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Uncertainty Assessment in High-Risk Environments Using Probability, Evidence Theory and Expert Judgment Elicitation

Stella Barberis Bondi
Old Dominion University

UNCERTAINTY ASSESSMENT IN HIGH-RISK ENVIRONMENTS USING PROBABILITY, EVIDENCE THEORY AND EXPERT JUDGMENT ELICITATION

by

Stella Barberis Bondi

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Approved by:

Resit Unal (Director)

Charles Keating (Member)

Ariel Pinto (Member)

Trina M. Chytka (Member)

ABSTRACT

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Stella B. Bondi

Old Dominion University, 2007

Director: Dr. Resit Unal

The level of uncertainty in advanced system design is assessed by comparing the results of expert judgment elicitation to probability and evidence theory. This research shows how one type of monotone measure, namely Dempster-Shafer Theory of Evidence can expand the framework of uncertainty to provide decision makers a more robust solution space. The issues imbedded in this research are focused on how the relevant predictive uncertainty produced by similar action is measured.

This methodology uses the established approach from traditional probability theory and Dempster-Shafer evidence theory to combine two classes of uncertainty, aleatory and epistemic. Probability theory provides the mathematical structure traditionally used in the representation of aleatory uncertainty. The uncertainty in analysis outcomes is represented by probability distributions and typically summarized as Complimentary Cumulative Distribution Functions (CCDFs). The main components of this research are probability of X in the probability theory compared to m_x in evidence theory. Using this comparison, an epistemic model is developed to obtain the upper

"CCPF – Complimentary Cumulative Plausibility Function" limits and the lower "CCBF – Complimentary Cumulative Belief Function" limits compared to the traditional probability function.

A conceptual design for the Thermal Protection System (TPS) of future Crew Exploration Vehicles (CEV) is used as an initial test case. A questionnaire is tailored to elicit judgment from experts in high-risk environments. Based on description and characteristics, the answers of the questionnaire produces information, that serves as qualitative semantics used for the evidence theory functions. The computational mechanism provides a heuristic approach for the compilation and presentation of the results. A follow-up evaluation serves as validation of the findings and provides useful information in terms of consistency and adoptability to other domains.

The results of this methodology provide a useful and practical approach in conceptual design to aid the decision maker in assessing the level of uncertainty of the experts. The methodology presented is well-suited for decision makers that encompass similar conceptual design instruments.

ACKNOWLEDGMENTS

It is rare for someone to create a new field of knowledge. This work is definitely not such an example but, rather, a reflection of the continuation in a certain direction of the work of someone who has strong beliefs in analysis methods – my teacher, advocate and friend Dr. Resit Unal of Old Dominion University, Engineering Management and Systems Engineering. Without his vision, foresight and strong support over the many years of research none of this would have been possible. It has been an immense privilege studying under him.

In my many years working for ODU, the other pillar of my intellectual life has been Dr. Charles Keating, Dr. Ariel Pinto, Dr. Rafael Landaetta and Dr. Mujde Erten-Unal. All contributed rich and broad insights to my study, and I was truly fortunate to have such a rare gift of inspiring educators. My thanks also go to the other faculty, staff and fellow students, especially Colin Borrows and David Ekker for their support and encouragement.

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I would also like to thank my loving and patient husband Robert who has fully supported me to meet the challenges of this endeavor. His strength, love and sacrifices are endless, unconditional and a source of great inspiration. Also my thanks go to my lovely daughters Helen and Gina for their part of encouragement and moral support, as well to Nicholas, Sophia and Lukas. Mostly, my sincere thanks go to my intellectual daughter Mina who provided the argumentative thoughts and witty insight to some of the details of this research.

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1. Introduction

1.1 Background

NASA's endeavor of exploring space and developing corresponding enabling technologies requires operating in extreme risk environments. In order to advance operational, technological, and explorative missions and assess acceptable safety parameters, NASA relies on experts to evaluate available data, interpret the significance of risk, and minimize the uncertainty between known and unknown variables (Chytka, 2003). Using a broad range of experts with focused specialties allows scientists and engineers to expand and utilize their knowledge in a specific area that could lead to safer operating environments.

Quantitative risk assessment is an attempt to answer questions of uncertainty such as: What can go wrong? How likely is it to go wrong? What are the consequences of going wrong? What is the level of confidence in the answers to each of the previous questions? In answering these questions for formal quantitative risk assessments one should: a) state the assumptions clearly and give appropriate justification; b) construct initiating events, fault trees, and event trees; c) quantify likelihoods typically using probability theory; d) conduct a sensitivity analysis; and e) document the entire analysis (Oberkampf, 2005). For several centuries, the idea of numerical degree of belief has been identified in both popular and scholarly form with the idea of chance: The two ideas are united under the name probability (Shafer, 1976). Aleatory uncertainty is a

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The format for this dissertation follows *American Psychological Association* style.

chance of a descriptive experiment, such as the throw of a dice or the toss of a coin (Shafer, 1976). Another example is the variations due to the physical system of the environment in the fatigue life of compressor and turbine blades, which are referred to as variability, irreducible, stochastic and random uncertainty (Oberkampf, 2005). Figure 1 represents the two forms of uncertainty and the means with which the information could be used properly to develop a quantification strategy based on the characteristics of the information.

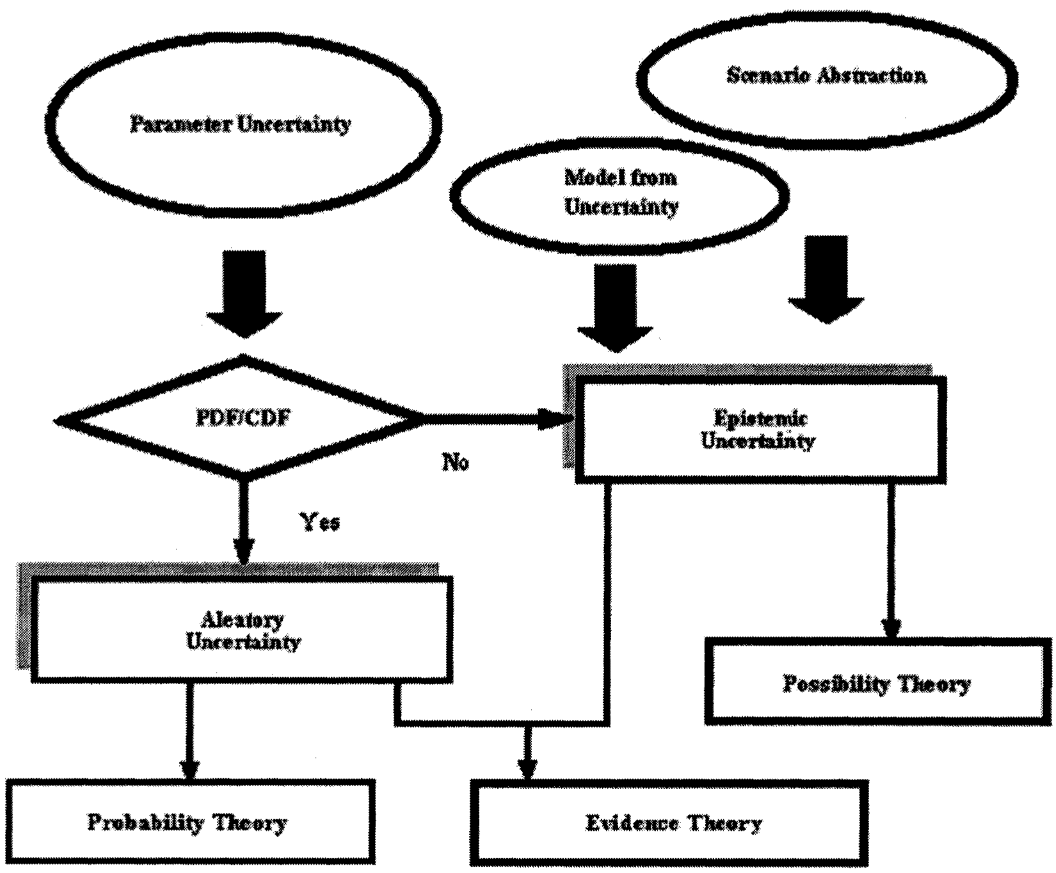


Figure 1. Uncertainty quantification strategy (adopted from Bae et al., 2003)

Epistemic uncertainty is due to a lack of knowledge of quantities or processes of the system or the environment and is also referred to as subjective, reducible and model form uncertainty. Examples include the lack of experimental data to characterize new material and processes, or the poor understanding of coupled physics phenomena (Oberkampf, 2005). Parameter uncertainties are most times aleatory but can be epistemic when insufficient data are available to construct a probability distribution function. Model form and scenario abstraction uncertainties, can emerge from boundary conditions, different choices of solution approaches, and unexpected failure modes due to lack of knowledge and information (Bae, 2003).

1.2 Problem Statement

Dangerous breakdowns in assessing uncertainty run rampant in high-risk environments. The key to finding the core of assessing uncertainty is to institute a system providing more accurate data and more effective transmittal of critical warnings to decision makers. Could the use of Dempster-Shafer's Evidence Theory aid decision makers in assessing operational uncertainty by providing an additional non-probabilistic measure?

A formal elicitation process by multiple experts is prepared to obtain probable reasoning based on previous experience from experts in high-risk environments. Combination and aggregation of the experts' input addresses and quantifies uncertainty. Since the distribution of probability needs to be characterized for large, complex systems, classic probability might not be suitable due to incomplete information as a result of lack of knowledge and statistical data. The results for each input or contribution of expert judgment are used for the development and comparison of Probabilistic and Non-Probabilistic methodology.

1.3 Synopsis of Dissertation

For high-risk, one-of-a-kind complex projects such as space exploration, historical data is scarce or does not exist; therefore, the use of probabilistic risk and uncertainty analysis approaches becomes a challenge. In such cases, asking the opinions of experts maybe the only alternative to data collection for making risk and uncertainty assessments (Conway, 2003). This is especially true for new space exploration system operational capabilities. Section 2 details the review of relevant literature including predecessor research and related research.

The previous work by others includes probability theory, which is a well-researched and practiced methodology that provides the mathematical structure traditionally used in the representation of aleatory and epistemic uncertainty. The probabilistic uncertainties in analysis outcomes are represented with probability distributions and are typically summarized as cumulative distribution functions (CDF) and complimentary cumulative distribution functions (CCDF). The most familiar technique is the Monte Carlo simulation. On the other hand, the extension of the efforts to define the development of a more robust system is the Evidence theory. Evidence theory provides a promising alternative to probability theory. It allows for a fuller representation of the implications of uncertainty as compared to a probabilistic representation of uncertainty. Evidence theory can handle not only aleatory uncertainty but epistemic uncertainty as well. As the probability of a given occurrence increases, the uncertainty logically will decrease. Probability theory and Evidence theory are comparable methodologies; however, they are conceptually inverse functions. In this study, Probability theory is utilized to addresses the probability of the occurrence of an event (system failure due to an anomaly) while Evidence theory is used to addresses the degree of uncertainty of whether an event will occur. This research suggests that the assessment of uncertainty of experts in high-risk environments may be better conveyed to decision makers by using both probabilistic and non-probabilistic theories. Figure 2 illustrates this process.

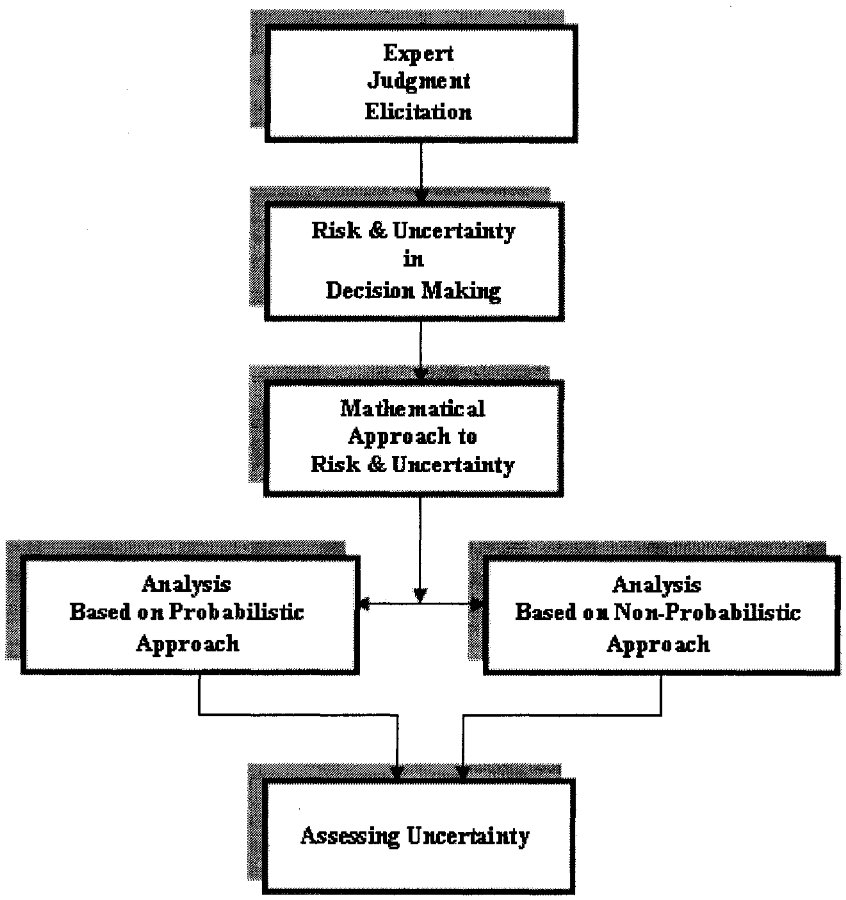


Figure 2. Literature review of relevant research

In Section 3, a research methodology is then presented as an extension of previous efforts to define the development of a more robust system. The mathematical structure of Probability theory, the Evidence theory based on Dempster-Shafer's work and the benefits of the proposed aggregation are explored. Cumulative Distribution Function (CDF) shows the probability of an occurrence is less than a given value, whereas the Complementary Cumulative Distribution Function (CCDF) shows whether the probability of an occurrence will exceed a given value; therefore, the CCDF enables the comparison of the graphical results of using both Probability theory and Evidence theory.

In Section 4, the proposed methodology is applied. This research relies heavily upon the inputs from the high-risk experts. The first part of this section involves eliciting expert judgment to derive the numerical raw data used in the analyses. An initial questionnaire is developed that addresses conditions encountered during high-risk operations and includes questions that will be proven useful for both Probability and Evidence theories. The questionnaire is utilized for uncertainty assessment, using NASA's Crew Exploration Vehicle (CEV) Thermal Protection System (TPS) as an example. The second part of this section focuses on the combination and aggregation of variables while taking into consideration the uncertainty of each expert's input. The last part of this section includes the results of the input of each expert, which are then applied in the development of the CDF and CCDF, relying strictly upon aleatory uncertainties. Then the upper plausible limits and lower belief limits are derived based upon a combination of aleatory and epistemic uncertainties.

Using a graphical method, this research provides various visual representations of the experts' uncertainty values to assist in the integration and assimilation of a decision strategy. This is accomplished by combining the graphs of the CCDF derived by the Probability theory and the upper and lower limits derived by the Evidence theory, which provides the decision maker with a very clear comparison of multiple experts' probabilistic risk assessment relative to their non-probabilistic risk assessment.

Traditional validation methods do not apply to this research; however, validation of contents and structure of the methodology was found appropriate for this research. This was accomplished through follow-up interviews with the experts in terms of interpretation of the questionnaire and usefulness of its application. Also, follow-up with the decision maker in regards to the overall methodology confirmed the usefulness of the results.

A combined approach utilizing Evidence Theory for assessment of both aleatory and epistemic uncertainties facilitates the assessment of subject matter expert's expertise and confidence, may be utilized for calibration, and has developed a tool that may allow decision makers in high-risk environments to assess uncertainty levels presented by multiple experts. In addition, the methodology presented could be applicable in a variety of disciplines including the aerospace technology, and could be used especially for adopting new technologies for future concepts. Figure 3 summarizes the research mapping.

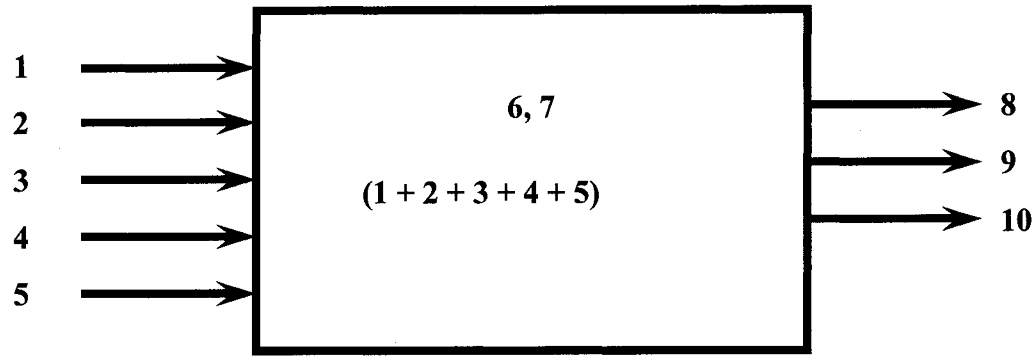


Figure 3. Research mapping

LEGEND:

1	Develop a questionnaire
2	Obtain pool of high-risk experts
3	Elicit high-risk experts to provide information regarding CEV addressing Construction, Installation, and Operations and the combination of all
4	Train experts and conduct a survey
5	Probabilistic analysis of findings using CDF and Monte Carlo simulation
6	Mathematically analyze results by using Evidence theory
7	Normalize results and aggregate findings
8	Assess results by identifying the level of uncertainty
9	Graph upper and lower limits of uncertainty and incorporate CCDF
10	Provide conclusions

2. Literature Review

2.1 *Expert Judgment Elicitation*

Expert-opinion elicitation has been defined as a formal, heuristic process of obtaining information or answers to specific questions about certain quantities, called issues, such as failure rates, failure consequences, and expected service lives (Ayyub, 2001). The role of experts in theoretical environments is critical in which their judgments can provide valuable information and insight in areas where limited "hard" data is available. Decision makers often rely on multiple opinions as a data set when historical or empirical statistics are deficient in a specific decision domain (Chytka, 2003). To explore the challenge problem issues, it is necessary to understand how experts solve problems. The problem solving process itself—the choice of parameters, the appropriate model, and interpretation of outputs—is a form of tacit, rather than explicit, knowledge, requiring the use of formal expert elicitation (Booker, 2004). Research in experimental psychology has shown that simply asking a person to provide a (numerical) probability, results in biased probability judgments (Shanteau, 1989). While a consensus approach to elicit knowledge or judgments from subject matter experts may yield acceptable results, it can be a time consuming process, and it may be hard to assign a degree of certainty to those decisions involving quantitative estimates (Conway, 2003).

The process for obtaining expert judgments with some appellation of confidence must be well structured to avoid the introduction of bias. To overcome biases, it seems necessary to have a well-structured process for probability elicitation. Such a process is called an *elicitation process* (Renooij, 2001), and it can be roughly divided into five stages:

1. Select and motivate the expert
2. Train the expert
3. Structure the questions
4. Elicit and document the expert judgments
5. Verify the results.

1. Expert selection. Ideally, for probability elicitation, an expert should be selected who has the necessary domain knowledge and who is familiar with assessing probabilities. However, due to the nature of expertise, there is often not a very large pool of experts to choose from. When eliciting probabilities for probabilistic networks, it is best to select an expert who has also been involved in building the structure of the network. This will also assist in preventing errors due to the possible existence of different definitions for certain variables (Renooij, 2001).

2. Train the expert. Once an expert has been selected and is willing to participate, he has to learn the art of probability assessment. To this end, the expert should first become familiar with the concept of probability and should learn to express his knowledge in the format required by the elicitation method used. Part of the training is done with probabilities for events whose frequencies can be checked. This allows for exposing biases in the expert's assessments and to practice the elicitation method. Several elicitation methods and representation formats can be tried to see which best fit the task, the experience and preferences of the expert. The amount of time spent on training depends on available time and other constraints. At the end of the training period, however, the expert should fully understand and feel comfortable with the methods to be used (Renooij, 2001).

3. Structure the questions. Before the actual elicitation takes place, several issues need to be addressed. The definitions of the variables and values for which probabilities are to be assessed should be documented so that this information can be easily and promptly conveyed to the expert during the elicitation (Renooij, 2001). The goal of elicitation is to capture the current state of knowledge however poor and uncertain it may be. At some point in the process, the expert and interviewer will reach the limits of what is currently known (Booker, 2004). After the important variables and values are determined, the conditioning circumstances that influence a variable's uncertainty need to be determined. For probabilistic networks, these conditioning contexts follow directly from the structure of the network. For each probability to be assessed, a question describing this probability should be prepared (Renooij, 2001).

4. Elicit and document the expert judgments. Various people will be present during the actual elicitation interviews. Initially, there will be one or more experts involved, interacting during elicitation (Renooij, 2001). The elicitor has to perform the following tasks:

- Clarify the inevitable problems of the experts with the interpretation of questions, definitions of variables and values;
- Record all information stated by the experts that cannot be expressed in the answering format, but may still be of use;
- Ascertain that the questionnaire was completed and all information was recorded appropriately;
- Insure expert awareness of the biases in the event of expectation of easy introduction.

Lastly, the elicitor should avoid coaching the expert and taking too much control; the expert should feel relaxed, not challenged, for he is the expert and the elicitor is not (Booker, 2003, Renooij, 2001). The elicitation method that is used should be straightforward, easy to handle, and not difficult to learn.

5. Verify the results. Verification is the process of checking whether the probabilities provided by the expert are well calibrated (conform to observed frequencies), obeys the laws of probability (are coherent) and is reliable (Booker, 2003).

In every field, there are some who are considered by their peers to be the best at what they do (Shanteau, 1992). In some domains, this is reflected by official recognition or job titles. In others, it comes from consensual acclamation. Experts are operationally defined as those who have been recognized within their profession as having the necessary skills and abilities to perform at the highest level (Shanteau, 1992).

