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Assimilating Non-Probabilistic Assessments of the Estimation of Uncertainty Bias in Expert Judgment Elicitation Using an Evidence Based Approach in High Consequence Conceptual Designs

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ABSTRACT

ASSIMILATING NON-PROBABILITSTIC ASSESSMENTS OF THE ESTIMATION OF UNCERTAINTY BIAS IN EXPERT JUDGMENT ELICITATION USING AN EVIDENCE BASED APPROACH IN HIGH CONSEQUENCE CONCEPTUAL DESIGNS

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One of the major challenges in conceptual designs of complex systems is the identification of uncertainty embedded in the information due to lack of historic data. This becomes of increased concern especially in high-risk industries. This document reports a developed methodology that allows for the cognitive bias, estimation of uncertainty, to be elucidated to improve the quality of elicited data. It consists of a comprehensive literature review that begins by defining a 'High Consequence Conceptual Engineering Environment' and identifies the high-risk industries in which these environments are found. It proceeds with a discussion that differentiates risk and uncertainty in decision-making in these environments. An argument was built around the identified epistemic category of uncertainty, the impact on hard data for decision-making, and from whom we obtain this data.

The review shifts to defining and selecting the experts, the elicitation process in terms of the components, the process phases and steps involved, and an examination of a probabilistic and a fuzzy example. This sets the stage for this methodology that uses evidence theory for the mathematical analysis after the data is elicited using a tailored elicitation process. Yager's combination rule is used to combine evidence and fully recognize the ignorance without ignoring available information.

Engineering and management teams from NASA Langley Research Center were

the population from which the experts for this study were identified. NASA officials were interested in obtaining uncertainty estimates, and a comparison of these estimates, associated with their Crew Launch Vehicle (CLV) designs; the existing Exploration Systems Architecture Study Crew Launch Vehicle (ESAS CLV) and the Parallel-Staged Crew Launch Vehicle (P-S CLV) which is currently being worked.

This evidence-based approach identified that the estimation of cost parameters uncertainty is not specifically over or underestimated in High Consequence Conceptual Engineering Environments; rather, there is more uncertainty present than what is being anticipated. From the perspective of maturing designs, it was concluded that the range of cost parameters' uncertainty at different error-state-values were interchangeably larger or smaller when compared to each other even as the design matures.

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CHAPTER I

INTRODUCTION

BACKGROUND

Researchers in various fields (including engineering, statistics, business, cognitive psychology, and others) have studied human judgment of how individuals make assessments of unknown events with minimal information both in 'experimental and naturalistic settings' (Booker & McNamara, 2004b). This capture of 'speculative knowledge' was identified as "pistis" (propositional knowledge based on belief) and "eikasia" (propositional knowledge based on conjecture) (see Figure 1) and is based on expert judgments and opinions regarding system issues of interest (Ayyub, 2001). Although these propositional knowledge categories may be tarnished by uncertainty, many engineering disciplines sought after certainty especially in decision making (ibid.).

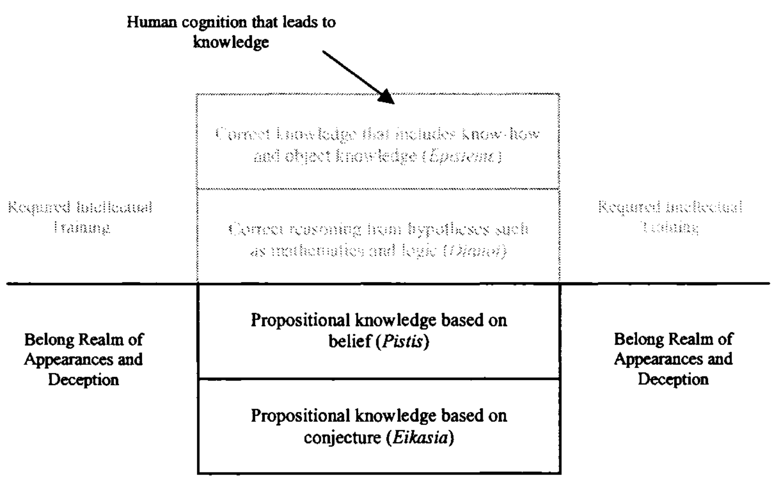


FIGURE 1: KNOWLEDGE CATEGORIES AND SOURCES (ADAPTED FROM AYYUB, 2001)

The journal model of, *The American Psychologist*, the journal of the American Psychological Association has been used herein for the referencing the formatting of this document.

A formal approach to eliciting and analyzing expert judgment dates back to the early 1980s, and was rooted specifically in 'early human cognition studies' and the 'emergence of Probabilistic Risk Assessment (PRA)' (Booker & McNamara, 2004a). "PRA relied heavily on expert judgment because, for most early problems, 'hard' (test, experimental, observational) data were sparse or nonexistent" (ibid., p. 332). The peak of expert judgment elicitation was reached, in terms of public confidence, as a result of the Vietnam War (Cooke, 1991).

Research Objective

The objective of this research was to provide some insight on the estimation of uncertainty bias found in expert judgment elicitation as it relates to decision making. This was done by a developed evidence based approach to elucidate and present information to aide the decision making process. Placed in a 'high consequence conceptual engineering environment', this approach was investigated by integrating in both the elicitation and the analysis process.

Synchronizing Terms

There are a few terms that will be encountered later in this document and are defined as presented by Booker and McNamara (2004b):

- *Lead expert*: analysis team collaborates closely with member(s) of the community of practice. These "native" collaborators are referred to as lead experts.
- *Analyst*: an individual or a team of individuals working to develop a model to support decision making.

- *Community of Practice (the social locus of the domain):* a group of people who organize their problem-solving activity in pursuit of a shared goal or interest.
- *Decision maker*: the individual who requires the output from the analysis to support a course of action; the lead expert may also be the decision maker.
- *Domains*: are bounded areas of human cognitive activity that are constituted by a mixture of real world referent (i.e., an object such as a system) and the experts' cognitive structures (i.e., the conceptual models that an expert uses when engaging in the problem associated with the system).
- *Experts*: individuals recognized by his or her pairs as having training and experience in his or her technical field; individuals within the community who own pieces or areas of the problem and who have documented experience working in the domain.
- *Problems*: are epistemic challenges through which communities of practice identify limits to domain knowledge.
- Elicitation of expert judgment - is a process of *gathering information* through a *response mode* in a *specified environment.*
- Under or overestimation of uncertainty - is the *failure* to identify or the *exaggeration* the actual amount of *uncertainty* in the *information* obtained during the elicitation of expert judgment within a *specified environment* respectively.
- High consequence conceptual engineering environments – is an *environment* in which the *level of negative results* obtained from a *course of action* taken by an *expert* to develop *a solution path* through the elaboration of *a solution principle* is high (presented by Pahl & Beitz, 1996).

SYNOPSIS OF THE RESEARCH REPORT

This document is structured under seven chapters, namely introduction, literature review, methodology, application of the methodology, results, discussion and conclusions. The literature review begins with a constructed definition of what is a high consequence conceptual engineering environment. It defines conceptual engineering, consequences in conceptual engineering and identifies the high risk industries in these environments are found.

The document proceeds with a discussion that differentiates risk and uncertainty, and attempts to relate these to decision making in high consequence conceptual engineering environments. The philosophical definitions of risk were given, that aided the categorization into subjective and objective, and leads into an epistemological approach emphasis. This section further discusses the categorization of uncertainty as aleatory and epistemic. An argument is built around epistemic uncertainty (the uncertainty category of interest for this study), the impact on hard data for decision making, and from whom we obtain this data.

Who is an expert? This became the question of interest at this point that lead to a shift in the literature review to the definition of an expert, a relationship of knowledge and ignorance to the expert, and the characteristics of an expert. Expert judgment is discussed in terms of the definitions, the majors fields in which they were developed and are found, and the uses and misuses. The elicitation of these judgments is discussed in terms of the components; i.e. the 'Building Block of Elicitation' - namely the elicitation techniques, modes of communication, elicitation situations, response modes, and aggregation schemes. The process phases and steps are presented as put forth by various authors while examining a probabilistic and a fuzzy example.

An emphasis is made on the importance and reasons for proper documentation of expert judgments. One of the contributions to this study is how this task aids in the elucidating of biases. These biases are explained in two categories, motivational and cognitive, and the respective bias reduction techniques are discussed. A definition to heuristics is given and a discussion is conducted on how these heuristics relate to biases based on the appropriateness of use. This is all tied into the estimation of uncertainty and identifies under what circumstances these estimates are under or overestimated.

A discussion of evidence theory is presented by initially showing a relationship between probabilistic approaches to quantify epistemic uncertainty. The literature identified indicates that this is not the best approach because it does not fully recognize our ignorance without ignoring available information. Evidence theory, using Yager's combination rule, will address this problem in the case of this research. This theory used for the mathematical analysis after the data is elicited, along with applying a tailored elicitation to address biases during the process, will provide a methodology that can be used to adequately elucidate this estimation of uncertainty bias.

