenario phase, the percentage of time that capabilities are not met at the required and marginal levels are reported.

2.3.2 Capability-based Risk Assessment

Maintaining the focus on capability-based planning, an assessment of the risk associated with a particular force structure can be derived using the probability that capabilities are not met, and frequency of scenario occurrence. The risk is defined in Eq. (7), where the mean yearly political risk (R) for a given scenario (s) is defined as the product of the annual frequency of occurrence (f), the impact (I) of failure to provide capability, and the probability the capability supply deployed is inadequate (P). The risk is then summed over all scenarios.

$$\mathrm{R} = \sum_{s} f_s I_s P_s \tag{7}$$

The first factor is assessed by averaging the number of times the scenario occurs yearly across all iterations. The second factor, known as impact score, can be provided as a subjective input by SME's. This allows the risk assessment to incorporate military judgement, often critical to balance the perceived effect of low impact-high frequency and high impact-low frequency scenarios. The third and final factor (P_s) is calculated from Eq. (8). The probability that the capability supply is inadequate can be defined in several ways, depending on how risk-averse the assessment should be. In general, it is a weighted summation of the percentage of time (P_{Tyche}) that the scheduler fails to provide capability to a scenario with a given asset assignment (A).

$$P_s = \sum_A w_A * P_{Tyche}(A) \quad (8)$$

Given that the Tyche scheduler can assign assets to meet capability at different levels, one highly risk-averse method would be to utilize three categories: where, due to force structure limitations, Tyche fails to assign assets altogether (*A=0*), and where *at least one* capability demand is *not* met at the required (*A=R'*) and marginal level (*A=M'*). The weights for each of the categories of capability failure can also be provided by SME input. In the case study, it will be assumed that $w_0 = 1.0$, $w_{R'} = 0.5$ and $w_{M'} = 0.1$.

The statistical nature of the risk measure also implies that there is an error on the estimation of the average. It is reported as twice the standard deviation (σ) of the mean distribution, where σ is estimated by the square root of the sample variance of the risk distribution divided by the number of iterations.

3 A CASE STUDY

Utilizing a simple case study, it is possible to illustrate the kinds of results Tyche can produce, as well as the types of problems that can be analysed. The case study is built around hypothetical asset types and scenarios, and the capabilities attributed to these assets are not intended to model capabilities of real force assets.

In this example, five generic capabilities (A, B, C, D, E) were created, along with two crewing and one transport capabilities for modelling dependencies. Five asset types (Air Asset, Air Crew, Sea Asset, Sea Crew, and Special Operations Force) can supply these capabilities, at various levels shown in Table 2. The Air Asset requires an Air Crew with a quantity of 3 persons, and can provide transport for up to 10 persons. The Sea Asset requires a Sea Crew, with a quantity of 70, and can provide transport for 100 persons. The Special Operations Force (SOF) is composed of 6 persons, and can be transported on either Air or Sea Assets.

Table 2: Asset capability supply.

Asset Type	Capability	Quality	Quantity
Air Asset	A	0.8	1
	B	0.7	6
	C	0.2	1
Sea Asset	A	0.7	1
	C	0.6	1
	D	0.9	1
SOF	E	1.0	1

Air Assets were modelled to have a 50% chance of requiring maintenance after use in a scenario, with a duration determined from a triangular distribution with minimum, most likely and maximum values of 1, 2, and 10 days. They were also restricted for use in 100 of every 365 days. The Sea Asset has a Short Work Period of 18-20-25 days 5 times per year. It also has a Docking Work Period of 100-180-365 days once every 5 years. Both Air and Sea Crews were constrained to take a quality-of-life break after every scenario for 5-5-10 days.

There were two bases: Air 1 and Sea 1, collocated together. There were four possible theatres, some favouring the assignment of air assets and others that are unbiased. Three scenarios (S1-S3) were defined to occur at two or more possible theatres, with requirements from Table 3. The scenario search domain was the same for all, including Air Assets from Air 1, Sea Assets from Sea 1, and SOF from Air 1.

