THE TYCHE AND SAFE MODELS: COMPARING TWO MILITARY FORCE STRUCTURE ANALYSIS SIMULATIONS

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ABSTRACT

In the past, several force structure analyses have been conducted for the Canadian Armed Forces using moderate fidelity (e.g., Tyche) and low-fidelity (e.g. Stochastic Fleet Estimation or SaFE) simulation models within optimization frameworks. Monte Carlo discrete event simulations like Tyche are computationally expensive and can only be used in optimizations that require few force structure evaluations. The SaFE model acts as a simple surrogate model that can be utilized by more global optimization techniques. SaFE, originally developed to study air mobility fleets, was adapted to accommodate a larger set of capabilities and more scheduling heuristics so that the performance of many force structures can be quickly assessed while minimizing a set of objectives. The amount of time required to find the SaFE optimal force structures is significantly less than using Tyche. This indicates that SaFE could be an important tool for discovering pareto-optimal force structures (within the space of all possible mixes) that would represent practical lower bounds on the force structure requirements for accomplishing expected future scenarios. The purpose of this paper is to compare and contrast the use of Tyche and SaFE through simulation optimizations on a given dataset.

INTRODUCTION

Determining the best future military force structure, comprised of a set of assets, to accomplish a set of defence and security tasks is a challenging undertaking. The set of tasks must be thoroughly investigated; requirements, frequencies, and durations for each task require definition. Potential assets must be identified and their abilities to meet task requirements assessed. Besides the necessity for accurate data from which to model, the force structure problem is further complicated by the deep uncertainty (Bui et al. 2009) inherent in modelling future environments. Thus, a force structure must be capable of addressing many possible combinations of future operational tasks. Furthermore, assets are large capital investments; accordingly, the goal is not only to find the appropriate force structure size and mix with respect to the devised future scenarios, but also the most capable structure at the lowest cost (Wojtaszek and Wesolkowski 2012).

Since large capital procurement projects undergo significant internal and external scrutiny, it is incumbent upon decision-makers to balance many conflicting objectives, justifying investments with anticipated needs. Due to the non-linear nature of the performance objective functions, as well as the length of computational time required to evaluate individual force structures, it is often not realistic to find a globally optimal structure in the time normally given to complete such studies. The computational complexity is exacerbated when searching for the pareto-optimal set of structures with respect to multiple objectives (Wojtaszek and Wesolkowski 2013). It is, therefore, critical that methodologies for quickly identifying optimal future force structures be investigated.

Two optimization-simulation approaches to force structure analysis used within the Defence Research and Development Canada's Centre for Operational Research and Analysis (DRDC CORA) are examined. The first approach uses a computationally intensive, Monte Carlo discrete event simulation model known as Tyche (Eisler and Allen 2012) within a direct search optimization framework. The model takes a top-down approach to test force structures, mimicing the decision of a military scheduler by assigning assets within a given force structure to scenarios as they arise. A single simulation run often requires hours to complete, and an optimization search can take weeks or months on today's desktop computers; necessitating an optimization procedure that requires relatively few steps to converge to the optimal force structure composition.

An alternative to the moderate-fidelity approach based on Tyche is the low-fidelity approach of DRDC CORA's Stochastic Fleet Estimation (SaFE) model (Wojtaszek and Wesolkowski 2013). SaFE is also a Monte-Carlo based simulation, which generates average yearly requirements from a dataset with frequency, duration, and capacity requirements for tasks (scenarios

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without a stochastic location element) and assets. However, the total force structure requirements are estimated from the bottom up, through a fixed matching of assets to scenarios, and no attempt is made to account for scheduling constraints (e.g., start and end dates). Given SaFE's relatively quick run time (approximately one millisecond on the same data run through Tyche), optimization is carried out over the solution space of all possible task to asset assignments, not just all of the force structure compositions.

Both models will be described subsequently in further detail. The optimization results of the Tyche and SaFE models will be compared, and their roles for military force structure analysis contrasted.