Engineering and management teams from NASA Langley Research Center were the population from which the experts for this study were identified. NASA officials were interested in obtaining uncertainty estimates, and a comparison of these estimates, associated with their Crew Launch Vehicle (CLV) designs; the existing Exploration Systems Architecture Study Crew Launch Vehicle (ESAS CLV) and the Parallel-Staged Crew Launch Vehicle (P-S CLV), which is currently being worked.

The conclusion of this evidence-based approach is it identified that the estimation of cost parameters uncertainty is not specifically over or underestimated in High Consequence Conceptual Engineering Environments; rather, there is more uncertainty present than what is being anticipated. From the perspective of maturing designs, it was concluded that the range of cost parameters' uncertainty at different error-state-values were interchangeably larger or smaller when compared to each other even as the design matures.

CHAPTER II

LITURATURE REVIEW

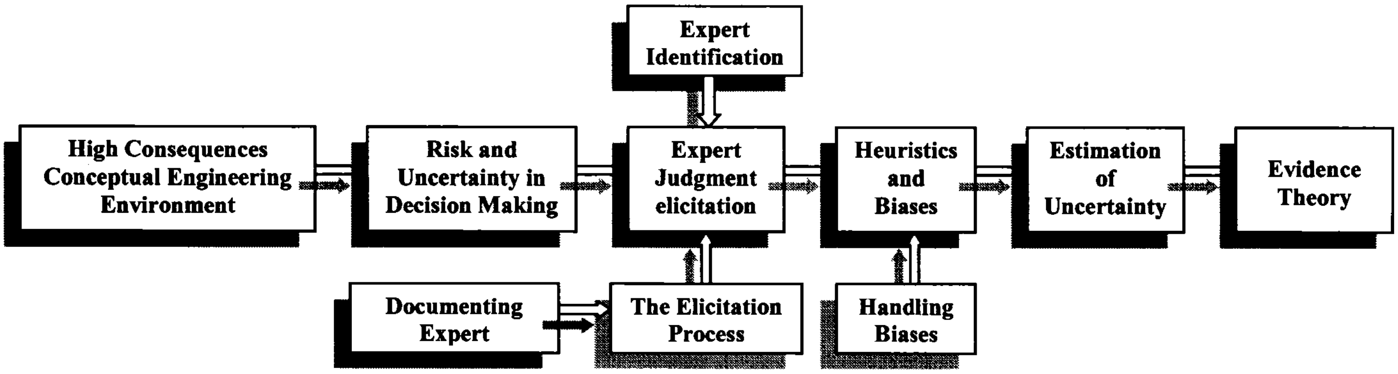


FIGURE 2: OUTLINE OF RELEVANT LITERATURE

HIGH CONSEQUENCE CONCEPTUAL ENGINEERING ENVIRONMENTS

Conceptual engineering can be considered the "first theory" of a complex system (Monroe, 1997). Designs in this phase are perhaps the most critical in the systems lifecycle (Wang et. al., 2002). It involves the initiation of high level descriptions of requirements, processes and a preliminary solution (McNeil et al., 1998). This preliminary solution is a path presented through the elaboration of a solution principle (Pahl & Beitz, 1996); an abstract ideas and tangible representations is formulated (Takala, 1989) and evaluated against the requirements.

Consequences in conceptual engineering vary depending on the level of perceived risks and uncertainties. In high consequence environments there is a "more than normal chance for damage to one's own life, the life of others or to material property" (Dietrich

& Childress, 2004, p. 1). Therefore, within these environments, mistakes and errors are often not tolerated due to the potentially catastrophic outcome associated with these mistakes or errors (Aase & Nybø, 2002).

These environments are normally found in high risk industries such as nuclear power plants, chemical plants, energy utility plants, transportation systems (space shuttles, aircrafts, and shipping), offshore installations, and some large construction projects (ibid.). The characteristics that can be used to characterize different types of high risk industries include complexity (ibid.), proximity to hazard (Reason, 1997), interdependencies (Perrow, 1986), and levels of risks and uncertainty. For this research, this is context that high consequence conceptual engineering environments are defined.

Reference	**Contribution to Literature/Research**
Aase & Nybø, 2002	Identifies industries in which high consequence environments are found along with the tolerance level for mistake or errors in these environments.
Dietrich & Childress, 2004	Discusses the characteristics of high consequence environments.
McNeil et al., 1998	Identifies the conceptual phase of the systems lifecycle as involving high level descriptions of requirements, processes and a preliminary solution.
Monroe, 1997	Defines conceptual engineering as the first theory of a complex system.
Pahl and Beitz, 1996	Discusses what preliminary solutions are.
Perrow, 1986	Contributes to the characteristics of high risk industries.
Reason, 1997	Contributes to the characteristics of high risk industries.
Takala, 1989	Discusses the tangible representation of the preliminary solutions against the requirements.
Wang et. al., 2002	Identifies the design phase in the systems lifecycle as being perhaps the most critical.

TABLE 1: SUMMARY OF CONTRIBUTIONS TO HIGH CONSEQUENCE CONCEPTUAL ENGINEERING ENVIRONMENT LITERATURE

Risk and Uncertainty in Decision Making

To support decision-making in a high consequence conceptual engineering environment, it is important to conduct a risk assessment that includes hazard identification, cause analyses, consequence analyses and obtain a set of risk description (Aven & Kristensen, 2005). The scientific basis is to obtain "knowledge about system performance and unknown quantities that are systematically described by models.... expert opinions and a coherent uncertainty assessments using the rules of probability" (ibid., p. 2). Because of the colloquial utilization of risk, issues of calculable probability are not necessarily important and "risk and uncertainty tend to be treated as conceptually the same thing" (Lupton, 1999, p. 9). However, a distinction between risk and uncertainty was given by Knight (1921) where it is argued that "the ability to attach probability measures to unknown outcomes distinguishes risk from uncertainty" (p. 9). He defines risk as "measurable uncertainty (where the distribution of outcomes in a group of instances is known by calculation), whereas uncertainty is immeasurable (where the distribution of outcomes is not known because it is usually impossible to form a group of instances to calculate)" (p. 233). This is supported by Althaus (2005) who indicated that "risk is an attempt to control the unknown by applying knowledge based on the orderliness of the world. Uncertainty, on the other hand, represents the totally random unknown and thus cannot be controlled or predicted" (p. 569).

There are five philosophical definitions of risk presented by Thompson in 1986, cited in Althaus (2005, p. 568). These definitions make an implicit distinction between "risk defined as a reality that exists in its own right in the world (e.g., objective risk and real risk) and risk defined as a reality by virtue of a judgment made by a person or the application of some knowledge." Here the latter is considered the epistemological approach to risk - "risk coming to exist by virtue of judgments made under conditions of uncertainty" (ibid., p. 569).

An epistemological approach emphasizes the subjective nature of risk versus the objective scientific view. In research conducted by Althaus (2005), various authors were cited supporting this approach. The focus was on determining why is there

Risk Philosophy	Philosophical Definitions
Subjective risk	The mental state of an individual who experiences uncertainty or doubt or worry as to the outcome of a given event.
Objective risk	The variation that occurs when actual losses differ from expected losses.
Real risk	The combination of probability and negative consequence that exists in the real world.
Observed risk	The combination of measurement obtained by constructing a model of the real world.
Perceived risk	The rough estimate of real risk made by an untrained member of the general public.

TABLE 2: FIVE PHILOSOPHICAL DEFINITIONS OF RISK

disparity in perception between expert and lay risk (Margolis, 1996). An assessment of what makes people risk-averse, risk-indifferent, or risk-takers (Trimpop, 1994 as cited by Althaus, 2005) was conducted and they explored the significance of trust (Cvetkovich & Lofstedt, 1999), blame (Hood & Jones, 1996), vulnerability, defense mechanisms (Joffe, 1999), and other aspects of motivation and cognition that characterize risk behavior (Kogan & Wallach, 1964). This epistemological (subjective) approach is generally characterized by the expert's uncertainty of the performance of the system being studied (Aven & Kristensen, 2005). "The performance is normally expressed by quantities that can be measured (such as money, loss of lives, etc.) and is often referred to as possible consequences" (ibid., p. 11).

