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Decision Analysis Applied to Small Satellite Risk Management

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Risk management plans improve the likelihood of mission success by identifying potential failures early and planning mitigation methods to circumvent any issues. However, in the aerospace industry to date, risk management plans have typically only been used for larger and more expensive satellites, and have rarely been applied to lower cost satellites such as CubeSats. Furthermore, existing risk management plans typically require experienced personnel and significant time to run the analysis.

The CubeSat Decision Advisor tool uses components of decision theory such as decision trees, multi-attribute utility theory, and utility elicitation methods to determine the expected utility of a mitigation technique alternative. Based on the user's value preference system, assessment of success probabilities, and resources required for a given mitigation technique, the tool suggests the course of action which will normatively yield the most value for the cost, people, and time resources required.

This research creates a risk management software tool never before available, and yet easily accessible and usable, for low cost small satellite missions. The target audience is primarily university labs, who could not otherwise afford expensive software packages. However, the interested parties now also include government, corporate, and international missions.

I. Introduction

Decision theory has commonly been used in applications of economics, investment strategy, game theory, medicine, the oil and gas industry, and operations engineering.[1-5] Existing applications in the aerospace industry are limited to large-scale missions or design studies.[6-10] This paper serves as the first known application of decision theory to the emerging topic of small spacecraft missions. The paper uses the methods of decision analysis in the area of risk management to identify the mission risk and/or root cause which, when mitigated, is the most efficient use of resources given the user-defined constraints of implementation cost, people required, and time to completion.

This paper describes a software tool created for solving this problem via multi-attribute utility theory combined with decision analysis principles. The tool is purposely designed for use by a spacecraft mission designer of any background or experience level and prompts the user to enter their mission-specific data, as well as provides options for the user to select the calculations they wish to analyze.‡

Small satellite missions, specifically CubeSats, are becoming more popular not only among universities, but corporate and government settings as well. CubeSats are satellites built using 10x10x10 centimeter cubes and were first developed at California Polytechnic Institue.[11] An initial effort has been made to appropriately scale risk management practices to these smaller satellites, since risks associated with larger (500 kg) class missions do not necessarily reflect risks associated with CubeSat missions. Earlier portions of this research have identified seven primary mission risks and 32 root causes for these risk events.[12,13] These risks and their associated root causes are used as the framework for the software tool which is described in this paper.

This paper first describes the mathematical foundation for the decision analysis and multi-attribute utility theory techniques employed in the software tool. Then, the tool itself is presented. Finally, the paper discusses the methods of validation and testing used on the tool to ensure its functionality and accuracy.

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‡ To learn more about the tool and obtain a copy visit https://sites.google.com/site/brumbaughresearch/research/-6-cubesat-decision-advisor.

II. Mathematical Background

Decision analysis makes use of decision trees and expected utility theory. Decision trees are a graphical representation for the possible outcomes of a set of alternatives. The trees typically contain decision and chance nodes, and a form of measuring preference of those outcomes. Utility theory is a manner of measuring the outcome preference and typically uses equations to describe a user's preference with respect to a certain variable. Furthermore, several variables can be used in multi-attribute utility theory to represent more complex situations which cannot be adequately explained in terms of one variable. Decision-makers can then use the decision trees combined with the expected utility theory to make their decisions. In the case of the CubeSat Decision Advisor software tool, users decide which mitigation technique will help them reduce the likelihood and/or consequence of a given mission risk.

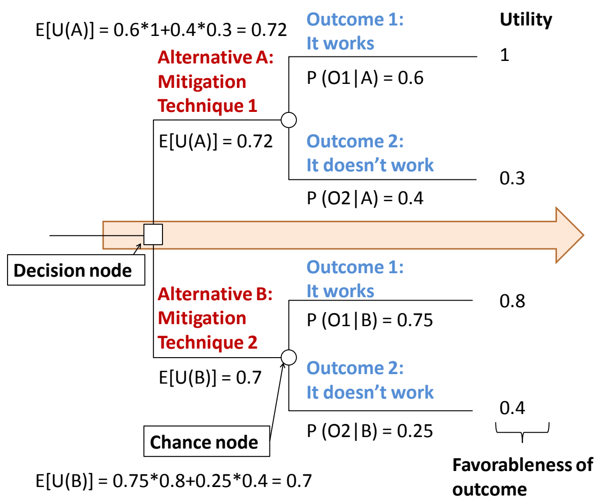

Figure 1. Example decision tree.

A. Decision Trees

A decision node is given by a square, and represents a choice to be made between several alternatives. The chance node is shown by a circle, and characterizes the possible outcomes of the alternative, typically noted by probabilities. An example decision tree is shown in Fig. 1 where there are two alternatives, A and B, each with two possible outcomes, O1 and O2. Note that decision trees may have any number of outcomes and associated probabilities; Fig. 1 simply represents a basic scenario related to this research in order to explain terminology. For alternative A, the choice to implement mitigation technique 1, the probability that the technique will be successful is $p(O1|A) = 0.6$, and therefore the probability that the technique will not be successful is $p(O2|A) = 1 - 0.6 = 0.4$. While in this illustration the probabilities for alternative B, implementing mitigation technique 2, are different than those for alternative A, this does not necessarily have to be the case. It is necessary, however, that the probabilities for outcomes of a single alternative sum to unity.

B. Utility Theory

In some cases, such as with money or time, it is easy to measure the preference of an outcome. However, not all variables can be ranked so easily; a more general approach is to use utility theory. Utility is defined as a true measure of value to the decision-maker.[14] Furthermore, by using utility as a common measurement, comparisons between alternatives can be made and a set of axioms may be established. Before outlining the rules of utility theory, Table 1 explains the language of denoting preference between two alternatives. The axioms of utility theory are: orderability, transitivity, continuity, substitutability, monotonicity, and decomposability. Further details regarding the axioms may be found in Ref. 14. It is assumed that all the axioms hold for the purposes of this research.

Table 1. Symbolic representation of alternative preferences

Symbols	Meaning
$A \succ B$	A is preferred to B
$A \sim B$	Indifference between A and B
$A \succcurlyeq B$	A is preferred to B

Once the axioms explained in Ref. 14 are met, a utility function may be created to map the degree of preference to a numerical format, and must follow the same axioms. Because the preferences are now expressed in a numerical format, the preference of a certain outcome, or lottery, can be calculated. For the purposes of this research, the utility of an outcome is determined by the method of expected utility. It is acknowledged that several other forms of utility calculations exist.[15,16] However, for the development of an initial software tool, expected utility was deemed to be the simplest to implement. Future iterations of the tool could implement these additional methods of utility assessment.

To determine the expected utility of an alternative, $E[u(\cdot)]$, the probability for each outcome of an alternative is multiplied by the utility value (u-value) for that outcome and summed over all the outcomes: $E[u(\cdot)] = \sum p_i u_i$. In the example provided in Fig. 1, the expected utility for alternative A would be $E[u(A)] = 0.6 * 1 + 0.4 * 0.3 = 0.72$. Similarly, for alternative B, $E[u(B)] = 0.75 * 0.8 + 0.25 * 0.4 = 0.7$. The decision-maker would be indifferent between these two alternatives when their expected utilities are equivalent: $E[u(A)] = E[u(B)]$. Otherwise, the decision-maker would choose the alternative with the greater expected utility.[17] In the example of Fig. 1, alternative A has the higher expected utility and normatively should be chosen.

In many cases it is necessary to determine a joint utility function which combines a set of important variables. Under the assumption of utility and preferential independence, a joint utility function, $u(x_1, x_2, \dots, x_n)$, can be obtained from the combination of the attribute utility functions, $u_i(x_i)$, by finding the k value which satisfies Eq. (1) given a user's preference system captured by the k_i values.[18] To obtain these k_i values, the decision-maker would be asked whether they prefer attribute x_1 at its best value while x_2 and x_3 are at their worst or whether they prefer attribute x_2 at its best value while x_1 and x_3 are at their worst. A series of such questions fully characterize the k_i values which then allows combination of the attribute utility functions into a joint multi-attribute utility function in accordance with Eq. (2). The k and k_i act as weights for the input parameters, placing a user-determined emphasis on the parameters when combining the attribute utility curves into the joint curve.

$$1 + k = (1 + kk_1)(1 + kk_2)(1 + kk_3) \quad (1)$$

$$ku(x_1, x_2, \dots, x_n) + 1 = \prod_{i=1}^{n} [kk_i u_i(x_i) + 1] \quad (2)$$

For the purposes of this research, the joint utility function $u(x_1, x_2, \dots, x_n)$ determines the user's utility value for the combination of cost, people, and time required for implementing a given mitigation technique. The expected utility value for the mitigation technique is therefore a function of this joint utility value as well as the probability of success for the technique outcome. The optimal mitigation technique choice is the technique which has the maximum expected utility value, as this technique will provide the most value for the given set of input parameters, including the users risk preferences. It is the identification of this optimal mitigation technique that is the primary purpose of the software tool.

Utility theory may independently be used in order to describe a preference system, but the theory is arguably more powerful when applied to decision analysis problems. By mapping a decision-maker's preference system to the decisions at hand, the decision-maker can analyze which outcomes will benefit their unique situation. This approach is used in the CubeSat Decision Advisor, described in Section III, to model the choice between mitigation techniques for reducing mission risk and help the user identify which technique best represents their preferences.

C. Eliciting Utility Preferences

The utility function can take many forms. During initial tool development, exponential, natural log, linear, and power equation forms were considered. After talking with experts regarding methods used in the decision analysis industry, it was determined to use the exponential function only, as it provided the most possibilities by simply changing the exponent parameter. The baseline exponential function is given in Eq. (3). The initial version of the tool found that $a = 0$ and $b = 1$ best represented logical utility preferences with four possible γ values for each of the attributes: cost, people, and time. These parameters are listed in Table 2. The attribute utility functions are scaled between the minimum value, 0, and maximum value designated by the user. Engineering judgment and experience led to the selection of the three sets of four utility functions, and it is acknowledged that an infinite number of alternative functions exist. However, for the purposes of this research, a few functions were selected with which to establish the software program.