Finally, asking experts for their "best professional judgment" is sometimes the only option when faced with a situation that has limited data or it is not fully understood (Morgan, 1990). Table 1 lists selected literature and their contributions in expert judgment elicitation.

Reference	Summary of selected literature in expert judgment elicitation
Ayyub (2001)	Expert-opinion elicitation has been defined as a formal, heuristic process of obtaining information or answers to specific questions about certain quantities, called issues, such as failure rates, failure consequences, and expected service lives.

Table 1. Summary of selected literature in expert judgment elicitation

Reference	Summary of selected literature in expert judgment elicitation
Booker et al. (2004)	To explore the challenge problem issues, it is necessary to understand how experts solve problems. The problem solving process itself is a form of tacit, rather than explicit, knowledge, requiring the use of formal expert elicitation.
Booker & McNamara (2004)	Verification is the process of checking whether the probabilities provided by the expert are well calibrated (conform to observed frequencies), obeys the laws of probability (are coherent) and is reliable
Booker & McNamara (2004)	To explore the challenge problem issues, it is necessary to understand how experts solve problems. The problem solving process itself is a form of tacit, rather than explicit, knowledge, requiring the use of formal expert elicitation.
Booker & McNamara (2004)	The goal of elicitation is to capture the current state of knowledge, however poor and uncertain it may be. At some point in the process, the expert and interviewer will reach the limits of what is currently known.
Chytka (2003)	The role of experts in theoretical environments is critical- their judgments can provide valuable information and insight in areas where limited "hard" data is available. Decision makers often rely on multiple opinions as a data set when historical or empirical statistics are deficient in a specific decision domain.
Conway (2003)	While a consensus approach to elicit knowledge or judgments from subject matter experts may yield acceptable results, it can be a time consuming process; it may be hard to assign a degree of certainty to those decisions involving quantitative estimates.
Morgan & Henrion (1990)	Asking experts for their "best professional judgment" is sometimes the only option when faced with a situation that has limited data or it is not fully understood.
Renooij (2001)	The process for obtaining expert judgments with some appellation of confidence must be well structured to avoid the introduction of bias. The elicitation process would ideally include the selection, motivation and training of experts, proper structuring of the questions to preclude bias, the actual elicitation and documentation phase, and verification of results.
Shanteau (1987)	Suggested to let those in a domain define the experts. In every field, there are some who are considered by their peers to be best at what they do.

Table 1. Continued - Summary of selected literature in expert judgment elicitation

Reference	Summary of selected literature in expert judgment elicitation
Shanteau (1989)	First, the characteristics originally were intended as a generic description for experts of all types. It is clear, however, that some characteristics apply more to one profession than another. Three characteristics – creativity, confidence, and communication – appear to have particular significance for auditing and accounting.
Shanteau (1992)	In some domains this is reflected by official recognition or job titles. In others, it comes from consensual acclamation. Experts are operationally defined as those who have been recognized within their profession as having the necessary skills and abilities to perform at the highest level.

Table 1. Continued - Summary of selected literature in expert judgment elicitation

2.2 Characteristics of High-Risk Environments

The report of the President's Commission on Implementation of US Space Exploration Policy, 2004, - "*A Journey to Inspire, Innovate, and Discover*", (Report by a Panel of National Academy of Public Administration for the NASA) claimed that NASA commonly is challenged with projects that are unique to global levels of knowledge without any proven record. In addition to the risk of catastrophic failures, personnel performing in high-risk environments are typically challenged by significant lack of historical data gaps. In some circumstances (like those explored by NASA), not only are data not readily available, but also are beyond the limits of global experience. Experts operating within this environment are usually confronted by significant data gaps, absence of rules and facts, and realization that their decisions may result in catastrophic failure (Kotra, 1996).

Booker (2004) claimed that complex problems tend to have one or more of the following characteristics:

• A poorly defined or understood system or process, such as high cycle fatigue effects on a turbine engine

• A process characterized by multiple exogenous factors whose contributions are not fully understood, such as properties of exotic materials

• Any engineered system in the very early stages of design, such as a new concept design for a fuel cell

• Any system, process, or problem that involves experts from different disciplinary backgrounds, who work in different geographical locations, and/or whose problem-solving tools vary widely, such as the reliability of a manned mission to Mars

• Any problem that brings together new groups of experts in novel configurations for its solution, such as detection of biological agents in war (Booker, 2004).

NASA's missions are complex and high-risk to say the least. Before setting out into the solar system or in any type of mission, there are a seemingly endless number of factors to take into consideration. These factors range from transit vehicles and trajectories, to crew safety and stay-times, to required resources and equipment, and much, much more (Young, 2000).

Table 2 lists selected literature and their contributions in high-risk environments.

Reference	Summary of selected literature in high-risk environments
Apostolakis (2003)	Quantitative Risk Assessment introduces the "risk informed" rather than "risk based" decision-making. Comparison of NASA technology to Nuclear Power industry by criticizing the level of accuracy of probabilistic findings.
Booker et al. (2004)	Concepts such as reliability and risk remain suitable for probabilistic interpretation and its use as a reference or standard for the entire complex problem. In addition, probability theory can also be consistent with the way some technical communities of experts think.
Booker & McNamara (2004)	Complex problems tend to have one or more of the following characteristics: • A poorly defined or understood system or process, such as high cycle fatigue effects on a turbine engine • A process characterized by multiple exogenous factors whose contributions are not fully understood, such as properties of exotic materials • Any engineered system in the very early stages of design, such as a new concept design for a fuel cell • Any system, process, or problem that involves experts from different disciplinary backgrounds, who work in different geographical locations, and/or whose problem-solving tools vary widely, such as the reliability of a manned mission to Mars • Any problem that brings together new groups of experts in novel configurations for its solution, such as detection of biological agents in war
Forester (1995)	Accident scenario characteristics, as represented by the behavior of critical parameters, can elicit or interact with certain human responses (e.g., complacency or anxiety) that facilitate the occurrence of an unsafe action or create situations that make certain processing mechanisms, strategies, or biases (e.g., recency effects, confirmation bias, and fixation) inappropriate or ineffective.

Table 2. Summary of selected literature in high-risk environments

Reference	Summary of selected literature in high-risk environments
Fragola & Bedford (2005)	For engineering applications it is common to use expert input in many areas of analysis. The impact of human activities in for example management, operating procedures, emergency procedures, maintenance, testing and inspection procedures.
Shanteau, Weiss & Thomas (1996)	A validity based approach. A CWS (Cochran-Weiss-Shanteau) tool that is useful in evaluating expert performance. It has been applied to air control simulation (High-risk environment).
Young (2000)	Interspace missions are, by virtue of the nature of the missions, characterized as high-risk.

Table 2. Continued - Summary of selected literature in high-risk environments

2.3 Risk and Uncertainty in Expert's Decision Making

Risk is often defined as a measure of the probability and severity of adverse effects. Even though some may use the term *risk management* to connote the entire process of risk assessment and management, it is commonly distinguished from *risk assessment* (Pinto, 2005). In risk assessment, the analyst often attempts to answer the following set of triplet questions: What can go wrong? What is the likelihood that it would go wrong? And, what are the consequences? Answers to these questions help risk analysts identify, measure, quantify, and evaluate risks and their consequences and impacts (Kaplan & Garrick, 1981). Risk management builds on the risk assessment process by seeking answers to a second set of three questions: What can be done and what options are available? What are the associated trade-offs in terms of all costs, benefits, and risks? And, what are the impacts of current management decisions on future options? Risk can be viewed as either objective or subjective (Haimes 1991, 1998). Objective risk is based strictly on probabilities of events, and subjective are tied to human judgment where further information would alter the person's assessment (Monroe, 1997).

"Uncertainty is the gap between certainty and the present state of knowledge" (Nikolaidis, 2005). Uncertainty is caused by lack of knowledge that also takes three forms: These forms are model, parameter and decision uncertainty. Modeling uncertainty can be the result of the use of approximations, conflicting expert opinions or using an incorrect form for the basic model. Parameter uncertainties can be the result of random errors in direct measurement. Decision uncertainty arises when there is controversy over how to compare or weigh objectives, how to select an index to determine risk, or how to quantify value and acceptable level of risk (Hampton, 2001). Extreme event risk is present in all areas of risk management (Haimes, 2004). Regardless weather the areas of concern are operational risk, insurance, market or credit, one of the most challenging items of risk management is the implementation of the most appropriate risk management models. This enables one to assess the rare but devastating events and permits the measurement of their consequences (McNeil, 1999).

Uncertainty plays a central role in the adaptive intelligence of human beings. Human intelligence categorizes and stores past experience in the form of generalized conditions to avoid unnecessary usage of the mental storage capacity required to retain "exhaustive" trial and error methods (Klir, 2001). Apostolakis identified the various phases that decision makers could follow in order to avoid risk and uncertainty. In his work he stated, "In every application a familiar pattern of progress is observed. Phase 1, the safety community of that industry is very skeptical about the usefulness of this new technology. Then during Phase 2, as engineers and decision makers become more familiar with the technology, they begin to pay attention to the insights produced by Quantitative Risk Assessment (QRA). Phase 3, confidence in QRA increases as more safety analysts use it and they begin to pay attention to the 'positive' insights. Entering Phase 3 usually requires a cultural change regarding safety management. This change is not always easy for engineers who have been using traditional 'deterministic' methods for years. In all three phases, risk insights alone are never the sole basis for decision-making" (Apostolakis, 2003).

"In the present research problem application, the preponderance of occurrences being assessed are in the distant future – as much as 20 or 30 years. Feedback involving actual results or occurrences is impossible" (Conway, 2003). Under extreme events, and given an intense level of interference with the decisional processes, modeling of uncertainty by a scientist could be challenging to develop (Coles and Powell, 1996).

Booker suggested that "because uncertainties (especially epistemic ones) are difficult to estimate, it is important to establish the uncertainty and analysis reference or standard for the entire problem as early as possible" (Booker, 2004-a). On the other hand, Conway and Unal argued that algorithm development is an important tool to minimization of risk and uncertainty (Unal et al., 2004). However, Tolson stated that when the space mission is at stake, "managing and modeling uncertainty plays a major role in aero-assisted missions at Mars and other planets. Atmospheric uncertainty plays a major role to "worse-case" or numerous "safety-margin" approaches that would probably lead to unforeseeable anomalies and may risk mission feasibility. Although improved understanding and modeling will contribute to reducing risk, there will always be a residual uncertainty" (Tolson, 2004). Table 3 lists a summary of selected literature on risk and uncertainty in decision-making process.

Reference	Risk and uncertainty in decision-making process
Apostolakis (2003)	In every application a familiar pattern of progress is observed. Phase 1, the safety community of that industry is very skeptical about the usefulness of this new technology. Then during Phase 2, as engineers and decision makers become more familiar with the technology, they begin to pay attention to the insights produced by Quantitative Risk Assessment (QRA). Phase 3, confidence in QRA increases as more safety analysts use it and they begin to pay attention to the "positive" insights. Entering Phase 3 usually requires a cultural change regarding safety management. This change is not always easy for engineers who have been using traditional "deterministic" methods for years. In all three phases, risk insights alone are never the sole basis for decision-making.
Baenen (1994)	Incorporates and exploits information about the structure of the knowledge representation to reduce the problem size and complexity taking into consideration risk and uncertainty.
Booker & McNamara (2004-a)	Because uncertainties (especially epistemic ones) are difficult to estimate, it is important to establish the uncertainty and analysis reference or standard for the entire problem as early as possible.
Hampton (2001)	Uncertainty caused by a lack of knowledge also takes three forms. These forms are model, parameter and decision uncertainty. Modeling uncertainty can also be the result of the use of approximations, conflicting expert opinions or using an incorrect form for the basic model. Parameter uncertainties can be the result of random errors in direct measurement. Decision uncertainty arises when there is controversy over how to compare or weigh objectives, selection of an index to determine risk, quantification of value and acceptable level of risk.

Table 3. Summary of selected literature to uncertainty in decision making

Reference	Risk and uncertainty in decision-making process
Helton (2004)	Epistemic uncertainty in model inputs are described: An initial exploratory analysis to assess model behavior and provide insights for additional analysis; A stepwise analysis showing the incremental effects of uncertain variables on complementary cumulative belief functions and complementary cumulative plausibility functions; A summary analysis showing a spectrum of variance-based sensitivity analysis results that derives from probability spaces.
Klir & Smith (2001)	Uncertainty plays a central role in the adaptive intelligence of human beings. Human intelligence generalizes past experience to conditions in order to avoid the combinational explosion in storage capacity required for "exhaustive" intelligent human beings employ trail and error methods that have yet to be fully realized in machines.
Monroe (1997)	Risk can be viewed as either objective or subjective. Objective risk is based strictly on probabilities of events, and subjective are tied to human judgment where further information would alter the person's assessment.
Nikolaidis (2005)	Uncertainty is the gap between certainty and the present state of knowledge
Oberkampf et al. (2005)	Aleatory Uncertainty is an inherent variation associated with physical system of the environment also referred to as variability, irreducible uncertainty, stodiastic and random uncertainty. Epistemic Uncertainty is an uncertainty that is due to a lack of knowledge of quantities or processes of the system or the environment. Also referred to as subjective, reductive and model form uncertainties.
Pinto (2005)	*Risk* is often defined as a measure of the probability and severity of adverse effects. Even though some may use the term *risk management* to connote the entire process of risk assessment and management, it is commonly distinguished from *risk assessment.*
Tolson et al. (2004)	Managing and modeling uncertainty plays a major role in aero-assisted missions at Mars and other planets. Atmospheric uncertainty plays a major role to "worse-case" or numerous "safety-margin" approaches that would probably lead to unacceptable payload penalties and may risk mission feasibility. Although improved understanding and modeling will contribute to reducing risk, there will always be a residual uncertainty.
Unal et al. (2004)	Algorithm development to minimization of risk and uncertainty.

Table 3. Continued - Summary of selected literature to uncertainty in decision making

2.4 Mathematical Approach to Risk and Uncertainty

In his classic 1976 book, Shafer stated the paradigm shift, which led him to formulate an alternative to the existing Bayesian formalism for automated reasoning, thus leading to what is commonly known as Dempster-Shafer (DS) evidential reasoning. The basic concept was that an expert's complete ignorance about a statement need not translate into giving 1/2 a probability to the statement and the other 1/2 to its complement, as was assumed in Bayesian reasoning (Shafer, 1976). Recently, engineers and scientists began recognizing the absolute necessity of defining and addressing uncertainty. In the new era of super-speed personal computers, technology is equipped to better handle complex analyses, yet only one mathematical framework is relied upon and used to represent uncertainty: the probability theory.

Probability theory and evidence theory are introduced as possible mathematical structures for the representation of the epistemic uncertainty associated with the performance of safety systems. A representation of this type is illustrated with a hypothetical safety system involving one weak link and one strong link that is exposed to a high temperature fire environment. Topics considered include: (1) the nature of diffuse uncertainty information involving a system and its environment; (2) the conversion of diffuse uncertainty information into the mathematical structures associated with probability theory and evidence theory; and (3) the propagation of these uncertainty structures through a model for a safety system to obtain representations in the context of probability theory and evidence theory with an uncertainty in the probability (Oberkampf, 2005).

Probabilistic networks are graphical models supporting the modeling of uncertainty in large complex domains. The framework of probabilistic networks was designed for *reasoning* and *uncertainty* (Renooij, 2001). Uncertainties exist in every aspect of decision-making process. Previous work has shown that experts in the field of aerospace technology, employing advanced knowledge, can provide extremely valuable information during the life cycle of the operation of the space launch vehicles (Monroe, 1997, Conway, 2003, Chytka, 2003). The proposed methodology is to develop a model utilizing high-risk environment experts and evidence theory that can assist in the task of quantifying uncertainty for aerospace vehicle technology. There are three types of uncertainty: Aleatory uncertainty, epistemic uncertainty and error as shown in Figure 4 (Agarwal, 2004).

TYPES OF UNCERTAINTY

Aleatory Uncertainty (variability, irreducible)	**Epistemic Uncertainty (reducible)**	**Error**
Inherent variation of the system	**Incomplete information**	
	Lack of Knowledge	
It can be mathematically modeled using probability theory	**Not enouh experimental data**	
	Different mathematical models	

Figure 4. Classification of uncertainty (adopted by Agarwal, 2004)

Probability theory provides the two mathematical structures traditionally used in the representation of uncertainty:

1. *Aleatory or random uncertainty* is an inherent uncertainty associated with the environment or some kind of physical system. Variability, random uncertainty, irreducible uncertainty, and stochastic uncertainty are other terms used describing aleatory uncertainty (Bae et al., 2003). An example is the atmospheric reaction of two different metals due to changes in temperature.
2. *Epistemic uncertainty* is due to lack of knowledge of quantities or processes of the system or the environment and appears to be subjective. Subjective uncertainty, incertitude uncertainty, and reducible uncertainty are other terms used describing epistemic uncertainty (Bae et al., 2003). An example is the presence of minimum amount of data that characterizes new processes and material.
3. *Error.* Estimation error is due to incompleteness of sampling information and our inability to estimate accurately the model parameters that describe inherent variability. Model imperfection is due to lack of knowledge or understanding of physical phenomena, or ignorance, and the use of simplified structural models, or errors of simplification (Der Kiureghian as cited by Nikolaidis, 2005).

Upper and lower probabilities are the basis that led to combination theory. Dempster's rule of combination can be directly extended for the combination of N independent and equally reliable sources of evidence and its major interest comes essentially from its commutativity and associativity properties. When Dempster's orthogonal sum rule is used for combining (fusing) information from experts who might disagree with each other, one obtains the usual Dempster-Shafer (DS) theory (Dempster, 1967a).

Debois stated that absolute reliability implies that the analyst is qualified to make distinctions between the reliability of experts, sensors and/or other sources of information and can express this distinction between sources mathematically (Dubois et al., 1992). According to Klir when he was describing the Generalized Information Theory (GIT), the following axiomatic requirements, each expressed in a generic form, must be satisfied whenever applicable:

1. Subadditivity–the amount of uncertainty in a joint representation of evidence (defined on a Cartesian product) cannot be greater than the sum of the amounts of uncertainty in the associated marginal representations of evidence.
2. Additivity–the two amounts of uncertainty considered under subadditivity become equal if and only if the marginal representations of evidence are non-interactive according to the rules of the uncertainty calculus involved.
3. Range–the range of uncertainty is [0, M], where 0 must be assigned to the unique uncertainty function that describes full certainty and M depends on the size of the universal set involved and on the chosen unit of measurement.
4. Continuity–any measure of uncertainty must be a continuous functional.
5. Expansibility–expanding the universal set by alternatives that are not supported by evidence must not affect the amount of uncertainty.
6. Branching/Consistency–when uncertainty can be computed in more ways, which are all acceptable within the calculus of the uncertainty theory involved, the results must be the same (consistent).

7. Monotonocity–when evidence can be ordered in the uncertainty theory employed (as in possibility theory), the relevant uncertainty measure must preserve this ordering.
8. Coordinate invariance–when evidence is described within the n-dimensional Euclidean space ($n \geq 1$), the relevant uncertainty measure must not change under isometric transformations of coordinates.

When distinct types of uncertainty coexist in a given uncertainty theory, it is not necessary that these requirements be satisfied by each uncertainty type. However, they must be satisfied by an overall uncertainty measure, which appropriately aggregates measures of the individual uncertainty types (Klir, 2004). Table 4 describes contributions and summary of selected literature in mathematical approach to uncertainty.

Reference	**Summary of selected literature in mathematical approach to uncertainty**
Ayyub (2001)	The purpose of aggregation of information is to meaningfully summarize and simplify a corpus of data whether the data is coming from a single source or multiple sources. Familiar examples of aggregation techniques include arithmetic averages, geometric averages, harmonic averages, maximum values, and minimum values.
Booker et al. (2004)	Aggregation of multiple expert estimates is a continuing research topic, but in the context of the challenge problems, it encompasses aggregation of the multiple interval estimates. Some common schemes include equal weights (maximum entropy solution), decision maker supplied weights, analyst supplied weights, experts weighting other experts, experts supplying self-weights, and Bayesian methods.

Table 4. Summary selected literature in mathematical approach to uncertainty

Reference	Summary of selected literature in mathematical approach to uncertainty
Dempster (1967a)	Upper and lower probabilities that led to combination theory. Dempster's rule of combination can be directly extended for the combination of N independent and equally reliable sources of evidence and its major interest comes essentially from its commutativity and associativity properties. When Dempster's orthogonal sum rule is used for combining (fusing) information from experts who might disagree with each other, one obtains the usual Dempster-Shafer (DS) theory.
Dubois & Prade (1992)	Absolute reliability implies that the analyst is qualified to make distinctions between the reliability of experts, sensors, or other sources of information and can express this distinction between sources mathematically.
Hampton (2001)	Probabilistic methods, Latin hypercube and traditional triangular distribution.
Klir (2004)	The following axiomatic requirements, each expressed in a generic form, must be satisfied whenever applicable: Subadditivity, Additivity, Range, Continuity, Expansibility, Branching/Consistency, Monotonocity, Coordinate invariance. When distinct types of uncertainty coexist in a given uncertainty theory, it is not necessary that these requirements be satisfied by each uncertainty type. However, they must be satisfied by an overall uncertainty measure, which appropriately aggregates measures of the individual uncertainty types.
Monroe (1997)	Risk and uncertainty was directly related to the complexity of system.

Table 4: Continued - Summary selected literature in mathematical approach to uncertainty

Reference	Summary of selected literature in mathematical approach to uncertainty
Oberkampf et al. (2005)	Probability theory and evidence theory are introduced as possible mathematical structures for the representation of the epistemic uncertainty associated with the performance of safety systems. A representation of this type is illustrated with a hypothetical safety system involving one weak link and one strong link that is exposed to a high temperature fire environment. Topics considered include (1) the nature of diffuse uncertainty information involving a system and its environment, (2) the conversion of diffuse uncertainty information into the mathematical structures associated with probability theory and evidence theory, and (3) the propagation of these uncertainty structures through a model for a safety system to obtain representations in the context of probability theory and evidence theory of the uncertainty in the probability.
Shafer (1976)	Shafer stated the paradigm shift, which led him to formulate an alternative to the existing Bayesian formalism for automated reasoning, thus leading to what is commonly known as Dempster-Shafer (DS) evidential reasoning. The basic concept showed that an expert's complete ignorance about a statement need not translate into giving 1/2 a probability to the statement and the other 1/2 to its complement, as was assumed in Bayesian reasoning.
Zadeh (1965)	Fuzzy sets, unions and intersections, properties and mathematical solutions.

