Design of a Maritime Security System under Uncertainty Using an Evolutionary Real Options Approach

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Abstract

This paper presents an evolutionary real options model of optimization by genetic algorithms and Monte Carlo simulation, to select the best maritime domain protection system configuration and a corresponding adaptive plan with the right amount of flexibilities to address uncertainty.
Monte Carlo simulations enumerate diverse terrorism threat paths, decision trees identify possible system (re)configuration and dynamic adaptive plans, and genetic algorithms evaluate and select near optimum solutions, acquiring and exercising the right real options at the right time. Genetic Algorithms are effective and efficient in both compositing suitable pieces of real options and formulating the overall dynamic strategy plan to adapt to various paths future may take. As the whole modelling approach is integrated, many interesting system properties emerge.

Keywords: real options, optimization of adaptive systems, Genetic Algorithms, Monte Carlo simulation.

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1 Introduction

Investments in maritime domain protection systems are affected by the uncertainty around the amount of terrorism in the next decade or more. Therefore the selection of a protection system that is justifiable and worthwhile to build requires a dynamic framework, considering how terrorism could possibly evolve and how the system could adapt, which becomes a complex practical challenge with the issue of a very large search space (curse of dimensionality).

To deal with that, this paper uses evolutionary computing and Monte Carlo simulations in combination with Real Option Valuation to quantitatively assess and optimize dynamic solutions.

Research work combining genetic algorithms and real options gained popularity in the last decade, and the pioneers (see example: Chen and Lee (1997), Chidambaran, Lee and Trigueros (1998)) used genetic algorithms or other evolutionary computing as a computational technique for option pricing. Dias (2001) and Lazo, Pacheco and Vellasco (2003) proposed using genetic algorithms to find the exercise regions (price and time) for real options in oil field developments. Contrary with those research applications, this paper proposes using genetic algorithms to composite suitable pieces of real options and formulates the overall dynamic strategy plan to adapt to various paths the future may takes.

Recently, more advanced applications start to combine various techniques to model uncertainties and flexibilities with decision trees (Borison, 2005) and genetic algorithms (Hassan et al., 2005; Hassan and de Neufville, 2006). This paper deals with a case of 109 real options in several stages and states and integrates Genetic Algorithms, Monte Carlo simulation, and Decision Trees to find an adaptive design. In this process, many complex system properties emerge.

2 Descriptions of the Problem and the Uncertainties

The terrorism threat in the Straits of Malacca, one of the world's most important shipping lanes, necessitates the development of a maritime domain protection system. The architecting and design of such a system, especially to prevent a Weapons of Mass Destruction (WMD) attack, is a very complex task, as the system faces many uncertainties in the future. "The threat of terrorism … comprises so many unknown variables that traditional cost-benefit analysis is rendered nearly impossible" (Maritime Transport Commission as quoted in Raymond (2005)).Terrorism attacks occur irregularly with little predictability and one often speaks of frequency of occurrence and the impact or consequences of an event. Hence, risk can be defined as:

risk = probability (statistical frequency) × consequences (monetary terms).

The issue remains that the probabilities and the consequences of occurrences are highly uncertain and unpredictable in the coming years, and a terrorism system conceived and designed today has to prevent acts of terrorism for a decade or more.

A potential solution is to incorporate flexibility into the system design in the form of options that can be exercised in the future as new information about situation changes arrives.

NPS (2005) carried out an extensive study to develop a maritime domain protection system to prevent and defeat terrorism in the Straits of Malacca. Using the same technical, evaluation model and system configurations, while considering uncertainties and flexibilities in addition, the present study shows what an evolutionary real options model of optimization can add to traditional system engineering process.

The maritime domain protection system (to counter the threat of a weapon of mass destruction) follows a modular architecture and consists of five different subsystems (sensors, C3I, force, land and sea inspection), each of which contains two or three alternative configurations, resulting in 109 feasible system configurations for the Weapons of Mass Destruction scenario. The performance and costs have been determined for each of these system configurations, and configurations with higher performances (i.e. resulting in the lowest risk of a successful attack) and lower costs are the better performing. The real option design approach is to identify the optimal mix of alternative subsystems that, when collectively implemented, enables the system to protect us from terrorism attack damages at a justifiable cost to build and maintain.