Table 2. Exponential parameters for attribute utility functions.

	Cost	People	Time
γ_1	0.0001	0.05	0.01
γ_2	0.0005	0.15	0.025
γ_3	0.001	0.25	0.05
γ_4	0.002	0.5	0.1

$$u(x) = a + be^{-\gamma x} \quad (3)$$

The four utility function choices for each of the three attribute utility attributes provide a starting point to determine the preference system of the user. To determine which function best describes a user's preference towards a certain attribute, industry applications typically ask the decision-maker a series of questions. There are many ways in which to ask these questions. The use of a single lottery system is called the Standard-Gamble method, whereas comparing two lottery scenarios is called a Paired-Gamble method. Assuming event A is the most preferred outcome, D is the least preferred, and events B and C fall in between A and D, Fig.2 and Fig. 3 explain the difference between the two methods, including the manners in which the lottery question may be posed.[20]

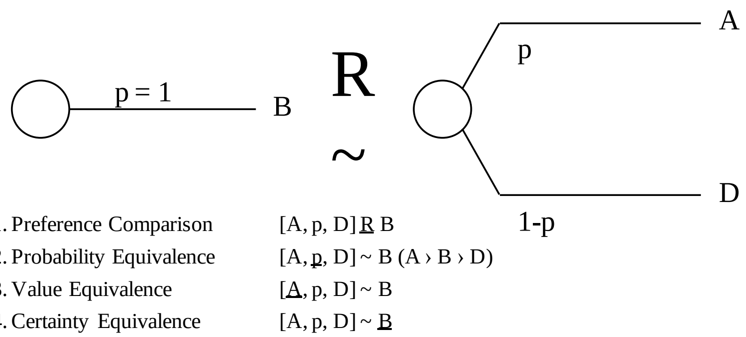

Figure 2. Standard-Gamble Method

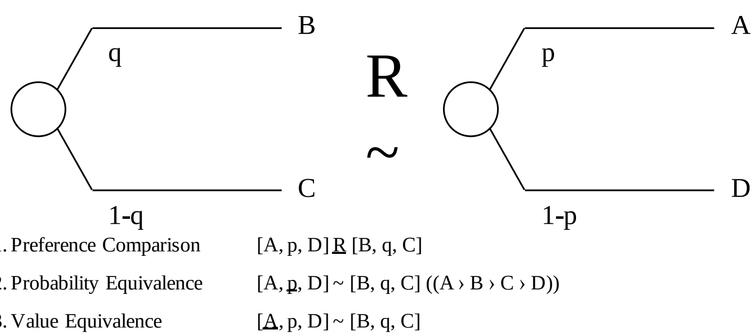

Figure 3. Paired-Gamble Method.

The Standard-Gamble method relies upon the use of comparing a guaranteed outcome to the possibility of obtaining either the most preferred or the least preferred outcome. This is illustrated in Fig. 2 where event A is the most preferred outcome and D is the least preferred. Event B falls somewhere in between the two such that, $A \succ B \succ D$. The Preference Comparison technique provides a probability of this A-D lottery and requests the decision-maker to decide whether the lottery is more desirable than the guarantee of event B. This comparison is denoted by the equivalence expression, [A, p, D] $\underline{\text{R}}$ B. It is the preference, R, which is being determined by the user and is therefore represented by an underline in its equivalence expression. The second comparison technique for the Standard-Gamble method is Probability Equivalence. In this scenario, it is the probability which is left for the user to determine and is thusly underlined in the expression, [A, $\underline{\text{p}}$, D] ~ B. What probability, p, would cause the user to be indifferent between a guarantee of event B and a possibility of the best or worst outcome? In other words, how likely would event A have to be before the user would accept a deal with a nonzero possibility of receiving their worst outcome? Similarly, the Value Equivalence method asks the user for the Event A which, given the probability and other outcomes, would cause the user to be indifferent between a chance at Events A or D, or receiving event B for certain. Since this method requires the user to enter the event A, it is represented by the expression [$\underline{\text{A}}$, p, D] ~ B. Finally, the Certainty Equivalence method asks the user for the event B which would make them indifferent between receiving B for certain and a chance at either event A or D. Event B therefore represents the user's certain equivalent for the lottery of a p probability for obtaining event A and a $(1-p)$ probability of obtaining event D.

Similarly as with the Standard-Gamble method, the Paired-Gamble method uses a lottery system to obtain user outcome preferences. The Paired-Gamble method, however, uses a set of two lotteries and asks the decision-maker to compare the two scenarios with one of three methods: Preference Comparison, Probability Equivalence, or Value Equivalence. These three methods are identical to their Standard-Gamble relatives, only now there are two lottery scenarios to consider, as depicted in Fig. 3. With two scenarios comes an additional event, event C. The preference order of these events is augmented to $A \succ B \succ C \succ D$. The Preference Equivalence, denoted by [A, p, D] $\underline{\text{R}}$ [B, q, C], asks the user to identify which lottery they prefer. Would the user prefer a p probability chance at their best scenario, or a q probability of receiving the second-highest scenario? Both scenarios have a possibility of obtaining one of the least desirable outcomes. The Probability Equivalence scenario, denoted as [A, $\underline{\text{p}}$, D] ~ [B, q, C], asks the user for the probability p which would make them indifferent between the lottery of experiencing event A with probability p and event D with probability $1-p$ or the lottery of experiencing event C with probability q and event

D with probability $1 - q$. Finally, the Value Equivalence, represented as [A, p, D] ~ [B, q, C], requests the user to identify the event A which would cause them to be indifferent between the same two scenarios.

As an example of each Standard-Gamble and Paired-Gamble situation, assume events A, B, C, and D are winning $100, $60, $20, and $0, respectively. Let the default p probability be 0.8 and the default q probability be 0.6; these are the p and q values unless the Gamble method requires the decision-maker to identify a probability. The Standard-Gamble Preference Comparison method asks the decision-maker to identify which lottery they prefer: (a) an 80% chance at winning $100 and a 20% chance at winning nothing, or (b) a guaranteed win of $60. The Probability Equivalence method asks a similar question, but requires the decision-maker to supply the probability of winning $100 which would make them indifferent between this lottery and a guaranteed win of $60. The Value Equivalence method returns to the default probability of 0.8 and asks the user to identify the outcome, with an 80% chance of winning, which would make them indifferent to a guaranteed win of $60. The Certain Equivalence method asks the decision-maker to decide what their guaranteed win value is which would make them indifferent between the default lottery of 80% chance of winning $100 and 20% chance of winning $0. This value is called the certain equivalent.

The Paired-Gamble methods are only slightly different from the Standard-Gamble comparisons in that the lotteries now feature a comparison between two scenarios. The Preference Comparison method now asks the users to indicate which lottery is more favorable: (a) an 80% chance at winning $100 and a 20% chance at winning $0, or (b) a 60% chance at winning $60 and a 40% chance at winning $20. The purpose of these comparisons is to determine the risk attitude of the decision-maker. Clearly, lottery (a) has a higher risk with a higher reward, but does this accurately describe the risk attitude of the decision-maker? The Probability Equivalence method once again asks the decision-maker for the probability which makes them indifferent between the two lotteries: (a) a p probability of winning $100 and a $(1 - p)$ probability of winning $20, or, (b) a 60% chance at winning $60 and a 40% chance at winning $20. Finally, the Value Equivalence method ask the decision-maker to indicate what outcome with an 80% chance of receiving would make them indifferent to a 60% chance at $60 and a 40% chance at $20.

The methods explained through example and summarized in Fig. 2 and Fig. 3 are a way in which to determine the decision-makers preference system. The Preference Comparison Paired-Gamble method is used in this software tool to establish the risk attitude of the user with regards to the individual attributes of cost, people, and time resources. The Probability Equivalence Standard-Gamble method is used to ascertain the manner in which the user is willing to trade worse outcomes of two individual attributes for a better outcome of the remaining attribute. The specific applications of these methods to the analysis of mitigation techniques are described in the next section.

III. Decision Advisor Software Tool

The preceding section described the principles of decision analysis used in the development of the CubeSat Decision Advisor. This section specifically describes how these concepts are used in practice throughout the software tool and describes the tool itself.

A. Theory as Applied to the Tool

The tool employs a normative risk management methodology with an interactive framework by which users can examine their spacecraft mission risks. Previous research identified seven primary mission risks: Schedule (SCH), Payload (PAY), Personnel (PER), Cost (COST), and three spacecraft risks (SC-1, SC-2, SC-3).[12] The same research also identified a total 32 root causes spread across the seven risks. While the tool has been built with regards to these seven risks and 32 root causes, any user would easily be able to modify them by changing the Visual Basic for Applications (VBA) code which is linked to the Excel file. However, the user would not easily be able to modify the number of risks or root causes, as the tool was built specifically for seven risks and 32 root causes. The risk management function of the software tool queries users for their choice of mitigation techniques and the probability of success for each technique, their cost, time, and people resource allocation, and their outcome preferences. Together, these inputs generate the utility curves which are then used for determining the expected utility of each mitigation technique and ultimately for providing the suggestions captured on the Summary page.

1. Utility Elicitation and Processing

The CubeSat Decision Advisor software uses the Preference Comparison Paired-Gamble method for obtaining the attribute utility function parameters, and employs the Probability Equivalence Standard-Gamble method to determine the k_i values for combining the attribute functions into the joint function per the discussion in the Utility Theory section. The elicitation of the attribute utility function asks a series of eight lottery comparison questions.

The determination of the k_i values exactly follows the Probability Equivalence Standard-Gamble method, and the user is requested to provide a probability that would make them indifferent between the attribute parameter scenarios.

To enter the attribute utility curve preferences, the user selects one of the following buttons on the Summary page: "Enter Time utility preference", "Enter Cost utility preference", or "Enter People utility preference," as shown in Fig. 4. Once an option is selected, the associated preference Graphical User Interface (GUI) will appear, such as the one shown for the Cost attribute in Fig. 5. The first screen for any of the attribute preference GUI screens will prompt the user to enter a maximum value to be used in the analysis. This maximum value identifies the best and worst scenarios. These limiting situations also scale the utility value results so that the best scenarios have a utility value of unity, and the worst situations have a utility of zero. The user must enter a maximum value, otherwise the program will not let them continue. For example, assume the maximum allowable cost to be spent on any mitigation technique is $5000.