Table 4: Continued - Summary selected literature in mathematical approach to uncertainty

2.5 *Analyses based in Probabilistic Approach*

Probability theory is a popular approach in uncertainty quantification in engineering problems. Ayyub stated this in his definition as "With the term *probability elicitation method*, we denote any aid that is used to acquire a probability from an expert" (Ayyub, 2001). Generally, a distinction is made between *direct* and *indirect* methods. With direct methods, experts are asked to directly express their degree of belief as a number, be it a probability, a frequency or an odds ratio. For expressing probabilities, however, people find words more appealing than numbers. This is probably because the vagueness of words captures the uncertainty they feel about their probability assessment; the use of numerical probabilities can produce considerable discomfort and resistance among those not used to it (Renooij, 2001). In addition, since directly assessed numbers tend to be biased, various indirect elicitation methods have also been developed. With these methods, an expert is asked not for a direct assessment, but for a decision from which his degree of belief is conditional (Renooij, 2001).

A complicating factor, as noted by Clemen (1986) and French (1986), is that everything is conditional on the decision maker. Moreover, the issue not only involves the decision maker's information about the events or variables of interest, but the possibility of dependence between this information and the experts' information. Even without these complications, the decision maker's perception of the experts (e.g., whether they are calibrated, whether there is dependence among the experts, whether cognitive biases are influencing the probabilities) plays an important role in the modeling process (Clemen, 1986, French, 1986). The need to combine expert's probabilities frequently arises in cases in which other available information about the events or variables of interest is very limited. Indeed, the lack of relevant data is often what motivates a decision maker to seek out expert opinions (Winkler, 1986).

Based on Baenen, Bayesian belief networks are rooted in traditional subjective probability theory, which builds on the foundation of Pascalian calculus. In subjective probability theory, the probability of a proposition represents the degree of confidence an individual has about that proposition's truth. This matches quite well to our knowledge base of information from a human expert in addition to his or her subjective beliefs about the accuracy of that information (Baenen, 1994). Before Bayesian belief networks are described, we must begin with the fundamentals of probability theory. Let A be some event within the context of all possible events E, within some domain, such that A 0 E and E is the event space.

The probability of A occurring is denoted by P(A). P(A) is the probability assigned to A prior to the observation of any evidence and is also called the *apriori* probability. This probability must conform to certain laws. First, the probability must be non-negative and must also be less than one; therefore,

$$\forall A \in E, 0 \le \mathrm{P}(A) \le 1 \qquad (1)$$

A probability of 0 means the event will not occur while a probability of 1 means the event will always occur. Second, the total probability of the event space is 1 or in other words the sum of the probabilities of all of the events A_i in E must equal 1.

$$\forall A \in E, \sum A_i = 1 \qquad (2)$$

Finally, we consider the compliment of *A*, *5A*, which is all events in *E* except for *A*. From equation (2) we then get:

$$\mathrm{P}(A) + \mathrm{P}(\neg A) = 1 \qquad (3)$$

Now consider another event in *E*, *B* such that *E* 0 *B*. The probability that event *A* will occur given that event *B* has occurred is called the conditional probability of *A* given *B* and is represented by P(*A* | *B*). The probability that both *A* and *B* will occur is called the joint probability and is defined by P(*A* 1 *B*) . P(*A* | *B*) is defined in terms of the joint probability of *A* and *B* by:

$$\mathrm{P(A|B)} = \frac{\mathrm{P(A \cap B)}}{\mathrm{P(A|B)}} \qquad (4)$$

Equation (4) can be further manipulated to yield Bayes Rule:

$$\mathrm{P(A|B)} = \frac{\mathrm{P(B|A)\ X\ P(A)}}{\mathrm{P(B)}} \qquad (5)$$

If these two events are independent, in that the occurrence of one event has no effect on the occurrence of the other, then P(*A* | *B*) = P(*A*) and P(*B* | *A*) = P(*B*). If we manipulate equation 5 still further we get:

$$P(A|B) = \frac{P(B|A) \ X \ P(A)}{[P(B|A) \ X \ P(A)] + [P(B|A) \ X \ P(\neg A)} \quad (6)$$

This lays the foundation for managing and manipulating uncertainty using probability theory in expert systems. It allows us to turn a rule around and calculate the conditional probability of *A* given *B* from the conditional probability of *B* given *A*.

Some of the advantages of Bayesian belief networks are that the representation is visual and easy to understand. It is also relatively straightforward to implement as the methodology for combining uncertainty follows set rules and procedures. Probability theory is a well-refined method for dealing with knowledge of unknown certainty (Baenen, 1994).

Bayesian belief networks still have some problems. They require large numbers of probabilities that must be obtained from the human expert. The number of probabilities is dependent on the complexity of the conditional dependencies in the domain. They also cannot represent cycles (eg. *A* implies *B* and *B* implies *A*) or infinite loops would occur during inference. Additionally, because the sum of all possible states must equal 1, when evidence reinforces the belief in some possible world, it correspondingly decreases our belief in all other worlds. This is not necessarily the case in real life (Baenen, 1994). Bayesian networks require us to make certain artificial assumptions about the independence of information/events leading to counter intuitive, possibly incorrect results (ibid, pp. 6-10). Table 4 is a summary of selected literature in probabilistic approach.

The CDF describes the probability distribution of a random variable X. For every real number x, the distribution function of X is defined by:

$$F(x) = P(X \leq x) \qquad (7)$$

where the right of x represents the probability that X takes on a value *less* than or equal to x and the left of x represents the probability that X takes on a value *greater* than x. The probability that X lies in the interval [a, b] is, therefore, $F(b) - F(a)$ if $a < b$ (Ayyub, 2001).

In this research, the analysis of how often the random variable is above a particular level. This is referred to "the exceedance question" and is necessary for the correlation with Evidence theory. This graphical analysis called the complementary cumulative distribution function (CCDF), which can be defined by:

$$F_c(x) = P(X > x) = 1 - F(x) \qquad (8)$$

CCDF curve is typically obtained by sampling based techniques and are, therefore, approximate. "These distributions mathematically describe a degree of belief, based on all of the available evidence (e.g., data, background knowledge, analysis, experiments, expert judgment), of the range and weight, in terms of likelihood, of the input values used in the analysis" (National Research Council, 1996). The complementary nature of the CCDF results in the right of x representing the probability that X takes on a value *greater* than or equal to x and the left of x representing the probability that X takes on a value *less* than x. Table 5 summarizes selected literature and previous contributions in probabilistic approach.

Reference	Selected literature in probabilistic approach
Ayyub (2001)	With the term probability elicitation method, it was denoted any aid that could be used to acquire a probability from an expert.
Baenen (1994)	Advantages of Bayesian belief networks: Representation is visual and easy to understand. It is also relatively straightforward to implement as the methodology for combining uncertainty follows set rules and procedures. Probability theory is a well-refined method for dealing with knowledge of unknown certainty
Baenen (1994)	Disadvantages of Bayesian belief networks: They require large numbers of probabilities that must be obtained from the human expert. The number of probabilities is dependent on the complexity of the conditional dependencies in the domain. They also cannot represent cycles or infinite loops would occur during inferencing. Additionally because the sum of all possible states must equal 1, when evidence reinforces the belief in some possible world, it correspondingly decreases our belief in all other worlds.
Booker & McNamara (2003)	Statistical Analysis based on probably theory.
Booker & McNamara (2004)	Because uncertainties (especially epistemic ones) are difficult to estimate, it is important to establish the uncertainty and analysis reference or standard for the entire problem as early as possible. Probability theory has become a fundamental theory for characterizing *aleatoric uncertainty*—uncertainty associated with phenomena such as random noise, measurement error, and uncontrollable variation. With aleatoric uncertainty, the common conception is that uncertainty cannot be further reduced or eliminated by additional information (data or knowledge).
Chytka (2003)	Bayesian methods and probability theory
Conway (2003)	Calibration based on a new developed logarithm using probability theory
Dempster (1967a)	Presented evidence theory in terms of probability. Subjective probability theory assumes that individuals are always able to conceive compound events out of union, intersection and complementation of a given list of elementary events.

Table 5. Summary of selected literature in probabilistic approach

Reference	Selected literature in probabilistic approach
Hampton (2001)	Uncertainty quantification based on Probabilistic methods.
Helton (2005)	Probability theory provides the mathematical structure traditionally used in the representation of epistemic (i.e., state of knowledge) uncertainty, with the uncertainty in analysis outcomes typically represented with probability distributions and summarized as cumulative distribution functions (CDFs).
Levi (1980)	Bayesian decision theory, an approach to probability
Monroe (1997)	Analyzed finding with cumulative distribution function and probability based principles.
Oberkampf et al. (2005)	In probability theory likelihood is assigned to a probability density function PDF. Treat epistemic uncertainty as possible realizations with no probability associated with those realizations obtained from sampling.
Park et al. (2005)	Uses Microsoft Excel Multiple Regression analysis and Probability Theory.
Renooij (2001)	This is probably because the vagueness of words captures the uncertainty they feel about their probability assessment; the use of numerical probabilities can produce considerable discomfort and resistance among those not used to it.
National Research Council (1996)	It is sometimes necessary to study how often the random variable is above a particular level. This is referred to "the exceedance question."

Table 5. Continue - Summary of selected literature in probabilistic approach

2.6 Analyses based on a Non-Probabilistic Approach

Dempster-Shafer Theory. The advantages of Dempster-Shafer theory lie in its ability to better represent ignorance as well as its structure allowing evidence supporting one possible world to not necessarily detract from belief in all other worlds. The disadvantages occur because of its implementational complexity and the requirement for exhaustive enumeration of all possible combinations of hypotheses. Dempster Shafer theory also lacks an effective methodology for extracting inferences (Baenan, 1994).

Before an analysis is performed, the relationship among the Fuzzy Measures must be explained. According to Klir (1995) it is obvious from their mathematical properties that possibility, necessity, and probability measures do not overlap with one another except for one very special measure, characterized by only one focal element, which is called a singleton. Probability theory coincides with the sub-areas of Evidence Theory in which Belief measures and Plausibility measures are equal. The differences in mathematical properties of these theories make each theory suitable for modeling certain types of uncertainty and less suitable for modeling others which is shown in Figure 5 (Klir, 1995).

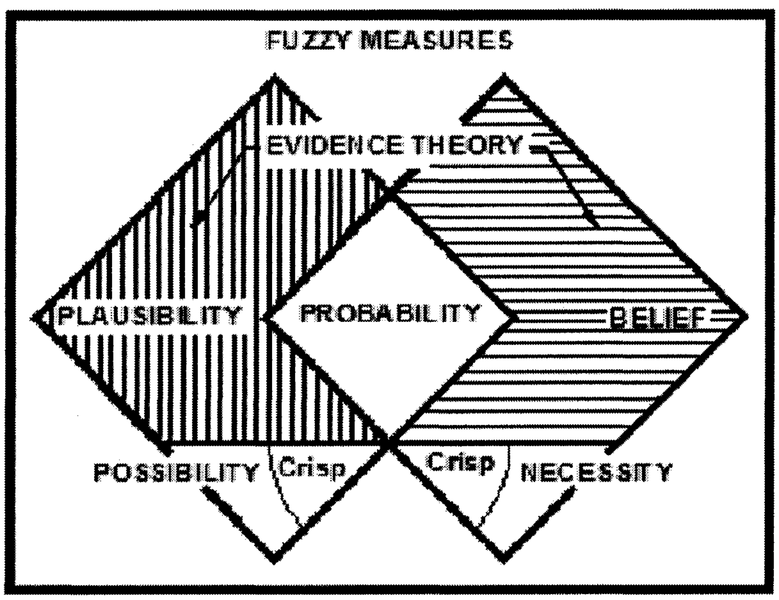


Figure 5. Relationship between plausibility, probability and belief (adopted/modified from Klir, 1995)

Is fuzzy logic better science than probability? No, it is a different science. Fuzzy logic and probability offer solutions to slightly different classes of problems. Fuzzy logic allows engineers to make explicit precision-versus-cost trade-offs. A fuzzy logistician would embrace the vagueness and make a model; if the model did not work, he would learn from the failure and build a better model (Almond, 1995).

Dubois used decision-maker uncertainty, which only require bounded, linearly ordered, valuation sets for expressing uncertainty and preferences, which is a testable descriptive approach of possibility theory. In this framework, pessimistic (uncertainty adverse) and optimistic attitudes can be captured (Dubois, 1992). A synthesis of the literature on non-probabilistic approach and their findings are listed in Table 6.

Reference	Selected literature on non-probabilistic approach
Almond (1995)	Is fuzzy logic better science than probability? No, it is a different science. Fuzzy logic and probability offer solutions to slightly different classes of problems. Fuzzy logic allows engineers to make explicit precision-versus-cost trade-offs. A fuzzy logistician would embrace the vagueness and make a model; if the model did not work, he would learn from the failure and build a better model.
Baenen (1994)	Comparison of Probabilistic with non-probabilistic methods.
Booker & McNamara (2003)	*Epistemic* (lack of knowledge, reducible with more information) refers to an absence of complete knowledge—uncertainty that can be reduced or eliminated by increasing knowledge or sample size.
Dubois & Prade (1992)	Decision-maker uncertainty, which only require bounded, linearly ordered, valuation, sets for expressing uncertainty and preferences. A testable descriptive approach of possibility theory. In this framework, pessimistic (uncertainty adverse) and optimistic attitudes can be captured.

Table 6. Summary of selected literature on non-probabilistic approach

Reference	Selected literature on non-probabilistic approach
Dubois, Prade (2001)	Nearest Neighbor" classifier method suggests (guarantees) the development of the model of uncertainty and handling of incomplete information. Formalized the principles of evidence expressed in terms of possibility and tested in hypothetical cases.
Klir (1995)	It is obvious from their mathematical properties that possibility, necessity and probability measures do not overlap with one another except for one very special measure, characterized by only one focal element, which is called a singleton. Probability theory coincides with the sub areas of Evidence Theory in which belief measures and Plausibility measures are equal. The differences in mathematical properties of these theories make each theory suitable for modeling certain types of uncertainty and less suitable for modeling others.

Table 6. Continued - Summary of selected literature on non-probabilistic approach

2.7 Evidence Theory

Dempster-Shafer Theory (DST) was started by Arthur Dempster in the 1960's and expanded by Glen Shafer in the 1970's (Dempster, 1967a, Shafer, 1976). Dempster felt there was a need for a new system of dealing with uncertainty because of two shortcomings he saw with the probability theory. The Evidence theory can be defined as a mathematical model that establishes upper and lower limits of likelihood – plausibility and belief respectively (Oberkampf, 2005).

There are three important functions in Dempster-Shafer theory: the *basic probability assignment* function (BPA or *m*), the *Belief* function (*Bel*), and the *Plausibility* function (*Pl*). The basic probability assignment (BPA) is a primitive of evidence theory. Generally speaking, the term "basic probability assignment" does *not* refer to probability in the classical sense. The BPA, represented by *m*, defines a mapping of the power set to the interval between 0 and 1, where the BPA of the null set is 0 and the summation of the BPA's of all the subsets of the power set is 1. The value of the BPA for a given set A (represented as $m(A)$), expresses the proportion of all relevant and available evidence that supports the claim that a particular element of X (the universal set) belongs to the set A but to no particular subset of A (Klir, 1998, Dempster, 1967a, Shafer, 1976).

The value of $m(A)$ pertains only to the set A and makes no additional claims about any subsets of A. Any further evidence on the subsets of A would be represented by another BPA, i.e. $B \subseteq A$, $m(B)$ would the BPA for the subset B. Formally, this description of m can be represented with the following three equations:

$$m: \mathrm{P}(X) \rightarrow [0,1] \tag{9}$$

$$m(\emptyset) = 0 \tag{10}$$

$$\sum_{A \in \mathrm{P}(X)} m(A) = 1 \tag{11}$$

where $\mathrm{P}(X)$ represents the power set of X, $\emptyset$ is the null set, and A is a set in the power set ($A \in \mathrm{P}(X)$) (Klir, 1998).

Some researchers have found it useful to interpret the basic probability assignment as a classical probability, such as (Chokr & Kreinovich, 1994), and the framework of Dempster-Shafer theory can support this interpretation. The theoretical implications of this interpretation are well developed in (Kramosil, 2001). This is a very important and useful interpretation of Dempster-Shafer theory but it does *not* demonstrate the full scope of the representational power of the basic probability assignment. As such, the BPA *cannot* be equated with a classical probability in general.

From the basic probability assignment, the upper and lower bounds of an interval can be defined. This interval contains the precise probability of a set of interest (in the classical sense) and is bounded by two no additive continuous measures called Belief and Plausibility. The lower bound *Belief* for a set A is defined as the sum of all the basic probability assignments of the proper subsets (B) of the set of interest (A) ($B \subseteq A$). The upper bound, *Plausibility*, is the sum of all the basic probability assignments of the sets (B) that intersect the set of interest (A) ($B \cap A \neq \varnothing$). Formally, for all sets A that are elements of the power set ($A \in \mathrm{P}\,(X)$), the following equations apply (Klir, 1998):

$$\mathrm{Bel}\,(\mathrm{A}) = \sum_{\mathrm{B} \mid \mathrm{B}\phi\mathrm{A}} \mathrm{m(B)} \qquad (12)$$

$$\mathrm{Pl}\,(\mathrm{A}) = \sum_{\mathrm{B} \mid \mathrm{B\ I\ A} \neq \varnothing} \mathrm{m(B)} \qquad (13)$$

The two measures, *Belief* and *Plausibility* are non-additive.

It is possible to obtain the basic probability assignment from the *Belief* measure with the following inverse function:

$$\mathrm{m}\,(A) = \sum_{\mathrm{B} \mid \mathrm{B}\phi\mathrm{A}} (-1)^{|\mathrm{A-B}|}\, Bel(B) \qquad (14)$$

where $|A\text{-}B|$ is the difference of the cardinality of the two sets. In addition to deriving these measures from the basic probability assignment (m), these two measures can be derived from each other. For example, *Plausibility* can be derived from *Belief* in the following way:

$$Pl(A) = 1 - Bel(\bar{A}) \qquad (15)$$

where *A* is the classical complement of *A*. This definition of Plausibility in terms of Belief comes from the fact that all basic assignments must sum to 1.

$$Bel\,(\bar{A}) = \sum_{B \mid B \phi \bar{A}} m(B) = \sum_{B \mid B\, 1\, A \neq \emptyset} m(\mathrm{B}) \qquad (16)$$

$$\sum_{B \mid B \phi \bar{A}} m(B) = 1 - \sum_{B \mid B\, 1\, A \neq \emptyset} m(\mathrm{B}) \qquad (17)$$

From the definitions of Belief and Plausibility, it follows that $Pl(A) = 1 - Bel(\bar{A})$. As a consequence of Equations 14 and 15, given any one of these measures ($m(A)$, $Bel(A)$, $Pl(A)$), it is possible to derive the values of the other two measures.

The precise probability of an event (in the classical sense) lies within the lower and upper bounds of *Belief* and *Plausibility,* respectively.

$$Bel(A) = P(A) = Pl(A) \qquad (18)$$

The probability is uniquely determined if $Bel\,(A) = Pl(A)$. In this case, which corresponds to classical probability, all the probabilities, $P(A)$ are uniquely determined for all subsets *A* of the universal set *X* (Yager, 1987). Otherwise, $Bel\,(A)$ and $Pl(A)$ may be viewed as lower and upper bounds on probabilities respectively, where the actual probability is contained in the interval described by the bounds. Upper and lower probabilities derived by the other frameworks in generalized information theory *cannot* be directly interpreted as *Belief* and *Plausibility* functions (Dubois and Prade, 1992).

In summary, Basic Belief Assignment (BBA) is not probability, but just a belief in a particular proposition irrespective of other propositions. The BBA structure gives the flexibility to express belief for possible propositions with partial and insufficient evidence and also avoids our making excessive or baseless assumptions in assigning our belief to propositions (Bae, 2003). The summary of selected literature on evidence theory is shown in Table 7.

Reference	Selected literature on evidence theory
Ayyub (2001)	A basic assignment can be related to the belief and plausibility measures; basic assignments of evidence are represented by a family of sets ($A_1, A_2 \ldots A_N$) that are constructed for convenience and for facilitating the expression and modeling of expert opinions.
Bae & Graudhi (2003)	Basic Belief Assignment (BBA) is not probability, but just a belief in a particular proposition irrespective of other propositions. The BBA structure gives the flexibility to express belief for possible propositions with partial and insufficient evidence and also avoids our making excessive or baseless assumptions in assigning our belief to propositions.
Booker (2004)	Expert judgment is a subjective probability—a quantitative statement that reflects an individual's degree of belief in the likelihood of a future and uncertain event, based on the knowledge and experience that the individual holds about similar past events. Subjective probability is part of epistemic uncertainty hence partially related to evidence theory.