There are two different categories of uncertainty, aleatory and epistemic. "Aleatory refers to uncertainty due to random variation or inherent variation. It is irreducible, includes the basic statistical concepts of variability, and the definition of probability as describing the uncertainty associated with the outcome of an experiment or event. By contrast, epistemic uncertainty is reducible and stems from a lack of knowledge" (Booker et al., 2004, p. 2). The latter is also referred to as "subjective uncertainty, reducible uncertainty, and model form uncertainty" (Oberkampf, 2005).This instigates a debate over the question of experts and the relative position of ignorance and knowledge in relation to risk (Althaus, 2005). For this study, as in previous research, we are not interested in proving that "risk is a thing" (the ontological foundation of risk), "But to deal with one's approach or attitude to risk, is it believable or knowable?" (ibid., p. 578). Therefore, in assessing future performance of a system being studied, we need to predict the relevant performance measures, and assess the uncertainty in these measures (Aven & Kristensen, 2005). Regardless of the type of uncertainty, they postulate common features - "the future performance of a system is unknown (uncertain), the consequences are unknown (uncertain) and any description of these consequences would be based on a number of assumptions seen through the eyes of someone and restricted to certain aspects" (ibid., p.12). Therefore, "who can we trust, who are the experts, how should expert knowledge be applied, how does ignorance and knowledge impact risk decisions, how does truth and error pertain to risk?" (Althaus, 2005, p. 578). For decision-making, information is need as "hard data" (ibid.); therefore we need judgments, assessments and processes to build understanding and trust.

Reference	Contribution to Literature/Research
Althaus, 2005	Distinguish between risk and uncertainty, and the categorization of risk.
Aven & Kristensen, 2005	Discusses risk assessment and its rational, the assessment of uncertainty in the relevant performance measure, the measures in relation to consequences in high consequence environments, and risk as a think (ontological foundation of risk).
Booker et al., 2004	Identifies and defines the two categories of uncertainty as being aleatory and epistemic.
Cvetkovick & Lofstedt, 1999	Contributes to the characteristics discussion of risk behavior.
Hood & Jones, 1996	Contributes to the characteristics discussion of risk behavior.
Joffe, 1999	Contributes to the characteristics discussion of risk behavior.
Knight, 1921	Contributes to the discussion of distinguishing between risk and uncertainty.
Kogan & Wallach, 1964	Contributes to the characteristics discussion of risk behavior.
Margolis, 1996	Adds to the discussion of the disparity in perception between expert and lay risk.
Oberkampf, 2005	Discusses the differentiating and modeling of the types of risk.
Thompson, 1986	Provides the five philosophical definitions of risk.
Trimpop, 1994	Identifies the risk philosophies - what makes people risk-averse, risk-indifferent, or risk-takers.

TABLE 3: SUMMARY OF CONTRIBUTIONS TO RISK AND UNCERTAINTY IN DECISION MAKING LITERATURE

WHO IS AN EXPERT?

An expert can be defined as a very skilled individual recognized by his or her peers as having much training and experience in their field of practice (Ayyub, 2001; Booker & McNamara, 2004b). Shanteau (1992) agrees by arguing that experts can be viewed as those who have risen to the top in a domain (they are the best at what they do) and in most domains experts gain their knowledge from a combination of formal training and on-the-job experience. Ayyub (2001) continues by stating that the expert is conscious of ignorance, one that realizes areas of deficiency in her/his own knowledge or that of the community, and strives to amend those gaps.

Examining previous work by Wright & Bolger (1992) and Shanteau (1987) a list of characteristics of expert would include: highly developed perceptual/intentional abilities; ability to decompose and simplify complex problems; greater creativity when faced with novel problems; ability to communicate their expertise to others; ability to sense what is relevant; ability to handle adversity; ability to adapt to expectations; ability to adapt their decisions; have a strong sense of self-confidence in their abilities; have an extensive, up-to-date content knowledge; and have a sense of responsibility.

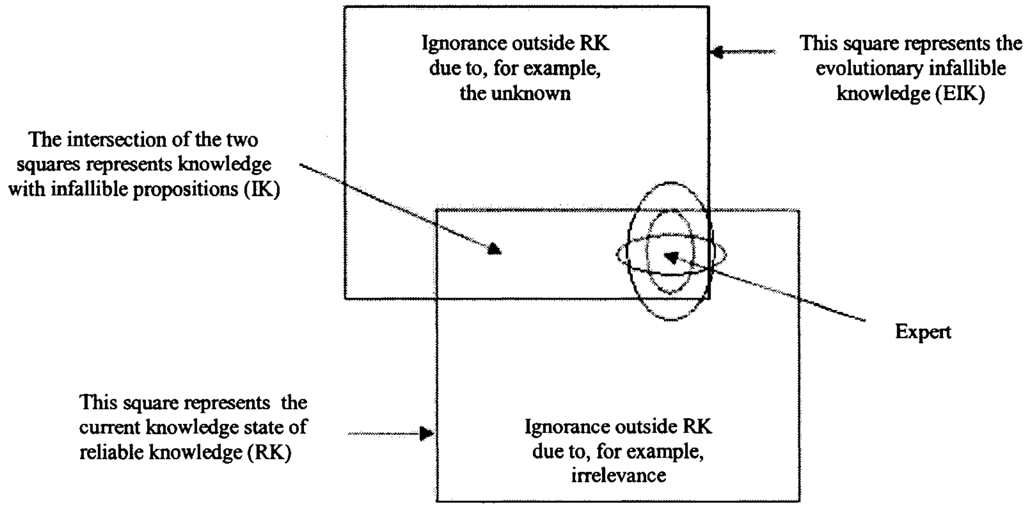


FIGURE 3: IDENTIFYING AN EXPERT (HUMAN KNOWLEDGE AND IGNORANCE) (ADAPTED FROM AYYUB, 2001)

In an effort to identify the state of knowledge of an expert, Figure 3 shows that Evolutionary Infallible Knowledge (EIK) of a system can be "intrinsically unattainable due to the fallacy of humans and the evolutionary nature of Knowledge" (Ayyub, 2001, Human Knowledge and Ignorance section, para, 2). The state of Reliable Knowledge

(RK) is a “snapshot of knowledge as a set know-how, object, and prepositions that meet justifiable true beliefs within reasonable reliability levels” (ibid.). He continued to argue that the intersection between EIK and RK is the knowledge based with Infallible Knowledge (IK) components - (“know-how, objects, and propositions” (para. 2)) thus the concept of set theory:

$$\text{Infallible Knowledge (IK)} = \text{EIK} \cap \text{RK} \qquad (1)$$

The expert’s knowledge identified here extends beyond the RK into the EIK “as a result of creativity and imagination” of the expert, and into the ignorance space outside of the knowledge base “as a measure of creativity and imagination” (ibid., para. 2).

The selection of an expert is dependent on the type of problem facing the analyst, the novelty of the project, and the social organization of tasks in the research setting; i.e. the pool of experts may be limited to members of the immediate research or engineering team (Booker & McNamara, 2004b). However, experts are selected to work on “complex problems precisely because of their expertise, not because they are able to avoid the use of judgment” (Keeney & Von Windterfeldt, 1989, p. 83).

Reference	**Contribution to Literature/Research**
Ayyub, 2001	Identifies and defines who should be considered as an expert.
Booker & McNamara, 2004b	Identifies and defines what should be considered in the selection of an expert.
Keeney & Von Windterfeldt, 1989	Contributes to the discussion of the reasons for selection of an expert.
Shanteau, 1992	Defines who should be considered an expert.
Shanteau, 1987	Contributes to the discussion on the characteristics of an expert.
Wright & Bolger, 1992	Contributes to the discussion on the characteristics of an expert.

TABLE 4: SUMMARY OF CONTRIBUTIONS TO EXPERT IDENTIFICATION LITERATURE

EXPERT JUDGMENT

The quantified beliefs of experts are generally obtained by an analyst through eliciting the subjective judgments about the value of that quantity in question (Mullin, 1986). This can be done by use of expert judgments, one of the two distinct forms in which expert knowledge is categorized and elicited; it refers to the contents of the expert's knowledge (Booker & McNamara, 2004a; Booker & McNamara, 2003). It is "the expressions of informed opinion, based on knowledge and experience that experts make in responding to technical problems" (Booker & Meyer, 1996, p. 2) and they give estimates of phenomena (qualitative or quantitative) or associated uncertainties to those estimates. Assumptions, heuristics, cues, and historical information used by the experts to provide estimates are also considered part of expert judgments (Booker et al., 2004).

Expert judgment can also be viewed as a representation ("a snapshot") of the expert's 'state of knowledge' at the time of responding to the technical problems (Keeney & Von Windterfeldt, 1991; Booker & McNamara, 2003; Booker et al., 2004; Meyer & Booker, 1991). It is typically elicited and analyzed when "data is sparse, difficult or costly to obtain, and open to differing interpretations" (Booker & Meyer, 1996, p. 3). The expert judgment is always part of any analysis, whether in the form of judgments made about appropriate data sources, model structure, or analytical techniques (Booker & McNamara, 2004b). Rarely are these tacit choices fully documented (or even acknowledged); instead, they are treated as a "natural" part of the research process (ibid.).

