Marine Transportation Application of Risk-Based Decision Making

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Decision making frequently involves determining parameters that are imbued with uncertainty. This sometimes involves the use of subjective, qualitative methods, such as a risk ranking matrix, in which consideration is given both to the probability of occurrence and the expected consequences of an event. These are found on the horizontal and vertical axes of the matrix; inside the matrix are blocks denoting the expected severity of the situation, with each block denoting risk levels, such as acceptable, moderate, serious, and critical. The decision maker makes a qualitative determination of both input parameters, and where the two intersect on the matrix determines the severity of the situation, which informs the action to be taken. The inputs (probability of loss and resulting damage) are typically imprecise. Recent research has criticized methods such as the risk ranking matrix as being ineffective and for giving users a false sense of security, which can have serious consequences at sea.

One alternative is the use of Monte Carlo (MC) simulations. MC simulation is a quantitative risk analysis technique where the inputs, such as the probability of a loss event, are modelled as statistical probability density functions (PDFs) rather than given imprecise labels, such as low, medium, or high. Once the inputs have been characterized as PDFs, a MC simulation program can determine the expected outcome thousands of times using random numbers along with the PDFs to determine the actual values of each input parameter for each particular instance the simulation is run. This will result in thousands of outcomes being generated. The aggregation of these outcomes allows the decision maker to determine the outcomes for the worst case scenario, the best case scenario, and the most likely scenario, along with the statistical probability of each scenario. Such a tool is more powerful and informative than a risk ranking matrix.

The paper begins with an overview of risk ranking matrices and associated problems. Next, we provide an overview of Monte Carlo simulation and explain its use in marine risk management situations. We then present a hypothetical case in which a Monte Carlo simulation is used to advise the course of action for a shipping company considering using the Northern Sea Route instead of the Suez Canal for shipping between Rotterdam and Yokohama. We conclude that the use of Monte Carlo simulation is a promising option for risk-based decision making at sea, that significant work is required in the area of characterizing input parameters as PDFs, and that training in the areas of probability and statistics should be an important part of the curriculum at MET institutions.

Keywords: Monte Carlo simulation, risk ranking matrix, marine risk-based decision making, quantitative risk-based analysis, Northern Sea route, Suez Canal.

1. Introduction

When operating a vessel, dealing with uncertainties and risk is a part of everyday life. Decisions will always have to be made in the face of uncertainty, but it is the job of ship operators to be responsible in their decision making processes to ensure that their decisions do not unnecessarily endanger the lives of workers at sea. Decision making is a process that is always made in the face of uncertain events with known outcomes. Therefore, it is imperative that decision making processes involving the ocean are as sound as possible to prevent loss of life and property.

One famous example of marine decision making gone awry is that of Captain Edward Smith and the RMS Titanic. It is generally acknowledged that Captain Smith was warned about the potential for ice in the path of the Titanic, but he chose to proceed at normal speed despite the risk. This is a classic example of an individual having to make a decision in the face of the unknown – to reduce speed and

reduce the probability of striking an iceberg or to sail on at normal speed without reducing the risk. While the answer will never be known, it is valid to question if Captain Smith were fully aware of the actually probability of colliding with an iceberg or the magnitude of the potential consequences, might he have made a different decision? This paper will examine risk-based decision making processes at sea, and in particular, the use of Monte Carlo simulation as a means to facilitate risk-based decision making.

A more recent example is that of the British Petroleum (BP) Deepwater Horizon oil spill in the Gulf of Mexico in 2010. In this case, BP admitted that it made the final decision on a crucial negative pressure test that had been misinterpreted as showing that the Macondo oil well had been properly sealed with cement when it had not [1]. This was a mistake that led to catastrophic failure with human casualties and financial losses of approximately $50B as of Nov. 2010 [2]. If the magnitude of the potential loss had been understood in this case, it is likely that BP may have proceeded differently. In essence, BP placed a roughly $50B bet at unknown odds that its interpretation of the negative pressure test results were correct, a situation that could have been avoided through the use of better risk-based decision making models.