Table 7. Summary of selected literature in evidence theory

Reference	Selected literature on evidence theory
Dempster (1967a)	An original contribution to evidence theory. Introduces the multi valued mapping from a space X to a space S carries a probability measure defined over subsets of X into a system of *upper and lower probabilities* over subsets of S.
Dubois & Prade (1992)	Upper and lower probabilities derived by the other frameworks in generalized information theory *cannot* be directly interpreted as *Belief* and *Plausibility* functions.
Hüllermeir, Dubois & Prade (2001)	Formalized the principles of evidence expressed in terms of possibility and tested in hypothetical cases.
Klir (1998)	From the basic probability assignment, the upper and lower bounds of an interval can be defined. This interval contains the precise probability of a set of interest (in the classical sense) and is bounded by two no additive continuous measures called Belief and Plausibility.
Klir & Smith (2001)	Explained the classification of uncertainties for evidence theory as monotone measures and non-additive measures that are called belief measures. When all focal elements in a given body of evidence are singleton's, the associated belief measure and plausibility measure collapse into a single measure that is formally equivalent to the classical probability measure which is additive.
Klir & Wierman (1998)	The basic probability assignment (BPA) is a primitive of evidence theory. Generally speaking, the term "basic probability assignment" does *not* refer to probability in the classical sense. The BPA, represented by *m*, defines a mapping of the power set to the interval between 0 and 1, where the bpa of the null set is 0 and the summation of the BPA's of all the subsets of the power set is 1. The value of the bpa for a given set *A* (represented as *m*(*A*)), expresses the proportion of all relevant and available evidence that supports the claim that a particular element of *X* (the universal set) belongs to the set *A*, but to no particular subset of *A*.

Table 7. Continued - Summary of selected literature in evidence theory

Reference	Selected literature on evidence theory
Oberkampf et al. (2005)	The Evidence theory can be defined as a mathematical model that establishes upper and lower limits of likelihood – plausibility and belief respectively. Evidence theory can correctly represent uncertainties from intervals, degrees of belief and probabilistic information. Early in development and use for complex engineering systems. In evidence theory likelihood is assigned to sets. CPF and CBF can be viewed as upper and lower probabilities of possible values. 1) Focus debate on epistemic uncertainty issues in uncertainty quantification. 2) Better understand the effect of assumptions commonly made in uncertainty quantification analyses. 3) Move towards agreement on the most effective ways of representing uncertainty for decision makers.
Sentz & Ferson (2002)	Dempster-Shafer theory does not require an assumption regarding the probability of the individual constituents of the set or interval. This is a potentially valuable tool for the evaluation of risk and reliability in engineering applications when it is not possible to obtain a precise measurement from experiments, or when knowledge is obtained from expert elicitation. An important aspect of this theory is the combination of evidence obtained from multiple sources and the modeling of conflict between them.
Shafer (1976)	The mathematical theory of Evidence. Deals with weights of evidence and with numerical degrees of support based on evidence. This theory does not focus on the act of judgment instead is amendable to mathematical analysis: the combination of degrees of belief or support based on one body of evidence.
Yager (1987)	Discusses Dempster-Shafer approach and measures of entropy, specificity for belief structures. Introduces alternative techniques for combining belief structures. Points out an important feature of combination rules as the ability to update an already combined structure when new information becomes available. This is frequently referred to as updating and the algebraic property that facilitates this is associativity.

Table 7. Continued - Summary of selected literature in evidence theory

2.8 Literature Summary - Gap Analysis

Table 8 summarizes the authors' contributions under their respective area of research. Although this table does not contain all reference in used in this document, it represents a comprehensive list of significant references:

T_1: Experts Judgment Elicitation
T_2: Risk and Uncertainty in Decision Making
T_3: Mathematical Approach to Risk and Uncertainty
T_4: Analyses based on Probabilistic Approach
T_5: Analyses based on Non-Probabilistic Approach
T_6: Evidence Theory

Authors	**T_1**	**T_2**	**T_3**	**T_4**	**T_5**	**T_6**
Almond (1995)					X	
Apostolakis (2003)		X				
Ayyub (2001)	X		X	X		X
Bae & Graudhi. (2003)		X	X			X
Baenen (1994)		X		X	X	
Booker et al. (2004)	X		X			X
Booker & McNamara (2003)	X			X	X	
Booker & McNamara (2004)	X	X		X		
Booker & McNamara (2004-b)	X					
Chytka (2003)	X			X		
Conway (2003)	X			X		
Dempster (1967a)			X	X		X
Dempster (1967b)			X	X		X
Dubois & Prade (1995)			X		X	X
Fishoff (1984)			X			
Friel et al. (1990)					X	
Fragola & Bedford (2005)		X				
Groen (2000)		X			X	
Hampton (2001)		X		X		

Table 8. Literature summary and author's contributions

Authors	T_1	T_2	T_3	T_4	T_5	T_6
Harmanec (1996)					X	
Helton (2005)		X		X		
Harmanec & Klir (1996)					X	
Helton & Oberkampf (2004)		X		X		
Hüllermeir, Dubois & Prade (2001)					X	X
Klir (1995)			X		X	X
Klir (2004)			X			
Klir & Folger (1998)						X
Klir & Smith (2001)		X				X
Levi (1971)				X		
Liu (2004)		X				
Monroe (1997)		X	X	X		
Morgan & Henrion (1990)		X				
Mourelatos & Zhoou (2005)		X				
Mullin (1986)	X					
Nikolaidis (2005)		X	X			
Oberkampf et al. (2005)		X	X	X		X
Park et al. (2005)				X		
Polya (1941)				X		
Renooij (2001)	X			X		
Sentz (2002)						X
Shafer (1976)			X			X
Shanteau (1987)	X					
Shanteau (1992)	X					
Shanteau & Peters (1989)	X					
Tolson et al. (2004)		X				
Unal et al. (2003)		X				
Yager (1987)						X
Zadeh (1965)			X			
Zadeh (1995)				X		
Bondi (2007)	**X**	**X**	**X**	**X**	**X**	**X**

Table 8. Continued - Literature summary and author's contributions

The literature review indicates that much research has been done on expert judgment elicitation and probabilistic risk analysis. Recent work combined expert judgment and probabilistic risk analysis to quantify input parameter uncertainty so that risk analysis can be performed. The literature review also suggests Evidence theory may be a useful approach to extend uncertainty and risk assessment; however, as Table 8 indicates, there does not appear to be much research on combining the three approaches of expert judgment, probabilistic risk analysis and Evidence theory, particularly with regard to high-risk operations. Such a methodology may prove to be a valuable addition to the literature in uncertainty and risk assessment.

2.9 The Research Problem and Significance

To support the study proposed, diverse work has been reported and used as tools of findings. Further, it is also evident that there is a firm basis for moving beyond the immediate effort to the ultimate goal of developing a comprehensive modeling aid for technology assessments for advanced launch vehicles. This research seeks to develop an approach that combines Expert Judgment Elicitation, Probabilistic risk assessment, and Evidence theory to better aid the decision maker in a high-risk environment. The questions to be answered by this proposed research are:

- Could Evidence theory be effectively utilized together with a Probabilistic approach for uncertainty assessments in high-risk environments?
- Could the use of Dempster-Shafer's Evidence Theory lead to better informing decision makers?

In particular, this research seeks a means of improvement in the methods of relaying information taken from high-risk experts to decision makers in order to identify levels of uncertainty and increase reliability in expert's assessments.

The vast majority of studies on calibration of expert judgment involving probability assessments have dealt with outcomes that are observed or recorded, either as past events or occurrences or as near-term future events. In contrast with probability studies, this particular research is expected to result in a tool that produces more meaningful limits of uncertainty, based on calibrated high-risk judgment elicitation and evidence theory. The tool enables calibrated predictions that ultimately turn out to be inaccurate; however, it is anticipated that the technique provides the assessment of uncertainty. Such is the case with the thrust of this effort –expert judgment elicitation, application of evidence theory and probability theory, and the combination data relative to construction, operations and installation, for multidisciplinary design considerations in future CEV concepts employing many as-yet-unproven technology advances.

3. Research Methodology

3.1 *Overview*

This research further develops the high-risk expert judgment elicitation methodology in an attempt to assess and quantify input parameter uncertainties. The findings are applied to conceptual launch vehicle design study by using Dempster-Shafer's Evidence Theory in conjunction with the Probability theory. Even though the parameter of uncertainty is quantified in terms of probabilistic distribution, a similar approach can be used with the Evidence theory. This involves tailoring for data collection and uncertainty quantification through interactions with the disciplinary experts. The methodology includes a capability for multi-expert judgment calibration and aggregation. The research results extend to quantify upper and lower limits of uncertainty over the construction, installation and operations anomalies that occur on the TPS in CEV.

This work is unique because calibration algorithms simulated by Monte Carlo random variable selection are created and applied to elicited expert judgment information using both Probability theory and Evidence theory. The elicitation is taken from selected experts of the Thermal Protection System in determining an expert's best estimate based on their knowledge, information and belief regarding the number of potential anomalies during the lifecycle of the CEV.

Through the use of a graphical method this research provides various visual representations of the experts' uncertainty values to assist in the integration and assimilation of a decision strategy. This is accomplished by combining the graphs of the CCDF derived by the Probability theory and the upper and lower limits derived by the

Evidence theory. As a result of the means with which the aggregated results are conveyed, the decision makers may have more confidence in their decisions. The end result is that levels of uncertainty can then be propagated throughout the overall system using simulation or analytical methods to determine overall design risk. This methodology provides the decision maker with a very clear comparison of multiple experts' probabilistic risk assessment relative to their non-probabilistic risk assessment, which addresses aleatory uncertainty that contains inherent randomness, epistemic uncertainty due to lack of knowledge, or a combination of both.

3.2 Expert Selection and Questionnaire Development

A primary problem in conducting risk analysis in conceptual launch vehicle design is the lack of historical data to quantify input parameter of uncertainty. Asking disciplinary high-risk experts for their best professional judgment may sometimes be the only option when data available is limited. In reference to launch vehicle design, Conway states, "[M]any expert judgment elicitation scenarios involve events whose occurrence can be validated, because they are either past events or near term future events. In such cases, calibration of the expert assessors can include feedback on their performance, which could be expected to improve future performance (self-calibration). In the present research problem application, however, the preponderance of occurrences being assessed is in the distant future – as much as 20 or 30 years. Feedback involving actual results or occurrences is impossible" (Conway, 2003).

An expert judgment elicitation methodology for assessing uncertainty was developed in a prior study (conducted for Vehicle Analysis Branch at NASA, Langley

Research Center). The methodology borrowed features from the fields of psychology, knowledge engineering, operations research and computer science (Monroe, 1997).

In the present study, the high-risk experts were selected by NASA, ensuring objectivity and assessing subjective conclusions. The researcher has no prior knowledge of the background and level of expertise of the experts. A questionnaire was developed to qualify and quantify uncertainty associated with design parameters as a probability distribution and is used by many researchers (Monroe, 1997, Conway, 2003, Chytka, 2004).

3.3 Definition of Input Variables

Designers of the TPS must address a series of complex problems as a result of the extreme variations of environmental factors in which the orbiter must operate. As a result, "a complete, integrated system was developed relying on different components to solve different problems" (Cooper and Holloway, 1981, Pate-Cornell & Fischbeck, 1990). It is thought that critical subsystem anomalies of the TPS maybe a function of Construction, Installation, and Operations. For the purposes of this research, Construction can be defined as the production portion of the TPS lifecycle, including design and manufacturing. Anomalies during this phase can include contamination of the tiles during fabrication, impurities in the raw materials, and lack of uniformity in tempering the tiles. Installation is defined as the portion of the TPS lifecycle that includes the original installation. Anomalies in this phase include misaligned tiles which reduces the strength of the bond, debonding of tiles, and pull test failure. Finally, Operations can be defined as the portion of the TPS lifecycle from initial lift-off through landing. Anomalies in this phase include extreme levels of pressure, heat, debris impact, and vibration (Pate-Cornell & Fischbeck, 1990).

3.4 Probabilistic Approach: Cumulative Distribution Function, Complementary Cumulative Distribution Function and Monte Carlo Simulation

Probability theory provides the mathematical structure traditionally used in the representation of aleatory uncertainty, with the uncertainty in analysis outcomes being represented with probability distributions and summarized as Cumulative Distribution Functions (CDFs) (Helton, 1997).

The probability distribution of a discrete random variable is a list of probabilities associated with each of its possible values. It is also sometimes called the probability function or the probability mass function. All random variables (discrete and continuous) have a CDF. It is a function giving the probability that the random variable X is less than or equal to x, for every value x (Mendenhall, 1995).

Any cumulative probability distribution may be expressed in cumulative form. The horizontal axis is the allowable domain for the given probability function. Since the vertical axis is a probability, it must fall between zero and one. It increases from zero to one as we go from left to right on the horizontal axis. A cumulative curve is typically scaled from 0 to 1 on the Y-axis, with Y-axis values representing the cumulative probability up to the corresponding X-axis value as shown in Figure 6.

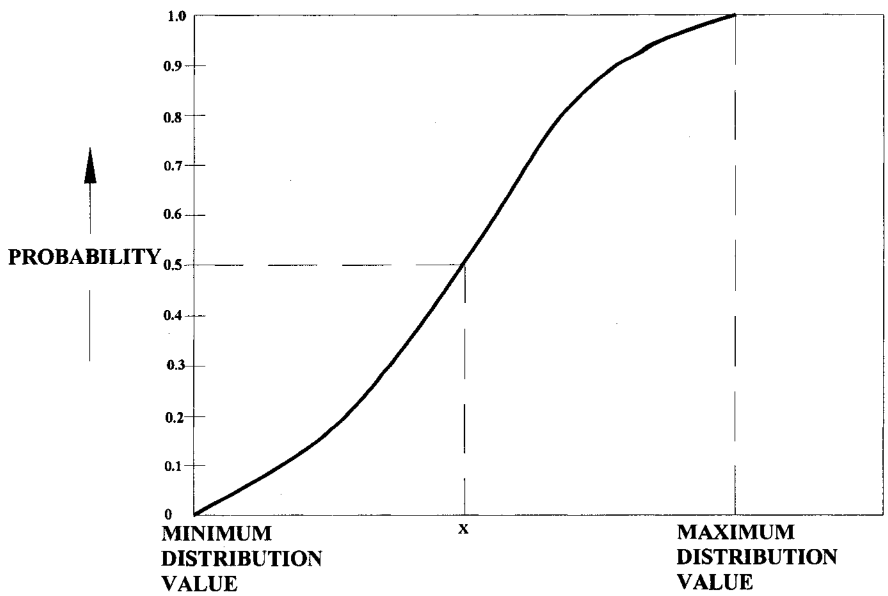


Figure 6. CDF Curve

The CDF describes the probability distribution of a random variable X. For every real number x, the distribution function of X is defined by:

$$F(x) = P(X \leq x) \qquad (19)$$

where the right of x represents the probability that X takes on a value *less* than or equal to x and the left of x represents the probability that X takes on a value *greater* than x. The probability that X lies in the interval [a, b] is, therefore, $F(b) - F(a)$ if $a < b$ (Ayyub, 2001). If one bases the level of inherent uncertainty to probabilistic methods only, the relative frequency of findings will be expressed as:

$$F(x) = \int_{\infty}^{xo} f(x)dx \qquad (20)$$

Using Monte Carlo simulation, the CDF curve could be obtained by:

$$f(x) = \frac{dF(x)}{dx} \qquad (21)$$

The reasoning is very important in understanding the cumulative curve in terms of sampling because the curve shape is based on the shape of the input probability distribution. The more likely outcomes will be more likely to be sampled. The more likely outcomes are in the range where the cumulative curve is the steepest. The more iterations, the smoother the cumulative curve becomes. This is referred to as "the exceedance question" and is necessary for the correlation with Evidence theory. This graphical analysis called the complementary cumulative distribution function (CCDF), which can be defined by:

$$F_c(x) = P(X > x) = 1 - F(x) \qquad (22)$$

CCDF curve is typically obtained by sampling based techniques and are, therefore, approximate. "These distributions mathematically describe a degree of belief, based on all of the available evidence (e.g., data, background knowledge, analysis, experiments, expert judgment), of the range and weight, in terms of likelihood, of the input values used in the analysis" (National Research Council, 1996). The complementary nature of the

CCDF results in the area right of x representing the probability that X takes on a value *greater* than or equal to x and the area left of x representing the probability that X takes on a value *less* than x (Ayyub, 2001). This study involves the analysis of how often the random variable is above a particular level as seen in Figure 7.

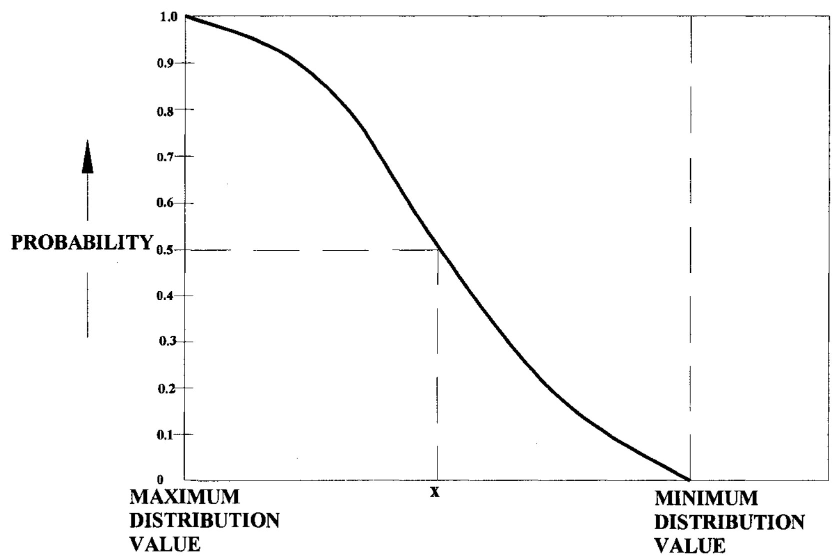


Figure 7: CCDF Curve

The application of aggregation of multiple judgments using the linear opinion pool method was developed for each subject matter expert by Chytka (2003). Chytka derived the aggregation process by using the calibrated distributions through importing the calibrated variables into @RISK® Software in terms of minimum, most likely and maximum values. The "RiskTriang" function provided an adequate number of data points, resulting in the Cumulative Distribution Function (CDF) by the use of Monte Carlo Simulation as well as the Complementary Distribution Function (CCDF).

Monte Carlo is a simulation tool capable of providing a relatively realistic representation of graphical results of "real data." Monte Carlo simulation uses random or pseudo-random numbers to sample from several specified probability distributions. The sampling in Monte Carlo is entirely random, meaning that a single sample may fall anywhere within the distribution range of the inputs. Given enough iterations, also known as repeated sampling, the input distributions can be entirely recreated. A sample of 1000 or more is usually sufficient to avoid clustering and fully sample the input (Monroe, 1997).

The computerized program @RISK® uses the input of sampling in a simulation to generate possible values from distribution functions. These sets of possible values are then evaluated using the Microsoft® Excel worksheet. As a result, sampling is the basis for the hundreds of thousands of "what-if" scenarios the program calculates from the worksheet.

An important factor to examine when evaluating sampling techniques is the number of iterations required to accurately recreate an input distribution through sampling. Less iteration results in less "efficient" methods of deriving the approximate distributions. Monte Carlo sampling often requires a large number of samples to approximate an input distribution, especially if the input distribution is highly skewed or has some outcomes of low probability.

3.5 Non-Probabilistic Approach: Evidence Theory

Probability theory has been criticized for lacking the capability of capturing epistemic uncertainty (Sentz and Ferson, 2002). Many theories have been developed and categorized into the "fuzzy measure theory" as a consequence of this criticism (Klir, 2004). Further, "neither classical probability theory nor classical possibility theory are sufficiently general to fully recognize our ignorance without ignoring available information" (p. 36). The Evidence theory can be defined as a mathematical model that establishes upper and lower limits of likelihood – plausibility and belief respectively (Oberkampf, 2005). It takes into account aleatory and epistemic uncertainty bounded by the belief and plausibility functions [Bel(A_i) , Pl(A_j)] and is found without any assumptions made on the information obtained from the experts.

This theory has numerous applications, including engineering, medicine, statistics, psychology, philosophy and accounting (Sun & Farooq, 2004). The following is a listing and brief overview of two rules used to aggregate evidence for this research:

3.5.1 Dempster-Shafer's combination rule

The Dempster-Shafer's combination rule is the first of its kind and the foundation for the other rules. The combination of basic assignments from two sources of information can be defined as (Ayyub, 2001):

$$m_{1,2}(A) = \frac{\sum\limits_{\text{all } A_i \cap A_j = A} m_1(A_i)\, m_2(A_j)}{1 - \sum\limits_{\text{all } A_j \cap A_k = \varnothing} m_1(A_i)\, m_2(A_j)} \qquad A = \varnothing \qquad (23)$$

The combination of independent sources of information is the basis of this rule, and it is characterized by the product combination rule. Shaffer explains this in his own statements as “Mathematically, Dempster's rule is simply a rule for computing, from two or more belief functions over the same set Θ, a new belief function called their *orthogonal sum*. The burden of our theory is that this rule corresponds to the pooling of evidence: if the belief functions being combined are based on entirely distinct bodies of evidence and the set Θ discerns the relevant interaction between those bodies of evidence, then the orthogonal sum gives degrees of belief that are appropriate on the basis of the combined evidence” (Shafer, 1976).

3.5.2 Yager's combination rule

While Dempster-Shaffer's rule allows for the combination of two expert opinions, Yager's combination rule enables the combination of more than two expert opinions. Ayyub states, “Expert opinions in the form of subjective probabilities of an event need to be combined into a single value and perhaps intervals for their use in probabilistic and risk analyses” (Ayyub, 2001). Suppose Bel_1 and Bel_2 are belief functions over the same frame of discernment $\Theta = \{\theta 1, \theta 2, \ldots, \theta n\}$ with basic assignments m_1 and m_2, and focal elements $A_1, A_2, \ldots, A_k$ and $B_1, B_2, \ldots, B_l$, respectively. Then Yager's combined basic assignments of the two sources of information can be defined as (Yager, 1987):

$$m_y(C) = \begin{cases} \sum\limits_{\substack{i,j \\ C = A_i \cap B_j}} m_1(A_i)\, m_2(B_j), & C \neq \Theta,\ \phi \\ m_1(\Theta)\, m_2(\Theta) + \sum\limits_{\substack{i,j \\ A_i \cap B_j = \phi}} m_1(A_i)\, m_2(B_j), & C = \Theta \\ 0, & C = \phi \end{cases} \tag{24}$$

3.5.2 Selecting a Combination Rule

According to Sentz and Ferson (2002), one should determine the requirements of the situation as disjunctive pooling, conjunctive pooling or tradeoff in order to select the appropriate combination rule. For example, the Dempster-Shafer's combination rule is applicable for conjunctive pooling, and Yager's combination rule is suited for tradeoff. They further explain that there must be consideration for the level of development of the theories and their use in the particular situation.