THE TYCHE MODEL

Tyche schedules the deployment of assets within a force structure to address a set of missions (Eisler and Allen 2012). Figure 1 illustrates the implementation of the Tyche model. On the top right, a fixed set of demands is created: missions to which a military force structure should endeavour to respond. These missions are created as scenarios, and may be broken down into one or more phases. Each phase may be random or scheduled, with its own frequency, duration (and associated probability distribution) and possible theatre locations, as well as a set of capability demands.

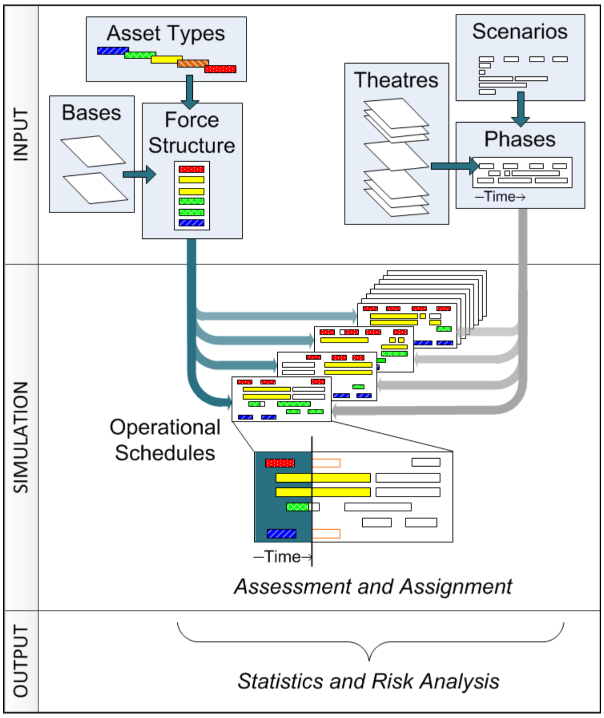

Figure 1: Tyche Model

Tyche can model a number of asset types, each supplying different capabilities. Force structures are constructed out of these asset types by specifying a quantity for each type and a physical location where they are based. To run a Tyche simulation, one force structure is selected to test a capability supply from the set of assets against demand requested from the given scenarios. Demand is constructed stochastically from the scenarios for frequency, start date, and duration in the schedules. Scenarios can be randomly generated using a Poisson process or scheduled at known intervals; durations are generated using uniform or triangular distributions. Assets within a force structure are then assigned to the schedule chronologically utilizing the policy to meet a single requirement by selecting from a list of available assets based on information that is known and actionable at the moment a mission occurs (Wu et al. 2009). The available assets within the force structure are assessed a numerical score for the capability used in the scenario and optional penalties for excess capability supply, timeliness into theatre, and scheduling conflicts. The scoring algorithm (Eisler and Allen 2012) factors in the quality, quantity, and subjective weighting of importance of capabilities matched between the supply and demand for a specific combination of assets. The combination of assets with the highest score is then assigned to the scenario in the operational schedule.

This process is repeated for all simulation iterations in a Monte Carlo approach (Robert and Casella 2004), and force structure performance is evaluated based on how well and how often the scenario's capability requirements are met. This is done in the form of statistics gathered from the collection of operational schedules on unmet capability demand per scenario, and by factoring in the frequency of scenario occurrence and political impact of failure to meet such requirements, to form a metric of political risk.

Performance Metric

The average yearly political risk R for a set of scenarios is defined as

$$R = \sum_{\forall s} f_s I_s P_s \qquad (1)$$

where the risk for a given scenario s is defined as the product of the annual frequency of occurrence f_s, the political impact I_s of scenario failure, and the percentage of time the capability supply deployed by the scheduler is inadequate P_s. The first factor is assessed by averaging the number of times the scenario occurs yearly across all schedules. The second factor, impact score, is provided by subject matter experts (SME) into the calculation. Each scenario is assigned to an impact category with an associated impact score. The third factor in the risk calculation is defined as a weighted calculation of the percentage of time that capability requirements are not met at various levels for the scenario (Eisler and Allen 2012).