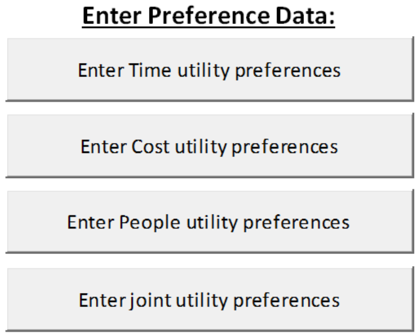

Figure 4. Entering preference data on the summary page.

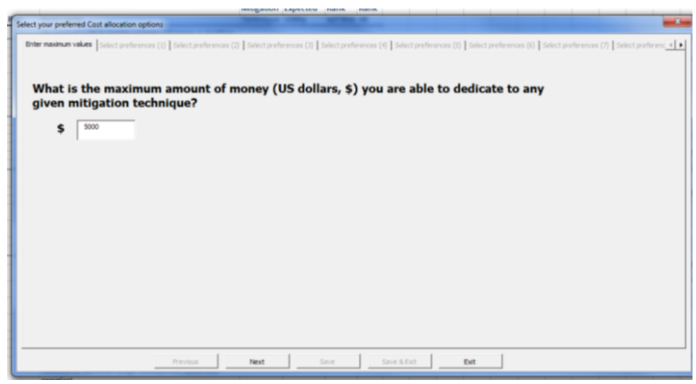

Figure 5. Entering maximum cost allowed.

Once the user has entered a maximum attribute value, the next eight screens go through a series of lottery comparison questions with the purpose of determining which exponential parameter best describes the user's value preference system. For a description of the utility function and parameters, see the previous section. Each question consists of a set of two lottery scenarios in which the user selects the more preferable scenario. By selecting one lottery over another, one of the utility function forms is selected. When the user finishes the series of eight questions, the tally of utility function selections is calculated and the function with the most scenarios selected is determined to be the user's preference system for the given attribute.

These lottery scenarios are created based on the user's defined maximum value and follow Utility Theory. Namely, the software is trying to find the certain equivalent that best describes the user's preferences. Recall that the utility functions follow an exponential form, $u(x) = a + be^{-\gamma x}$, with $a = 0$ and $b = 1$. Therefore, changes in utility function are solely due to the change of the gamma parameter. Because the attribute utility functions are scaled according to Eq. (4), the best and worst scenarios correspond to a utility of 1 and 0, respectively, and the utility of the certain equivalent is then the probability of the lottery. This is because of expected utility calculations: $p * u(best) + (1-p) * u(worst) = p * 1 + (1-p) * 0 = p$. Rather than asking the user to supply a probability or a certain equivalent value, it was decided to provide two lottery options and have the user select the more preferred scenario; each option represents a different γ parameter for the exponential utility function. These certain equivalent options were calculated based on four probabilities, 0.1, 0.25, 0.5, and 0.75. Thus, these four probabilities represent the certain equivalent utility value. The certain equivalent value, x, may then be calculated Eq. (5) and are shown, rounded as in the software, in Table for each probability and γ value.

$$u' = \frac{e^{-\gamma x} - e^{-\gamma x_{worst}}}{e^{-\gamma x_{best}} - e^{-\gamma x_{worst}}} \tag{4}$$

$$x = -\frac{1}{\gamma}\ln\left(u \cdot \left(e^{-\gamma x_{best}} - e^{-\gamma x_{worst}}\right) + e^{-\gamma x_{worst}}\right) \tag{5}$$

Table 3. Lottery parameters for each attribute and exponential value.

	Cost Attribute			
p	$\gamma_1 = 0.01$	$\gamma_2 = 0.025$	$\gamma_3 = 0.05$	$\gamma_4 = 0.1$
0.1	$4,371	$3,499	$2,244	$1,151
0.25	$3,497	$2,332	$1,366	$693
0.5	$2,191	$1,229	$686	$346
0.75	$1,035	$521	$285	$143
	People Attribute			
p	$\gamma_1 = 0.05$	$\gamma_2 = 0.15$	$\gamma_3 = 0.25$	$\gamma_4 = 0.5$
0.1	9	8	7	4
0.25	7	6	5	3
0.5	4	3	2	1
0.75	2	1	1	1
	Time Attribute (days)			
p	$\gamma_1 = 0.01$	$\gamma_2 = 0.025$	$\gamma_3 = 0.05$	$\gamma_4 = 0.1$
0.1	27	26	24	19
0.25	28	26	21	13
0.5	18	15	11	7
0.75	9	7	5	3

With a maximum allowable cost of $5000, the first lottery scenario is shown in Fig. 6. This scenario provides two lottery options and asks the user to identify which option more accurately represents their opinion of the cost attribute. The best scenario is defined as a mitigation cost of $0 while the worst case scenario is defined as a cost of the maximum allowable amount. The left-side lottery is asking whether the user thinks $1151 is the certain equivalent of a 10% chance at the best scenario and a 90% chance at the worst scenario. Essentially, if someone were to say, "I guarantee that the mitigation cost will be $1151," would the user find this guarantee equivalent to a 10% chance at the best and a 90% chance at the worst scenarios? Or, as the right-side lottery suggests, does the user value a higher cost, but a higher chance at the best scenario? Is a guarantee of $3497 equivalent to a 25-75 chance at the best and worst scenarios? Most panels of lottery scenarios ask this question: is the user willing to sacrifice a higher chance at the worst scenario for a lower attribute value? If the answer is consistently yes, the user's responses will result in selecting the most conservative utility function. Some of the panels serve as consistency checks in that the questions purposely ask if the user would prefer a lower attribute value for a lower risk value. If the decision-maker is logical, they would consistently prefer the lower value-risk combination.

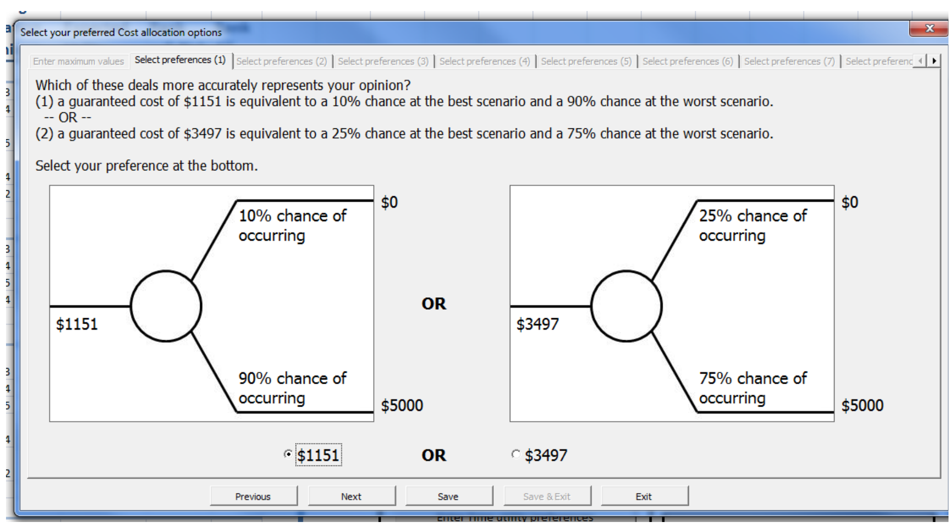

Figure 6. Example lottery scenario for Cost attribute preference.

After submitting the preferences for each of the attributes to obtain three separate attribute utility functions, the user must supply their preferences for the combination of these attribute functions into the joint utility curve. Fig. 4 shows the option, "Enter joint utility preferences" from which the user can identify their preferences of the combined attributes.

After selecting the "Enter joint utility preferences" option, the user will see the screen given in Fig. 7. This lottery uses the Probability Equivalence Standard-Gamble method and asks the user to supply a probability, p, which would make them indifferent between receiving a specified guaranteed outcome and a p probability chance at the best scenario with a $(1 - p)$ chance at the worst scenario. There are only three panels for eliciting the joint utility preferences, as the resulting three values fully characterize the manner in which to combine the attribute utility functions into a joint function.

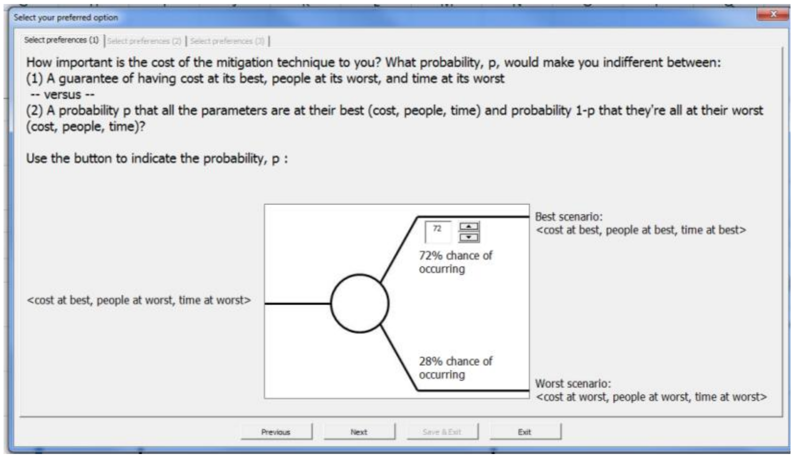

Figure 7. Entering joint utility preferences.

The first panel shows a guaranteed outcome of cost at its best, people at its worst, and time at its worst. This combination is denoted by <cost at best, people at worst, time at worst>. Let the lottery of this first panel be denoted as L_1 and represent a chance with p_1 probability that all the attributes are at their best with a $(1 - p_1)$ probability the attributes are at their worst. Recall that the best scenario consists of $0, 0 people, and 0 days to implement the mitigation technique, whereas the worst scenario consists of the maximum allowable values of each of the attributes. The user is asked to specify what probability p_1 would make them indifferent between the lottery L_1 and a guaranteed set of attribute values consisting of the best cost, $0, but the maximum number of people and time required for the mitigation technique implementation. Basically, the user is asked for the percentage of the "perfect" case they view the <cost at best, people at worst, time at worst> scenario. Similarly, the second panel asks the user for their preference of <cost at worst, people at best, time at worst> while the third panel focuses on <cost at worst, people at worst, time at best>.