Optimization of the Problem

The optimization problem can he stated as follows:

Objective:

Maximize System Performance = Risk Saved = (Attack Damage without the protection system – Attack Damage with the system in place) [1, 2]

Subject to:

- *Minimize total system cost*[1, 2]
- *Alternatives design technical availability*[1, 2]

Decisions:

- *The system in initial stage*[1, 2]
- *Subsequent adaptive plans to upgrade/downgrade the system* [2]
- *The threshold level of terrorism to activate subsequent plans* [2]

Given Input:

Performance and costs of each alternative designs[1, 2]

Initial forecasted terrorism prevention requirement[1, 2]

Subsequent new information on the terrorism prevention requirement[2]

[1] applied in traditional system engineering design
[2] applied in evolutionary real option design process

3 Evolutionary Real Options Model

Real options recognize and address uncertainties and therefore change the processes of system design, the kinds of elements designers embed into the system, and the way managers valuate the system and practice risk management.

As the terrorism risk fluctuates, the requirements on the system change accordingly. Higher maritime risk will require higher performing protection system and can justify the higher associated system costs, and vice versa. Monte Carlo simulation is utilized to generate various paths terrorism risk may take in the coming decade by a modified lognormal stochastic process. The standard deviation of terrorism risk in the coming decade is used to represent how certain we feel about our forecast. This study assumes that the maritime domain protection system has a lifespan of ten years, and the system can update its configuration in the third and sixth year. Real options are different from financial options in that real options lack the relatively real-time market for financial options and can only be designed and exercised over a longer period of time. In this case, as a maritime security system takes years to develop, there are only 2 decision points when the system can exercise real options in the 10-year lifespan

A trinomial decision tree can represent the decision to exercise real options in the 2 decision points. At a decision point, the system may reconfigure itself depending how the terrorism risk has developed at that time. The two decision points in a trinomial tree result in 9 paths of decision and 13 different configurations (see figure 1). As the design space is very large (13 nodes each with 109 possible configurations, making it in the magnitude of 10 to the power of 26), genetic algorithms are used to optimize the set of system configurations ("config" in Figure 1) under uncertainties.

2007			2010			2013		
Normalized Risk	% of Each Senario	Config	Normalized Risk	% of Each Senario	Config	Normalized Risk	% of Each Senario	Config
						0.35	3.23%	6
			0.48	10%	27	0.38	2.38%	22
						0.41	4.67%	72
						2.66	76.41%	10
1.00	100%	14	1.00	87%	6	2.89	4.05%	28
						3.19	6.81%	83
						2.75	1.10%	42
			3.11	2%	35	5.05	0.57%	85
						9.55	0.77%	89
Risk Std. Dev.:		14.4%	Add. switch cost:		5%	Discount rate:		10%

Figure 1. Trinomial Decision tree (risks are normalized, and configurations are indexed)

The GA optimizes the system value over a 10-year period under different conditions by looking for the optimal configuration (a “roadmap” consisting of an initial configuration and subsequent adaptation plan). The decision tree (figure 1) shows to which configuration to switch and the thresholds of terrorism risk at which to switch. The optimization is a multi-objective search driven by Genetic Algorithms. The often-used objectives are Net Present Value (NPV) related.

$$NPV = \sum_{i,j} f_{i,j}(threshold_{i,j}, config_{i,j}),$$

$threshold_{i,j}$ is the threshold value to get into branch j at stage i

$config_{p,q}$ is the configuration used in branch j at stage i

$f_{i,j}(threshold_{i,j}, config_{i,j})$ is the NPV in branch j at stage i

Integrally, the model determines the optimal set of configurations for all the decision nodes in the tree. For example, the configuration that is giving the best performance in a stage may not be chosen because it may not embed suitable re-configurabilities to deliver the best overall performance over time. As $config_{i,j}$ affects the NPV in the following stages i+n (n=1, 2, 3…). Optimisation not only needs to consider the impact of a configuration over the NPV in that stage, but also over future paths in the decision tree. The capability to reconfigure the MDP system is seen as real options, and those real options also come with costs. The Genetic Algorithms identify the situations where it is worthwhile to put those real options.