Optimization Framework

Tyche was designed as a tool to evaluate and compare individual force structures. There is no optimization built in to drive the search for better force structure compositions. However, Tyche can be used inside an optimization framework, provided that the algorithm does not require a significant number of force structure evaluations due to the computational cost associated with each simulation run. An optimization is conducted within the solution space of all possible force structure compositions, with Tyche evaluating the performance of each feasible structure.

A force structure analysis study conducted internally by DRDC CORA used the Hooke-Jeeves algorithm (Hooke and Jeeves 1961), modified to combine a local exploratory search with a global pattern search, to perform the optimization procedure. Starting from an initial force structure composition, the exploratory search makes cumulative incremental changes to each asset type to determine if the objective value improved. The best combination of local improvements is used to drive the pattern search for larger step sizes. Although this algorithm can easily get trapped in local optima, it has two major advantages for application with Tyche. First, it requires few function evaluations, which are computationally costly. Second, it is simple enough not to require automation, given that manual input is required to set up force structures within Tyche.

Two primary objectives were defined to determine optimal force structures: minimizing total force structure risk and size. Due to the discrete political impact categories, the risk minimization was then defined in two ways, each used to drive separate optimizations. The first optimization minimized total risk and structure size, where a change in force structure was retained if the total risk decrease was deemed statistically significant. Noting that the standard error *SE* was estimated using the sample variance of the risk distribution divided by the square root of the number of schedule realizations and, assuming that the distribution can be normally approximated, the statistical significance was calculated in pairwise comparisons where the ±2 *SE* intervals did not overlap (Payton et al. 2003).

A second optimization minimized risk per impact category until a threshold of acceptable risk (as defined by military SMEs) was reached. That is, a change in force structure was retained if the risk in any impact categories showed a statistically significantly decrease. Again, the number of assets in the force structure was minimized by rejecting changes (i.e., with asset additions) that showed no statistically significant improvements. The search was terminated once the risk in each impact category met the given threshold within the bounds of the statistical significance. The procedure is illustrated by the following pseudo code on the force structure of composition $\vec{x}$, a vector count of each asset type, α as the pattern search acceleration factor and $\vec{\delta}$ as the pattern search step vector:

procedure *modifiedHJ(* $\vec{x}$ *,* α *,* $\vec{\delta}$ *) with*
    DO WHILE termination criterion not met
        // Exploratory search
        $\vec{\Delta}$ *= step size, initially as vector of zeros for total number of asset types*
        FOR i = 1 to number of asset types
            $x_{i_{new}} = x_i + \delta_i$
            Evaluate simulation at $\vec{x}_{new}$
            $IF\left[R(\vec{x}_{new}) - 2SE_{R(\vec{x}_{new})}\right] < \left[R(\vec{x}) - 2SE_{R(\vec{x})}\right]$
                $\Delta_i = \delta_i$
            ENDIF
        NEXT
        // Pattern search
        DO WHILE $\vec{x} \neq \vec{x}_{new}$
            $\vec{x}_{new} = \vec{x} + \vec{\Delta}$
            Evaluate simulation at $\vec{x}_{new}$
            $IF\left[R(\vec{x}_{new}) - 2SE_{R(\vec{x}_{new})}\right] \geq \left[R(\vec{x}) - 2SE_{R(\vec{x})}\right]$
                $\alpha = \alpha - 0.5$ *, as acceleration factor*
                $\vec{\Delta}_{new} = \alpha\vec{\Delta}$ *, where all* Δ_i *values must be integers and* $MIN(\Delta_i) = 1$
            ENDIF
        LOOP
    LOOP