These three panels are asking the user to decide which, if any, of the attributes they value more highly. It is possible to have all attributes viewed equally, in which case the probability values would be the same for each of the three panel scenarios. Users may value one or more of the attributes higher than the others. As an example, assume the user valued cost more highly than the people or time required to complete the mitigation technique, but viewed time and people as equally valuable. The responses for each of the panels in this case could be: $p_1 = 0.9,\ p_2 = 0.7,\ p_3 = 0.7$. A probability value of 0.9 for cost at its best signifies that the user believes this scenario is 90% of the best case possible. Similarly, people, p_2, and time, p_3, at their best are 70% of the best scenario.

The probability values obtained through the three joint utility elicitation panels are equivalent to the k_i values necessary for combining the attribute utility functions into a joint utility function. That is, $p_1 = k_1,\ p_2 = k_2,\ p_3 = k_3$. With these k_i values, the k value needed to properly combine the attribute utility functions can be found implicitly by an Excel Solver routine following Eq. (1) and then into the joint function according to Eq. (2). Once the user submits their joint attribute probability values via the GUI, these k_i values are stored, and the software tool automatically calculates the k value required to satisfy Eq. (1). With the attribute utility functions and k_i values properly defined, the software tool is able to calculate the joint utility value (u-value) for any combination of cost, people, and time inputs. The resulting u-value is then scaled by the best and worst scenarios. It is these scaled u-values which are used in the decision tree analysis.

2. Decision Trees and Utility Calculations

The software tool decision tree framework is illustrated in Fig. 8. The mission risks and associated root causes, as identified by previous research, and identified mitigation techniques are represented as decision nodes, since the user faces the decision of which risk and root cause combination to mitigate as well as the technique to implement. The chance node consists of the possibilities that the mitigation technique fully works, partially works, and does not work. The user provides the necessary inputs data: probabilities, resource allocations, and the choice of mitigation technique through a series of Graphical User Interfaces (GUIs). In addition, the software tool prompts the user for their cost, time, and people value preference systems as explained in the previous section. After submitting all this data, the user prompts the tool to calculate the expected joint utilities and output the results on the summary page. With the analysis completed by the software tool, the user may then decide which risks or root causes to mitigate.

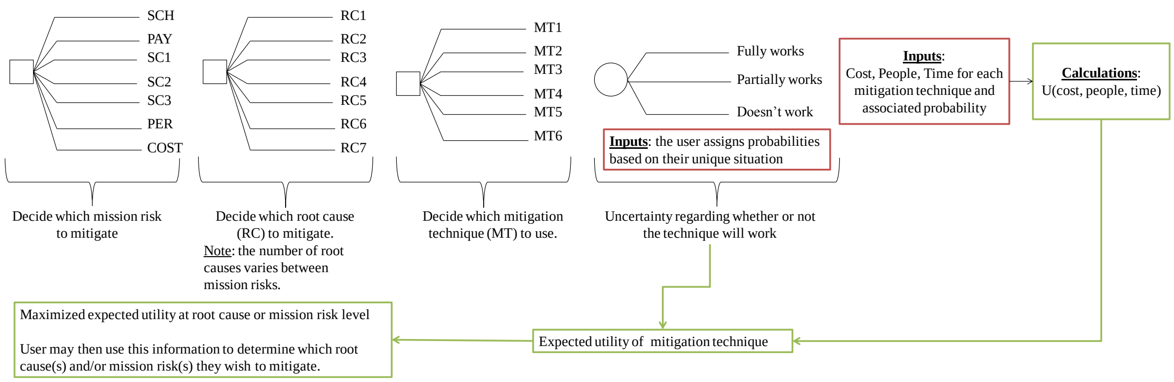

Figure 8. Decision analysis framework

The framework of Fig. 8 gives a high-level view of the entire tool while Fig. 9 shows a representative image of the Schedule (SCH) mission risk decision tree. Note that the tool is too large to view easily in images. To learn more about the tool, please visit the research website mentioned on the first page. The other six mission risks have a similar decision trees. The root causes are in numerical order down the page, each with the associated six mitigation

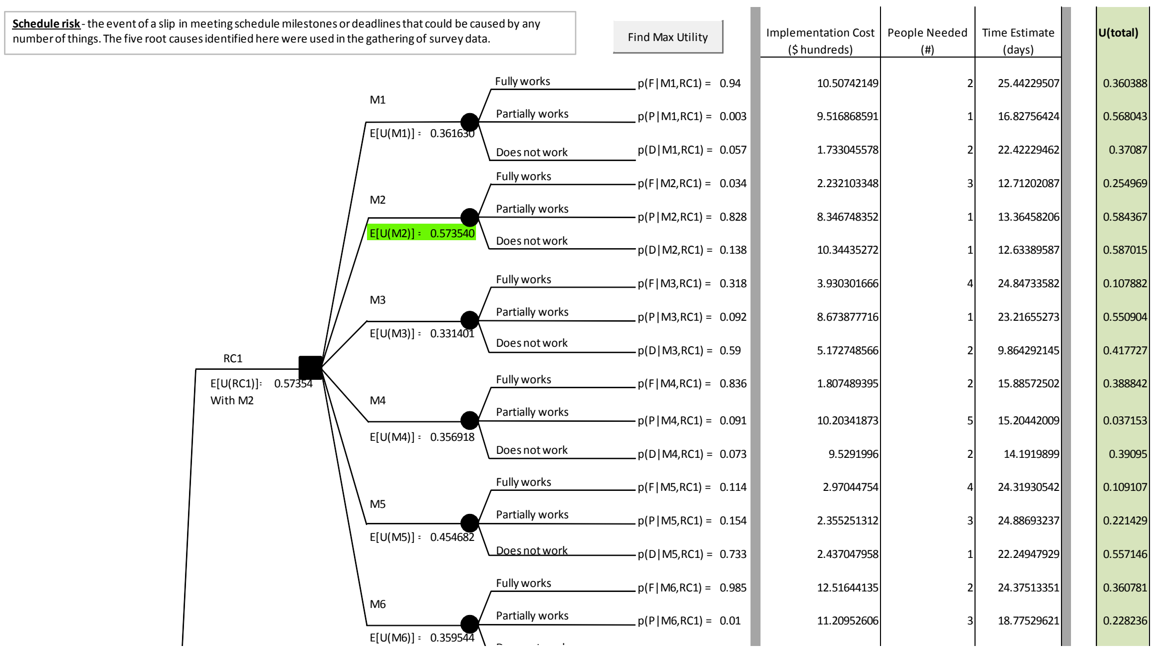

Figure 9. Portion of Schedule (SCH) decision tree

techniques selected for analysis and the three possible outcomes of fully works, partially works, and does not work. When entering the data for each root cause, the user can choose to select up to six mitigation techniques but need not select all six. Any piece of information not provided is assumed to be zero and will not affect the decision analysis techniques. Similarly, if the user deems one of the root causes does not apply to their mission, they need not enter data for that root cause. The input data of cost, people, and time needed for technique implementation are listed to the right of the decision tree, in line with the mitigation technique to which they reference. The joint utility value completes the tree to the right of these input parameters.

Once the user has provided all the necessary input parameter data, they must select the option to replace their data into the decision tree, using the "Replace values and probabilities" option shown in Fig. 10, which appears in the Options bar of the Summary Page. This button places the entered data in the appropriate location of the appropriate risk decision tree. Should the users realize they had incorrectly input data, they are able to update the information in the Form Responses sheet at any time, and simply click the button again to replace the new data.

After ensuring the replaced data is correct, the user may select "Only calculate utilities" from the Calculations option bar shown in Fig. 10, and the software will automatically calculate the expected utility for each mitigation technique of each root cause for all mission risks. The utility functions themselves, as defined in the Utility Theory section, are user-defined functions in Excel VBA. The functions rely upon the user preference system obtained from the Utility Elicitation methods mentioned previously. These values fully define not only the utility functions for a given attribute, but the manner in which the single functions are combined to the joint utility function. If "Only summarize utilities" is selected, the software highlights the mitigation technique with the maximum expected utility per each root cause, and places this information in a box at the root cause level of the decision tree as well as on the Summary Page. "Calculate and summarize utilities" first calculates the mitigation technique expected utilities and then summarizes these on the decision tree and on the Summary Page. It is recommended to always use the "Calculate and summarize utilities" option, so as to avoid having calculated the utilities but not having replaced the summary information. However, the options exist in separate buttons for tool flexibility. Refer to the Utility Theory section for explanations of expected utility theory.

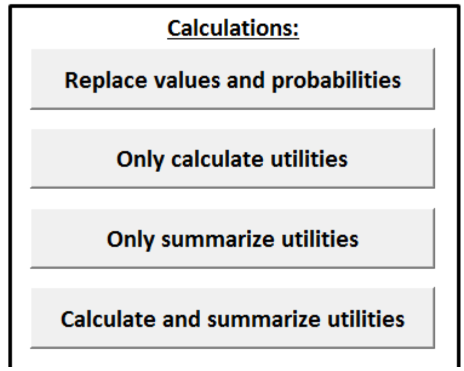

Figure 10. Calculations options on Summary page.

Once the utilities have been calculated, and the summaries provided not only on the mission risk worksheets but on the Summary page, the user is ready to make their decision. The Summary page lists all of the mission risks, their root causes, the associated best mitigation technique, and expected utility values. In addition, the Summary page lists the rank of that root cause expected utility within the mission risk as well as compared to all root causes. Normatively, the user would choose to mitigate the root cause which has the highest expected utility, with an overall rank of 1. The highest expected utility means that the mitigation technique has the user-defined best combination of success probabilities and cost, people, and time required for implementation. However, it may be possible that the user can afford to implement more than one mitigation technique. The rankings allow the user to successively apply their resources to reduce their mission risk in the most effective manner.