2. Risk Ranking Matrix-Based Decision Making

A popular method of assessing risk in marine industries is the risk ranking matrix, such as the one shown in Figure 1, which is from the 2011 annual report of PotashCorp [3]. This matrix is representative of the risk ranking matrices commonly used in ocean industries, although they are commonly tailored to suit the needs of the company or situation in question. When making a risk-based decision, consideration is given both to the likelihood of occurrence of the threat in question along with the expected consequences, and where the two intersect on the matrix determines the severity of the situation. For instance, an event that is considered 'probable' with a severity level of 3 (labelled Acceptable in this case) leads to a risk ranking of B, which as explained below, is considered to be a 'Major' risk that is to be addressed at the next available opportunity. One issue that is apparent with this matrix is that "Severity" and risk ranking are categorized using the same titles. A risk ranking of "Acceptable" can be found under the "Extreme" severity category. This alone could be very confusing when discussing a risk-based situation. For example, when one says the risk is low, does he or she mean that the overall assessed risk ranking is low, or does it mean that the severity is low, in which case, the assessed risk ranking might actually be major?

Furthermore, several researchers have recently pointed out flaws of using risk ranking matrices in industry. For example, Cox, as summarized by Talbot [4], pointed out the following limitations of risk ranking matrices:

1. They can correctly and unambiguously compare only a small fraction of randomly selected pairs of hazards and can assign identical ratings to quantitatively different risks;

2. They can mistakenly assign higher qualitative ratings to quantitatively smaller risks to the point where with risks that have negatively correlated frequencies and severities, they can lead to worse-than-random decisions;

3. They can result in suboptimal resource allocation as effective allocation of resources to risk treatments cannot be based on the categories provided by risk matrices;

PotashCorp Risk Management Ranking Methodology						
Risk Ranking Matrix		SEVERITY OF CONSEQUENCE				
		1	**2**	**3**	**4**	**5**
		Negligible	Low	Acceptable	Major	Extreme
LIKELIHOOD OR FREQUENCY	**5** Probable (0-6 months)	C	B	B	A	A
	4 High (6 months-2 years)	D	C	B	B	A
	3 Medium (2-10 years)	D	D	C	B	B
	2 Low (10-50 years)	E	D	D	C	B
	1 Remote (> 50 years)	E	E	D	D	C

A Extreme: Initiate mitigation activities immediately to reduce risk. If such activities cannot sufficiently reduce risk level, consider discontinuation of the applicable business operation to avoid the risk.

B Major: Initiate mitigation activities at next available opportunity to reduce risk. If such activities cannot sufficiently reduce the risk level, board approval is required to confirm acceptance of this level of risk.

C Acceptable: Level of risk is acceptable within tolerances of the risk management policy. Additional risk mitigation activities may be considered if benefits significantly exceed cost.

D Low: Monitor risk according to risk management policy requirements, but no additional activities required.

E Negligible: Consider discontinuing any related mitigation activities so resources can be directed to higher-value activities, provided such discontinuance does not adversely affect any other risk areas.

Figure 1 PotashCorp Risk Management Ranking Methodology [3]

4. Categorizations of severity cannot be made objectively for uncertain consequences. Assessment of likelihood and consequence and resulting risk ratings require subjective interpretation, and different users may obtain opposite ratings of the same quantitative risks.

Point number 2 is particularly troublesome as it indicates that in some circumstances, the decision maker is better off making a random assessment of risk than using the matrix – making the matrix "worse than useless," in the words of Cox [5]. As well, Wall argues that users of risk matrices claim risk scores provide the information needed to rank risks [6]. According to Wall, this is a baseless claim as the theory of decision making and research results describing actual decisions produce models that do not support the risk scoring in risk matrices, leading Wall to question the validity of risk scores obtained from risk ranking matrices. This makes the study of alternatives, such as the use of Monte Carlo simulation for risk-based decision making, that much more important.

3. Monte Carlo Simulation

Monte Carlo (MC) simulation is a method for modelling the output of a system that has varying inputs. In a system that has many varying inputs, it is often impractical to determine the expected outcome using deterministic methods as the inputs themselves cannot be determined with certainty. In such cases, Monte Carlo simulation may provide greater insight into how a system behaves.