A subsequent a greedy search is then applied to trim the solution. Trimming is carried out only if the modified Hooke-Jeeves algorithm is successful at either minimising the total risk to zero or the risk per category under the specified threshold. This trimming step is necessary since the pattern search can add several assets from different types at the same time, leading to a larger structure than necessary to achieve the specified objective. The trim procedure is illustrated by the following pseudo code on the force structure of composition $\vec{x}$:

procedure *Trim(* $\vec{x}$ *)*
    DO WHILE termination criterion met
        FOR i = 1 to number of asset types
            $x_{i_{new}} = x_i - 1$
            Evaluate simulation at $\vec{x}_{new}$
            IF termination criterion NOT met
                $x_{i_{new}} = x_i$
            ENDIF
        NEXT
        Evaluate simulation at $\vec{x}_{new}$

DO WHILE termination criterion NOT met

FOR all reductions to $\vec{x}$

Select i *with the maximum reduction of* $R(\vec{x}_{new})$ *and reverse change by* $x_{i_{new}} = x_i + 1$

NEXT

Evaluate simulation at $\vec{x}_{new}$

LOOP

LOOP

The results of the optimizations of the Tyche runs will be discussed in comparison with the results of the SaFE simulation optimization (as conducted on the same input data set) after a description of the SaFE model and its optimization framework is given.

THE SAFE MODEL

Like Tyche, SaFE is also a capability-based model that uses a Monte-Carlo approach to determine possible force structures based on the tasks that must be performed. It uses a dataset of task frequency, asset- and task-specific durations, and capability (in the case of air mobility (Wojtaszek and Wesolkowski 2013), these were passenger and freight capacities) requirements to derive demand over a stochastically generated number of tasks. The force structure is built from the bottom up, where its composition is computed such that there are sufficient assets to accomplish an average set of tasks. Since assets are matched to tasks via capabilities, there can be many assignment combinations. Force structures generated by SaFE are input into an (usually multi-objective) optimization procedure so that assets can be traded off against each other based on common capability. Given that SaFE is a bottom-up task-driven model, if in one solution the number of assets of a particular type increases (in comparison to another solution), then the number of assets of a different type which has similar capability will usually decrease.

To illustrate the differences between SaFE and Tyche, consider Figure 2. Instead of building a force structure out of a variety of asset types at a number of bases to test during a simulation, SaFE exhaustively matches each task to a specific asset or groups of assets. This asset to task assignment is done in a capability-based manner ahead of the optimization proper in order to limit the solution space to all feasible asset assignments. Each individual asset to task assignment is known as a configuration.

On the top right of Figure 2, demand is generated stochastically from a set of tasks, using frequencies and durations derived from triangular distributions. Asset-specific duration distributions (uniform) are also defined for completion of each task, and computed based on the configuration in use. For each iteration, the total demand can be calculated as time required for each asset type. The total time for each asset type is then averaged over all iterations to form the average annual demand. The number of assets required in the force structure to satisfy this average level of demand is computed simply as the whole number of assets that can provide such time (for example, 2.6 years of average annual demand requires 3 assets within the force structure). The sample variance of these durations is also computed to determine how much the demand varies across all of the scenarios.