4 Results and Discussions

4.1 value of flexibility

The difference of the NPV of the flexible architecture compared with that of a traditional peak design is the added value of real options. Figure 2 shows the histogram of system value of both the real option design and the peak design. The vertical lines give the mean Net Present Values, which are 1,536 million USD and 4,249 million USD respectively for the fixed and flexible designs. Figure 3 shows the same thing by a Value at Risk (VaR) graph, which shows that the fixed design has 49% chance of ending up with a negative net present value, while the flexible design has only 19% of getting a loss. Also, the maximum possible loss for the fixed design is 2,600 million USD versus 417 million USD for the flexible design. The maximum net present value obtainable with a flexible system is considerably higher. Although the graph is truncated on its right, it can already be seen that for instance at 95% the curve for the flexible design is much further to the left that the curve for the fixed design. In the very middle range, where the curve of the fixed design is to the right of the curve of the flexible design, the fixed design performs better. This represents an area where future turns out to be very certain and follows what forecast tells. In this narrow range, peak design is outperforming, because real option designs carry extra costs of having flexibilities. Overall, the VAR clearly indicates the better performance of the real option design compared to a peak design.

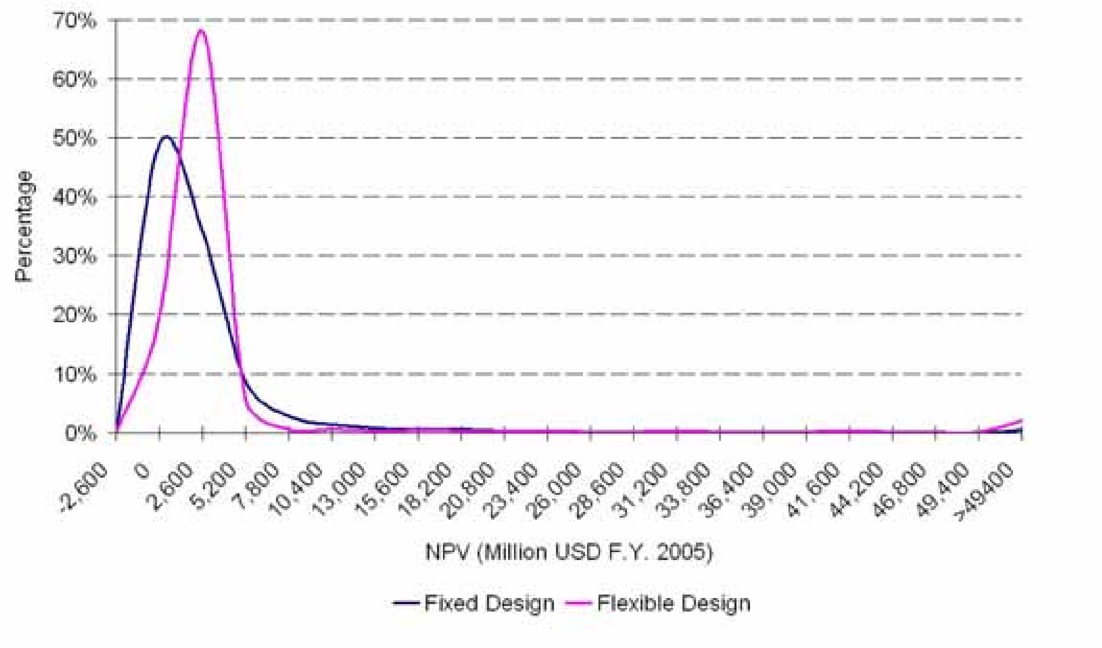

Figure 2. Histogram for fixed and flexible design.