B. Description of Tool

The CubeSat Decision Advisor software tool contains a number of worksheets, each of which serve a different purpose.

The Summary page, represented in Fig. 11, displays all the relevant information needed to make a decision regarding which mitigation technique is the most effective way to decrease the mission risk likelihood and/or consequence given the user's preference system, assessment of success probabilities, and resources required for a given mitigation technique. The Summary page also contains the Options bar, displayed in Fig. 12, which allows users to enter the relevant information for, and select, the analysis they wish to complete.

The Mitigation Techniques sheet displays all the possible mitigation techniques for each risk and root cause. This sheet allows users to select a pre-defined mitigation technique, or to write one of their own into the analysis.

Once the user enters information through the Options Bar on the Summary page, the results are captured in the Form Responses sheet. The user will be able to edit this page in the event they realize they entered data incorrectly. The data from the Form Responses sheet is used in the calculations and analysis throughout the tool, therefore it is imperative to ensure the data is correct.

Mission Risk	Root Cause	Winning Mitigation Technique	Associated Expected Utility	Rank w/i Risk	Rank All	Fully Works Cost	Fully Works People	Fully Works Time	Partially Works Cost	Partially Works People	Partially Works Time	Doesn't Works Cost	Doesn't Works People	Doesn't Works Time
Schedule	The event of a slip in meeting schedule milestones or deadlines.													
RC1	Inability to find desired spacecraft components	With M3	0.318979788	5	26	6.263332	3	12.66944	10.2374935	3	20.2854156	2.41396904	3	21.2902355
RC2	Mechanical design delays (such as issues with the CAD or drawings)	With M4	0.322655377	4	19	11.28644	4	22.3505	1.01858139	2	14.0314102	9.25723076	3	14.0122223
RC3	Software design delays (such as basic component functionality or embedded coding issues)	With M5	0.350805354	3	12	13.76102	2	5.826721	5.25983334	2	15.9847212	13.8210678	2	27.6825333
RC4	Delay due to issuse with payload provider (may be related to delivery of EDU or flight unit, documentation, or interface issues)	With M4	0.370916416	2	5	9.551907	1	27.0887	5.83312988	2	21.0925007	6.33551598	1	11.3970375
RC5	Delay due to inadequate documentation	With M2	0.459951607	1	1	7.094498	1	20.58936	3.83512974	4	22.7975655	1.26394272	1	9.86307144
Payload	The event of failure to gather payload data.													
RC1	Software interface issues between payload and spacecraft bus	With M3	0.318979788	4	26	6.263332	3	12.66944	10.2374935	3	20.2854156	2.41396904	3	21.2902355
RC2	Hardware/electrical interface issues between payload and spacecraft bus	With M4	0.322655377	3	19	11.28644	4	22.3505	1.01858139	2	14.0314102	9.25723076	3	14.0122223
RC3	Payload malfunction due to mechanical issues	With M5	0.350805354	2	12	13.76102	2	5.826721	5.25983334	2	15.9847212	13.8210678	2	27.6825333
RC4	Payload malfunction due to software issues	With M4	0.370916416	1	5	9.551907	1	27.0887	5.83312988	2	21.0925007	6.33551598	1	11.3970375
SC-1	The event of inability to communicate with the spacecraft.													
RC1	No frequency on which to communicate with spacecraft due to delay in receiving frequency allocation	With M3	0.318979788	5	26	6.263332	3	12.66944	10.2374935	3	20.2854156	2.41396904	3	21.2902355
RC2	Failure of spacecraft radios (due to either hardware or software issues)	With M4	0.322655377	4	19	11.28644	4	22.3505	1.01858139	2	14.0314102	9.25723076	3	14.0122223
RC3	Failure of spacecraft antennas due to improper deployment or activation	With M5	0.350805354	3	12	13.76102	2	5.826721	5.25983334	2	15.9847212	13.8210678	2	27.6825333
RC4	Failure of ground station radios (due to either hardware or sofware issues)	With M4	0.370916416	2	5	9.551907	1	27.0887	5.83312988	2	21.0925007	6.33551598	1	11.3970375
RC5	Failure of ground station antennas (due to either hardware or software issues)	With M2	0.459951607	1	1	7.094498	1	20.58936	3.83512974	4	22.7975655	1.26394272	1	9.86307144
SC-2	The event of inability to gather health data from spacecraft.													
RC1	Failure of flight computer (due to either hardware or software issues)	With M3	0.318979788	5	26	6.263332	3	12.66944	10.2374935	3	20.2854156	2.41396904	3	21.2902355
RC2	Failure of sensors gathering health data (due to either hardware or software issues)	With M4	0.322655377	4	19	11.28644	4	22.3505	1.01858139	2	14.0314102	9.25723076	3	14.0122223
RC3	Failure of actuators causing unstable spacecraft motion (due to either hardware or software issues)	With M5	0.350805354	3	12	13.76102	2	5.826721	5.25983334	2	15.9847212	13.8210678	2	27.6825333
RC4	Failure of power regulation/battery system (due to either hardware or software issues)	With M4	0.370916416	2	5	9.551907	1	27.0887	5.83312988	2	21.0925007	6.33551598	1	11.3970375
RC5	Failure of solar panels to generate power (due to either hardware or software issues)	With M2	0.459951607	1	1	7.094498	1	20.58936	3.83512974	4	22.7975655	1.26394272	1	9.86307144
RC6	Unexpected thermal environment caused system issues	No data entered	0	6	33									

Figure 11. Portion of summary page showing all mission risks.

The next seven worksheets in the CubeSat Decision Advisor software tool represent the seven mission risks listed in Table 4: Schedule (SCH), Payload (PAY), Spacecraft-1 (SC-1), Spacecraft-2 (SC-2), Personnel and Management (PER), and Cost (COST).[12] Each sheet contains the mission risk decision tree with pre-defined root causes and mitigation techniques to be analyzed. Note that the root causes do not have a description on the tree itself, and could be redefined by the user. The only time the root causes are defined is on the user interface where data is entered. The user-entered data is reflected the right-most columns of the decision tree – probabilities, implementation cost, people needed, and time estimates. A portion of the Schedule mission risk is shown in Fig. 9, the other mission risks are similar in format, but will differ based on the users inputs.

The ucurves sheet contains the data obtained from eliciting the user's preference system. The restore worksheet replaces the current data with the default example case. This is primarily helpful for users wanting to begin working with the software tool.

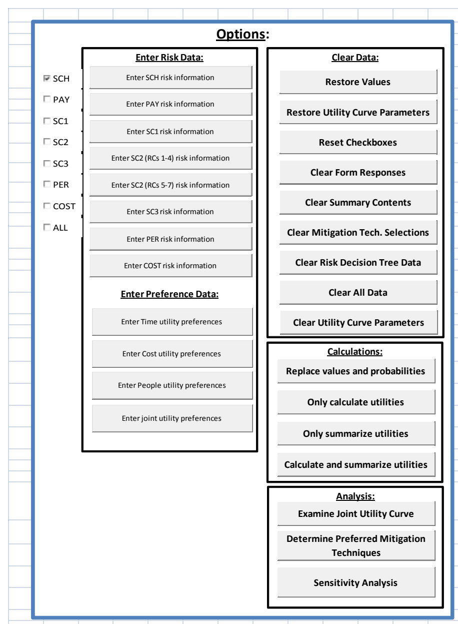

Figure 12. Options Bar on Summary Page.

After obtaining the user attribute preferences as explained in the Utility Elicitation section, the user enters their unique mission parameters for analysis through a graphical user interface (GUI) such as the one shown in Fig. 13. A separate GUI exists for each mission risk, and each GUI includes all of the root causes for that mission risk along the tabs. The user selects the mitigation techniques they wish to analyze, as well as provides their estimates of success probabilities and resource allocation of cost, time, and people required for each mitigation technique. The user is then able to identify, based on their unique set of preferences and probabilities, the mitigation technique which will yield the maximum expected utility for a single root cause of a single mission risk. The maximum root cause utility values for all mission risks are then recorded on a summary page where the user can identify the technique(s) they wish to implement in order to reduce the mission risk(s).

Table 4. Seven mission risks with descriptions.

Mission Risk (Acronym)	Description
Schedule (SCH)	The event of a slip in meeting schedule milestones or deadlines.
Payload (PAY)	The event of failure to gather payload data.
Spacecraft-1 (SC1)	The event of inability to communicate with the spacecraft.
Spacecraft-2 (SC2)	The event of inability to gather health data from spacecraft.
Spacecraft-3 (SC3)	Inability to meet spacecraft standards (i.e. international standards for spacecraft design, development, launch, and operation).
Personnel and Management (PER)	The event of insufficient personnel management.
Cost (COST)	The event of lack or delay of funding.

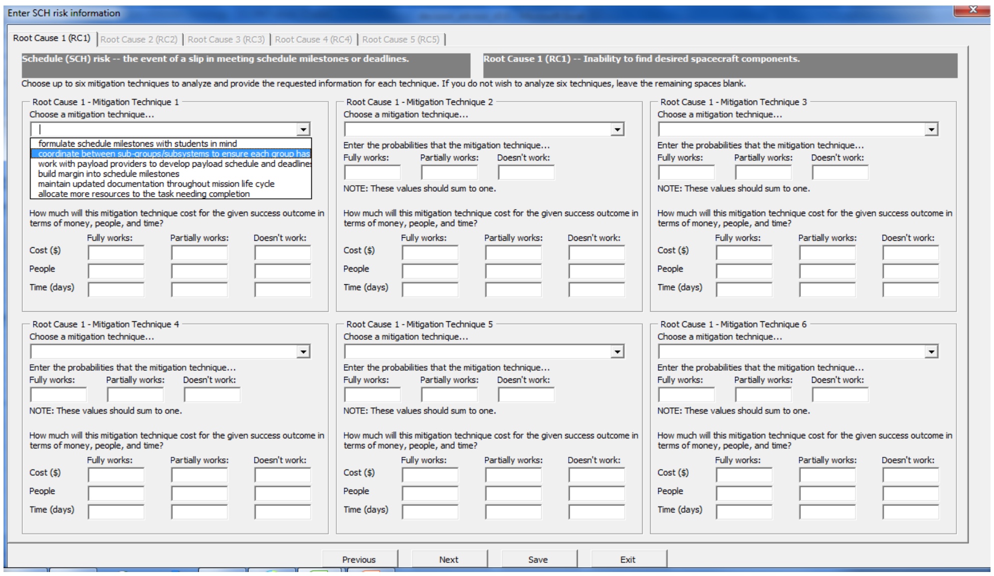

Figure 13. Mission parameter input graphical user interface.