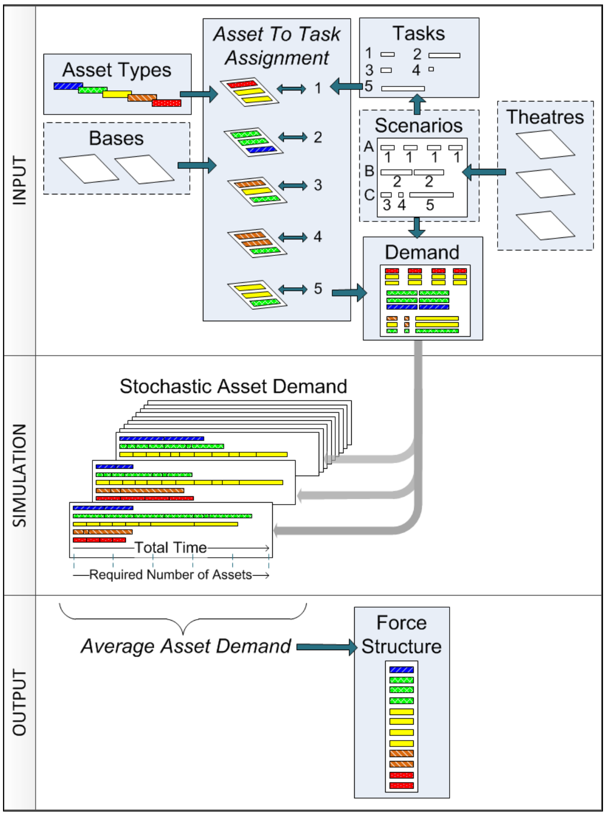

Figure 2: SaFE Model

Essentially, SaFE assumes a much simplified world where only total time on task for each asset type is needed to compute force structure requirements. It does not take into consideration event scheduling, such as task start and end times, task cancellation or prioritization, or other assignment constraints. SaFE yields the best possible representation of task requirements and, thus, underestimates realistic task requirements to produce a lower bound on a required force structure. Due to this simplification, SaFE can be used in an optimization framework to generate and evaluate force structures much more quickly than even the most efficient Monte Carlo discrete event simulation. This improved speed is vital when searching for optimal structures, a process that requires many force structures to be evaluated.

For analyses where higher fidelity is required, the SaFE model could be exploited as a preprocessing tool. It may reduce the problem space by eliminating large number of inefficient options and, thus, reduce the cost of using higher fidelity tools such as Tyche.

Adaptation to New Data

In Figure 2, there are several objects indicated with dashed lines, such as bases, theatres, and scenarios. These are common concepts between Tyche and SaFE; however, SaFE does not provide direct support for such data entry. To accommodate these concepts, the following adaptations were made:

- Multiple bases: assets of the same type defined at different locations and with different transit times to theatre (as asset-specific task completion durations).
- Scenarios with a probability of occurring at more than one theatre and/or more than one phase per scenario: handled through data manipulation to obtain a suitable equivalent of multiple tasks in SaFE.
- Asset assignment dependent upon availability at the time a scenario arises in the simulation: Tyche would send the same unique set of assets to a scenario every time if there were no limits on the number of assets available, but to enable the SaFE model to use an optimization mechanism for configuration generation, possible asset to task assignments are calculated as those that provide all the capabilities at the required level while also providing a minimum of excess capability.
- The effect of asset types that act as force multipliers: captured by modelling a single additional asset type with enhanced capabilities.

Performance Metric

The objective of the optimization is to search for force structures that are capable of fulfilling the average requirements and are minimal with respect to size, scenario duration, and risk of failure.

The force structure size objective (E_{size}) is an evaluation of the number of assets resulting from the chosen configuration and identifies structures which require minimal resources but are still capable of accomplishing the average scenario. The size objective is defined as

$$E_{size} = \sum_{a \notin m} F(a) + w \cdot F(m) \tag{3}$$

the summation of the number (F) in each asset type (a) plus a small weighted (w=0.01) total to account for the number of a single type of relatively low-value force multiplier assets (m).

The scenario duration objective function evaluates the average time it takes to accomplish a scenario. The duration objective (E_{time}) is defined as

$$E_{time} = \sum_{s} \delta(s), \text{ where } \delta(s) = \max_a \left(d_s(a)\right) \tag{4}$$

where $d_s(a)$ is the time it takes one asset of type a to accomplish its portion of all instances of scenario s, and $\delta(s)$ is the maximum time it would take any of the assigned assets to complete the scenario (thus the duration of the asset that travels furthest to the theatre is the one that defines the duration for the whole configuration). This assumes that all assets travel at the same speed, and that all assets must arrive at the theatre before the scenario can commence.