MC simulation is a process that works by sampling values for input parameters from probability density functions (PDFs) that represent the input parameters. If the model calculates the output enough times, with input parameters randomly selected from the input PDFs, the model will eventually calculate the outcome for virtually every possible combination of input parameters – thus producing virtually every possible outcome. MC simulations not only theoretically produce all possible outcomes for a simulated problem, but also the probability of any particular outcome occurring can be computed. Essentially, it allows a decision maker to look at many, many 'what-if' situations as the input variables are randomly selected over and over again to produce the entire range of possible outcomes. MC simulation is best explained by example, as in the following section.

3.1 Example of a Monte Carlo Simulation Analysis

Liu and Kronbak [7] presented a case study which examined the economic viability of shipping from Rotterdam to Yokohama via the Northern Sea Route versus the conventional Suez Canal route as shown in Figure 2 [8]. They compared two basic scenarios to determine which was more economically viable – Option A: Buying a regular 4300 TEU vessel and shipping year round through the Suez Canal; Option B: Buying an ice class 4300 TEU to be used in the NSR during the months the NSR is navigable and which would be used for the Suez Canal route the rest of the year. The idea is that due to the significantly shorter distance though the NSR, option B trips will, on average, require significantly less time than the option A trips, thus allowing for more trips annually and generating more annual revenue using option B. Whether it is more profitable is another question.

Figure 2 The Northern Sea Route and the Suez Canal Route [8]

In this section of the paper, we will revisit this case study and create a Monte Carlo based analysis of the same question using the information and assumptions used by Liu and Kronbak [7]. As the purpose of this section of the paper is simply to present an illustrative example of using Monte Carlo simulation for marine risk-based decision making, we will refrain from critically examining the information used and assumptions made by Liu and Kronbak. Note that all dollar amounts in the following discussion are US dollars (USD).

3.2 Input Data for Monte Carlo Simulation

In their analysis, Liu and Kronbak [7] examine the economic viability of the using the NSR when it is navigable versus the Suez Canal under differing scenarios: the NSR is navigable for 91, 182, and 274 days in a given year (with differing ice cover scenarios in each case), bunker prices are $350, $700, or $900 per ton, and the icebreaking fee is set at $4M, $2M, $0.6M, and $0. They take each of these data points and compare them discretely. For example, what is the expected profit if the NSR is open 274 days, bunker costs $700/ton, and icebreaking fees are $4M? This produces a 9 × 9 matrix for the option B, which is then repeated three times for an assumed 50%, 85%, and 100% reduction in ice breaking fees. This produces four tables for option B. With a Monte Carlo analysis, our goal is to reduce this to a more straightforward comparison of the two options by modelling the differing input parameters as probability density functions (PDFs), which are then used to calculate the expected

profits under randomly varying input conditions. The analysis of all these outputs taken together can help make an informed decision about which option is more economically sound.

Here are the assumptions made and data used in the Monte Carlo simulation, which have been adapted from Liu and Kronbak [7]:

- Bunker prices per ton follow a triangular distribution (350, 700, 900);
- The number of days in any particular year that the NSR is navigable is represented by a triangular distribution (91, 182, 274);
- The icebreaking fee for the NSR varies uniformly between $0 and $4M;
- Annualized Capital Cost for non-ice class 4300 TEU is $4.4M;
- Annualized Capital Cost for ice-class 4300 TEU is $5.28M;
- Daily operating cost for non-ice 4300 TEU is $8925;
- Daily operating cost for ice-class 4300 TEU is $6100;
- Average ship speed in water containing ice is 10 knots;
- Average ship speed in ice free water is 18 knots;
- Fuel consumption per nm in ice water is 0.5 tons;
- Fuel consumption per nm in ice free water is 0.3 tons;
- Distance via NSR is 7100 nm;
- Distance via Suez Canal route is 11400 nm.