While the software tool may be used fully with pages and capabilities mentioned above, the user may desire the use of the following additional analysis options illustrated in Fig. 12.

1. Examine Joint Utility Curve

This option will direct the user to the Joint worksheet where there exists an interactive plot. The user must enter the number of people for which they wish to view the joint utility curve in order to hold one attribute constant for viewing in a 3-D manner, and then select the "PLOT!" button. Recall that the joint utility curve gives the user's preference system with respect to all three variables – cost, people, and time – required for a given mitigation technique. This plot details the importance of certain values of the cost, people, and time parameters. The user may determine the utility of any given set of parameters by examining the data table.

2. Determine Preferred Mitigation Techniques

This option directs the user to the Additional ("Addtl") page where the mitigation technique preferred the most number of times within a mission risk is displayed. This helps the user determine if there are any mitigation techniques which would be useful across the entire mission risk, not just for a given root cause. Note that the displayed mitigation technique should match with the mode for each mission risk category of the "Winning Mitigation Technique" column of the Summary page.

3. Sensitivity Analysis

This option requires the user to first indicate which risks they wish to analyze by checking or unchecking the checkboxes within the Options panel.The sensitivity analysis looks at the user's input and determines how the output would be affected if the user's preferences were slightly different. That is, the program re-calculates the decision result with different u-curve preference information in the form of varying k and gamma values. Recall that the k values are used to combine the individual parameter utility functions while the gamma value is a parameter of the utility function itself. The sensitivity analysis is meant to provide the user a sense of how their decision would change if their preference system was slightly different. This additional capability is based on the same algorithms employed by the validation and testing sensitivity analysis to be explained in the next section.

IV. Validation and Testing

Since there is no inherent data set associated with the Decision Advisor with which to test the assessment accuracy of the tool, and no similar existing tool is readily accessible, validation and testing is completed via case study analysis. Mathematically simple cases provided a method of error-checking the software to ensure that known results were obtained when the associated inputs were supplied. Sensitivity analysis supplied insights into how the decisions would change should a parameter only slightly deviate from its nominal value. Monte Carlo analysis investigated the effect of different combinations of parameters on the chosen mitigation technique and expected utility value. A full case study was completed on the ARMADILLO 3U CubeSat mission (described below) with current data to illustrate the impact this software tool can make on a mission at any point of its development cycle. Finally, the software tool was released to the Small Satellite community with a request to return feedback in addition to the data input and resulting conclusions for further case study material.

A. Mathematically simple cases / error checking

Before running more detailed validation and testing cases, it was necessary to ensure that the software tool was functionally correct. To do this, a series of mathematically simple or error-checking cases were devised. These cases consisted of inputs which would nominally yield a set of obvious outputs, if the software tool was working appropriately. Because both the inputs and nominal outputs were known, the accuracy of the tool could be established.

1. Missing or inappropriate data

The tool must be able to handle missing or blank data, since the user may wish to only analyze a single risk or root cause. As such, test cases were created to determine whether or not the tool would flag missing data as an error. One test case focused on the Schedule risk and provided inputs for two mitigation techniques (MT) associated with root cause (RC) 1, one MT with RC2, RC3 and RC4 were left blank, and two MTs associated with RC5. Thus, both data left blank within the root cause as well as whole root causes left blank were tested. The result was that the software tool treats missing data as if it is a zero value and indicates on the Summary page that no data was entered. It should be noted that a probability value may be left blank only if the remaining values sum to unity, or no data for the mitigation technique is entered. However, cost, time, and people input parameters may be left blank at any time. Another test case examined the outcome should a user leave the utility preferences blank. Since these values are necessary to determine the expected utility, the tool is unable to calculate the utilities and initially returned an error message. After implementing this test case, a feature was added so that when the user selects the calculation option, the tool automatically checks to make sure all the appropriate utility preference data has been entered. If any of the utility values are missing, then a message box appears with the missing data listed.

The input parameter user interface also checks to ensure the values are numeric. Should a user enter a non-numerical value, e.g. $, %, *, then a message box appears when the user tries to Save the input parameters. The message box lists the boxes which contain a non-numerical value and the user is asked to change the values entered.

2. Maximum and Minimum Input Values

Because of the way the attribute utility functions are scaled, a maximum attribute parameter would yield a utility value of zero while a minimum attribute parameter would yield a utility value of one. Similarly, if all the attributes were at their maximum, then the joint utility would be zero. If all the attributes were at their minimum values, then the joint utility value would be one. These relationships provide a set of test cases to ensure that the utility values are properly calculated. A set of maximum values is shown in Table 5. The minimum values are all zero, since it is not reasonable to have negative cost, people, or time.

Table 5. Maximum values for validation methods

	Cost (USD $)	People (# people)	Time (days)
Maximum value	5000	10	20

A first test case used all maximum values to ensure that the resulting utility calculations were all zero. Fig. 14 shows the decision tree result of this all maximum values test case. Notice that the far right column consists only of zeros and the expected utility value is also zero. The far right column, though, is the joint utility. This joint utility value will only be zero if all the attribute values correspond to the maximum values as indicated by the user. A similar test case was developed to test the tool response when all the minimum input parameters, namely all zeros, were entered. The result was a set of utility values equaling one, as expected. A final set of test cases employed involved testing inputs which go above and below the maximum and minimum values indicated by the user. Going above the maximum value for all three input parameters simply resulted in a negative utility. A negative utility value is not impossible; it simply indicates that the parameter is not acceptable given the user's preferences. No error notification exists for parameters above the maximum value primarily because a negative utility is only achieved when all three parameters are beyond the limit. Also, it is possible that the user may wish to investigate values beyond the designated maximums. An input value less than the minimum, namely a negative value, results in a message box during parameter entry indicating the user must supply a different value, since negative time, people, or cost is not within the scope of this research.

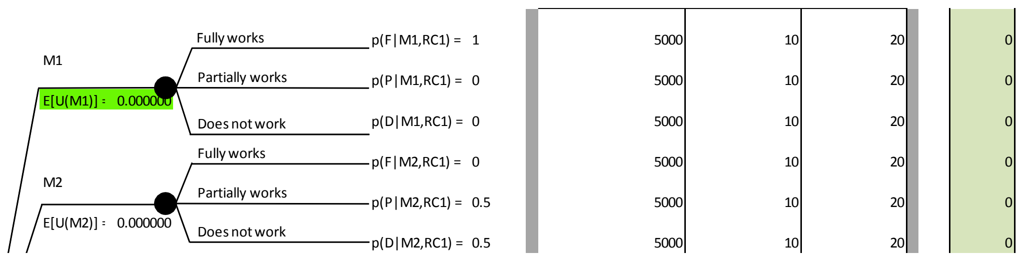

Figure 14. Example maximum value test case decision tree result

3. Modifying utility curve parameters

The utility curve parameters describe the user preference of a specific attribute – cost, people, or time. A set of test cases were devised to test how the software tool would react when these utility curve parameters were altered. In a way, these test cases comprised a controlled sensitivity analysis, because specific combinations of the gamma parameters were used in order to determine if changing the gamma values in a known fashion would result in a predicted outcome.

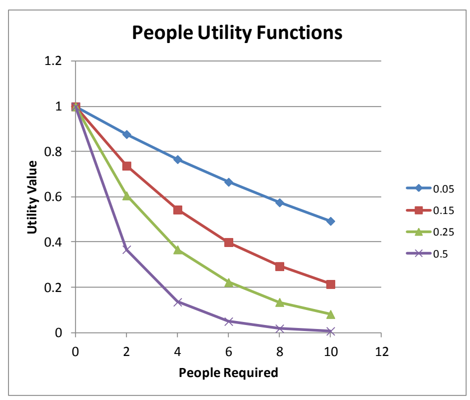

Figure 15. People utility functions for varying gamma parameters

The utility functions, such as the People functions in Fig. 15, show that with a lower gamma value, the same input parameter will yield a larger utility value. And so, all other values being the same, it is expected that a decrease in the gamma parameter would yield higher utility values. However, this is only true in the joint utility values for decreasing the people gamma. In fact the utility values decrease in the cost gamma case, and mostly increase in the time gamma cases. These outcomes could be due to the interaction of all three input parameters. This theory of interaction can be tested by examining the individual utility values for each gamma changing case.

Table 6 shows the individual utility values for each gamma changing case. Case 1 involved changing the cost gamma value while Case 2 changed the people value and Case 3 changed the time value. The baseline shows the starting utility values for the case that the technique fully works. The Cost, People, and Time sections contain only their attribute utility value. For example, the Cost section values are only the cost utility values, since the other input parameters did not change and the utility value therefore stays the same. From this data, it is shown that as the gamma parameter is decreased (increasing

Table 6. Utility value interaction due to changing gamma values

Baseline			Cost		
Cost	**People**	**Time**	**Case 1a**	**Case 1b**	**Case 1c**
0.980199	0.367879	0.904837	0.99005	0.995012	0.999
People			**Time**		
Case 2a	**Case 2b**	**Case 2c**	**Case 3a**	**Case 3b**	**Case 3c**
0.606531	0.740818	0.904837	0.951229	0.97531	0.99005

case letters a-b-c), the utility value increases as expected. Therefore, the non-increasing trend seen in the joint utility values must be due to interaction between all three of the cost, people, and time input parameters.

4. Modifying gamma and input parameters

Since the equations for the attribute utility functions are negative exponential curves, as the exponent increases, the utility value decreases. While the previous section outlined a set of test cases which studied the effects of changing only the utility curve parameter, gamma, a separate set of test cases were created to test the combined effect of changing both the input and gamma parameters. Four test cases were created using large and small gamma and input values, as shown in Table 7. These four test cases consisted of the (A) large gamma-small input, (B) large gamma-large input, (C) small gamma-large input, and (D) small gamma-small input. The large gamma-large input should yield the smallest utility value while the small gamma-small input value should yield the largest utility value.