Six force structures were tested. It was assumed that there was one crew per platform, and force structures are labelled according to the number of [Air Assets, Sea Assets, SOF]. The first three structures, [6,4,6], [3,2,3] and [1,1,1] looked at decreasing fleet sizes across all assets. Three additional structures reduced a single asset type from the largest, [6,2,6], [3,4,6], and [6,4,3]. The risk measure was computed using three for impact score, with values of 1.0 for S1, 1.5 for S2, and 5.0 for S3, and is shown in Figure 2.

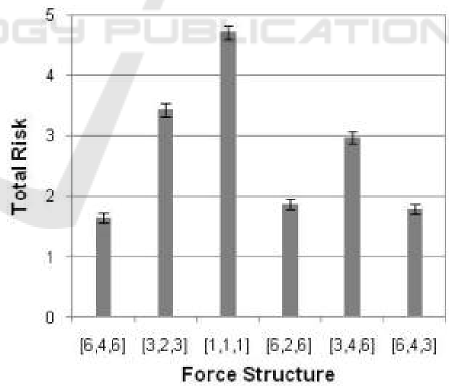

Figure 2: Case study results.

As illustrated, the risk of not being able to fulfil scenario capability requirements increases with decreasing fleet size. The simple parametric decrease in assets of a given type indicates that force structure [6,2,6] and [6,4,3] do not have a statistically significant difference in performance, and are near the large [6,4,6] structure. However, when Air Assets are removed [3,4,6], the risk increases sharply.

This case study is representative of the force

Table 3: Scenario timing and capability demand.

Scenario: Phase	Type, Frequency	Theatre, Probability	Duration, Response Time (Days)	Capability, Quantity	Required, Marginal Quality	Weight (All Non-Essential)	Scoring Criteria, Weight, Scale, Threshold
S1:P1	Random 3.0 / year	1, 0.2 2, 0.8	20-30-60 25	A, 1 B, 15 C, 2	0.8, 0.4 0.7, 0.2 0.4, 0.1	2 4 1	Capability,10,1,1 Conflict,1,1,100
S2:P1	Scheduled 1.0 / year Starting on Day 30	1, 0.25 2, 0.25 3, 0.25 4, 0.25	30-60-90 15	A, 1 C, 2 E, 2	0.6, 0.4 0.4, 0.1 1.0, 1.0	2 1 2	Capability,10,1,1 Conflict,1,1,100 Timeliness,1,1,20
S3:P1	Random 0.33 / year	3, 0.8 4, 0.2	90-150-180 30	A, 1 B, 15 C, 2 E, 4	0.9, 0.4 0.7, 0.2 0.4, 0.1 1.0, 1.0	2 4 1 2	Capability,10,1,1 Conflict,1,1,100 Timeliness,5,1,8
S3:P2	Follow-on, With P1 duration ≥ 150 days	Same as P1	90-150-180 30 No overlap with P1	A, 1 B, 15 C, 2 D, 1 E, 4	0.9, 0.4 0.7, 0.2 0.4, 0.1 0.5, 0.3 1.0, 1.0	2 4 1 1 2	Capability,10,1,1 Conflict,1,1,100 Timeliness,5,1,8

structure analysis that can be performed with Tyche, as well as options analysis around force structures of interest. While Tyche is not integrated into an optimization framework, simulation optimization to determine the optimal fleet with respect to some objective (minimum risk, structure size, cost, etc.) can still be performed, albeit in a less efficient way.

Tyche is also useful for performing options analysis, capability gap analysis, testing new capability architectures, and evaluating force structure performance in the face of changing requirements. As well, the rate of usage of assets can be examined to determine the effects of readiness and sustainment policies on performance in operations. For example, in the case study, the Sea Asset goes through a number of work periods. The length and frequency can be varied to determine the effect on risk. Similarly, with crews, operations and personnel tempo constraint policies can be varied.

4 CONCLUSIONS

This paper described a Monte Carlo discrete event simulation for joint force structure analysis. The Tyche tool is currently used by DRDC CORA and, while it has not yet been employed for a formal joint force structure study, it exhibits potential advantages for strategic level capability-based planning. Development is already underway to rectify known modelling limitations. Additional research avenues include optimization of asset assignment over the entire requirements list at a given point in time and implementing a rolling time-horizon policy for forecasted demand.

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