Expert judgment is used in technical fields, e.g. medicine, economics, engineering, risk/safety assessment, knowledge acquisition, decision sciences, pharmaceuticals, environmental studies, to name a few (Booker et al., 2003; Booker &

Meyer, 1996; Keeney & Von Windterfeldt, 1991). These judgments are used to assess situations to provide estimates on new, rare, complex, or otherwise poorly understood phenomena; to forecast future events; to determine what is currently known and not known; if a problem is worth attention; to better understand the dimensions of a problem; to develop alternatives; to decide what data to and not to collect; to integrate and interpret the data collected to solve problems; and to choose what model to build (Keeney & Von Windterfeldt, 1989; Meyer & Booker, 1991). However expert judgments are "not equivalent to technical calculations based on universally accepted scientific laws or to the availability of extensive data on precisely the quantities of interest" (Keeney & Von Windterfeldt, 1989, p. 85). Therefore expert judgments should be used explicit when addressing problems where neither of these is available.

Within the scope of this study, the two fundamental reasons for using expert judgment are (1) to structure the technical problem, e.g. experts may determine which data are relevant for analysis, which variables (input and response) or analysis methods are appropriate, and which assumptions are valid; (2) to provide estimates, e.g. experts may estimate failure or incidence rates, determine weighting factors for combining data sources, or to characterize uncertainty. These expert judgments can be combined with other forms of data, e.g. "in reliability analysis, an expert's estimate can be used as a prior distribution for an initial reliability" (Booker & Meyer, 1996, p. 3). There are cases in which expert judgments are inappropriately used "to avoid gathering additional management or scientific information…these judgments should complement information to be gathered, not substitute for it" (Keeney & Von Windterfeldt, 1989, p. 85-86).

There are two forms of gathering data through expert judgment: informal and formal. From the informal perspective, experts are asked to provide judgments "off the top of their heads" (Meyer & Booker, 1991, p. 6). Oppositely, the formal means of gathering data through expert judgment usually involve selecting experts to promote diversity of judgments according to specified criteria, designing the elicitation method to including debiasing training, communicating findings through complete and clear documentation, and preserving the inherent uncertainty in the findings (Hora & Iman, 1989). This is coherent with the advantages of the formal approach put forth by Meyer & Booker (1991): more time and care taken in the elicitation aiding documentation.

Reference	Contribution to Literature/Research
Booker et al., 2004	Contributes to the discussion of the definition and what constitute expert judgment.
Booker et al., 2003	Contributes to the discussion of reasons for using expert judgment.
Booker & McNamara, 2003	Contributes to the discussion on the characterization of expert knowledge and the definition and uses of expert judgments.
Booker & McNamara, 2004a	Identifies expert judgment as being one form in which expert knowledge is characterized.
Booker & McNamara, 2004b	Addresses the quantification of expert judgment.
Booker & Meyer, 1996	Defines expert judgment, identifies the use and reasons for use of expert judgment, and addresses the combination of expert judgment with other forms of data.
Cooke & Goossens, 2004	Contributes to the discussion of the reasons for use of expert judgment.
Hora & Iman, 1989	Discusses what constitute a formal approach of gathering expert judgment as data.
Keeney & VonWindterfeldt, 1989	Discusses the situations that are inappropriate for use of expert judgment.
Keeney & VonWindterfeldt, 1991	Contribute to the definition of expert judgment, and its uses.
Meyer & Booker, 1991	Contributes to the definition of expert judgment.
Mullin, 1986	Identifies expert judgment as quantified beliefs of the experts.

TABLE 5: SUMMARY OF CONTRIBUTIONS TO EXPERT JUDGMENT LITERATURE

EXPERT JUDGMENT ELICITATION

The formal elicitation approach draws from various fields of study such as cognitive psychology, anthropology, statistics, decision analysis, and knowledge acquisition (Meyer & Booker, 2001). The elicitation has five basic components and is "the process through which an analyst obtains knowledge in the form of expert judgments from one or more subject-matter experts" (Booker & McNamara, 2004a, p. 332). This knowledge acquisition (gathering of expert judgment) is usually achieved by designed methods through verbal or written communication modes. This is done by using the appropriate technique in its respective situations, in the specified response mode, and aggregated if one or more experts are used.

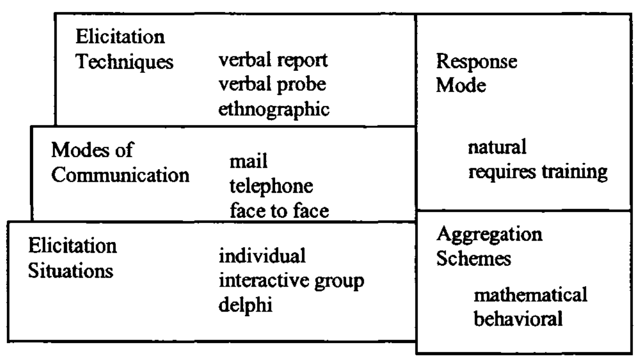


FIGURE 4: BUILDING BLOCKS OF ELICITATION (ADAPTED FROM MEYER & BOOKER, 2001)

There are .various methods for eliciting expert judgments. These methods include individual interviews, interaction groups (Meyer & Booker, 2001) and the Delphi method (Dalkey, 1969; Linstone & Turot, 1975; Wright & Bolger, 1992; Lock, 1987; Meyer & Booker, 2001). Some other methods that have been used include brainstorming (Lock, 1987), and the Nominal Group Technique (Gustafson et al., 1973; Lock, 1987; Wright &

Bolger, 1992) and Monroe's Approach (Hampton, 2001). Regardless of the adapted method, they can be tailored to adhere to the following basic elicitation principles by (1) utilizing terms and methods derived from the way experts communicate within the local culture of the organization of interest, and (2) to documentation all assumptions, cues, heuristics, reasons, conditions and steps in problem solving (Booker & McNamara, 2003). The later (documentation) provides traceability for why and how choices were made. This is an important task because the state of knowledge is constantly changing and updating with new information in light of the old (Booker et al., 2003).

The elicitation defines the quality of the data extracted based on its design and implementation. This extracted data may differ depending on the type of information required; whether the expert's reasoning is requested or not; the knowledge and preference of the experts, decision makers, and analysts; who performs these tasks, experts and/or the analyst; the time and resources available; the degree of interaction; the amount of structure in the process; the degree of facilitation; the response mode in which the experts estimates are elicited; and the communication mode (Szwed, 2002; Meyer & Booker, 1991). Therefore, the elicitation process must be well defined to ensure consistency in the data obtained.

The Elicitation Process

An idea elicitation process would include selecting, motivating and training of experts; appropriate structuring of the question to prevent bias; the eliciting and documenting of the required data; and verifying the data gathered (Renooij, 2001; Meyer & Booker, 2001; Ayyub, 2001). The main personnel involved in this process are "the interviewer or elicitor, documenter, analyst, an lead expert, the decision maker, and the experts participating in the elicitation" (Booker and McNamara, 2004a, p. 333).

The formal phases and steps utilized in this study for structuring and designing of the elicitation are briefly outlined below. These phases and steps are adapted from Meyer & Booker (2001), Booker et al. (2003) and Ross et al. (2002).

Phase 1 involves determination of whether judgment can be feasibly elicited. Questions that should be addressed: "Does the problem involve rapid response?", "Can the potential experts *think aloud*?", "Has there been prior use of expert judgment?" etc.

Phase 2 involves the determination of the best alternative for eliciting the expert judgment - in a probabilistic or alternative framework such as possibilistic, fuzzy, evidence, etc. This is dependent on the experts' thought process – is it in terms of subjective probability or not, and the degree of impreciseness of the knowledge elicited.

Phase 3 involves designing the elicitation. The steps involved in this phase are:

Step 1 - Identifying a lead expert who can provide reasons, goals, or motivations for campaigning the process. This individual is often the initial contact and should be utilized to obtain and ensure the continuous participation of the participants.

Step 2 - Constructing representations of the method that experts will use to measure and forecast the performance/reliability of the system. This is initiated by asking the lead expert how the "community represents and thinks about the system". From this, a mechanism should be implemented to incorporate all available information and a framework should be developed to display the results of the expert judgment.

Step 3 - Drafting the questions. Through the lead expert, the phenomena (variables) of interest are identified, how these are to be assessed, and what metrics or terms used within the local culture of the organization.

Step 4 - Planning the interview situation. The lead expert is asked to provide information on what elicitation situation would be the best, groups/teams or individual, is an analytically aggregate multiple expert estimates or reaching a consensus preferred?, or should estimates be anonymous? etc.

Step 5 - Selecting the experts. A strategy for the selection of the experts should be developed with the lead expert, and consideration should be given to factors such as the community of practice, experts' affiliations and publications, the diversity among the experts, along with their availability.

Step 6 - Motivating the participation of the experts. The lead expert is asked for inhibitors and motivators to participation. These, are then enhanced and mitigated into the elicitation design. It is important to identify factors that will help the experts do the jobs.