Table 7. Changing both gamma and input values

	Cost (USD hundreds $)	People (# people)	Time (days)
Small Gamma	0.0001	0.05	0.01
Large Gamma	0.002	0.5	0.1
Small input	5	2	1
Large input	10	6	10

The results for this test are given in Table 8. As expected from theory, when both the gamma and input parameters are small, the highest joint utility value is observed. Similarly, when both the gamma and input parameters are large, the lowest joint utility value is obtained. These values were first calculated by hand for the software tool to verify. The tool matched the calculations exactly.

Table 8. Changing both gamma and input values results

	Cost	People	Time	Joint
A	0.9900	0.3679	0.9048	0.6502
B	0.9802	0.0498	0.3679	0.2954
C	0.9990	0.7408	0.9048	0.6040
D	0.9995	0.9048	0.9901	0.8842

B. Sensitivity Analysis

By conducting a sensitivity analysis, it is possible to determine how the choice of mitigation technique is subject to change given a slight modification of preferences. This is particularly insightful because users may realize during the course of inputting their data that they had misrepresented their preferences. Namely, how they value cost, people, and time. Because of the infinite combinations of inputs, an assumed set of probabilities, cost, people, and time parameters were held constant throughout the sensitivity analysis. Additionally, only one risk, Schedule, was analyzed, since the same inputs on other mission risks would yield the same output. Instead, the utility function k values and gamma parameters were varied in order to examine how changing preferences would change the decision analysis outcome. Modifying all of the parameters will be described in the Monte Carlo Analysis section.

With four gamma parameters for each of the three attributes, 64 different gamma value combinations were possible. To bound the testing set, k_i value combinations were limited to values between 0.2 and 1 in increments of 0.2. Thus, with three attributes, there were a total of 64 k_i value combinations. The k value is then dependent upon the three k_i values according to Eq. (1). A software program stepped through each gamma and k value combination and calculated the winning choice of mitigation technique and its associated expected utility for each root cause within the Schedule risk.

Recall the probabilities and attribute values are constant for all gamma and k value combinations. Thus, the result shows only the effect of changing the gamma and/or k values in the utility function calculations. That is, the results relate to changing the utility curve or the manner in which the utility curves are combined. The histograms shown in Fig. 16 illustrate the number of times a certain combination of gamma or k values yielded the maximum expected utility. The more spread out the root cause is on the histograms of Fig. 16, the more susceptible the root cause is to fluctuations in gamma or k values. That is, a slight change in a user's preference will yield a different mitigation technique and expected utility result. As illustrated in Fig. 16, Root Cause 3 and Root Cause 5 appear to be the most unstable due to their more varied distributions than the other root causes. This behavior could be explained by the input parameters of those specific root causes. In other words, the combination of probabilities and attribute values affects the utility values, and a slight change in gamma and k values may sway the mitigation technique choice.

Figure 17 shows a more detailed picture of the maximum expected utility values as a function of the gamma and k value combination trials. Across the ucurve combo trials in Fig. 17 (a), there is a 16 data point period – after 16 combinations, the first ucurve function is moved to the next parameter value, and the program continues to go through other parameters possible values. Clearly, the maximum expected utility value occurs at any combination of the first ucurve (representing cost) and the first (smallest) option of the other ucurve parameters (time, people). Conversely, when the non-cost parameters are their last (largest) options, the expected utility will be at its minimum.

Interestingly, there is more variation when changing the ucurve parameters than when the k values are changed. Both the ucurve and k value combination analyses have short and long periods corresponding to the change in parameters.

This sensitivity analysis was based on a pre-determined set of input parameters as an effort to see how the software tool would handle parameters changing by incremental amounts. The result was satisfyingly interesting that a sensitivity analysis capability was built into the tool so that users may produce their own sensitivity analysis to see how their decision could change if their preferences were slightly different. The sensitivity analysis tested the decision analysis output dependence upon the input parameters. There are levels of interaction due to the attribute utility values being a function of multiple inputs, and the joint utility value being a function of the attribute values with additional inputs. All in all, the sensitivity analysis provides insights into how the decision may change should user preferences slightly vary.

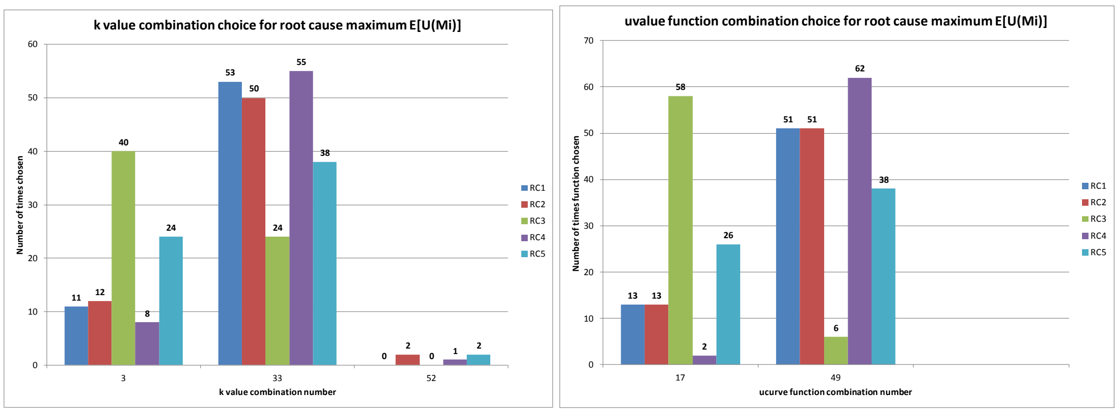

Figure 16. (a) Histogram of k combination yielding maximum expected utility. (b) Histogram of gamma combinations yielding maximum expected utility

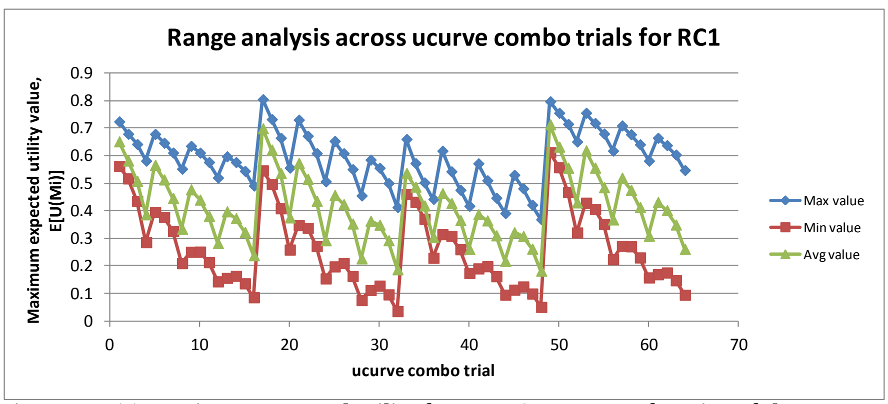

Figure 17. (a) Maximum expected utility for Root Cause 1 as a function of the gamma combination trials.

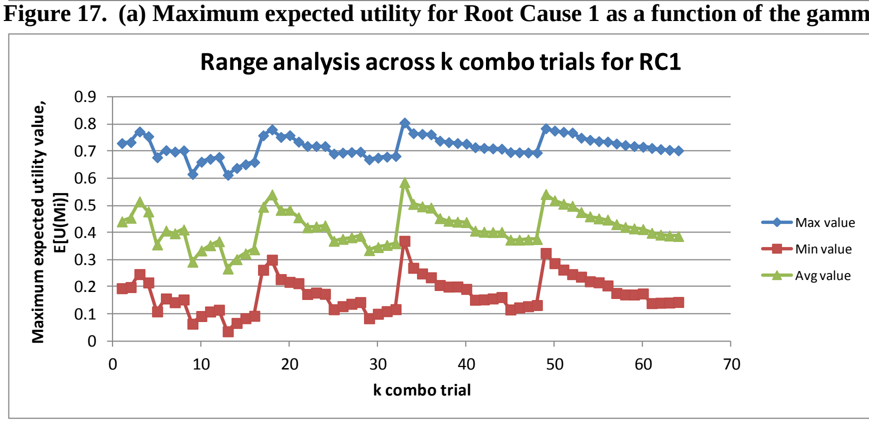

Figure 17. (b) Maximum expected utility for Root Cause 1 as a function of the k combination trials.

C. Monte Carlo Simulation

While the sensitivity analysis looked at only changing the gamma and k values while keeping a set of input parameters constant, the Monte Carlo simulation changed the input parameters as well. The same 64 combinations of gamma and k values were used in this analysis as in the sensitivity analysis. Additionally, 21 probability combinations were created based on probabilities ranging from 0 to 1 in increments of 0.2. A constraint of probabilities summing to unity was applied to these probabilities totalling 21 unique combinations. Cost was varied from \$0 to \$5000 in increments of \$500. The people parameter was varied from 0 to 10 in increments of 2. Time was varied from 0 to 30 days in increments of 5. Therefore, there were a possible 11 cost, 6 people, and 7 time values. Between the probability, attribute, gamma, and k values, there were the order of 10^{12} possible combinations for a single mitigation technique. Therefore, modeling an entire risk was out of the question, and the Monte Carlo analysis focused on modeling the parameter choices for a single mitigation technique. Additionally, the results from a single mitigation technique are applicable to the remaning techniques across all of the mission risks.