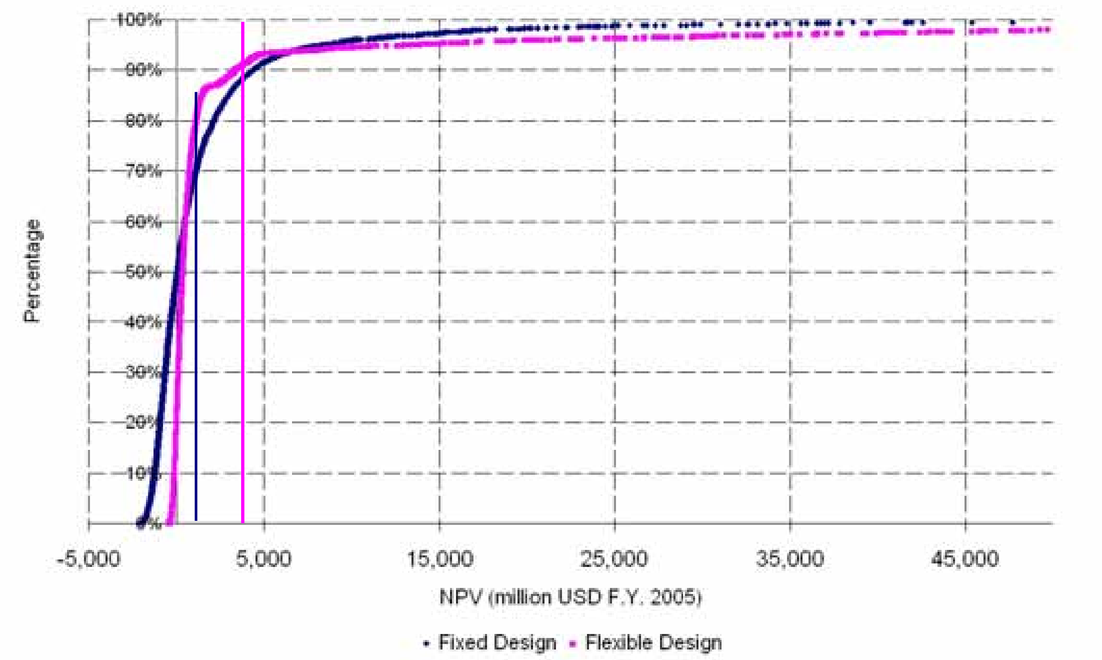

Figure 3. VaR graph for fixed and flexible design.

4.2 Project Mean Value versus Standard Deviation of terrorism risk

As there is very large search space and GA is conceptually a randomized search, multiple runs of Genetic Algorithms generally produce varying results. Therefore it is beneficial to run it a few times to try to obtain a better optimal solution. In this study, 27 runs were carried out for each case with two objectives: 1). the average NPV for all paths, and 2). the 5% of all NPVs from the bottom. The first objective aims to improve the mean project value, and the second objective serve as risk management tool to reduce the possible lost of the project.

We run the model varying the standard deviation of terrorism risk with a step of 0.05 from 5% (designers are very confident about the forecast about level of terrorism) to 90% (designers are really not confident about the forecast). Figure 4 shows the NPV of the Real Option design under different standard deviations of the degree of terrorism risk (the confidence about the forecast). The added value of using the real option design for the maritime domain protection system is higher as the confidence around the forecast is less. This is a well-known finding in real options analysis: as the uncertainty rises, the value of options increases, as one can act on positive opportunities and avoid losses.