Step 7- Pilot testing the questions and the interview setting. A pilot test is conducted on selected experts (may include the lead expert) and feedback is obtained to improve the design.

These steps can be utilized in the respective framework adapted for analysis.

Phase 4 involves perform the elicitation and documentation of the results. Experts' uncertainty estimates may necessitate translation into "uncertainty distributions, a common performance metric, or quantification". Any assumption etc. made to the experts' judgments need to verified, to minimize the possibility of misinterpretation.

Phase 5 takes into account the representation of the expert judgment for the experts' review and refinement. The documentation framework mentioned in Step 2 should present the information to be reviewed by the experts for refinement. This refinement allows for focusing on the framework (probabilistic, possibilistic, fuzzy, evidence, etc.) of interest.

Phase 6 involves facilitation of multiple experts' judgment comparison. Where there are multiple experts judgments, these should be compared to evaluate weather there is major differences in the judgments, the application of different methods rules etc., and if appropriate, experts' quantification.

The following table (Table 6) makes a comparison of the tasks involved in the above phases and steps, in respect to a probabilistic vs. a fuzzy approach. Bayes in 1763 initiated a personalistic theory for assessing subjective judgments and is probable one of the more common theories today. The "theorem specified that a human's degree of belief could be subjective to an objective, coherent, and measurable mathematical framework within subjective probabilities" (Ross et al., 2002, p. 4). From this, in the1960's, Dempster introduced a theory of evidence "which, for the first time, included an assessment of ignorance, or the absence of information" (ibid.) - evidence theory is discussed in a later section. In the 1980's, researchers' investigations began to show strong relationships between evidence, probability, and possibility theories (a variant of fuzzy set theory) with what is called fuzzy measures (Klir & Folger, 1988). The following table presents the elicitation phases, steps with examples given by Ross et al. (2002) - a probabilistic example of auto reliability and a fuzzy example of radioisotopes.

Phases, Steps	**Probability Example: Auto Reliability**	**Fuzzy Example: Radioisotopes**
Determine whether experts judgment can be feasibly elicited	Feasibility indicated by prior (informal) use of experts' judgment.	Feasibility indicated by prior (informal) use of experts' judgment.

Determine the best framework for eliciting the expert judgment - in a probabilistic or alternative such as possibilistic, fuzzy, evidence, etc.	Experts thought in terms of numeric likelihoods; the mathematical foundations of subjectivist probabilities were a plus.	Incoming information was imprecise; one lead expert preferred fuzzy for the quick creation of a robust expert system.
Design the Elicitation		
1. Identify the Expert(s).	One self-identified lead expert identified additional advisors at the national and international levels.	One lead expert volunteered himself and identified another advisor.
2. Construct representations of the way that the experts measure or forecast the phenomena of interest.	Representations included reliability success trees, and failure modes.	Representations focused on features evident in plots of gamma-ray spectrum and of the second derivative of the spectra.
3. Draft the questions.	What is your expected, number of incidents per thousand vehicles to fail to meet specifications? Best-case number? Worst-cast number?	What are you fuzzy rules concerning a peak and these linguistic variables: low, medium, and high energy and very good, or somewhat good?
4. Plan the interview situation.	Team interviews because the experts worked in teams.	Separate interviews followed by structured joint interviews.
5. Select the experts.	The advisor selected the auto products for reliability characterization, which determined the selection of teams, already composed of experts.	The advisor identified the two locally and recognized experts.
6. Motivate participation by the experts.	The advisor carefully drafted the formal request for participation by cover memo and followed up with telephone calls.	The motivation of participation by the advisor was very informal because this was an in-house effort and therefore was only two experts.
7. Pilot test the questions and interview situation.	Extensive pilot tests of the sets of questions and the cover letter (for motivating participation) were performed via. teleconferencing.	Pilot tests of the questions were conducted on the lead expert and led tom refinement in how the fuzzy rules were elicited.
Eliciting and documenting the expert judgment	Advisor and those he designated lead the team interviews, elicited and recorded the subjective probability estimates, assumptions, and failure modes.	The researchers elicited and documented the experts' fuzzy rules, membership functions, the information, and assumptions the experts considered.
Representing the expert judgment for the experts' review and refinement.	Teams' performance estimates were represented as probability distributions and updated their estimates as new information becomes available.	The researchers and the experts refined the fuzzy rules and membership functions. The experts refined their fuzzy rules, in structured joint interviews. The experts' reviews led to labels and caveats being placed on the expert judgment.
Facilitating the comparison of multiple experts' judgments.	Comparisons were done between proposed designs and options for testing, instead of between experts' judgments.	We compared expert's fuzzy rules, assumptions, quantifications, and the difference to the bottom line in using one expert's judgment over another.

TABLE 6: ELICITATION PHASES, STEPS AND EXAMPLES (ADAPTED FROM ROSS ET. AL, 2002)

The goal of a formal elicitation of expert judgments is quantitatively expressed data. However, it is important to note that "the elicitation process itself is really *qualitative* and *inductive*" (Booker & McNamara, 2004b, p. 13). This means that the analyst should "understand how experts structure the problem, how they weigh and combine different sources of information (e.g., computer models vs. experimental data) in making decisions, and how uncertainty is conceptualized" (ibid., p. 14).

Documenting Expert Judgment

Documenting the judgments of the expert(s) is an extremely important element of any elicitation process. "It is desirable to make the reasoning on which explicit expert judgments are based as clear as possible" (Keeney & Von Windterfeldt, 1989, p. 85). Irrespective of the method of analyst chosen in selecting experts for both expertise and judgment elicitation, emphasizes must be placed on documenting the rationale and method for doing so (Booker & McNamara, 2004a). This is because "expert knowledge projects are often loosely documented, informal, implicit, and they are often criticized for being *soft* or *biased*" (ibid., p. 14).

Documentation provides the means for understanding and updating changes. Any assumptions or data used should be listed along with the logic supporting their relevance and includes the analysis process to feedback to the experts for updates (Keeney & Von Windterfeldt, 1989; Booker & McNamara, 2004a). In addition, "documentation not only includes recording everything during the elicitation, but also recording the preparations and pilot study experiences" (ibid., 17). The primary goal of "eliciting and utilizing expert knowledge is to capture the current state of knowledge-accomplished by formal elicitation and thorough documentation" (ibid., p. 17).

Reference	Contribution to Literature/Research
Ayyub, 2001	Contributes to the discussion of what constitute an idea elicitation process.
Booker et al., 2003	Addresses the documentation during the elicitation process for tractability.
Booker & McNamara, 2003	Addresses the tailoring of the elicitation process, and identifies the formal phases and steps involved in this process.
Booker & McNamara, 2004a	Discusses what is involved in the formal structuring of the elicitation process, and the importance of documenting expert judgments.
Booker & McNamara, 2004b	Identifies the elicitation process as being really qualitative and inductive.
Dalkey, 1969	Contributes to the methods of eliciting expert judgments.
Gustafson et al., 1973	Contributes to the methods of eliciting expert judgments.
Hampton, 2001	Contributes to the methods of eliciting expert judgments.
Keeney & VonWindterfeldt, 1989	Contributes to the discussion on documenting expert judgments.
Klir & Folger, 1988	Identifies the relationship between evidence, probability and possibility theories as fuzzy measures.
Linstone & Turot, 1975	Contributes to the methods of eliciting expert judgments.
Lock, 1987	Contributes to the methods of eliciting expert judgments.
Meyer & Booker, 1991	Addresses factors that cause data to differ in the elicitation.
Meyer & Booker, 2001	Contributes to the methods of eliciting expert judgments, discusses the building block and what constitute an idea elicitation process, and identifies the formal phases and steps of the process.
Renooij, 2001	Discusses what constitute an idea elicitation process.
Ross et al., 2002	Identifies the formal phases and steps involved in the elicitation process.
Szwed, 2002	Addresses factors that cause data to differ in the elicitation.
Wright & Bolger, 1992	Contributes to the methods of eliciting expert judgments.

TABLE 7: SUMMARY OF CONTRIBUTIONS TO EXPERT JUDGMENT ELICITATION LITERATURE

Heuristics and Biases

Simons (1955, 1956) developing the theory of 'bounded rationality', "which postulates that individuals do not search for optimal choices but instead, due to time constraints and limited computational capacity, seek a solution which satisfactorily meets their level of aspiration and then terminate their search" (Hammond, 2000, p. 54), thus leading to biases and errors. Kahneman et al., (1982) and Thys (1987) studies of psychometric focused on the fundamental level and to understand its relation to expert judgments, respectively (Ayyub, 2001). This area of study has been the benchmark for "the quality and utility of expert judgment by comparing human cognitive assessments to the quantitative predictions of probabilistic statistical models" (Booker & McNamara, 2004b, p. 13-18). With this set as a standard, they also argued that this "early research clearly indicated that human cognition is not consistently logical; instead, it is vulnerable to sources of bias and error that can severely compromise its utility in probabilistic statements" (ibid., p. 13-19). These errors and biases may not be intentional, but need to be addressed because it may cause the integrity of such judgments to be degraded.