If the NSR is navigable, the amount of ice free water (for which navigation speed is higher than ice infested water) is directly proportional to the number of days that the passage is navigable. It is represented by the following formula:

$$ice\ free\ water\ (nautical\ miles)\ = 3.3 \times days\ navigable + 6100 \qquad (1)$$

The data regarding ice water/non-ice water distances in Liu and Kronbak's analysis is not exactly linear, but it is close enough that we have used the two outside points ([91, 6400] and [274, 7000]) to characterize all points in between for the purposes of this example [7].

3.3 Modelling the Simulated Trips

For either option A or B, the idea is to model the costs and revenue associated with many individual trips using Microsoft Excel and the @Risk software, which allows for the use of probability distributions that are not native to Excel, such as the triangular distribution. For the simulation, each line on the spreadsheet represents one simulated trip and its associated costs and revenues. Once many trips are simulated for a given option, the expected profit can be annualized by calculating the average number of trips that could be taken in a given year and multiplying that number by the expected profit per trip, which is just the average of the profits of all the trips for a given option.

Option A							
Simulated Trip Number	Bunker Price	Fuel Consumption	Fuel cost	Capital Cost	Operating Costs	Suez Canal fee	Profit for trip
1	480.21	3420	1642311.55	318112.63	160972.22	240800	$637,803.60
2	817.76	3420	2796753.09	318112.63	160972.22	240800	-$516,637.94
3	693.90	3420	2373149.60	318112.63	160972.22	240800	-$93,034.45
4	567.80	3420	1941889.95	318112.63	160972.22	240800	$338,225.19
5	647.51	3420	2214488.02	318112.63	160972.22	240800	$65,627.13
6	807.60	3420	2761979.99	318112.63	160972.22	240800	-$481,864.85

Table 1 Sample Simulated Trips for Option A

Table 2 Sample Simulated Trips for Option B

Option B				NSR												Suez						
Simulated Trip Number	Random number to determine route	Number days NSR expected to be navigable in given year	Probability of NSR open at a given point in the year	NSR	Suez Canal	Bunker Price	Ice Water (nm)	Non-Ice Water (nm)	Transit time (days)	Fuel consumption (tons)	Fuel Cost	Capital Cost	Operating Costs	Transit Fees	Profit for NSR trip	Fuel Consumption	Fuel cost	Capital Cost	Operating Costs	Suez fee	Profit for Suez Canal trip	Profit for trip
1	0.369280	192.9	0.528	1	0	694.21	365.7	6734.3	17.1	2203.1	1529438.40	247544.88	152728.86	1112973.38	-42685.53	3420	2374184.69	318112.63	235520.83	240800	-168618.16	-42685.53
2	0.417345	143.4	0.393	0	1	693.74	527.9	6572.1	17.4	2235.6	1550916.75	251889.54	155409.41	2092005.61	-1050221.31	3420	2372594.49	318112.63	235520.83	240800	-167027.95	-167027.95
3	0.481659	156.7	0.429	0	1	832.71	484.5	6615.5	17.3	2226.9	1854369.05	250726.19	154691.65	3642941.45	-2902728.35	3420	2847880.52	318112.63	235520.83	240800	-642313.99	-642313.99
4	0.055631	196.1	0.537	1	0	441.62	355.2	6744.8	17.1	2201.0	972010.06	247261.53	152554.04	790535.83	837638.54	3420	1510325.29	318112.63	235520.83	240800	695241.24	837638.54
5	0.584452	121.4	0.333	0	1	728.71	600.0	6500.0	17.5	2250.0	1639593.91	253821.03	156601.08	3360437.24	-2410453.25	3420	2492177.52	318112.63	235520.83	240800	-286610.98	-286610.98
6	0.039121	186.0	0.510	1	0	700.17	388.2	6711.8	17.2	2207.6	1545730.07	248146.54	153100.07	2821759.29	-1768735.96	3420	2394592.46	318112.63	235520.83	240800	-189025.93	-1768735.96

The modelling of option A, year round shipping via the Suez Canal, is straightforward as the only parameter that actually varies is the price of fuel. All other parameters are presented as average values (i.e. revenue per trip) in Liu and Kronbak's paper and are treated as constants for the Suez option. Refer to Table 1 for sample simulation results for option A.