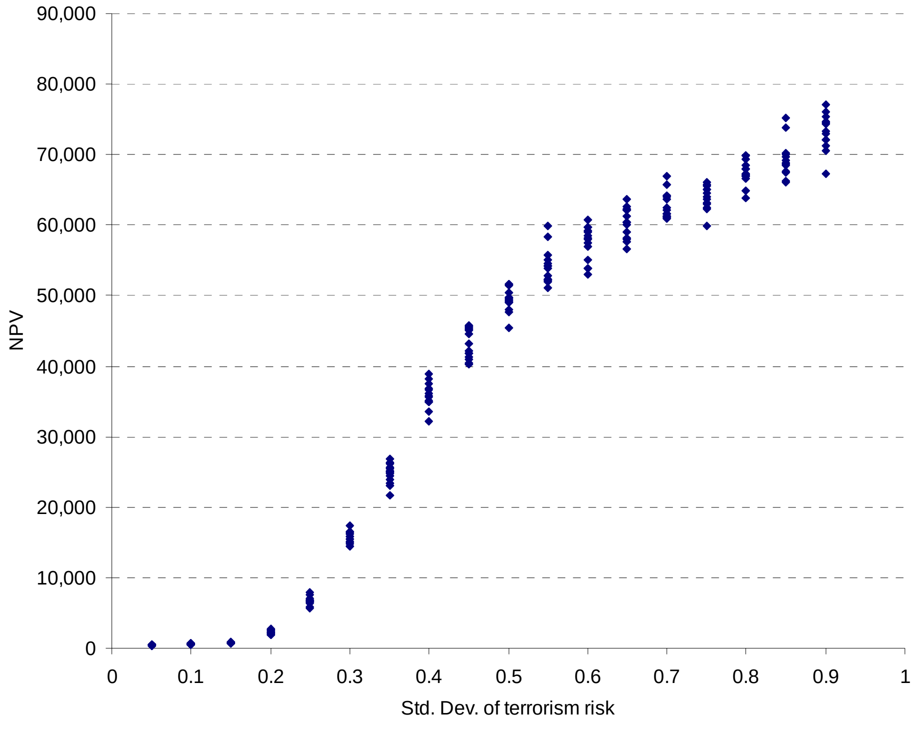

Figure 4. NPV of MDP versus Standard Deviation of terrorism risk.

4.3 Project 5 Percentile Value versus Standard Deviation of terrorism risk

As uncertainty about terrorism risk increases, the second objective, the 5% percentile of NPV, declines slightly. In each standard deviation, the GAs run 27 times, and Figure 5 shows that the upper frontier of the NPV 5% is smooth, while the lower frontier is noisy. Some of the results among the 27 GA runs could arguably be better optimized, especially in the middle portion of uncertainty. It is interesting to find GAs are having more difficulties to reach a better solution in the middle portion of the uncertainty level, and the underlying causes are not very clear. An explanation could be that it is easier for the GAs to find good solutions in the higher or lower end of uncertainties, where possible number of configurations is less, but it becomes tougher in the middle part, as the possible combination of solutions is the most complex. More real option studies led by Multi-objective Genetic Algorithm searches are needed to confirm this finding.