There are numerous biases that must be taken into consideration when seeking experts' judgments (Spetzler & Stael von Hostein, 1975). Booker & McNamara (2003, 2004a, 2004b) defined a bias as a skewing from a reference point (reality) that degrades the quality of elicited judgments or data, and contribute to uncertainty ("a statistical bias or a shift from the mean value is not implied").

There are two categories of biases identified by Meyer & Booker (2001).

(1) Motivational biases (behavior and personal agenda based) - the expert judgment is skewed from the standpoint of the expert's thoughts. The motivational biases are

presented in the following table (Meyer & Booker, 2001, p. 42).

Bias	Definition
Group Think	Group social pressure to slant responses or silently acquiesce to what experts believe will be acceptable to the group.
Misinterpretation	Inadequate translation of knowledge into response, usually by the interviewer or analyst (poor, incorrect or bad translation of information).
Wishful Thinking	Experts' hopes influence their judgment (wanting something makes it a reality).
Impression Management	Responding according to politically correct interpretations from social pressure or individuals who are not physically present or responding in a manner to please those present.

TABLE 8: DEFINITIONS OF MOTIVATIONAL BIASES (ADAPTED FROM MEYER AND BOOKER, 2002)

(2) Cognitive biases (thinking-based) - the expert judgment is considered skewed from the standpoint of mathematical or logic rules, usually because of the ways in which the expert mentally processes information. The cognitive biases (also contributing to uncertainty) are present in the following table (Meyer & Booker, 2001, p. 44).

Bias	Definition
Anchoring	Experts cannot move from first impression thinking when solving a problem or fails to adjust preconceived notions in light of new data/information.
Inconsistency	Confusion, e.g. differing assumptions or definitions can lead to inconsistency. Memory problems and fatigue also contribute.
Availability	How easily an expert can retrieve particular events from long-term memory. A common realization of this relates to how experts cannot accurately account for rare events, depending upon their personal knowledge or experience.
Underestimation of Uncertainty	Experts often think they know more than they really do, from overconfidence.

TABLE 9: DEFINITIONS OF COGNITIVE BIASES (ADAPTED FROM MEYER AND BOOKER, 2002)

Because these biases can degrade the quality of elicited data and question the validity of using expert judgment as a source of data (Booker & McNamara, 2004b), these biases must be controlled, monitored and analyzed for its impacts (McNamara & Booker, 2001).

Kahneman & Tverskey, (1972; also Kahneman et al., 1982) proposed several cognitive processes referred to as heuristics. These are "process of discovery that is not necessarily structured" (Ayyub, 2001, Scientific Heuristics section, para. 1) and are presented in the following table (Kahneman et al., 1982).

Scientific Heuristics	Definition
Representativeness	The subjective judgment of the extent to which the event in question "is similar in essential properties to its parent population" or "reflects the salient features of the process by which it is generated" (p. 69).
Availability	Is "an ecologically valid" (p. 164) "clue for assessing frequency or probability, because instances of large classes are usually reached better and faster than instances of frequent classes" (p. 11).
Anchoring and Adjustments	Is a cognitive process in which decision makers' first make "estimates by starting from an initial value" that is dynamically adjusted "to yield a final answer" (Gilovich et al., 2002, p. 121).

TABLE 10: DEFINITIONS OF SCIENTIFIC HEURISTICS (ADAPTED FROM KAHNEMAN ET AL., 1982)

These Heuristics reduces the complexity of judgment tasks making then more tractable for decision making with limited mental resources, and often claims to yield answers that approximate the accurate judgment (Morgan & Henrion, 1990; Wright & Bolger, 1992), and reducing the introduction of biases. An example of appropriate use of heuristics in a situation that reduces biases is one that challenges the expert to support his or her reasoning (Monroe 1997). Hoch (1984) found that by doing this, the judgments were noticeable influenced - by asking for these reasons, the judgment was debiased

(Hoch, 1984; Morgan & Henrion 1990). In addition, Mullin (1986) suggests that experts describe situations that may lead to the adjustment of their judgment. However, it is important to note that depending on how these heuristics are applied, they themselves can introduce or becomes the source of biases in judgments provided.

Handing Biases

In addressing cognitive biases, the category of interest, limited "programs" exists in the attempt to handle these biases. Cleaves (1986) presented an approach to which McNamara & Booker (2001) compared their proposed program. Although they agreed that "focusing on cognitive biases" and to "anticipate biases by the judgment processes in which they are likely to occur (namely, hypothesis and solution generation, decision rule articulation, uncertainty assessment, and hypothesis evaluation)" (p. 45), their program anticipates biases by the respective component in which they are likely to be revealed. They added that it is also important to have a real time emphasis. The program developed by Meyer & Booker (2001) is presented as follows:

Step 1 - Anticipate Which Biases are Likely to Occur: The biases which are likely to occur should be anticipated in the various components; i.e. the elicitation process, mode of communication, response mode and aggregation scheme (see Table 11, "*Index of Selected Biases*" adapted from Meyer & Booker 2001, p. 133). Hora & Iman (1989) and Keeney & VonWinterfeldt (1989, 1991) suggests spending approximately half a day with the expert to explain some of the common heuristics that is found in making judgments bases on the anticipated biases (*Step 3 in this process*).

Step 2 - Redesign the Planned Elicitation to Make It Less Prone to the Anticipated Biases: By anticipating the biases, the elicitation can be redesigned based on factors such as the definition and information of the bias. Depending on the component in which the bias occurs, some of the "*Suggestions for Countering Selected Biases*" can be implemented in the redesign (see Table 12, adapted from Meyer & Booker 2001, p. 178).

Elicitation Component	View of Bias	Source
Elicitation Situation		
Individual Interview	Motivational	Social pressure data gathering
	Motivational	Wishful thinking
	Cognitive	Inconsistency
Delphi	Motivational	Wishful thinking
	Cognitive	Inconsistency
	Cognitive	Anchoring
Interactive Group	Motivational	Social pressure data gathering
	Motivational	Wishful thinking
	Cognitive	Inconsistency
Modes of Communication		
Face to Face	Motivational	Social pressure data gathering
	Motivational	Wishful thinking
	Cognitive	Underestimation of uncertainty
Telephone	Motivational	Social pressure data gathering
	Motivational	Wishful thinking
	Cognitive	Availability
	Cognitive	Anchoring
	Cognitive	Underestimation of uncertainty
Mail	Motivational	Social pressure impression management
	Motivational	Wishful thinking
	Motivational	Misinterpretation by analyst
	Cognitive	Inconsistency
	Cognitive	Availability
	Cognitive	Anchoring
	Cognitive	Underestimation of uncertainty
Response Mode		
Complex ones such as probability, Bayesian updates, and uncertainty Measures.	Motivational	Misinterpretation by expert
	Cognitive	Inconsistency
	Cognitive	Underestimation of uncertainty
Aggregation		
Behavioral Aggregation	Motivational	Social pressure, group thinking

TABLE 11: INDEX OF SELECTED BIASES (ADAPTED FROM MEYER & BOOKER 2001)

Step 3 - Making the Experts Aware of the Potential Intrusion of Particular Biases and Familiarize Then to the Elicitation Procedures: As indicated above, Keeney &

VonWinterfeldt (1989, 1991) suggested to spend approximately half a day to inform the experts on the common heuristics that is found in making judgments under uncertainty conditions. Meyer & Booker (2001) added that they should understand the potential causes of the biases, and acquaint then to the elicitation procedures. This will reduce some of the inconsistencies that may be encountered if the experts are not consciously attempting to address these factors.