Bayesian probabilities are traditional applications of probabilistic methods to epistemic and subjective uncertainty (Sentz & Ferson, 2002). The Evidence theory essentially "combines the Bayesian notion of probabilities with the classical idea of sets where a numerical value signifying confidence can be assigned to sets of simple events rather than to just mutually exclusive simple events" (Bogler & Wright, 1992). Comparing Bayesian probabilities to evidence theory, Dempster-Shafer combination rule applied in Evidence theory is more "efficient and effective" than the Bayesian judgment rule found in Bayesian probabilities because "the former does not require a priori probability and can process ignorance" (Sun & Farooq, 2004).

Yager (1987) proposed a combination rule that is a modified version of Dempster-Shafer combination rule due to some limitations to this approach, such as the counter-intuitive results for some pieces of evidence (Zadeh, 1979, 1984, 1986), computational expenses and independent sources of information (Yager, 1987) as explained in (Sun & Farooq, 2004). Yager's rule is considered to be the most prominent of the alternative combination rules based on the class of unbiased operators developed and addresses counter-intuitive results (Yager, 1987).

In reference to Dempster-Shafer's rule, Yager's (1987) stated, "it can be easily shown that the operation of orthogonal sum of belief structures (m) satisfies the following properties" (p. 110):

(1) Commutativity:

$$m_1 \oplus m_2 = m_2 \oplus m_1 \qquad (25)$$

(2) Associativity:

$$(m_1 \oplus m_2) \oplus m_3 = m_1 \oplus (m_2 \oplus m_3) \qquad (26)$$

He indicated that these two properties allows us to combine multiple belief structures (m) by repeating the application of Dempster-Shafer's rule, thus $m_1, m_2, \ldots\ldots.. m_n$ are n pieces of evidence combined as:

$$m = m_1 \oplus m_2 \oplus \ldots. \oplus m_n \qquad (27)$$

Yager's general framework was developed "by look[ing] at combination rules where associative operators are a proper subset". The algebraic properties satisfied by this rule are commutativity and quasiassociativity (ibid.).

The basic assignment (m)

A basic assignment (m) is an assessment of the likelihood of an element "x" of "X" to each set in the family of sets identified (Ayyub, 2001).

A basic assignment can be conveniently characterized by:

$$m\colon P_x \rightarrow [0,1] \qquad (28)$$

A basic assignment must satisfy the following two conditions:

$$m(\varnothing) = 0 \qquad (29)$$

$$\sum_{all\, A \subseteq Px} m(A) = 1 \qquad (30)$$

If $m(A_i) > 0$ for any i, A_i is also called a *focal element.*

These three functions can be viewed as alternate representations of uncertainty regarding the same parameter x.

The bounds of uncertainty are identified by the two functions known as:

Belief (lower) function:

$$Bel\ (A_i) = \sum_{all\ Aj \subseteq Ai} m(A_i) \qquad (31)$$

Plausibility (upper) function:

$$Pl\ (A_i) = \sum_{Aj \cap Ai \neq \varnothing} m(A_j) \qquad (32)$$

The belief measure and plausibility measure as presented by Ayyub (2001) are as follows:

The belief measure (Bel)

The belief measure (*Bel*) should be defined on a universal set X as a function that maps the power set X to the range [0,1] as given by:

$$(Bel): P_x \longrightarrow [0,1] \qquad (33)$$

where P_x is the set of all subsets of X and is called the *power set* of X. The power set has $2^{|X|}$ subsets in it.

The plausibility measure (Pl)

The belief measure (*Bel*) has a dual measure called the plausibility measure (*Pl*) as defined by the following equation:

$$Pl(A) = 1 - Bel(\overline{A}) \qquad (34)$$

where A is a subset that belongs to the power set P_x.

It can be shown that the belief and plausibility functions satisfy the following condition for each A in the power set:

$$Pl(A) \geq Bel(A) \qquad (35)$$

According to Belief and Plausibility Functions, the likelihood for Event A lies in the interval [Bel(A), Pl(A)] as shown in Figure 8 (Bae, 2003).

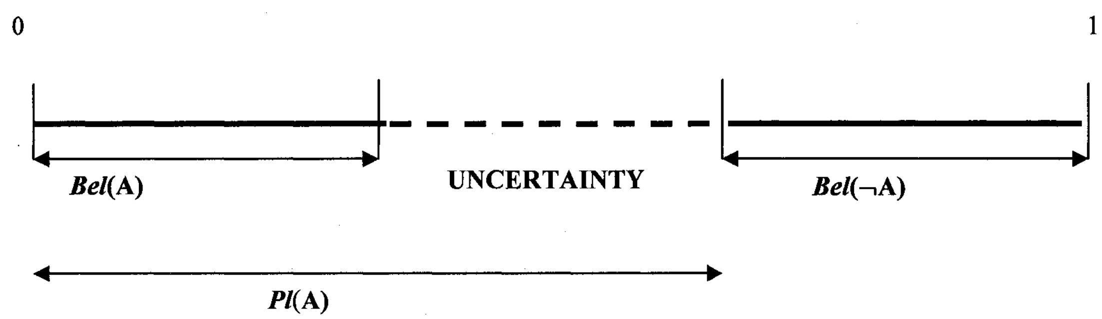


Figure 8. Belief (Bel) and plausibility (Pl) relationship (Bae, 2003)

Dempster-Shaffer methods of Evidence Theory is applied by identifying the upper limit of uncertainty called Cumulative Plausibility Function (CPF) and lower limit of uncertainty called Cumulative Belief Function (CBF). Figure 9 is the graphical representation of the CPF and CBF.

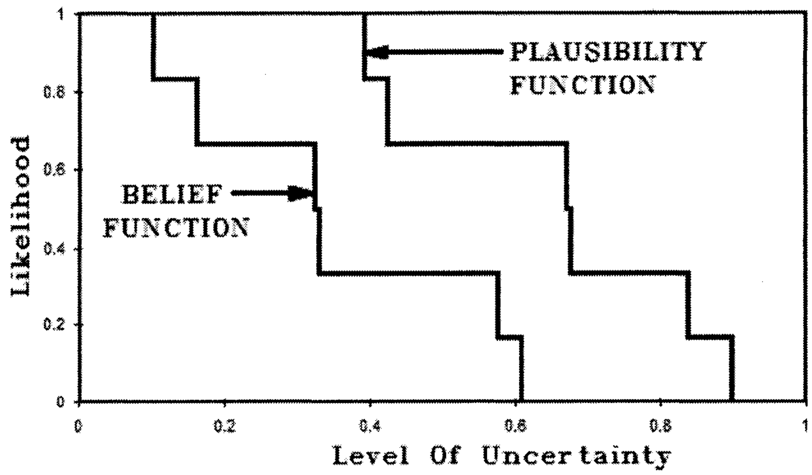


Figure 9. Graphical representation of CPF and CBF

3.6 Aggregation Methodology

Uncertainty quantification using the Evidence theory in a low-risk environment has been previously explored (Bae, 2003). Due to the incomplete information and a lack of knowledge and statistical data that exists in large complex systems, Bae's study called into question whether the Probability theory is suitable because the requirement to characterize the distribution of probability is not compatible. "Evidence theory, also known as Dempster-Shafer theory, is proposed to handle the epistemic uncertainty that stems from lack of knowledge about a structural system. Evidence theory provides us with a useful tool for aleatory (random) and epistemic (subjective) uncertainties" (Bae, 2003). Given the lack of information in high-risk environments, it is more reasonable to present boundaries for the result of uncertainty quantification, as opposed to a single value of probability.

Using a graphical method, this study provides various visual representations of the experts' uncertainty values to assist in the integration and assimilation of a decision strategy. This is accomplished by combining the graphs of the CCDF derived by the Probability theory and the upper and lower limits derived by the Evidence theory, which provides the decision maker with a very clear comparison of multiple experts' probabilistic risk assessment relative to their non-probabilistic risk assessment.

3.7 Framework

Bae explored uncertainty quantification using the Evidence Theory in a low-risk environment (2003). According to the study, "[B]ecause of the need to characterize the distribution of probability, classical probability theory may not be suitable for a large complex system such as an aircraft, in that our information is never complete because of lack of knowledge and statistical data. Evidence theory, also known as Dempster-Shafer theory is proposed to handle the epistemic uncertainty that stems from lack of knowledge about a structural system. Evidence theory provides us with a useful tool for aleatory (random) and epistemic (subjective) uncertainties" (Bae, 2003).

Although a similar mathematical framework is developed by this research, the differences between the two studies are:

- The present research problem application is a high-risk engineering environment that uses exploratory state of the art technological innovative ideas.

- The preponderance of occurrences being assessed are in the distant future; as much as 20 or 30 years. Feedback involving actual results or occurrences is impossible" (Conway, 2003).
- A formal expert judgment elicitation is performed.
- A questionnaire specifically designed to accommodate these specific fields in engineering during the operations phase of the project life cycle is distributed and data is collected.
- The uncalibrated limits of each entry are incorporated into a spreadsheet and values are assigned.
- A normalization is performed to prepare the values into Dempster-Shaffer's Evidence Theory format.
- The Basic Belief Assignments structures is assigned in a way to obtain a combined pinion ($m_{1,2}$) as shown in the following equation:

$$m_{1,2}(A) = \frac{\sum\limits_{\text{all } A_i \cap A_j = A} m_1(A_i)\, m_2(A_j)}{1 - \sum\limits_{\text{all } A_j \cap A_k = \varnothing} m_1(A_i)\, m_2(A_j)} \qquad A = \varnothing \qquad (36)$$

where A_i and A_i denote propositions from each of the sources. In the above equation, the denominator can be viewed as a conflict or contradiction among the information given by the independent sources. According to Dempster's rule, even when irregularities or conflicts are noticed among the answers of the expert's judgment, each conflict will be disregarded. The data will be normalized with the complimentary degree of contradiction because it is designed to use consistent opinions.

- The degrees of belief and plausibility are obtained.
- The findings are aggregated.
- A combined judgment is produced indicating the limits of uncertainty – the upper bounds and lower bounds of belief and plausibility.

4. Research Results and Analysis

4.1 Overview

Under the supervision of NASA Langley Research Center, the future aerospace Thermal Protection System (TPS) for the Crew Exploration Vehicle (CEV) was selected for the application of the aggregation methodology. The deployment of this methodology incorporates uncertainty assessment in high-risk environments using expert judgment elicitation through a combined probabilistic and non-probabilistic approach. A combined approach for assessment of both aleatory and epistemic uncertainties facilitates the assessment of subject matter expert's expertise and confidence is utilized for calibration. This research further develops the high-risk expert judgment elicitation methodology in an attempt to assess and quantify input parameter uncertainties. The findings are applied to CEV design study by using Dempster-Shafer's Evidence Theory in conjunction with the Probability theory. Even though the parameter of uncertainty is quantified in terms of probabilistic distribution, a similar approach can be used with the Evidence theory. In addition, the methodology presented could be proven applicable in a variety of disciplines and could be particularly useful for adopting new technologies for future concepts.

Figure 10 shows the logical step-by-step order of operations with which the methodological conclusions of this study were derived.

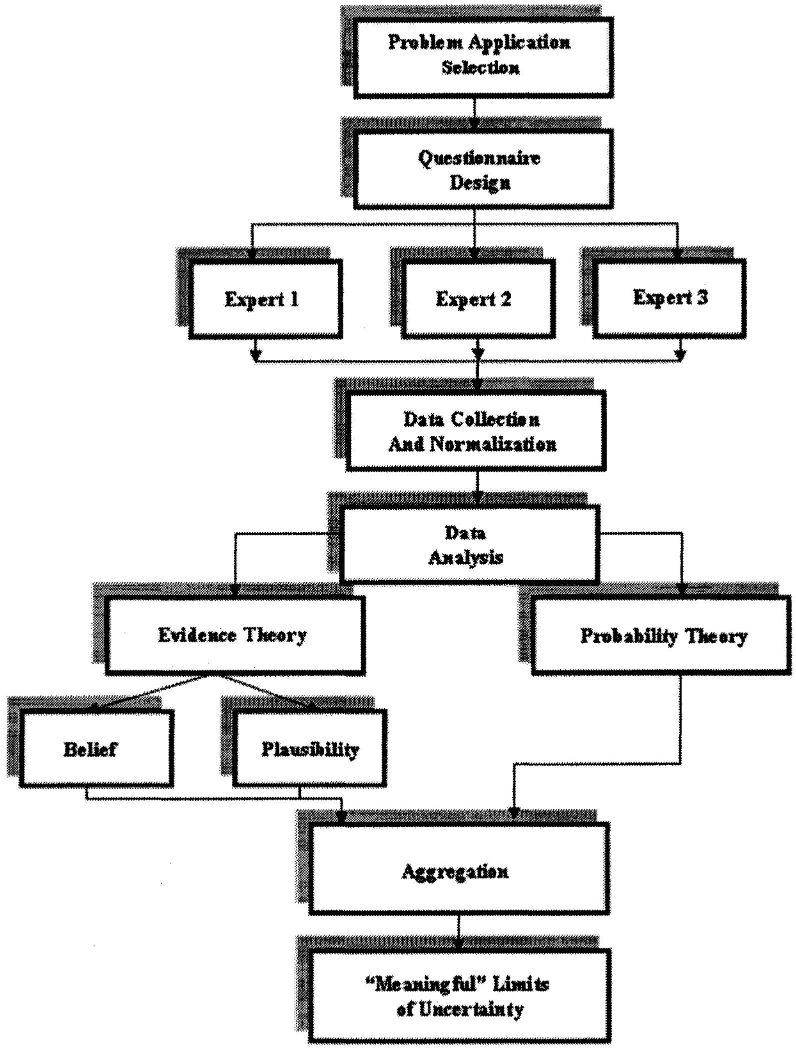


Figure 10. Process of data collection and analysis

The future aerospace CEV, which has highly uncertain variables, was selected for the application of the aggregation methodology under the supervision of NASA Langley Research Center. The researcher adapted a previously developed questionnaire in order to meet the criteria and mathematical models selected. A pre-selected panel of experts agreed to participate in this study. This research was exempted by the Institutional Review Board for the protection of experimental subjects due to the careful design and deployment of the questionnaire instrument. The expert judgment elicitation methodology included background data of experts for the determination of confidence, risk and philosophy profile.

Once the expert judgment elicitation questionnaire assembly was complete, a meeting was coordinated with the pre-selected subject-matter experts and the researcher. The questionnaire was personally administrated to the experts. Once the data was collected, a normalization factor was applied to each expert's input based on the summation of all options to comply with Evidence theory operations.

The results of the input of each expert are then applied in the development of the CDF and CCDF, relying strictly upon aleatory uncertainties. Cumulative Distribution Function (CDF) shows the probability of an occurrence is less than a given value, whereas the Complementary Cumulative Distribution Function (CCDF) shows whether the probability of an occurrence will exceed a given value; therefore, the CCDF enables the comparison of the graphical results of using both Probability theory and Evidence theory.

Through the questionnaire, each expert was asked the likelihood of each scenario. The experts provided three values of the likelihood of anomaly. These values represent low, moderate and high likelihood. The experts also provided their personal opinion as to which of the values is most likely to occur. The basic assignment of each expert is used in an additive manner to compute the unions of belief and plausibility measures. Then the aggregated results are input into Monte Carlo simulation using @RISK® program (Palisade, 2004). Lastly, meaningful limits of uncertainty are derived and conveyed in a clear and concise graphical representation that will potentially enable decision makers to better assess uncertainty levels presented by multiple experts in high-risk environments.

4.2 Problem Application Selection

The future aerospace Crew Exploration Vehicle (CEV) was selected for the application of the aggregation methodology under the supervision of NASA Langley Research Center. Although this research is versatile and potentially has a wide range of uses, the utilization of the aggregated methodology in this problem application is ideal due to the availability of experts in this field and the pertinence of the subject matter. In addition, this research was carried out as part of a multi-disciplinary endeavor to expand current knowledge of uncertainty assessment.

The questionnaire and the questionnaire application process were reported to Institutional Review Board (IRB) representatives of Old Dominion University, and copies of the questionnaire were furnished. It was concluded that this research would qualify for an exemption from full IRB procedures for human subject research based on the questionnaire output NOT being damaging in any way (civil or criminal liability, employability, or financial) to subject participants, and NOT dealing with sensitive aspects of any subject's behavior. It was also determined that the utilization of as few as three experts was adequate for this study.

The system chosen for the present research is the Thermal Protection System (TPS) for the conceptual CEV, which has highly uncertain variables. The three variables chosen that best describe possible anomalies during the TPS lifecycle are Construction (production), Installation (debonding of tiles), and Operations (debris damage at lift-off that causes burn through), and all combinations.

Construction can be defined as the production portion of the TPS lifecycle, including design and manufacturing. Installation is defined as the portion of the TPS lifecycle that includes the original installation. Operations can be defined as the portion of the TPS lifecycle from initial lift-off through landing.

4.3 Questionnaire Design

The Questionnaire followed a combination of Monroe (1997), Conway (2003) and Chytka's (2003) methodologies. The experts are asked to consider the input parameters and select an option representing the believed assessment based on the given selection of anomalies and the nominal values. Traditionally, the level of expertise of the participating experts in any field and especially in a high-risk environment has been the focus of many decision makers. The questionnaire is compiled from previously noted findings based on literature review. The expert judgment elicitation questionnaire is shown in Appendix A. Expertise is categorized into different segments including:

- Age can be related to the level of expertise
- Degree of expertise compared to peers in the same discipline
- Self-assessment of his/her level of expertise
- Background questions place the expert in a level with respect to the confidence level

- Assessment of his attitude or philosophy manifests the confidence in judgment

Additional indicator selection was offered to the experts, in case the values were above or below the pre-selected nominal values. The experts were asked to rate each input parameter using the likelihood option of each critical system failure due to the given anomalies. The scale used to determine each input parameter in a qualitative format was a 5-point rating scale (Low, Low/Moderate, Moderate, Moderate/High, and High). If the expert believed that the given values should be modified, he was asked to provide a new point estimate for the nominal value. He was also allowed to provide any scenarios that may change his estimates and any reasoning, or assumptions used to reach his conclusions.

In order to evaluate the TPS of the CEV, causes of possible anomalies must be determined by the experts. These anomalies will be analyzed with respect to: (i) construction; (ii) installation; (iii) operations; (iv) the union between construction and installation; (v) the union between construction and operations; (vi) the union between Installation and Operations; and (vii) the union between Construction, Installation and Operations. The previous performance characteristics could assist the decision makers to assess future mission requirements. Each relationship may be comprised by a set of parameters, which defines the estimation relationship.

A list of input parameter variables with associated nominal values for subject matter experts compiled the TPS associated with the conceptual design team. The classical Nominal Group Technique was used to identify the most highly uncertain input parameters from the list, using Pareto principle approach (Chytka, 2003).

The questionnaire was comprised of three sections – Background, Anchoring, and Assessment of Uncertainty. The experts were asked several anchoring questions and specific questions based on their general knowledge and expertise in terms of the TPS. They were then asked to select one of the answers using scales provided. During the estimation, the experts were asked to add any other possible critical subsystem failures due to anomalies not already included in the questionnaire. The experts were asked to list the factors that influence their thinking processes and asked to provide comments and suggestions for future improvements of the questionnaire. The entire sample of expert judgment elicitation questionnaire is shown in Appendix A.

Following earlier work (Monroe, 1997, Conway, 2000, Hampton, 2001, Conway, 2003, Chytka, 2003), the questionnaire is modified to address not only the importance of the previous findings but as to set-up the current research mode. The main objective of this research is to highlight a series of parameters that may impact overall operations and support requirements for a spacecraft for possible modification. For each parameter the expert is asked to indicate the probable cause of each failing part, whether it is isolated or in combination with other parts. Further the expert is asked to identify to the best of his or her knowledge whether this anomaly was caused by:

- Construction
- Installation
- Operation
- A union between construction and installation

- A union between construction and operation
- A union between installation and operation, or
- A union between construction, installation and operation.

In the present study, the high-risk experts were pre-selected by NASA from a target population of NASA-Langley Research Center aerospace engineers and are recognized subject-matter experts. The pre-selection ensures objectivity and assesses subjective conclusions. The researcher has no specific prior knowledge of each expert's background and level of expertise prior to administering the questionnaire.

4.4 Data Collection

Once the expert judgment elicitation questionnaire assembly was complete, a meeting was coordinated with the pre-selected subject-matter experts and the researcher. The experts were briefed as to the intent, the layout and design of the questionnaire. The experts were then given the opportunity to request clarification on the questionnaire instrument. No clarification was requested at that time. The experts were given printed copies of the questionnaire and asked to complete it to the best of their knowledge. Once completed, the questionnaires were returned to the researcher for analysis.

Figure 11 illustrates the questionnaire response process.