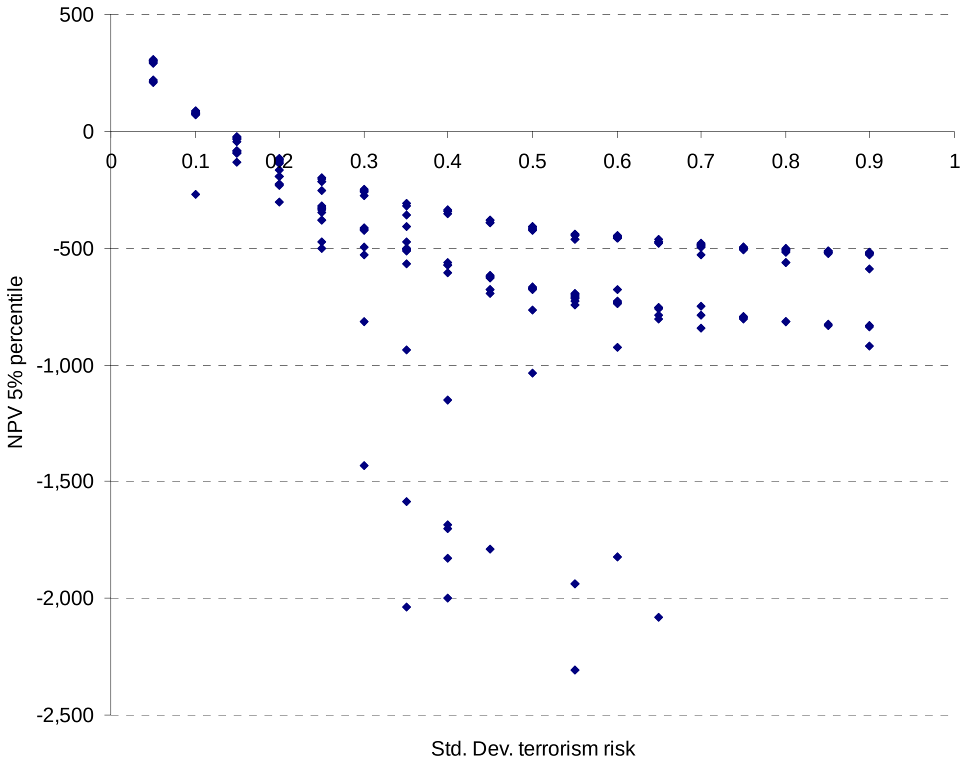

Figure 5. The 5% Percentile NPV versus Standard Deviation of terrorism risk.

4.4 Threshold of Decision Making versus Standard Deviation of terrorism risk

One feature of the decision tree used in this study is that Genetic Algorithms select the threshold of terrorism levels to switch to different configurations (see an illustration in figure 6). For example, Genetic algorithms may choose to partition all the possible risk levels into 3 branches equally, and use one cheaper configuration for the lower 1/3 of all risk levels, one medium level solution for the mid 1/3, and one expensive configuration for the upper 1/3 risk levels. Genetic algorithms can also decide to use one common configuration for the entire 90 percentile of the risk levels from bottom, and turn to a high performing configuration for the 90-98 percentiles, and use a very high performing configuration only for the top 2 percentile of very high risk levels. The GAs decide at which level the configurations should be changed based on the system performance over the whole lifespan of the project.

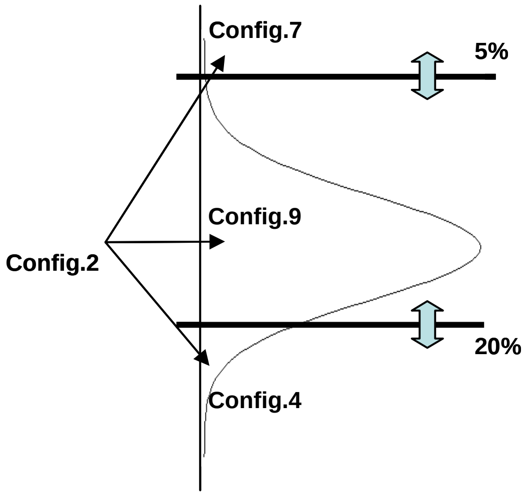

Figure 6. GAs decide at which level the configurations should be changed

The results revealed that at different levels of uncertainties, Genetic Algorithms use different shapes of decision trees to deployment different kind of adaptive plans. When the standard deviation of terrorism risk is from 30% to 50%, Genetic Algorithms usually use a bigger upper branch. When standard deviation of risk lies between 50% and 75%, GAs use a bigger middle branch, and as the standard deviation is between 75% and 100%, the popular strategy is to divert most of the paths at lower branch. Genetic Algorithm chose to do so entirely because that gives better performances for the system. The phenomenon is very interesting, but we have yet to understand the reason behind this. We do not know whether this is an endemic property of this maritime domain protection system or whether this phenomenon would emerge in other applications.

The study has also examined a lot of other system properties, among them the medium of the NPV, the relationship between the multi-objectives, the capability of GAs to find a good solution under different settings, the impact of switching cost of reconfigurations, and etc. Many of them are not intuitively easy to understand. With the large complexity, we believe there are a lot more system properties to be discovered.

5 Conclusions

Real options analysis does show the value of flexibility in a system and results in a roadmap for deploying the system, providing a better performance than traditional peak design can offer. The methodology integrates Genetic Algorithms, Monte Carlo Simulations and Decision Trees to deal with the complexity of multiple real options

along many uncertain paths future can take. Practitioners – managers, investors, and system designers can use the methodology to design and valuate many similar large scale projects.
The integral modelling shows quantitatively that the value of flexibility is highly sensitive to the underlying uncertainty level. It derives many interesting findings. Genetic algorithms is very effective in finding initial designs, suitable real options, and adaptive design, and GAs apply different deployment strategies for the decision tree at different levels of uncertainties by altering the thresholds of decision changing.

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