The modelling of option B, shipping via the NSR part of the year and Suez Canal for the remainder, is slightly more complex because it involves conditional probability and several input variables that varied. Given that the costing is different depending on which route is taken, the first thing that has to be determined for an individual trip is whether it will be through the NSR or the Suez Canal, and this is dependent on the number of days in a given year that the NSR is navigable. A number of navigable days is generated by @Risk from the triangle distribution for NSR navigable days, and that number is divided by 365 to give the probability that the NSR will be navigable during any particular instance during a given year. Another random number between 0 and 1 is then generated, and if this number is less than the probability that the NSR will be navigable, the trip will be through the NSR. Otherwise the trip will be through the Suez Canal. This is denoted by a 1 or a 0 in the NSR or Suez Canal column for each trip instance. Then the expected profit for each route is calculated and multiplied by its corresponding trip column. For example, if NSR =0, Suez Canal =1, NSR Profit = $400,000, and Suez Canal profit = $500,000 for a particular line, the overall profit for that line will be $500,000 as it indicates that the Suez Canal route was taken in that instance.

As per formula 1, the number of navigable days is also used to determine how much of the NSR trip will be ice free, which will then be used to calculate the trip duration and the fuel consumed on the ice-free and non-ice-free portions of the trip (which each have different speeds and rates of fuel consumption). These figures are then used to calculate the cost of fuel consumed on a given trip. The capital cost for a trip is given by the annual capital cost of the ship in question divided by 365 and then multiplied by the calculated trip duration (in days). Operating costs are simply the length of the trip in days multiplied by the daily operating cost as noted above.

Table 1 shows sample simulations for option A, and Table 2 shows sample simulations for option B.

For illustrative purposes, each option was simulated with 500 trips. For option A, the simulated per trip (except for Annualized Profit) results are as follows:
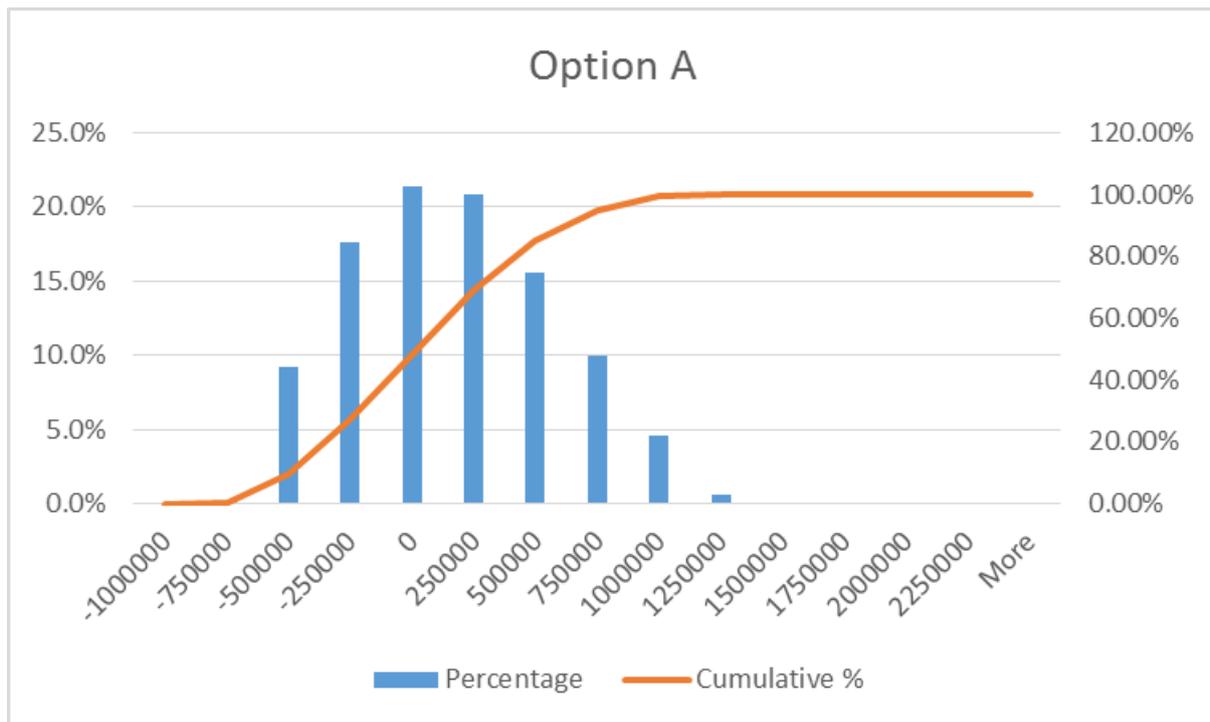
Average profit	$50,489.45
Standard Deviation	$386,686.43
Minimum Profit	-$764,189.79
Maximum Profit	$1,003,731.28
Annualized Profit	$698,348.83