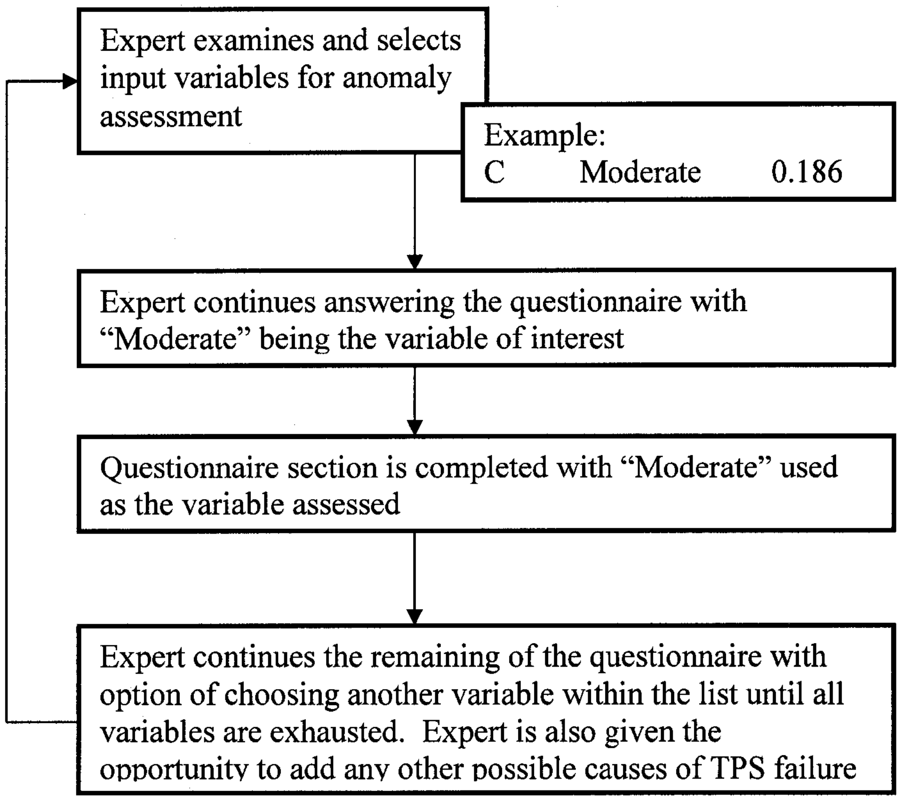


Figure 11. Questionnaire response flow schematic

4.5 Normalized Assessments

To use the Evidence Theory, the combination of expert opinions should not exceed the value of one. In order to achieve this, a normalization factor must be applied to each expert's input based on the summation of all options (Ayyub, 2001). The basic assignment of each expert can be used in an additive manner to compute the unions of belief and plausibility measures: The solution then can be expressed in a form of minimum and maximum probabilities of the Evidence Theory (Dempster, 1967a and

1967b). After this process is performed on the results for two experts, the judgments are united to produce the combined judgment of belief and plausibility.

After the combined judgment of the first two experts is achieved, the third expert's values are introduced through Yager's combination rule. Once these computations are complete, the aggregated results are input into Monte Carlo simulation through Palisade's @RISK® program (2004).

4.6 Data Analysis

4.6.1 Monte Carlo Simulation

Aggregation of multiple experts is a common mathematical technique to assist decision makers. Monte Carlo simulation has the capacity to aggregate the empirical distributions. Monte Carlo is a computational tool that arbitrarily generates a large collection of models pursuant to the probability distribution for the purposes of uncertainty analysis (Palisade, 2004). Monte Carlo simulation was used as a means of analysis to produce results similar to the Complementary Cumulative Distribution Function curve showing the upper limits and lower limits of plausibility and belief measures for the varying values of displacement. The computerized program @RISK® uses the input of sampling in a simulation to generate possible values from distribution functions. These sets of possible values are then evaluated using the Microsoft® Excel worksheet. As a result, sampling is the basis for the hundreds of thousands of "what-if" scenarios the program calculates from the worksheet.

4.6.2 Probabilistic Risk Assessment

The questionnaire was used to collect expert's assessment of the possible percentage of anomalies occurring with regard to TPS. "It is thought that critical subsystem failures of the Thermal Protection System (TPS) maybe a function of Construction (production), Installation (debonding of tiles) and Operations (such as, debris damage at lift-off that causes burn through). If you think there may be other causes, you will be asked to list them later in the questionnaire" (Appendix A). The categories used for the selection of the critical failures of the TPS were Construction, Installation, and Operations and/or possible combinations of the above. Through the questionnaire, each expert was asked the likelihood of each scenario. The experts provided three values of the likelihood of anomaly. These values represent low, moderate and high likelihood. The experts also provided their personal opinion as to which of the values is most likely to occur. (Figure 12 presents each expert's assessments for construction, installation, operations, and the unions in minimum, most likely, and maximum likelihood numbers.)

PROBABILITY TO PRODUCE CDF					
Expert 1		**Expert 2**		**Expert 3**	
Construction		**Construction**		**Construction**	
Min	0.0750	Min	0.0010	Min	0.0500
Most Likely	0.2000	Most Likely	0.0500	Most Likely	0.3250
Max	0.5000	Max	0.1000	Max	0.5000
Installation		**Installation**		**Installation**	
Min	0.0750	Min	0.1000	Min	0.0500
Most Likely	0.2000	Most Likely	0.5000	Most Likely	0.3250
Max	0.5000	Max	1.0000	Max	0.5000
Operations		**Operations**		**Operations**	
Min	0.0010	Min	0.0010	Min	0.0500
Most Likely	0.0500	Most Likely	0.0100	Most Likely	0.3250
Max	0.1000	Max	0.0500	Max	0.5000
C U I		**C U I**		**C U I**	
Min	0.0750	Min	0.1000	Min	0.0500
Most Likely	0.1375	Most Likely	0.5000	Most Likely	0.1500
Max	0.4000	Max	1.0000	Max	0.5000
C U O		**C U O**		**C U O**	
Min	0.0750	Min	0.0010	Min	0.0500
Most Likely	0.1125	Most Likely	0.0500	Most Likely	0.3250
Max	0.3000	Max	0.1000	Max	0.5000
I U O		**I U O**		**I U O**	
Min	0.0750	Min	0.1000	Min	0.0500
Most Likely	0.2000	Most Likely	0.5000	Most Likely	0.3250
Max	0.4000	Max	1.0000	Max	0.5000
C U I U O		**C U I U O**		**C U I U O**	
Min	0.1000	Min	0.2000	Min	0.0500
Most Likely	0.3000	Most Likely	1.1000	Most Likely	0.3250
Max	0.4000	Max	1.5000	Max	0.5000

Figure 12. Assessment for detection of anomalies, from questionnaire

Cumulative Distribution Function (CDF) shows the probability of an occurrence is less than a given value, whereas the Complementary Cumulative Distribution Function (CCDF) shows whether the probability of an occurrence will exceed a given value; therefore, the CCDF enables the comparison of the graphical results of using both Probability theory and Evidence theory. Triangular distributions were defined in terms of minimum (a), most likely (c) and maximum values (b). The location of c in reference to a and b determines how much probability exists on either side of c.

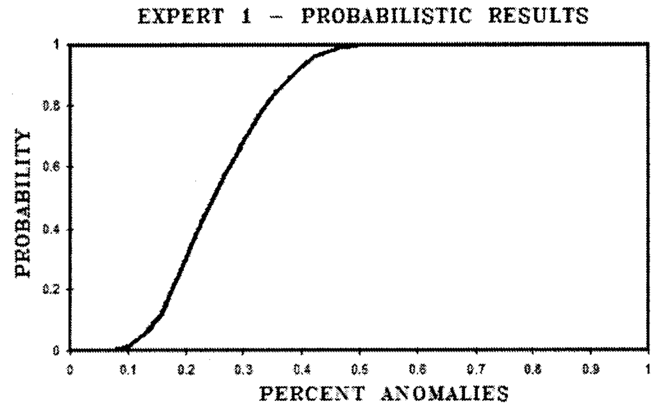
1. The values provided by each individual expert were imported into the @RISK® software in basic form – minimum (low), most likely (moderate), maximum (high) values – and triangular distributions are built for each variable assessing the uncertainty using the "RiskTriang" function. The aggregation algorithm is coded into a separate input cell as shown in Figure 13. The results of this aggregation are the values of the combined distributions that are "most likely."

```
=RiskTriang(0.075,0.2,0.5)*0.17+RiskTriang(0.075,0.2,0.5)*0.17+
RiskTriang(0.001,0.05,0.1)*0.04+RiskTriang(0.075,0.1375,0.4)*0.11+
RiskTriang(0.075,0.1125,0.3)*0.09+RiskTriang(0.075,0.2,0.4)*0.17+
RiskTriang(0.1,0.3,0.4)*0.25
```

Figure 13. Aggregation algorithm for expert 1

2. The simulation settings module permits the specification of how much iteration one wants to use, and the type of sampling preferred. For this application, Monte Carlo simulation was selected. A sample of 5000 iterations was selected for the one simulation that would produce the CDF for each expert.

3. The CDF curve is drawn. For comparison reasons, the same scale is used for the x-axis and y-axis for all experts. Then, the CCDF curve is also drawn and both functions are plotted for Expert 1 in Figure 14. Steps 1 through 4 are repeated for Expert 2 in Figure 15 and Expert 3 in Figure 16.



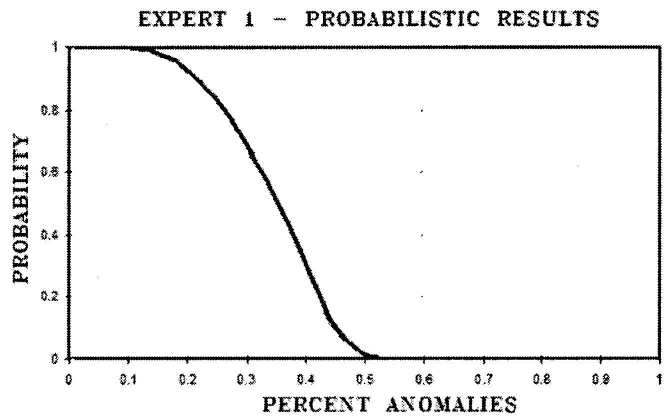


Figure 14. CDF and CCDF of expert 1

The value of the x-axis represents the cumulative percentage of anomalies that occur during the entire lifecycle of the CEV. The value of the y-axis represents the probability that these anomalies will result in critical system failure. The CDF curve in Figure 14 was developed as a result of the responses of Expert 1 and indicates that it is this Expert's opinion that if approximately fifty percent of the previously defined anomalies occur, total system failure is most likely to take place. Although system failure is still possible, a ten percent occurrence of the defined anomalies overall would not nearly be as great a risk in the opinion of Expert 1. This expert's assessment of anomalies is within the bounds of approximately 0.08 to 0.50.

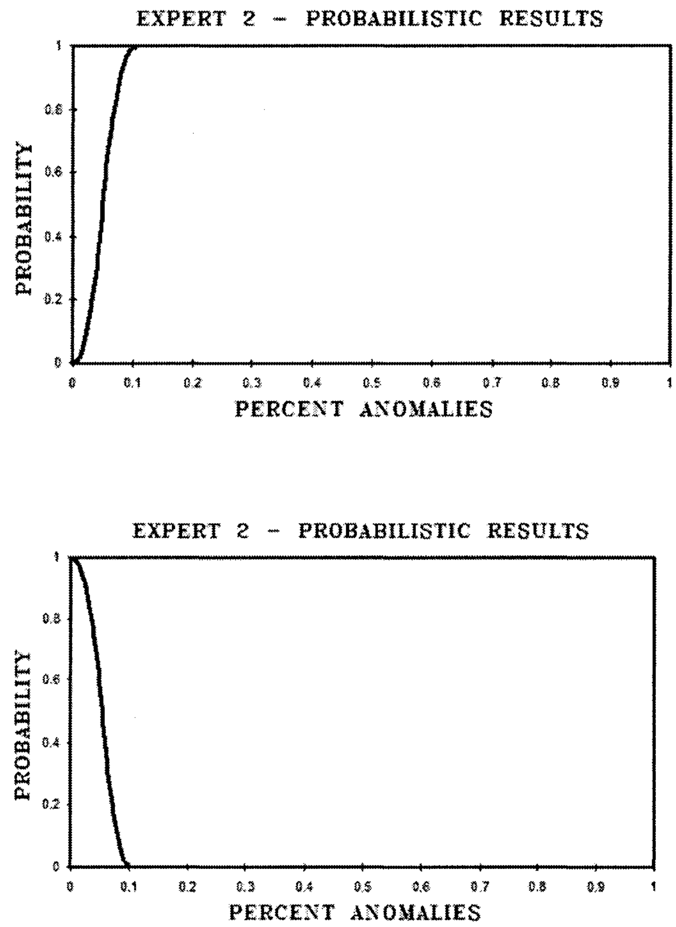


Figure 15. CDF and CCDF of expert 2

The CDF curve in Figure 15 was developed as a result of the responses of Expert 2 and indicates that it is this expert's opinion that if approximately ten percent of the anomalies occur, total system failure is most likely to take place. As a matter of fact, it is this expert's opinion that just about any occurrence of anomalies will result in catastrophic system failure. This expert's assessment of anomalies is within the bounds of approximately 0.00 to 0.10.

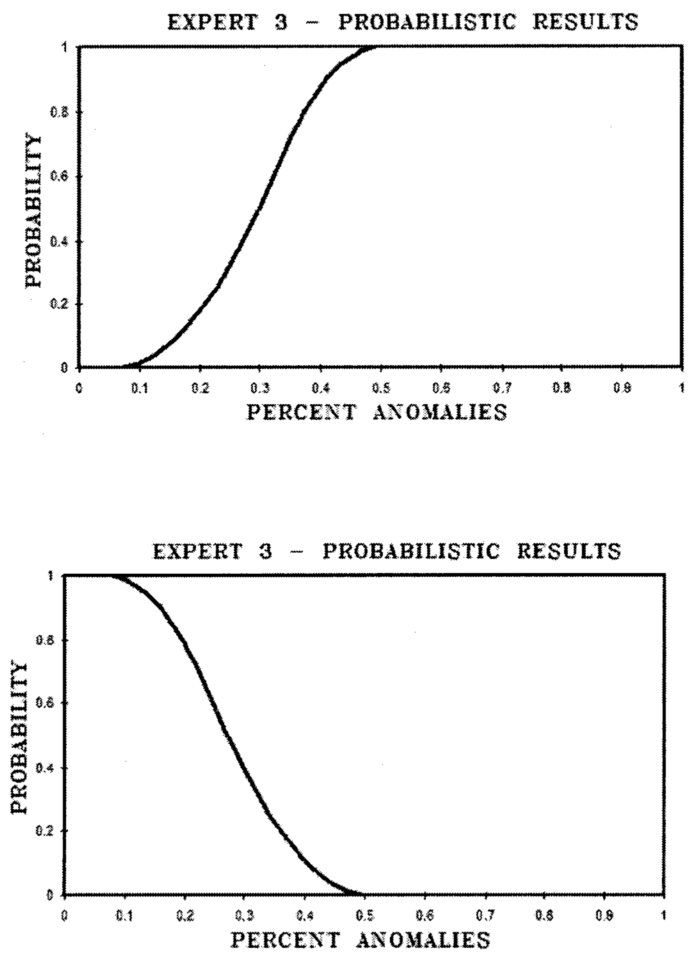


Figure 16. CDF and CCDF of expert 3

The CDF curve in Figure 16 was developed as a result of the responses of Expert 3. This expert's bounds are largely similar to those of Expert 1; however, the difference in the shape of the curve is an indicator of the variance of the options selected. The curve based on the opinion of Expert 3 is more linear than Expert 1's curve. This expert's assessment of anomalies is within the bounds of approximately 0.08 to 0.50.

In probabilistic terms, the more likely outcomes are in the range where the cumulative curve is the "steepest" (Palisade, 2004). Based on the probabilistic results presented by the three experts, one might select Expert 2 as the most certain; however, the results do not supply sufficient information to make that determination.

4.6.3 Non-Probabilistic Risk Assessment Using Evidence Theory

The expert assessments from the questionnaire are also incorporated into the basic probability assignment (m) of the Evidence theory for the computation of the Belief (lower) and Plausibility (upper) limits of uncertainty; however, before beginning the computations, the basic probability assignment must be normalized to follow the rules of the Evidence theory, which dictates that the summation of all inputs (Failure Causes) must equal to one. The normalized factor is the sum of all basic probability assignment values provided by each expert. The normalized factor for Expert 1 is 1.20, Expert 2 is 2.71 and Expert 3 is 2.10 as can be seen in Figure 17. The normalized factor of 1.20 is multiplied by each basic probability assignment. For example, the construction error's basic assignment was 0.20 * 1.20 = 0.17. A similar simple operation is performed for the remaining anomalies for each expert.

EVIDENCE THEORY TO PRODUCE UPPER AND LOWER LIMITS OF UNCERTAINTY						
Failure Cause	EXPERT 1		EXPERT 2		EXPERT 3	
	Basic Assignment	Normalize	Basic Assignment	Normalize	Basic Assignment	Normalize
C = Construction Error	0.20	0.17	0.05	0.02	0.33	0.15
I = Installation Error	0.20	0.17	0.50	0.18	0.33	0.15
O = Operations Error	0.05	0.04	0.01	0.00369	0.33	0.15
C U I	0.14	0.11	0.50	0.18	0.15	0.07
C U O	0.11	0.09	0.05	0.02	0.33	0.15
I U O	0.20	0.17	0.50	0.18	0.33	0.15
C U I U O	0.30	0.25	1.10	0.41	0.33	0.15
TOTAL	1.20	1.00	2.71	1.00	2.10	1.00

Figure 17. Normalization of basic assignment of all experts

The next step is to substitute the normalized basic assignments into m_1 basic assignment column. Figure 18 lists the possible failure causes based on Dempster-Shafer's Belief and Plausibility functions as follows:

- The first three failure causes (C, I, & O) or subsets are directly mapped into the belief column.
- The values of CUI are the additive values of C, plus I, plus CUI.
- The values of CUO are the additive values of C, plus O, plus CUO.
- The values of IUO are the additive values of I, plus O, plus IUO.
- The assignment of CUIUO was computed based on the equation shown, to obtain a total of one for the assignments provided by each expert.

$$\sum_{all\ A \in Px} m(A) = 1 \qquad (37)$$

The belief and plausibility measure was computed based on the following equations for any set $A_i \in P_x$:

$$Bel(A_i) = \sum_{all\ A_j \subseteq A_i} m(A_i) \qquad Pl(A_i) = \sum_{all\ A_j \cap A_i \neq \varnothing} m(A_j) \tag{38}$$

As an example, Figure 18 shows that belief for Expert 1 is 0.17 and plausibility is 0.63. These numbers indicate a measure of the lower and upper limits of uncertainty for Expert 1 as expressed by the expert. A similar operation is repeated for Expert 2.

BELIEF COMPUTATIONS						
SUBSET*	EXPERT 1		EXPERT 2		COMBINED JUDGMENT 1,2	
Failure Cause	m_1	Bel_1	m_2	Bel_2	$m_{1,2}$	$Bel_{1,2}$
C = Construction Error	0.17	0.17	0.02	0.02	0.15	0.15
I = Installation Error	0.17	0.17	0.18	0.18	0.35	0.35
O = Operations Error	0.04	0.04	0.00	0.00	0.05	0.05
C U I	0.11	0.45	0.18	0.39	0.13	0.62
C U O	0.09	0.30	0.02	0.04	0.05	0.25
I U O	0.17	0.38	0.18	0.37	0.16	0.56
C U I U O	0.25	1.00	0.41	1.00	0.11	1.00
TOTAL	1.00		1.00		1.00	

PLAUSIBILITY COMPUTATIONS						
SUBSET*	EXPERT 1		EXPERT 2		COMBINED JUDGMENT 1,2	
Failure Cause	m_1	Pl_1	m_2	Pl_2	$m_{1,2}$	$Pl_{1,2}$
C = Construction Error	0.17	0.63	0.02	0.63	0.15	0.44
I = Installation Error	0.17	0.70	0.18	0.96	0.35	0.75
O = Operations Error	0.04	0.55	0.00	0.61	0.05	0.38
C U I	0.11	0.96	0.18	1.00	0.13	0.95
C U O	0.09	0.83	0.02	0.82	0.05	0.65
I U O	0.17	0.83	0.18	0.98	0.16	0.85
C U I U O	0.25	1.00	0.41	1.00	0.11	1.00
TOTAL	1.00		1.00		1.00	

Figure 18. Dempster-Shafer's belief and plausibility for experts 1 and 2

The application of Yager's rule allows us to further expand the number of experts. The combined judgment generated by Experts 1 and 2 is transferred into Figure 19 and the third expert's basic assignment is computed. The results produce the combined judgments of all three experts.

BELIEF COMPUTATIONS						
SUBSET*	EXPERT 1,2		EXPERT 3		COMBINED JUDGMENT 1,2,3	
Failure Cause	$m_{1,2}$	$Bel_{1,2}$	m_3	Bel_3	$m_{1,2,3}$	$Bel_{1,2,3}$
C = Construction Error	0.15	0.15	0.15	0.15	0.21	0.21
I = Installation Error	0.35	0.35	0.15	0.15	0.40	0.40
O = Operations Error	0.05	0.05	0.15	0.15	0.17	0.17
C U I	0.13	0.62	0.07	0.38	0.05	0.66
C U O	0.05	0.25	0.15	0.46	0.05	0.42
I U O	0.16	0.56	0.15	0.46	0.10	0.66
C U I U O	0.11	1.00	0.15	1.00	0.03	1.00
TOTAL	1.00		1.00		1.00	

PLAUSIBILITY COMPUTATIONS						
SUBSET*	EXPERT 1,2		EXPERT 3		COMBINED JUDGMENT 1,2,3	
Failure Cause	$m_{1,2}$	$Pl_{1,2}$	m_3	Pl_3	$m_{1,2,3}$	$Pl_{1,2,3}$
C = Construction Error	0.15	0.44	0.15	0.54	0.21	0.34
I = Installation Error	0.35	0.75	0.15	0.54	0.40	0.58
O = Operations Error	0.05	0.38	0.15	0.62	0.17	0.34
C U I	0.13	0.95	0.07	0.85	0.05	0.83
C U O	0.05	0.65	0.15	0.85	0.05	0.60
I U O	0.16	0.85	0.15	0.85	0.10	0.79
C U I U O	0.11	1.00	0.15	1.00	0.03	1.00
TOTAL	1.00		1.00		1.00	

Figure 19. Yager's rule belief and plausibility for experts 1, 2 and 3

Lastly, the lower bounds or minimum value is called Belief and the upper bounds or maximum value is called Plausibility. These bounds or values are converted to a cumulative graphic form for each expert. In order to interpret these graphs, the following information needs to be recognized:

- The y-axis represents the expert's assessment of the likelihood of NASA's TPS system failure
- The x-axis represents the range of the expert's estimated confidence interval or the level of uncertainty.

When an expert provides through the use of the questionnaire an interval, then the expert is telling the researcher that the true value could be anywhere within this interval.