The force structure size and scenario duration objectives are evaluated using the average duration output from SaFE. However, the requirements of any iteration may vary from that of the average iteration. To mitigate the effects of this uncertainty, a risk-based objective is used, which is an evaluation of the ability of a configuration to accomplish all iterations. The risk objective (E_{risk}) is computed by

$$E_{risk} = 1 - \prod_{a} \pi(a) \tag{5}$$

as the probability that at least one asset will not be able to accomplish its requirements. The probability that an asset will be able to fulfill its requirements is given as $\pi(a)$ (Willick et al. 2010).

Optimization Framework

A single simulation run in SaFE is conducted for a given asset to task assignment configuration over 10^4 iterations (typically) of one year in duration each. An average force structure can then be calculated to meet the average set of demand over all iterations. The space of all possible configurations is very large (Wojtaszek and Wesolkowski 2013) – significantly larger than the force structure composition solution space. Since this large configuration space cannot be exhaustively searched in a practical amount of time, a metaheuristic is required.

Given that multiple objectives are considered, a multi-objective optimization algorithm needs to be used to provide a set of non-dominated solutions with respect to these objectives. Among the multi-objective algorithms that exist (Deb 2005), a well-studied one that has been utilized previously with Safe is the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II). NSGA-II is an elitist evolutionary algorithm that groups individual solutions into non-dominated fronts, and uses a crowding-distance operator to preserve diversity of solutions (Deb et al. 2002). Each solution comprises a configuration of asset to task assignments, and a base distribution for each asset. The NGSA-II pseudo code is not provided here, as it is adequately given in a variety of references, including (Deb et al. 2002).

RESULTS

The study dataset included 164 scenarios and 28 theatres. There were 14 asset types modeled, each at two possible bases. The results of the asset to task assignment algorithm generates 7.4 x 10^{62} possible configurations over all scenarios.

The NSGA II was run 50 times with 1 000 individuals (configurations) for 10 000 generations each with a mutation rate of 20%. Multiple runs were used to ensure the repeatability of the results obtained with respect to quality. The quality of the results was assessed using a hyper-volume measure (Fleischer 2003). The non-dominated fronts of the last generation over each run were combined into a single set of individuals, and then the non-dominated sorting algorithm was performed on this set to give the combined non-dominated front over the solutions from the 50 runs. The hyper-volume of the last generation of each run was then computed and compared to the hyper-volume of the combined non-dominated front. The hyper-volume average and standard deviation over all the runs corresponded to 96%±3% with respect to the combined best non-dominated front. Therefore, the quality of the results from each run can be considered to be similar to the others, and, therefore, analysis in the remainder of this section is carried out on the results of one of the runs.

Figure 3 shows a plot of E_{time} versus E_{size} for the 81 configurations in the non-dominated front, with the colour of each point representing the value of E_{risk}. This figure shows the trade-off between the size of the force structure and the risk of not being able to fulfill all of the demand in an iteration.

When looking at configurations with the same value of E_{size}, configurations with lower E_{time} have higher E_{risk}, thus demonstrating that there is a risk of not being able to assign assets from the closest base to theatre. The lowest value of E_{risk} over the non-dominated configurations is 0.27, indicating that the duration of asset use in an iteration may deviate significantly from the average. Recall that E_{risk} does not take into account the timing of scenarios within an iteration and the requirement that scenarios must be performed within time windows. Therefore, the risk of a force structure produced by optimizing SaFE not being able to satisfy all of the demand in a given iteration may be greater than E_{risk}.

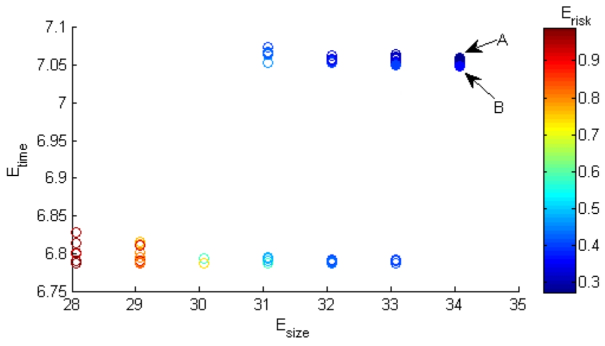

Figure 3: Plot of Objective Values for Configurations in the Non-Dominated Front

As mentioned previously, the same force structure can be computed from different configurations. For example, configurations A and B shown in Figure 3 both result in the same force structure, but configuration A has lower E_{risk} (0.27 vs. 0.36) and higher E_{time} (7.06 vs. 7.05). These differences are due to differences in the assets assigned to each scenario and the base from which the assets are assigned.