Group Think	Two approaches can help counter the social pressure from group think (Meyer, 1986, pp. 95-96). Using the first approach, the interviewer can attempt to prevent those factors that contribute to group think. For instance, the interviewer can stop the elicitation and warn the group members about group think. If the group contains an official or even a natural *ex officio* leader, the interviewer can ask for his or her responses either last or in private. In addition, if someone other than the interviewer leads the group meeting, this person can be encouraged to be nondirective during the meetings. An explanation of the group-think phenomenon usually convinces such leaders that better discussions and data will result from there avoiding leading. The other approach is to try to counter the effects of group think with an opposite bias – anchoring. One technique for forecasting anchoring is to require the group members to write down their judgments and reasons. In this way, they are more likely to anchor to their own judgments rather than silently acquiesce to someone else's. If the experts discuss their judgments, each person can record and report his or her response before the floor is open to discussion. Once individuals have publicly announced their view, they are unlikely to spontaneously modify it. (However, hey will still modify their view if someone raises a valid point that they had not previously considered).
Wishful Thinking	The tendency towards wishful thinking can be countered by making it more difficult for expert to indulge in it. If the experts must explain their answer in detail, it will become apparent whether there was any objective basis for their responses.
Inconsistency	Two techniques can help reduce inconsistency. The first technique addresses the aspects of the elicitation that contribute to the inconsistency. As mentioned earlier, fatigue contributes to inconsistency. If the interviewer notes that the experts have become more inconsistent with time, he or she can quickly end the meeting or schedule a break. In general, experts can participate in discussion or problem solving for a maximum of two hours before becoming tired. (Experts often signal their fatigue either by providing briefer responses or by learning forward or break in their chairs.) Faulty memory also contributes to inconsistency. If at the beginning of every session the statements of the question, definitions, assumptions, and response mode are reviewed, the experts will be more consistent between and within themselves. In addition, if much time elapses between this first review and when the experts' judgments are requested, the question can be worded to include some of the above information. For example, *What rating would you give to the importance of element X over Y to the reaching of goal Z?* If they use a response mode (in this case a Saaty pairwise comparison) they will need to have the definition of the scale available. Another technique that helps reduce inconsistency is to have the group members monitoring their own consistency (Meyer, 1986, p. 96). This technique was successfully employed in a simple interactive group elicitation where the experts were able to watch the interviewer's monitoring of inconsistency and then to mimic the interviewer's performance (Meyer, Peaslee & Booker, 1982). The experts received copies of a matrix of the elements being judged, the criteria on which these elements were being judged, and their past judgments. When the experts monitor their own consistency they may wish to change an earlier judgment to reflect their current thinking. If their reasoning does not violate the logic of the model or the definitions, they can be allowed to make the change. This process often helps the experts discover that they had forgotten to include some pertinent information. After this addition, some of the judgments may require redoing. If Saaty's Analytic Hierarchy Process (1980) had been applied and its results indicated high inconsistency, the experts could review and redo the affected judgments.

Availability	Stimulating the expert's memory associations can counter availability bias. In general, group discussion will cause the expert to think of more than just the first readily accessible information. In addition, free association can introduce to single experts or those in groups. [Free association has the expert or experts quickly generate any elements that might have bearing on the question (Meyer, 1986, p. 94).] Free association is similar to brainstorming or the Crawford Slip method (Boose & Gaines, 1988, p. 38). The experts are asked refrain from being critical to generate the widest possible pool of ideas. (The numbers of ideas are later narrowed to those judged to be most pertinent to the question.) A related technique is to hierarchically structure the presentation of the question information so that it flows from the general to the specific. In this way, the expert can consider the pertinent information before reaching a solution. This strategy fires as many memory associations as possible so that the maximum number of relevant associations enters into the expert's final judgment.
Anchoring	Techniques similar to those used to counter availability bias are used to counter anchoring. In particular, giving the expert input from other experts as in a Delphi situation or an interactive group makes it more difficult for the expert to anchor to his or her first impression. Another technique involves asking the experts for extreme judgments before obtaining their likely ones (Cleaves, 1986, pp. 9-10). Three additional ideas for countering availability bias from Boose and Shaw (1989, p. 70) follow: (1) ask the experts to describe how other experts might disagree with their responses, (2) ask the experts to temporarily forget recent events, and (3) aggregate outcomes with small probabilities into a single, larger class to reduce the perceived joint impact in cases in which probabilities estimates are elicited.
Underestimation of Uncertainty	May be reduced by asking the expert to further disaggregate the parts of the question and give estimates of the quantities of interest for each small part. In this way, the experts are less likely to overlook something: the knowledge engineers can check at this point whether the details of each of the experts' thinking correctly reflect their answers. If the underestimation occurs in a planning problem, a comprehensive list of events that could upset the plans can be elicited from the expert (Boose & Shaw, 1989, p. 72). Creating this list may make the experts realize that they should take some of these possibilities into account in their problem solving.

TABLE 12: SUGGESTIONS FOR COUNTERING SELECTED BIASES (ADAPTED FROM MEYER & BOOKER, 2001)

Step 4 - Monitor the Elicitation for the Occurrence of Biases: Many biases have signs that indicate their occurrence (see Table 13 below, "*Signs of Selected Biases*" adapted from Meyer & Booker, 2001, p. 171). These signs can be detected by the elicitor but require the expert to verbalize their thoughts and answers (ibid.).

Step 5 - Adjust, in Real Time, to Counter the Occurrence of Biases: This step includes the identification of ways to reduce particular biases. This involves implementing the "*Suggestions for Countering Selected Biases*" in both of the following approaches: impeding those factors contributing to a particular bias or to employ the opposite bias (Meyer & Booker, 2001).

Group Think	There are several signs that predict the development of a group think situation. In general, no one voices a difference of opinion: the experts appear to defer to one or more members of the group (Meyer, 1986, p. 95).
Wishful Thinking	Wishful Thinking is indicated if the expert were previously judged to have something to gin from their answers and if the experts appear to answer quickly and with very little thought.
Inconsistency	A number of signs can indicate inconsistency. The interviewers can detect many inconsistencies when the experts verbalize their thoughts and answers. In particular, the interviewers can discern when a response mode or rating is being applied more easily through time (Meyer, 1986, p.94). Experts tend to apply the extremes of a rating scale more easily as they become fatigued. The interviewers can also hear when the experts contradict assumptions that they made earlier. For example, a tank expert chooses two very different routes through the mapping terrain because the second time, he unconsciously assumed that his company was the main effort and therefore *had to push hard*. Inconsistency can also be monitored by use of Bayesian-based scoring and ranking techniques. During the elicitation, the experts' judgments can be entered into a scoring and ranking program, such as that of Saaty's Analytical Hierarchical Process (1980), to obtain a rating of their consistency, Then, if the inconsistency index from this method remains too high, indicating significant inconsistency, the experts can redo their judgments.
Availability	A potential problem with availability bias is indicated if the experts do not mention more than one or two considerations in giving their answers. If the experts only consider a few things, these were probably the most easily remembered and their answers are likely to be skewed to reflect these few.
Anchoring	Suspect anchoring bias when an expert receives additional information from experts or other sources during the elicitation but never waivers from his or here first impression. For example, reactor code experts were asked to compare the performance of their computer models to plots of experimentally generated data. They often commented on their first impression. When they examined the plots more closely, they typically found places where the computer model did not capture the experimental phenomena. However, the experts usually adjusted upward or downward from their initial assessment rather than revising it completely (Meyer & Booker, 1987).

TABLE 13: SIGNS OF SELECTED BIASES
(ADAPTED FROM MEYER & BOOKER, 2001)

Step 6 – Analyze the Data for the Occurrence of Particular Biases: Following Steps 4 or 5, a mathematical test can often determine the occurrence of a cognitive bias, such as uncertainty estimation (Meyer & Booker, 2001), as in the context of this study.

Reference	Contribution to Literature/Research
Ayyub, 2001	Contributes to the discussion of psychometrics; the fundamental level and to understand its relation to expert judgments.
Booker & McNamara, 2003	Contributes to the definition of a bias in expert judgment.
Booker & McNamara, 2004a	Contributes to the definition of a bias in expert judgment.
Booker & McNamara, 2004b	Identifies Psychometrics as the benchmark for the quality and utility of expert judgment by comparing human cognitive assessments to quantitative predictions of statistical models, and defines a bias in expert judgment.
Hammond, 2000	Contribute to the discussion of "Bounded Rationality."
Hoch, 1984	States that asking for reasons for judgments can aide in the debiasing process.
Kahneman et al., 1982	Presents psychometrics as focused on the fundamental level of expert judgments, and proposes the cognitive processes- heuristics.
Kahneman & Tverskey, 1972	Proposes the cognitive processes- heuristics.
Keeney & VonWindterfeldt, 1989	Contributes to the discussion on handling of biases.
Klir & Folger, 1988	Contributes to the discussion on handling of biases.
Meyer & Booker, 2001	Defines the categories of biases and a program to handle these biases.
Morgan & Henrion, 1990	Indicates that heuristics reduces the complexity of the judgment tasks for traceability, and asking for reasons for judgments aides the debiasing process.
Monroe, 1997	Presents an example of appropriate use of heuristics.
Mullin, 1986	Indicates that describing situations in the process, depending on heuristics used, may produce biases.
Renooij, 2001	Discusses the structuring of the process to avoid the introduction of biases.
Simons, 1955, 1956	Contribute to discussion of "Bounded Rationality."
Spetzler & Stael von Hostein, 1975	Indicates that there are numerous biases that must be taken into account when seeking expert judgments.
Thys, 1987	Presents psychometrics to understand its relations to expert judgments.
Wright & Bolger, 1992	Indicates that heuristics reduces the complexity of the judgment tasks making it more traceable.