For example: One wants to determine the solution space and/or confidence interval for Expert 1 at which a 40 percent likelihood of a negative impact on TPS system failure. From the graph, the solution space/confidence interval is between (a) and (b) and, therefore, between 0.30 and 0.83. For comparison purposes, the same scale is used for the x-axis and y-axis for all experts and functions are plotted for each expert. Figures 20 – 22 show the graphical representation of each expert's belief and plausibility judgments.

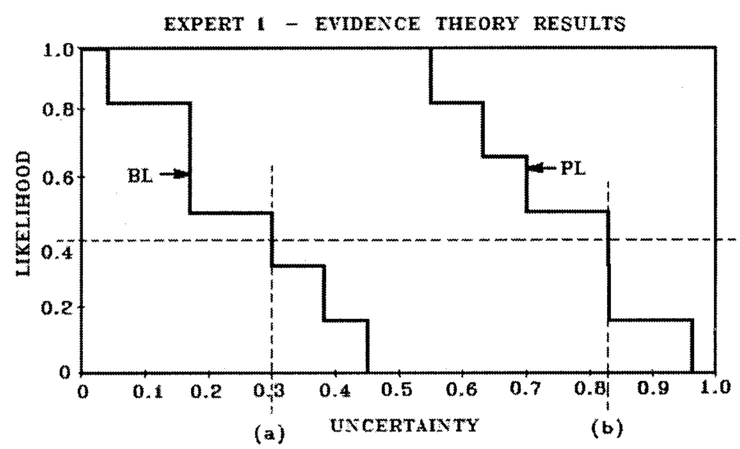


Figure 20. Evidence theory graphical results for expert 1

Figure 20 is a graphical representation of uncertainty based upon the total combined evidence obtained from Expert 1 during the elicitation process and illustrates the boundaries of belief and plausibility of this expert's hypothesis with regard to the unknown parameter. This unknown parameter is the likelihood of system failure due to the pre-defined anomalies and the various unions. The upper and lower limits shown in this graph are indicators of a conservative, minimum risk taker expert with equal levels of certainty and uncertainty.

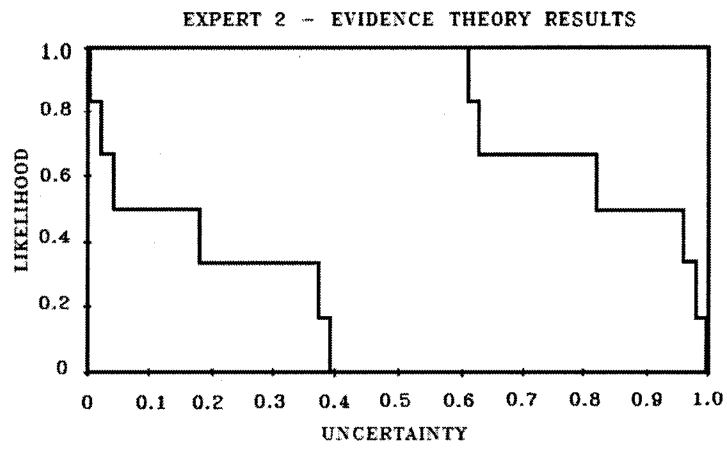


Figure 21. Evidence theory graphical results for expert 2

Much like the previous figure, Figure 21 is a graphical representation of uncertainty based upon the total combined evidence obtained from Expert 2 during the elicitation process and illustrates the boundaries of belief and plausibility of this expert's hypothesis with regard to the unknown parameter; however, Figure 21 shows Expert 2 expressing greater levels of uncertainty than Expert 1.

Evidence theory allows both researcher and decision maker to assess the values of the belief (minimum) and plausibility (maximum) of an extended cumulative distribution function. If the separating distance between minimum and maximum values is as great as shown in Figure 21, then the level of uncertainty is large; meaning, that there is a clear indicator that additional data is required before a decision is made. The results based on this particular expert's responses do not provide the decision maker with a tangible model on which to base a decision, making the results of the Evidence theory for this expert inconclusive.

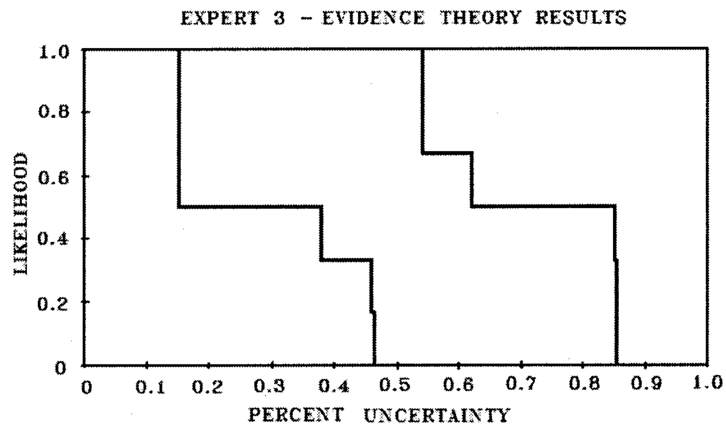


Figure 22. Evidence theory graphical results for expert 3

Figure 22 is the graphical representation of uncertainty based upon the total combined evidence obtained from Expert 3 illustrating the boundaries of belief and plausibility of this expert's hypothesis with regard to the unknown parameter. Figure 22 indicates Expert 3 expressing less variance between upper and lower limits of uncertainty than Experts 1 and 2.

The separating distance between minimum and maximum values in this Figure is much narrower than is seen in Figure 21. This indicates that the level of uncertainty for this expert is much smaller by comparison. The results based on this particular expert's responses provide the decision maker with a stronger model.

4.7 Aggregation of Probability and Evidence Analysis

The graphical combination between CCDF and Evidence theory is an unaltered or unmanipulated representation of the experts' results. The intention of this study is not, by any means, to perform an evaluation of experts. Rather, it is intended to be an application and true representation of uncertainty assessments of actual experts in real high-risk environments and provide a visual representation of the experts' uncertainty value for integration and assimilation in to a decision strategy.

The opinion of Expert 1 shows consistency in terms of the results of the Probability and Evidence Theory; however, it is difficult to determine the level of uncertainty of the decision when evaluating probabilistic results alone without the assistance of the evidence theory as shown in Figures 14 and 20.

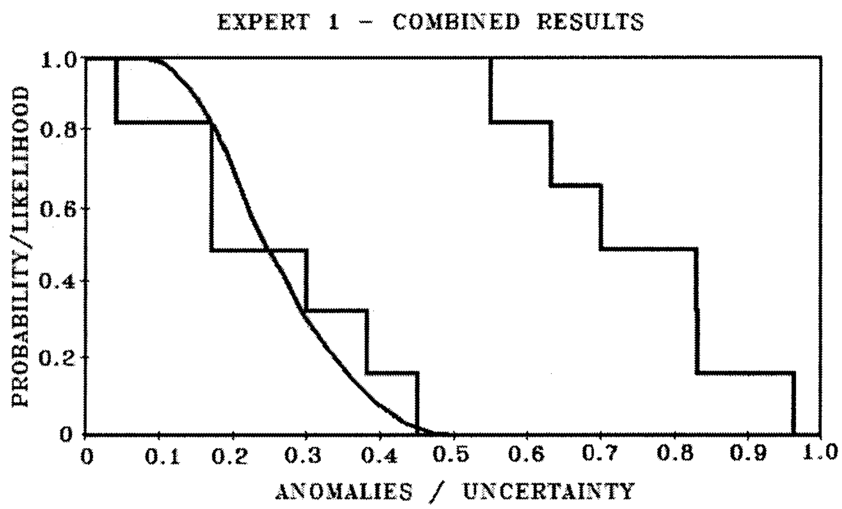


Figure 23. Probability & Evidence theory graphical results for expert 1

Figure 23 represents the combined graphical results using both probabilistic and non-probabilistic results based on the responses of Expert 1. The CDF was derived using Monte Carlo simulation to analyze the numerical input of Expert 1. Then the complement of the CDF is calculated and graphed as shown. The upper and lower bounds derived through the use of Evidence theory are then imposed on the graph. The intervals between belief and plausibility are wide, which indicates that this Expert's level of uncertainty is reasonably large; however, the estimation falls under the most pessimistic part of the range. Although the probabilistic distributions do not have to be enclosed by the upper and lower limits of the Evidence theory, both probabilistic and non-probabilistic results are consistent.

The graphical combination between CDF and Evidence Theory of the opinion of Expert 2 shows confidence in his assessment that virtually any occurrence of anomalies would almost certainly result in total system failure; however, the non-probabilistic assessment of his uncertainty level is significantly greater than the other experts (See Figure 24).

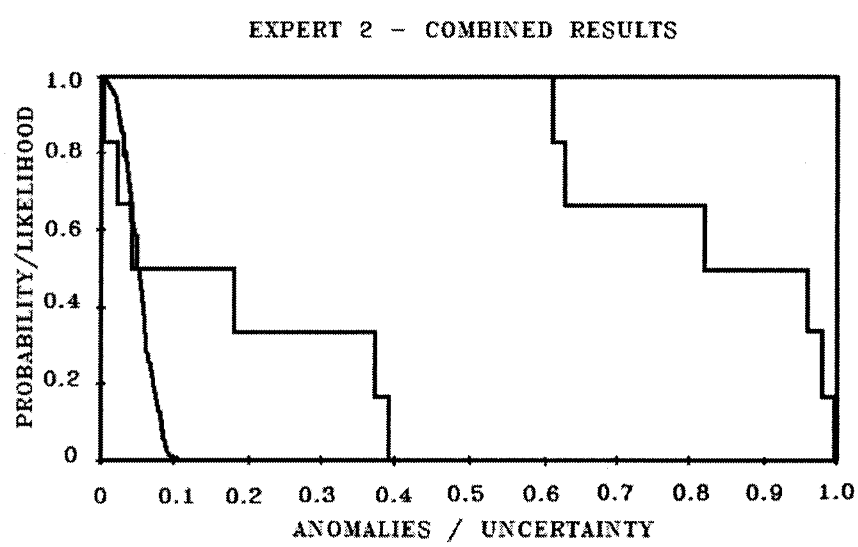


Figure 24. Probability & Evidence theory graphical results for expert 2

The level of uncertainty of Expert 2 is much greater than both experts due to the extremely wide separation between belief and plausibility. The horizontal distance between belief and plausibility provides a clear assessment of the uncertainty level of this expert that adds very inconclusive results to the findings. If evaluation was based strictly on a probabilistic assessment, the expert's opinion would argue that any given anomaly on any part of the TPS development could be proven catastrophic; however, the evidence supports a wide range of uncertainty of his decision.

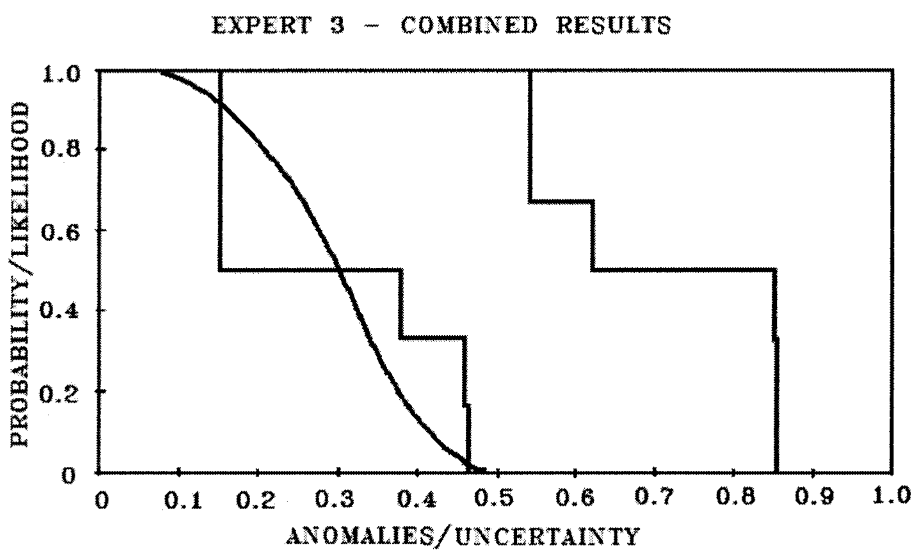


Figure 25. Probability & Evidence theory graphical results for expert 3

Figure 25 represents the combined graphical results using both probabilistic and non-probabilistic results based on the responses of Expert 3. The probabilistic results for this expert are much like the results for Expert 1; however, the probabilistic results when superimposed upon the non-probabilistic graph paint a different picture. Like Expert 1, this expert's CCDF falls on the pessimistic part of the range, and both the probabilistic and non-probabilistic results for this expert are consistent. The marked differences in this expert's graphical results are the narrow range between belief and plausibility and the small variance of the CCDF. Expert 3's probabilistic and non-probabilistic assessments show that the evidence supports this expert's assessment of the probability of system failure as a result of the given anomalies and are very well balanced.

In an attempt to further analyze the uncertainty for each expert, a parallel scale of each expert based on a specific anomaly was developed, which could be visualized as a birds-eye-view of the curves. Figure 26 shows possible anomalies due to construction for all three experts. For Expert 1, the top line indicates probabilistic uncertainty range. The lower line shows a difference between Belief and Plausibility values taken from Figures 18 and 19.

Expert 1's assessment of level of uncertainty for both Probability and Evidence theories are similar. The ranges of uncertainty as seen in Figure 26 for Expert 1 are roughly the same. Expert 2's probabilistic assessment is extremely steep in comparison to the broad level of non-probabilistic uncertainty indicating inconsistency in the level of uncertainty with this particular technology. Expert 3's probabilistic assessment is more reliable by comparison to the level of non-probabilistic uncertainty, and the assessments made were consistent for both theories. When evaluating the level of knowledge among the three experts, it appears as though Expert 3 is more experienced and consistent and the decision maker should place more weight upon this expert's advice.

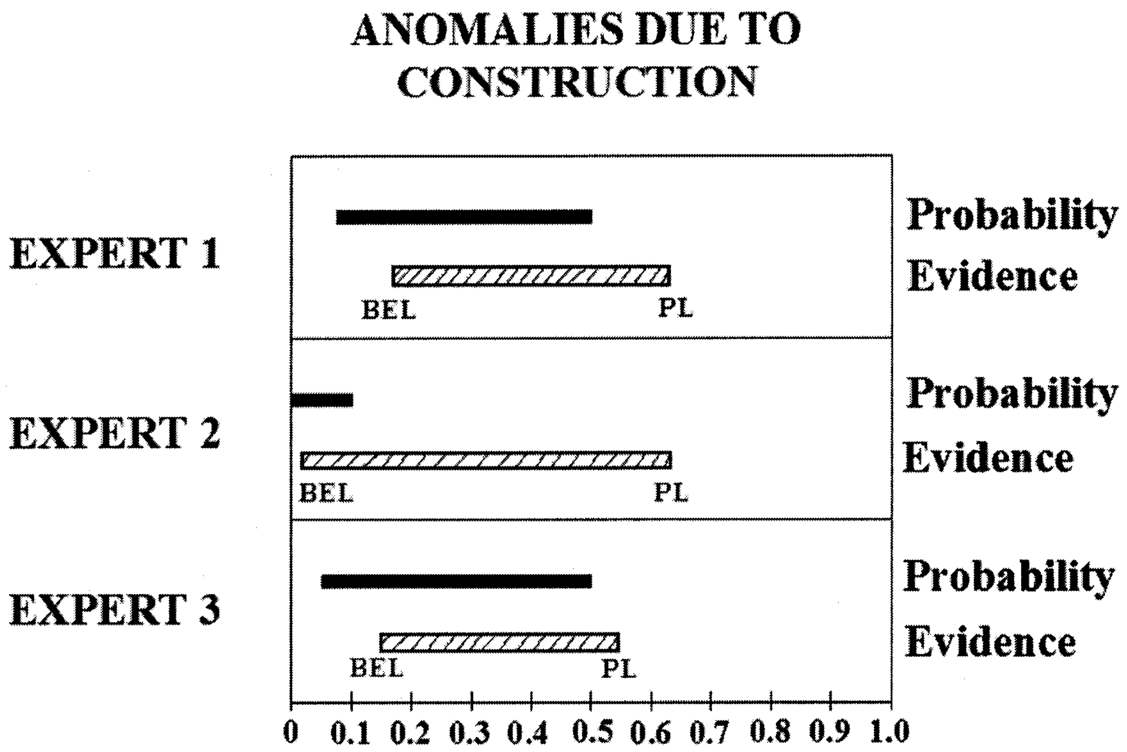


Figure 26. Expert assessment of anomalies due to construction

Figure 27 demonstrates probable anomalies due to Installation by all three experts, and the results for Experts 1 and 3 are largely congruent to the results displayed in Figure 26. Expert 1's probabilistic assessment is slightly smaller in comparison to the level of non-probabilistic uncertainty, and Expert 3's probabilistic assessment is slightly greater in comparison to the level of non-probabilistic uncertainty. Expert 2's probabilistic assessment, however, is much larger in comparison to the level of non-probabilistic uncertainty. This Expert's responses indicate that the level of uncertainty is high because the cumulative distribution is extremely wide and the results are confirmed by the Evidence graph showing the variance of the levels of uncertainty.

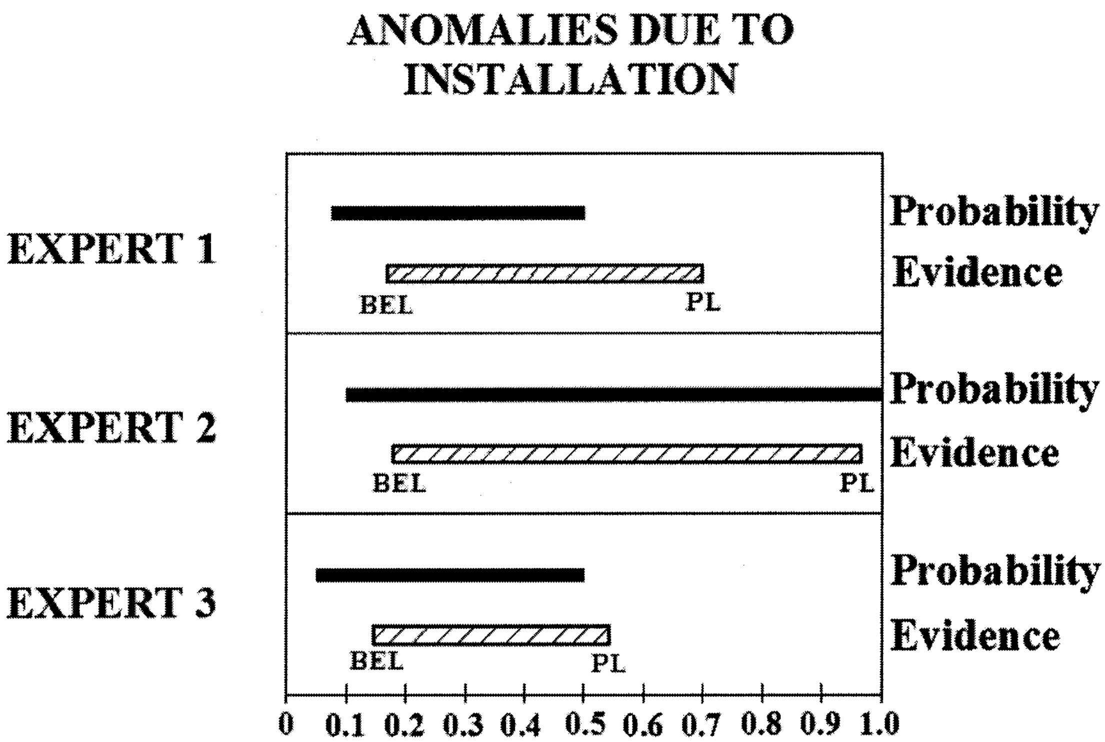


Figure 27. Expert assessment of anomalies due to installation

Figure 28 demonstrates probable anomalies due to Operations by all experts. Both Experts 1 and 2's probabilistic assessments are much smaller in comparison to the level of non-probabilistic uncertainty. Expert 3's probabilistic assessment is similar size with the level of non-probabilistic uncertainty, reflecting this Expert's consistency and balance shown in his responses.

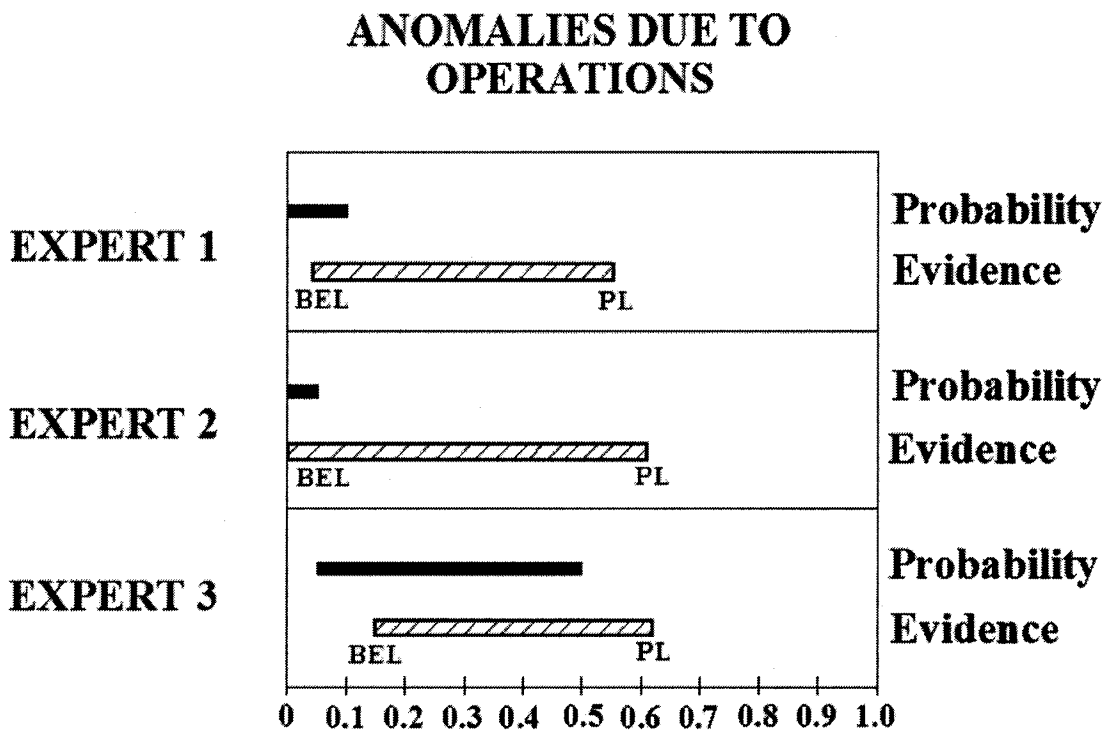


Figure 28. Expert assessment of anomalies due to operations

The above figures indicate the information that can be gained from using the combined probabilistic and non-probabilistic approach. Even though probabilistic assessments quantify an uncertainty range, Evidence theory results provide comparable information that adds a dimension to probabilistic results. These results may indicate that an expert's confidence in assessment maybe much lower than a probabilistic assessment alone indicated.