For option B, the simulated per trip (except for Annualized Profit) results are as follows:

Average profit	-$468,162.25
Standard Deviation	$971,193.42
Minimum Profit	-$3,181,065.23
Maximum Profit	$1,550,458.83
Annualized Profit	-$7,770,219.23

In each case, the annualized profit figure is calculated by determining the average number of trips expected per year for each scenario and multiplying that number by the average profit per trip. While these numbers are somewhat informative for the decision making process in that they convey the average and extreme results for each scenario, they do not convey the entire picture. For instance, how likely is it that a trip will result in a profit greater than $0.5M for either option? Such a question is one that MC simulation can help answer.

Figures 3 and 4 show histograms of the profit distributions for each option which were generated from the MC simulations. For option A, the profit distribution appears to follow a triangular distribution. For option B, where there were multiple variables that had different distributions, the profit distribution is mostly centred around the $0 mark with lower probabilities of values occurring in the extremities of the distribution. From these histograms, one can see not only the extreme and average profit values but every value in between along with the probabilities of their occurrence. This is one of the biggest benefits of MC simulation. For instance, for option A, there is an approximate 16% probability that the profit of any given trip will be between $500K and $750K, which is easily seen with the aid of a histogram.

Figure 3 – Illustrative Histogram for Option A

As for the decision to be made in this example, if would depend on the criteria of the shipping company in question. While neither option seems particularly appealing from a profit point of view, option A, with an annualized profit of approximately $700K, seems more preferable than option B with its annualized loss of $7.8M. Ultimately, the outcomes of the analysis can only be as good as the data and assumptions that are used as the basis for the analysis. In this case, while we are confident in the methodology, we do not feel strongly enough about the underlying assumptions and data that we