Within the 81 non-dominated configurations, there are 24 distinct force structures. The ranges of number of each asset type over these structures are shown in Table 1. When compared to the force structures run through Tyche (three distinct force structures were used to seed the initial values for two separate optimizations to produce six final structures), the upper bounds on these ranges are similar to or slightly less than the SME force structures for most assets. This result indicates that the SME force structures could theoretically satisfy the average iteration requirements with respect to the duration of asset usage with some unused asset capacity. The force structures from the optimization conducted using Tyche are much larger in number for most asset types than the upper bound on the range of non-dominated structures, indicating that they could theoretically satisfy the average iteration requirements with a large amount of unused asset capacity (which may be necessary to meet scheduling constraints).

Comparison of Suggested Force Structures

The force structure compositions produced using the SaFE model were run back through the Tyche

Table 1: Range of Number of Assets in Recommended Force Structures

	Type 1		Type 2		Type 3		Type 4		Type 5		Type 6		Type 7		Type 8	
Base	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**
SaFE	3-4	2-3	2	2	1-2	2	2-4	4-7	0-1	1	1	1	1-2	3-5	2-3	4-5
SME	3-6	3-6	2	2	2	2	5-6	6-7	1	2	0-1	0-1	3	5	7	8
Tyche	10-14	10-14	5-6	5-6	3-4	4	10-14	11-14	1-2	2-3	1-2	2-3	1-3	1-5	6-8	7-8

simulation in order to compare results with common metrics. Each force structure was run for 1 000 iterations. Of the three SaFE objectives, only E_{size}, a good indicator of force structure size, is independent of the model. E_{time} and E_{risk} are associated with specific asset to scenario assignment configurations, of which there may be multiple for the same force structure composition, and cannot readily be generated for the SME or Tyche recommended force structures. As a result, comparisons will primarily be made on correlations between E_{size}, political risk, and E_{risk}. The set of force structures chosen for this comparison comprise all of the force structures from the final generation of the NSGA-II, not just the 24 in the non-dominated front. This set comprises 274 distinct structures, and was chosen to provide a better statistical analysis. In the amount of time it took to run an evolutionary optimization procedure to find 24 non-dominated force structures (less than 24 hours), the Tyche simulation was only able to evaluate approximately 77 force structures (2.5 hours per force structure, running 8 simulations in parallel).

Performance evaluations using SaFE are not as precise when compared to Tyche because the SaFE evaluations are based on average requirements. In addition, the risk measures used are not directly comparable, since the political risk objective is a weighted sum of stochastic scenario performance, where each scenario is weighed according to the political impact of not being able to provide its required capability. The E_{risk} objective, on the other hand, does not distinguish between the importance of different scenarios.

Another issue with comparing E_{risk} and the political risk for a force structure is that there may be multiple values of E_{risk} for a given structure due to the possibility of multiple configurations for the asset to task assignment. In order to determine which value of E_{risk} to use for each force structure, the correlation coefficient is computed between the structure's political risk and each of the minimum, mean, and maximum values of E_{risk}. The resulting correlation coefficient values are 0.62, 0.63, and 0.63, respectively; thus indicating that there is very little difference among these values. All that can be said here is that the higher values of E_{risk} for a force structure may be slightly more reflective of the political risk computed using Tyche than the lower values. The mean value of E_{risk} will be used for the remainder of this section with the assumption that using either of the other values will not significantly change the analysis. The positive correlation obtained here shows that there is some potential in using SaFE to estimate the risk of a force structure, although Figure 4 shows that there are force structures with lower total political risk but larger E_{risk} than other structures; therefore, more work would be required to formulate a risk measure usable with SaFE that is more reflective of the political risk measure.