The graphical method used in this research provides various visual representations of the experts' uncertainty values to assist in the integration and assimilation of a decision strategy. The combination of the graphs developed by the CCDF derived by the Probability theory and the upper and lower limits derived by the Evidence theory, could provide the decision maker with a very clear comparison of multiple experts' probabilistic risk assessment relative to their non-probabilistic risk assessment.

One of the biggest challenges for a decision maker is to understand and translate the level of uncertainty of the experts. Modeling the uncertainty is an efficient approach for the decision maker to visualize uncertainty given. This combined approach utilizing Evidence Theory for assessment of both aleatory and epistemic uncertainties facilitates the assessment of subject matter expert's expertise and confidence, may be utilized for calibration, and has developed a tool that may allow decision makers in high-risk environments to assess uncertainty levels presented by multiple experts. Finally, the methodology presented could be applicable in a variety of disciplines including the aerospace technology, and could be used especially for adopting new technologies for future concepts.

4.8 Limits of Uncertainty Assessment

A big challenge of the concurrent research was to maintain neutral levels of uncertainty when changing mathematical models of aleatory and epistemic uncertainty during formalization of findings. To achieve this "neutrality," the researcher used the same amount of information presented by the expert's for both Probabilistic analysis and Evidence theory. The mathematical formulation of each theory leads to the graphical results of the CDF and the upper and lower bounds of uncertainty. There was no information added, replaced or eliminated from the input of variables. Rather all answers were preserved and used as given.

Given the nature of high-risk operations, many times decisions are made under critical conditions wherein decision makers are not afforded adequate time for a robust questionnaire follow-up. Practical means to facilitate a follow-up that can satisfy these stringent time constraints need to be developed.

4.9 Validation

The current research is an attempt to assess the levels of uncertainty for future TPS design through expert judgment elicitation, using the maximum amount of experts within this region and applying Probability and Evidence theories. Each time there is a knowledge-based situation that utilizes human experts, assistance from previous findings on using methods of validation is a necessity. Validation is defined as "the process of determining the degree to which a model or simulation is an accurate representation of the real world from the perspective of the intended uses of the model or simulation" (DoD, 2003).

According to Shepard, the four validity tests are content, predictive, concurrent and construct (Shepard, 1993). Content validity is based upon an individual's performance on a "defined" universe of tasks. Predictive validity is used to forecast future performance and involves the collection of criterion data after the test. Concurrent validity is more appropriate when the proposal of a new test substitutes a less convenient measure that is already being accepted. Finally construct validity is needed when making inferences about invisible attributes of a person's character, such as intelligence or anxiety (Shepard, 1993).

The questionnaire in this study is based upon the instrument developed by Chytka (2003). Her method of instrument validation is comparable to that of Shepard; however, whereas Shepard's methodology has four aspects, Chytka employs a Validation Triad.

Validation was performed in the current study based on three aspects: Content validity, performance validity and structural validity (Chytka, 2003). The subject-matter experts were interviewed in person relative to the content validity. They were asked for comments with regard to the questionnaire instrument about:

- Ease of use
- Appropriateness of structure and scaling method
- Clarity of context and content

The decision maker was then interviewed in person relative to the performance validity as well as the structural validity of the methodology. The decision maker was asked to comment relative to decision-making strategies on:

- The efficacy and increased value of the aggregation
- The effectiveness of the uncertainty representation
- The usefulness and applicability of this method beyond the current study

The validation results from the interviews with the subject-matter experts indicate that the questionnaire is clear, prudent and concise. The interview with the decision maker verified that the results are representative, and are useful, practical and well-structured. Further, the decision maker indicated that this methodology will assist decision makers to assess the level of uncertainty in conceptual design.

The validation of the mathematical models used for this research is based on Sell's model dimensions to validation: consistency, completeness, soundness, precision and usability (Sell, 1985). Sell defines consistency as "the same inputs resulting in the same outputs." In addition, both theories have practical applications and are considered to be an extension of the soundness requirement due to the precision of probabilistic outcomes (Sell, 1985). Completeness is an attribute within the range of the model's application that allows all outcomes to be derived and all sets of inputs to produce an output. This research was designed to preclude bypassing any of the steps involved. Soundness demands that everything derivable through the operations also be true. The Probability theory and the Evidence theory are established mathematical models that produce consistent, complete and pertinent results.

The mathematical models used for this research followed precisely the rules dictated by their perspective theories. The data and graphical analyses produced resulted from the computational use of all the formulas presented in Chapter 3 – Methodology.

5. Conclusions

5.1 Discussion

Many factors contribute to the analysis of a solution space in high-risk environment. While mathematical models used to assess uncertainty, such as the probabilistic approach, have had successful applications, the results are not as robust as is required for high-risk operations. This research relies heavily upon the inputs from the high-risk experts and involves eliciting expert judgment to derive the numerical raw data used in the analyses. An initial questionnaire was developed that addresses conditions encountered during high-risk operations and includes questions that were useful for both Probability and Evidence theories. The questionnaire was utilized for uncertainty assessment, using NASA's Crew Exploration Vehicle (CEV) Thermal Protection System (TPS) as an example. This research focused on the combination and aggregation of variables while taking into consideration the uncertainty of each expert's input and the results, which were then applied in the development of the CDF and CCDF, relying strictly upon aleatory uncertainties. Then the upper plausible limits and lower belief limits were derived based upon a combination of aleatory and epistemic uncertainties.

As with probabilistic analysis, results show that a clear-cut interpretation of Evidence theory graphs alone may not be possible. For example, Expert 3's judgment seemed to indicate most confidence given the narrowest range between belief and plausibility, where Expert 2's judgment seemed to indicate the least confidence with the largest range between belief and plausibility; however, such a conclusion may be misleading without further investigation. Expert 1's results indicated that he had more confidence in his opinion than Expert 2, yet his opinion had less balance than Expert 3. Using a graphical method, this research provided various visual representations of the experts' uncertainty values to assist in the integration and assimilation of a decision strategy. This could provide the decision maker with a very clear comparison of multiple experts' probabilistic risk assessment relative to their non-probabilistic risk assessment.

A combined approach utilizing Evidence Theory for assessment of both aleatory and epistemic uncertainties demonstrated in this research could provide insights required to reach a more informed decision. The combined approach facilitates the assessment of subject matter expert's expertise and confidence and may be utilized for calibration. This research and application study has developed a tool that may allow decision makers to assess uncertainty levels presented by the experts. In addition, the methodology presented could be applicable in a variety of disciplines including the aerospace technology, and could be used especially for adopting new technologies for future concepts.

This research has made the following contributions:

- Contribution to theoretical findings: Explored the boundaries among high-risk environments and addressed uncertainty by utilizing both a probabilistic method and Evidence theory using expert judgment elicitation.
- Contribution to Methodology: This research demonstrated a framework that may be utilized in constructing upper and lower limits of uncertainty for a more meaningful representation to the decision makers.
- Contribution to Practice: Provided combined method specifically designed to assist in addressing uncertainty in high-risk engineering environments.

The above results are achieved by performing expert judgment elicitation with a specific questionnaire designed for the operations and support phase of a space transportation system.

The main objective of this research has been to seek alternative approaches that can aid the decision maker to assess the level of uncertainty of expert judgment when historical data is scarce. The intent of this research was not proving that Probability Theory is better than Evidence Theory or vice versa, rather to expand the comparative evidence of the findings. Further, the graphical combination between CCDF and Evidence theory is an unaltered or unmanipulated representation of the experts' results. The intention of this study is not, by any means, to perform an evaluation of experts. Rather, it is intended to be an application and true representation of uncertainty assessments of actual experts in real high-risk environments and provide a visual representation of the experts' uncertainty value for integration and assimilation into a decision strategy. Sometimes overconfidence in one's opinion is a mark of inexperience, thus rating one's level of expertise based on uncertainty level is not prudent.

Using probabilistic approach or Evidence theory alone could produce inconclusive results that can potentially cause flawed decisions; however, a combined approach as demonstrated in this research can provide more useful information to the decision maker. Probability theory is a well-researched and practiced methodology that provides the mathematical structure traditionally used in the representation of aleatory uncertainty. The probabilistic uncertainties in analysis outcomes are represented with probability distributions and are typically summarized with CDF. The most familiar technique is the Monte Carlo simulation. Probabilistic uncertainty analysis is very widely used, has undergone many proofs, has numerous mathematical derivations, and is understood by many because of its simplicity; however, Probability theory has had some recent critiques due to the random nature of the outcome, some recent failures, and has been criticized as a theory of chance. Many innovators in this field agree that a more comprehensive means of assessing uncertainty is needed. Consequently, the extension of the efforts to define the development of a more robust system has lead to the development of the Evidence theory. Evidence theory provides a promising alternative to probability theory. It allows for a fuller representation of the implications of uncertainty as compared to a probabilistic representation of uncertainty. Evidence theory can handle not only aleatory uncertainty but epistemic uncertainty as well. It provides the decision maker with a range of values as opposed to a single arbitrary value. It also allows for different types of uncertainty. Experts in this field agree that of the new methods of assessing uncertainty, Evidence theory is a very strong model; however, Evidence theory is not widely used, is yet to have any applications in the engineering field, and is understood by very few. Probability theory and Evidence theory are comparable methodologies; however, they are conceptually inverse functions in that as the probability of a given occurrence increases, the experts' uncertainty logically will decrease. In this study, Probability theory is utilized to address the probability of the occurrence of an event (system failure due to an anomaly) while Evidence theory is used to addresses the degree of uncertainty of whether an event will occur. In order to successfully integrate the Evidence theory into engineering applications, a bridge must be built between current practices and the future. This research suggests that the assessment of uncertainty of experts in high-risk environments may be better conveyed to decision makers by using both probabilistic and non-probabilistic theories.

5.2 Study Limitations and Delimitations

Many researchers agree that Expert Judgment Elicitation can be used in areas where there is limited or no historical data (Monroe, 1997, Hampton, 2001, Conway, 2003, Chytka, 2003). One of the major limitations of this study is that only three experts were utilized; however, the pool of experts is small in terms of level of expertise with regard to the TPS technology that can be used for the proposed transportation system.

Another limitation of this research is addressing the bias generated by the experts. Reduction of bias is extremely desirable in many public and private corporations. The high-risk experts were selected by NASA for this study, ensuring objectivity and assessing subjective conclusions; however, the researcher has no prior knowledge of the background and level of expertise of the experts. Additionally, psychological and personal issues are not used as part of this study's parameters. Expert's qualification criteria such as confidence level and risk ranking have not been addressed. The intent of this research was only to compare probabilistic and Evidence theory approaches for uncertainty assessments using expert judgment elicitation. Also results indicate further development and applications may be needed before it can fully utilized in decision making.

5.3 *Extensions of Research*

Evidence theory raises more questions than answers, which could, in turn, make more uncertainty assessments and could lead into valuable findings for one-of-a-kind systems when no operational data is available. Evidence theory is leading to a self assessment of the experts when evaluating a new technique that leads to critical thinking. Evidence theory does not provide a concrete non-probabilistic assessment; rather it provides an enhancement of probabilistic analysis. This theory needs to be developed further.

Traditional methods for uncertainty assessment may not be consistently functional; therefore, there is an absolute need for improvement in the analysis process to address and quantify appropriate alternate models. Proper and improved methods of expert judgment elicitation should be exercised based on qualified expert opinions, while mixtures of mathematical models both probabilistic and non-probabilistic should be utilized. An improved understanding of types of dependencies between aleatory and epistemic uncertainties should be developed with ease of applicability in mind.

Evidence theory needs additional development in order to become practical. Nevertheless, results can be used to develop a new calibration function to further the research of expert assessment calibration developed previously by Conway (2003). "The behavior of a complex system is probabilistic in nature and can never be totally predicted or know in advance of system deployment. The more complex a system becomes the higher degree of uncertainty associated with the system performance (outputs/outcomes generated)" (Keating et al., 2004). Further study is needed for the application of the combined approach to Systems of Systems Engineering in assessing uncertainty. Further study is also needed for the relationship between complexity and high-risk environments and the applicability of the Evidence theory to both. Given the nature of high-risk operations, many times decisions are made under critical conditions wherein decision makers are not afforded adequate time for a robust questionnaire follow-up. Practical means to facilitate a follow-up that can satisfy these stringent time constraints need to be developed.

Finally, improved sampling methods should be introduced through accelerated methods using a more comprehensive sensitivity analysis based on knowledge and expertise in an attempt to identify consistency of the bounding methods.

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APPENDIX A:

Expert Judgment Elicitation Sample Questionnaire

Input Parameter Uncertainty Questionnaire

1. USER ID: The last four digits of your phone number in reverse order.

2. Your Age:

3. Relative to TPS design in general, rate your own level of expertise on a scale of 1 to 5 (Please select one option):

   1 (low)
   2 (low/average)
   3 (average)
   4 (average/high)
   5 (high)

4. Place yourself among other colleagues with similar experience working in the same discipline. How would you compare yourself to your colleagues with respect to expertise on a scale of 1 to 5?

   1 (much less than colleagues)
   2 (less than colleagues)
   3 (about the same)
   4 (more than colleagues)
   5 (much more than colleagues)

5. In making estimates related to TPS input parameters, you are generally:

   Accurate with a high degree of confidence
   Accurate without a high degree of confidence
   Low accuracy with a high degree of confidence
   Low accuracy with a low degree of confidence

6. Thinking about predicting the likelihood associated to a particular event, do you normally predict:

   More than actually occurs?
   Less than actually occurs?
   About the same amount/number of times that actually occurs?

7. In estimating associated uncertainty in your subject area, would you say it is better to be:

   Close to the actual value without a lot of confidence in your estimates?
   Not very close to the actual value, but with a high degree of confidence in your estimates?

8. Do you think it is better for project success to:

   Set, in advance, the completion dates for a high-risk project?
   Establish, in advance, technical milestones for a high-risk project?

9. Do you think it is better for a project success to:

   Estimate, in advance, cost outlays for a high-risk project?
   Identify, in advance, cost elements for a high-risk project?

10. Do you think it is better to:

    Identify, at conceptual design review, scenarios for the successful projects?
    Predict, at conceptual design review, technical performance characteristics of a completed hardware?

11. What is your estimate of the percentage of purity of the raw material (amorphous silica fiber) used for the TPS on the orbiter?

12. How confident are you on the above estimate?

    0 - 20%
    21 - 40%
    41 - 60%
    61 - 80%
    81 - 100%

It is thought that critical subsystem failures of the Thermal Protection System (TPS) maybe a function of Construction (production), Installation (debonding of tiles) and Operations (debris damage at lift-off that causes burn through). If you think there may be other causes, you will be asked to list them later in the questionnaire.

Assessment due to construction (production) anomalies

13. What is the likelihood of critical system failure due to construction anomalies? Please select one of the following options:

    Low
    Low/Moderate
    Moderate
    Moderate/High
    High

14. What does low mean to you?

    Less — Please indicate how much less: ☐
    0.05%
    0.075%
    0.10%
    More — Please indicate how much more: ☐

15. What does moderate mean to you?

    Less — Please indicate how much less: ☐
    0.15%
    0.20%
    0.25%
    More — Please indicate how much more: ☐

16. What does high mean to you?

    Less — Please indicate how much less: ☐
    0.30%
    0.40%
    0.50%
    More — Please indicate how much more: ☐

17. Provide any scenarios that may change your estimates.

☐

18. Provide reasoning, or assumptions used to reach above conclusions.

☐

Assessment due to installation anomalies

19. What is the likelihood of critical system failure due to installation anomalies? Please select one of the following options:

    Low
    Low/Moderate
    Moderate
    Moderate/High
    High

20. What does low mean to you?

Less	Please indicate how much less:
0.05%	
0.075%	
0.10%	
More	Please indicate how much more:

21. What does moderate mean to you?

Less	Please indicate how much less:
0.15%	
0.20%	
0.25%	
More	Please indicate how much more:

22. What does high mean to you?

Less	Please indicate how much less:
0.30%	
0.40%	
0.50%	
More	Please indicate how much more:

23. Provide any scenarios that may change your estimates.

24. Provide reasoning, or assumptions used to reach above conclusions.

Assessment due to operations (debris damage at lift-off, burnout) anomalies

25. What is the likelihood of critical system failure due to operations (debris damage at lift-off, burnout) anomalies? Please select one of the following options:

    Low
    Low/Moderate
    Moderate
    Moderate/High
    High

26. What does low mean to you?

    Less — Please indicate how much less: [ ]
    0.05%
    0.075%
    0.10%
    More — Please indicate how much more: [ ]

27. What does moderate mean to you?

    Less — Please indicate how much less: [ ]
    0.15%
    0.20%
    0.25%
    More — Please indicate how much more: [ ]

28. What does high mean to you?

    Less — Please indicate how much less: [ ]
    0.30%
    0.40%
    0.50%
    More — Please indicate how much more: [ ]

29. Provide any scenarios that may change your estimates.

30. Provide reasoning, or assumptions used to reach above conclusions.

Assessment due to construction and installation anomalies

31. What is the likelihood of critical system failure due to construction and installation anomalies? Please select one of the following options:

    Low
    Low/Moderate
    Moderate
    Moderate/High
    High

32. What does low mean to you?

    Less — Please indicate how much less: ☐
    0.05%
    0.075%
    0.10%
    More — Please indicate how much more: ☐

33. What does moderate mean to you?

    Less — Please indicate how much less: ☐
    0.15%
    0.20%
    0.25%
    More — Please indicate how much more: ☐

34. What does high mean to you?

    Less — Please indicate how much less: ☐
    0.30%
    0.40%
    0.50%
    More — Please indicate how much more: ☐

35. Provide any scenarios that may change your estimates.

36. Provide reasoning, or assumptions used to reach above conclusions.

Assessment due to construction and operations anomalies

37. What is the likelihood of critical system failure due to construction anomalies? Please select one of the following options:

    Low
    Low/Moderate
    Moderate
    Moderate/High
    High

38. What does low mean to you?

    Less — Please indicate how much less: ☐
    0.05%
    0.075%
    0.10%
    More — Please indicate how much more: ☐

39. What does moderate mean to you?

    Less — Please indicate how much less: ☐
    0.15%
    0.20%
    0.25%
    More — Please indicate how much more: ☐

40. What does high mean to you?

    Less — Please indicate how much less: ☐
    0.30%
    0.40%
    0.50%
    More — Please indicate how much more: ☐

41. Provide any scenarios that may change your estimates.

☐

42. Provide reasoning, or assumptions used to reach above conclusions.

☐

Assessment due to installation and operations anomalies

43. What is the likelihood of critical system failure due to construction anomalies? Please select one of the following options:

    Low
    Low/Moderate
    Moderate
    Moderate/High
    High

44. What does low mean to you?

    Less — Please indicate how much less: ☐
    0.05%
    0.075%
    0.10%
    More — Please indicate how much more: ☐

45. What does moderate mean to you?

    Less — Please indicate how much less: ☐
    0.15%
    0.20%
    0.25%
    More — Please indicate how much more: ☐

46. What does high mean to you?

    Less — Please indicate how much less: ☐
    0.30%
    0.40%
    0.50%
    More — Please indicate how much more: ☐

47. Provide any scenarios that may change your estimates.

48. Provide reasoning, or assumptions used to reach above conclusions.

Assessment due to construction, installation and operations anomalies

49. What is the likelihood of critical system failure due to the combination of all three variables; construction, installation and operations anomalies? Please select one of the following options:

Low
Low/Moderate
Moderate
Moderate/High
High

50. What does low mean to you?

Less — Please indicate how much less:
0.05%
0.075%
0.10%
More — Please indicate how much more:

51. What does moderate mean to you?

Less — Please indicate how much less:
0.15%
0.20%
0.25%
More — Please indicate how much more:

52. What does high mean to you?

Less — Please indicate how much less:
0.30%
0.40%
0.50%
More — Please indicate how much more:

53. Provide any scenarios that may change your estimates.

54. Provide reasoning, or assumptions used to reach above conclusions.

55. Critical sub-system failures of the TPS may be due to other than construction, installation and operations. Please add any other possible critical sub-system failures* of the TPS to the following text block:

* Loss of mission and/or loss of crew

Please allow us to modify our questionnaire and return to you with an updated version.

Please provide comments and/or suggest improvements to this questionnaire:

Your feedback is appreciated.
Your knowledge and expertise will have great impact on this research.
Thank you very much.

VITA

Stella Barberis Bondi

Department of Engineering Management and Systems Engineering

Old Dominion University

Norfolk, Virginia 23529

Stella Barberis Bondi earned her Bachelor of Science in Civil Engineering from Old Dominion University in Norfolk, Virginia in 1999. She received a Masters in Engineering Management degree from Old Dominion University in 2003. Her career included twenty-two years with engineering consulting firms. Her latest assignment was Project Engineer working for a land development company. Her academic experience includes working for four years as an adjunct faculty member for Tidewater Community College and one year as part-time adjunct faculty for Old Dominion University. While pursuing her doctorate, she taught synchronous and asynchronous courses for Old Dominion University.