would necessarily make recommendations based on this particular data. The purpose of this example is simply to present an illustrative example of how MC simulation could be used for marine risk-based decision making. If the input data accurately reflect current realities, the results of the analysis would be valid if enough simulated trips for each scenario were carried out. Therefore, ensuring that input data and probability distributions are as accurate as practicable is crucial to any decision making carried out with MC simulation. For instance, in this example, it would be crucial to incorporate the latest information regarding the NSR shipping fees and expected if the results of the simulation were expected to be relied upon. Furthermore, in their original analysis of NSR vs. Suez Canal shipping, Liu and Kronbak [7] made a simplifying assumption regarding cargo availability by assuming an average load factor of 60%. In reality, cargo availability, like other parameters considered in the simulation, is variable in nature. As such, if cargo availability were also properly modelled as a probability density function as part of the simulations, it would also make the outcomes more reliable.
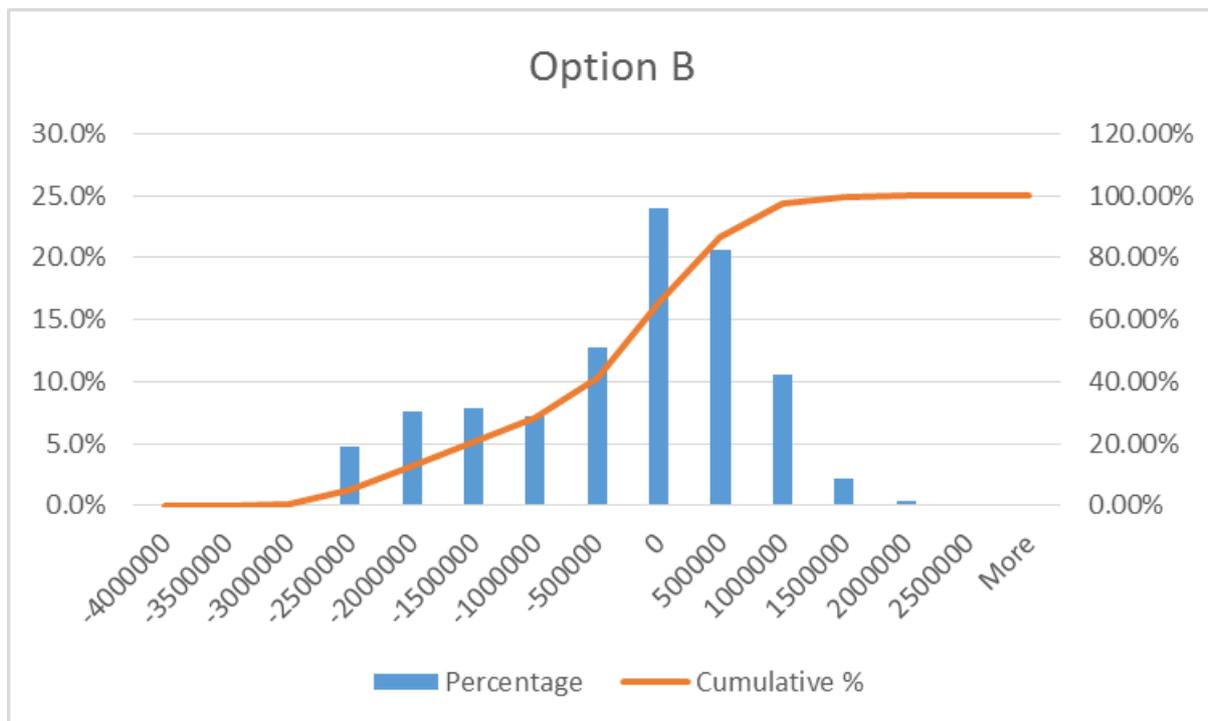

Figure 4 – Illustrative Histogram for Option B

4. Conclusions

Decision making in any industry is often the result of weighing many unknown parameters to determine a best course of action. The risk ranking matrix is one method currently widely used in marine risk-based decision making. Recent research has called into question the efficacy of this tool and the validity of any conclusions drawn from such an analysis.

We have examined an alternative process for marine risk-based decision making, one that uses Monte Carlo simulations to give the decision maker a better understanding of the scenario. Using Monte Carlo simulations, the decision maker can examine many, thousands or more if necessary, what-if scenarios whose outcomes will vary as the inputs change for each instance of a particular simulation. In general, while no one particular outcome is of special significance, if the input parameters reflect reality, the outcomes will be generated in quantities that are proportional to their probabilities of actual occurrence. Therefore, not only does this allow the decision maker to see the range of potential outcomes, but also the likelihood that any particular outcome, or range of outcomes, will occur. This makes MC simulations a powerful tool for marine risk-based decision making. As mentioned earlier,

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the analysis can only be as strong as the data upon which it is based. Therefore, care must be taken to ensure that input parameters are modelled to reflect reality as closely as possible.

If a Monte Carlo methodology is to be used for marine risk-based decision making, it does have obvious staffing and training implications. Given that it is crucial that input parameters be accurately modelled and classified as appropriate statistical distributions, anyone using MC simulation should have training in probability and statistics. Such training would also be very useful to anyone interpreting the outcomes of a Monte Carlo simulation. Therefore, training in the areas of probability and statistics should be an important part of the curriculum at MET institutions.

Acknowledgements

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