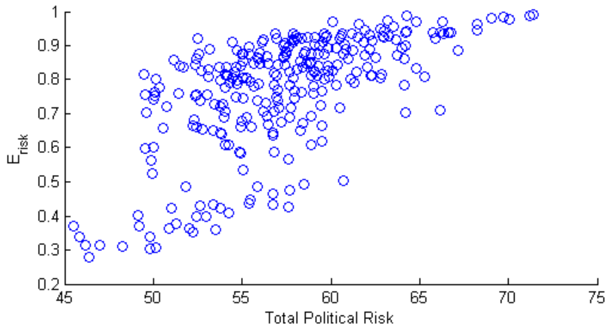

Figure 4: E_{risk} vs. Total Political Risk for the SaFE-produced Force Structures

By plotting E_{size} versus total political risk for the 274 SaFE, 2 SME, and 6 Tyche-recommended force structures, Figure 5 is obtained. There are three distinct clusters in the graph: the low political risk structures recommended by the Tyche optimization, the smaller SME-recommended structures with higher risk, and the even smaller SaFE generated structures with yet higher risk. From this plot, it can be seen that SaFE-recommended structures have the highest political risk and lowest size, while Tyche-recommended structures have the lowest political risk and the largest size.

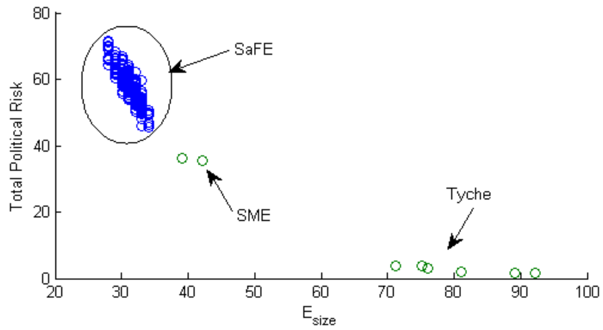

Figure 5: Size vs. Total Political Risk Objectives for All Recommended Force Structures

In SaFE, the assumption is that the occurrence of all tasks can be arranged in the most advantageous way for the entire force structure over time. It is clear that computing a force structure using a model based on several problem simplifications such as SaFE results in structures of lower size and, as a consequence, higher political risk. Figure 5 shows that SaFE and Tyche could be used as lower and upper bounds, respectively, on the number of assets needed within a force structure, and thus provides decision makers with realistic force structure size bounds.

CONCLUSIONS

The SaFE model was successfully used in a multi-objective optimization framework to find optimal force structures with objectives to minimize fleet size, scenario duration, and risk of failure. A set of SaFE-derived force structures was then evaluated using the Tyche simulator in order to assess their political risk. The results showed that SaFE-recommended force structures have the highest political risk and lowest size, while the Tyche-recommended force structures have the lowest political risk and the largest size. Thus, results from SaFE and Tyche could be used respectively as lower and upper bounds on the number of assets required within a force structure, and provide decision makers with more realistic bounds on the political risk objective. SaFE appears to provide a lower bound on the force structure size since it is a model based on several constraint relaxations. In addition, there is some correlation between total political risk and E_{risk} although E_{risk} was not designed to estimate political risk.

The amount of time required to find the SaFE non-dominated configurations was less than 24 hours, whereas running a Tyche simulation required 2.5 hours per force structure; therefore, SaFE should be investigated further as a quick preprocessing tool that can sort through vast numbers of structures which can then be analyzed in more detail in Tyche. Furthermore, SaFE can also be modified to compute force structures that are capable of satisfying different levels of iteration requirements. For example, instead of using mean asset durations, the asset durations could be chosen such that they are greater than those of a user-specified percentage of iterations.

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