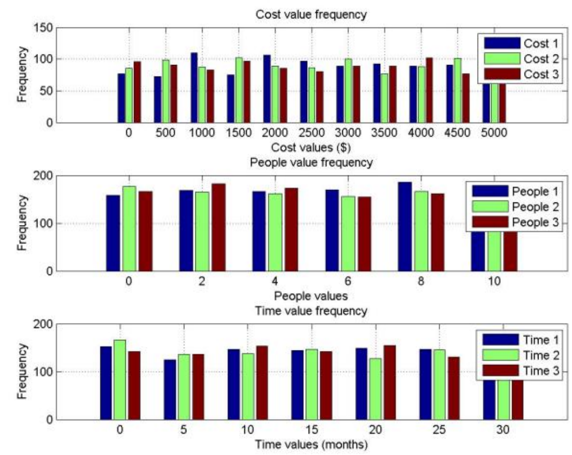

Figure 18. Individual run histogram of cost, people, and time parameters chosen for the Monte Carlo simulation

The purpose of the Monte Carlo simulation was to model the decision analysis outcome for the possible sets of inputs. 100 runs of 1000 samples in each run resulted in 100,000 trials for this analysis. The decision analysis outcome is based on the maximum expected utility. For each run, the inputs resulting in the maximum expected utility were stored as well as plotted. In this way, analysis could be completed on an individual run as well as on an aggregated basis.

Since no prior distribution was imposed on the input parameters, the Monte Carlo simulation should call upon each parameter an approximately equal number of times. This should be true both in terms of an individual run as well as the entire compilation of data. Figure 18 shows the approximately even distribution of cost, people, and time parameters chosen on an individual run basis. The aggregate data shows a similar trend.

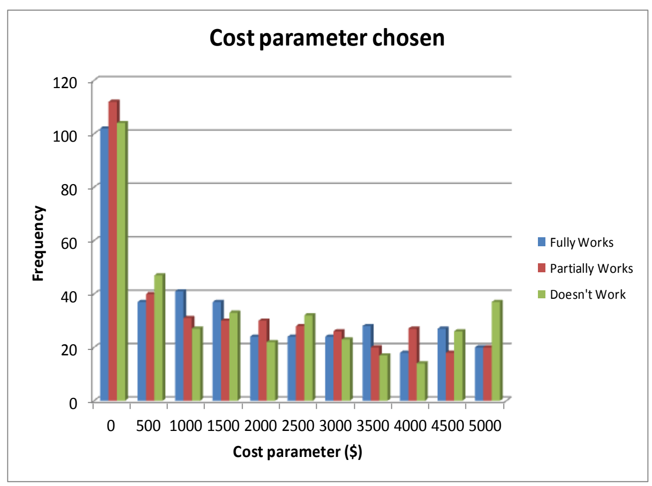

Figure 19. Cost parameter chosen in Monte Carlo simulation for the maximum expected utility value.

The sensitivity analysis of the previous section assessed the effect of input parameters on changing the expected utility value and the mitigation technique choice. The Monte Carlo simulation is an effort to validate the decision theory applied in the software tool. In other words, the simulation shows that certain combinations of parameters yield the maximum expected utility as expected from decision theory. Matching theory, the minimum possible attribute parameters yielded most of the maximum expected utility values, as shown in Fig. 19 for the cost parameter. Similar plots exist for the people and time parameters. Note that the minimum value does not always provide the maximum expected utility. The other values may at times provide the maximum expected utility due to the other input parameters and the utility preference information. For example, if cost is not preferred as highly as people, then a higher cost value may be offset by a lower people value. Additionally, probabilities can play a significant role in a larger attribute value still resulting in a maximum expected utility.

The Monte Carlo simulation showed that the decision theory applied in the tool was working properly. Results were obtained which match theory. Namely, lower input parameters, higher probabilities on lower input parameters, or lower probabilities on higher input parameters are more likely to generate maximum expected utility values.

D. ARMADILLO Case Study

The mathematically simple cases, sensitivity analysis, and Monte Carlo simulation were all based on artificial data. A case study was created using the ARMADILLO 3-Unit CubeSat mission[23] with input parameters current as of September 2014. The full set of inputs can be found in the Decision Advisor User's Guide.[§] Analysis of the output resulted in Table 9 in which the overall top five mitigation techniques are listed. These are the mitigation techniques across the seven mission risks with all 32 root causes which would be most advantageous to mitigate given the users preferences. Interestingly, risk analysis methods[13] applied to the ARMADILLO mission in its current status resulted in the identification of the COST and SCH risks as the highest concern. Table 9 shows four methods to help mitigate several of the root causes to combat these highest concern risks. PER was the lowest concern, but it obviously has one of the easiest and most worthwhile root causes to mitigate according to Table 9. The Loss of Hardware root cause was deemed a personnel risk because of the possibility that team members may not adequately track their handling of hardware and the team may physically lose the hardware or it may be damaged without knowing the reason. A simple mitigation technique to implement is to introduce a hardware tracking method such as certification logs. This mitigation technique seems to work well for the Texas Spacecraft Lab.

Table 9. Top five mitigation techniques for ARMADILLO case study

Mission Risk	Root Cause	Explanation	Mitigation Technique	Expected Utility	Overall rank
COST	RC2	COTS component price increases	Include contingency in budget allocations	0.893	1
COST	RC1	Incomplete understanding of projected total mission costs	Include contingency in budget allocations	0.879	2
SCH	RC1	Inability to find desired spacecraft components	Allocate more resources to the task needing completion	0.871	3
SCH	RC2	Mechanical design delays	Allocate more resources to the task needing completion	0.871	3
PER	RC2	Loss of hardware	Have tracking method for hardware (e.g. inventory system, certification logs)	0.856	5

E. Small Satellite Community case studies

As of October 2014, the Decision Advisor software tool was released to a small set of mission designers in an effort to gather initial feedback and work through any preliminary errors. The tool is being released to the general Small Satellite community in January 2015. With each release, the community is asked for feedback as well as their inputs and conclusions. The feedback will be incorporated to improve future iterations of the tool. The inputs and resulting conclusions obtained by using the Decision Advisor will be used as additional case studies to show the tool's functionality and usefulness.

V. Conclusion

A new Excel-based software tool has been validated and is ready for small satellite mission designers to use in an effort to increase the understanding of mission risks and contribute to the mission success for low-cost small satellite missions. The Decision Advisor tool allows users to determine how they can best mitigate seven categories of risk based on their mission-specific preferences. Before now, access to such software tools has been restricted to larger budget mission or would cost projects an extraordinary amount of money and time to develop internally.

[§] For a copy of the user's guide, please visit: https://sites.google.com/site/brumbaughresearch/research/-6-cubesat-decision-advisor

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References

[1]Vrijling, J.K, et al, "A framework for risk criteria for critical infrastructures: fundamentals and case studies in the Netherlands," Journal of Risk Research, 7 (2004) 569-579

[2]Majzoub, R., et al, "Investigation of Risk Acceptance in Hand Transplantation," The Journal of Hand Surgery,

[3]Abrahamsen, E.B., and Aven, T., "On the consistency of risk acceptance criteria with normative theories for decision-making," Reliability Engineering & System Safety, 93 (2008) 1906-1910

[4]Aven, T., and Vinnem, J.E., "On the use of risk acceptance criteria in the offshore oil and gas industry," Reliability Engineering and System Safety, 90 (2005), 15-24

[5]Brito, A.J., et al., "A multicriteria model for risk sorting of natural gas pipelines based on ELECTRE TRI integrating Utility Theory," European Journal of Operational Research 200 (2010) 812-821.

[6]Greenfield, M.A., "Risk Management 'Risk as a Resource'," Langley Research Center, 14 May 1998

[7]Frank, M.V., "Choosing among safety improvement strategies: a discussion with example of risk assessment and multi-criteria decision approaches for NASA," Reliability Engineering and System Safety. 49 (1995) 311-324.

[8]Matheson, J.E., and Roths, W.J., Decision Analysis of Space Projects: Voyager Mars. Howard, R.A., and Matheson, J.E. (eds.) (1981a), Readings on the Principles and Applications of Decision Analysis, Vol. 2,Strategic Decisions Group, Menlo Park, CA., 445-475.

[9]NASA Johnson Space Center, International Space Station Risk Management Plan, SSP 50175, Revision C, (2009).

[10]NASA, Probabilistic Risk Assessment Procedures Guide for NASA Managers and Practitioners, 2nd ed., NASA/SP-2011-3421, 2011.

[11]Nugent, R., Munakata, R., Chin, A., Coelho, R., Puig-Suari, J. (2008): “The CubeSat: The Picosatellite Standard for Research and Education,” AIAA Space 2008 Conference, San Diego, California, September 8-11, 2008, Paper AIAA 2008-7734.

[12]Brumbaugh, K.M., Lightsey, E.G., Systematic Approach to Risk Management for Small Satellites, Journal of Small Satellites. 2 (2013) 147-160.

[13]Gamble, K.B, Lightsey, E.G., "CubeSat Mission Design Software Tool for Risk Estimating Relationships," Acta Astronautica, Accepted June 2014.

[14]Ang, A., and Tang, W., Probability Concepts in Engineering Planning and Design, Volume 2 – Decision, Risk, and Reliability, John Wiley & Sons, New York, 1984.

[15]Abdellaoui M. Parameter-free elicitation of utilities and probability weighting functions. Manage Sci 2000;46:1497–512.

[16]W.R. Hughes, A note on consistency in utility assessment, Decision Science, 21, pp 882-887 (Fall 1990).

[17]Matheson, J.E., and Howard, R.A., An Introduction to Decision Analysis. Howard, R.A., and Matheson, J.E. (eds.) (1981a), Readings on the Principles and Applications of Decision Analysis, Strategic Decisions Group, Menlo Park, CA., 17-56.

[18]Keeney, RL and Raiffa, H, 1976. Decisions with Multiple Objectives: Preferences and Value Tradeoffs John Wiley.

[19]Howard, R.A., Decision Analysis [Manuscript in Progress]. June 2005.

[20]Farquhar, Peter, "Utility Assessment Methods," Management Science, 30 (1984), pp 1283-1300

[21]“Risk Management Guide for DoD Acquisition,” (2006): 6th ed., Department of Defense.

[22]NASA. (2008): “Agency risk management procedural requirements,” NASA Procedural Requirements, NPR 8000.4A.

[23]Brumbaugh, K. Kjellberg, H., Lightsey, G., “In-Situ Sub-Centimeter Space Debris Detection Using CubeSats.” American Astronautical Society GNC Conference, Breckenridge, CO. February 3-8, 2012.