TABLE 14: SUMMARY OF CONTRIBUTIONS TO HEURISTICS AND BIASES LITERATURE

Estimation of Uncertainty

Anchoring is defined as a cognitive process in which experts first make "estimates by starting from an initial value" to base and adjust their final answers. This anchoring process has been suggested to be the cause of hindsight biases (Hawkins & Hastie, 1990), specifically, "knowledge of the outcome acts as an anchor that influences judgments of the predictability of outcomes" (Gilovich, et al., 2002, p. 134). Experts may "perform a few steps of computation and estimate the product by extrapolation or adjustment" (Kahneman , et al., 1982, p. 15). However, because adjustments are typically insufficient, this may lead to inappropriate estimations of uncertainty. Kahneman , et. al. (1982) cited a study by Bar-Hillel (1973) that demonstrated and concluded that a "stated probability of an elementary event provides a natural starting point for the estimation of the probabilities of both conjunctive and disjunctive events" (p.15).

Successful completion of an undertaking, such as in a conceptual design environment, the probabilities will be overestimated in conjunctive (connective or chain like) problems and will be underestimated in disjunctive (logic forming or funnel like) problems; bias produced as a consequence of anchoring incidental from the "structure of events" (Kahneman , et. al., 1982). They continue to argue that in a general sense, this overestimation of probability of conjunctive events will lead to "unwanted optimism" of success. In contrast, underestimation of probability of disjunctive events will lead to failure thus is considered in the evaluation of risk. Slovic et al. (1982) added that "overestimation causes were dramatic and sensational events, whereas underestimation causes tend to be unspectacular events, which claim one victim at a time and are common in nonfatal form" (p. 467).

Slovic, et al., (2002), cited in Gigerenzer & Fieldler (2003), stated "the highly publicized causes appear to be more affectively charged, that is, more sensational, and this may account for both their prominence...and their relatively overestimated frequencies" (p. 414). The overestimation of low frequency events has also been discussed as evidence for people's "genuine, psychologically meaningful pessimism" (Armor & Taylor, 2002, p. 335), as opposed to the underestimation of high frequency events suggesting "unrealistic optimism," (Gigerenzer & Fieldler, 2003, p. 8). This occurrence can be assumed from an "unbiased mind in an environment with unsystematic error", causing regression toward the mean, thus the overestimation of low risks and underestimation of high risks (Gigerenzer, 2003).

A "comprehensive assessment of uncertainty cannot rest solely on statistical analysis" (Henrion & Fishhoff, 2002, p. 666). This is because of the subjectivity in estimating uncertainty; subjective judgment is unavoidable in estimating uncertainty (Morgan & Henrion 1990). In support of handling subjectivity in estimating uncertainty, McNamara & Booker (2001) highlighted a few distinguishing features in their program for handling biases. They indicated that it anticipates the respective component (i.e. the elicitation process, mode of communication, response mode and aggregation scheme) in which uncertainty is likely to be revealed while having a real time emphasis. In addition to a mathematical analysis to assess the estimation of uncertainty, this program of handling biases will also be adapted in an attempt to elucidate biases while having a real time emphasis.

Reference	Contribution to Literature/Research
Armor & Taylor, 2002	Identifies overestimation of low frequency events as evidence for people's genuine, psychologically meaningful pessimism.
Gigerenzer & Fieldler, 2003	Argues that underestimation of high frequency events suggests unrealistic optimism.
Gigerenzer, 2003	Concludes- overestimation of low risk and underestimation of high risk.
Gilovich et al., 2002	Addresses the anchoring and adjustment heuristic, and also contribute to the discussion on the estimation of uncertainty.
Henrion & Fishoff, 2002	Indicates that a comprehensive assessment of uncertainty cannot rest solely on statistical analysis because of the subjectivity in estimating uncertainty.
Kahneman et al., 1982	Identifies that the overestimation of uncertainty in conjunctive problems and underestimation of uncertainty in disjunctive problems are biases produced as a consequence of anchoring.
Morgan & Henrion, 1990	States that subjectivity is unavoidable in estimating uncertainty.
Slovic et al., 2002	Indicates that overestimation causes are and sensational events and underestimation causes tends to be unspectacular events.

TABLE 15: SUMMARY OF CONTRIBUTIONS TO ESTIMATION OF UNCERTAINTY LITERATURE

EVIDENCE THEORY

"Recent criticisms of the probabilistic characterization of uncertainty claim that traditional probability theory is not capable of capturing epistemic uncertainty" (Sentz & Ferson, 2002, p. 8). This has lead to the development of many theories constituting the discipline referred to as "monotone measure theory" or "non-additive measure theory" (also known from old literature as "fuzzy measure theory") in which evidence theory is instituted (Klir, 2004). This evidence theory takes into account aleatory and epistemic uncertainty that is 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; thus, consistent and rigorous, giving more precise and unbiased limits (Ayyub, 2001).

The philosophical grounding of evidence theory is the foundation of the methodology of this research. It is considered to be a generalized form of probability and possibility theories (Bae et al., 2003). Klir (2004) adds that "neither classical probability theory nor classical possibility theory are sufficiently general to fully recognize our ignorance without ignoring available information. However, one can deal with this problem adequately by using Dempster-Shafer theory" (i.e. evidence theory) (p. 36). This theory has been applied in various fields, and includes engineering, medicine, statistics, psychology, philosophy and accounting (Sun & Farooq, 2004). There are various rules that are utilized to combine evidence (ibid. pp. 197-212). These rules are referred to as the "Conjunctive and Disjunctive Combination Rules of Evidence (namely, Dempster-Shafer's combination rule, Yager's combination rule, Dubois and Prade's combination rule, DSm's combination rule and the Disjunctive combination rule)" and are follows:

Dempster-Shafer's combination rule

The Dempter-Shafer's combination rule is the original from which all others were derived. The combination of basic assignments from two sources of information can be defined as (Ayyub, 2001):

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

This rule is based on, and emphasizes the combination of independent sources of information (basic assignments). This is the characterized by the product combination rule.

Yager's combination rule

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):

$$m_y(C) = \begin{cases} \sum\limits_{\substack{i,j \\ C = A_i \cap B_j}} m_1(A_i)\, m_2(B_j), & C \neq \Theta, \phi \\ m_1(\Theta)\, m_2(\Theta) + \sum\limits_{\substack{i,j \\ A_i \cap B_j = \phi}} m_1(A_i)\, m_2(B_j), & C = \Theta \\ 0, & C = \phi \end{cases} \tag{3}$$

Dubois and Prade's combination rule

Given the same conditions as Yager's combination rule, then Dubois and Prade's combined basic assignments of the two sources of information can be defined as (Dubois & Prade, 1988):

$$m_{DP}(C) = \begin{cases} \sum\limits_{\substack{i,j \\ C = A_i \cap B_j}} m_1(A_i)\, m_2(B_j) + \sum\limits_{\substack{i,j \\ C = A_i \cap B_j \\ A_i \cap B_j = \phi}} m_I(A_i)\, m_2(B_j), & C \neq \phi \\ 0, & C = \phi \end{cases} \tag{4}$$

DSm's combination rule

This rule can be represented in two forms and their combined basic assignments of the two sources of information can be defined as (Dezert, 2002):

1. *The classical DSm combination rule for free DSm model:*

$$\forall C \in D^{\Theta}, \quad m(C) = \sum_{\substack{A, B \in D^{\Theta} \\ A \cap B = C}} m_1(A)\, m_2(B) \tag{5}$$

where: D^{Θ} denotes the hyper-power set of the frame Θ.

2. *The general DSm combination for hybrid DSm model $\mathcal{M}$*

$$\forall A \in D^{\Theta}, \quad m_{\mathcal{M}(\Theta)}(A) \triangleq \phi(A)\,[S_1(A) + S_2(A) + S_3(A)] \tag{6}$$

where:

i. Φ(A) is the characteristic non emptiness function of a set A, i.e. Φ(A) = 1 if A /2 ; and Φ(A) = 0 otherwise.
ii. $\Phi \triangleq \{\Phi_{\mathcal{M}}, \Phi\}$. $\Phi_{\mathcal{M}}$ is the set of all elements of D^{Θ} that have been forced to be empty through the constraints of the model M and Φ is the classical/universal empty set.
iii. $S_1(A)$ _ $m_{\mathcal{M}}{}^{f}{}_{(\Theta)}(A)$, $S_2(A)$, $S_3(A)$

Disjunctive combination rule

Suppose $\Theta = \{\theta 1, \theta 2, \ldots, \theta n\}$ is a frame of discernment with n elements, the basic assignments for 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 the disjunctive combined basic assignments of the two sources of information can be defined as (Sun & Farooq, 2004):

$$m(C) = \begin{cases} \sum\limits_{\substack{i,j \\ C = A_i \cup B_j}} m_1(A_i)\, m_2(B_j), & C \neq \phi \\ 0, \quad C = \phi \end{cases} \tag{7}$$

for any $C \subseteq \Theta$. The core of the belief function given by m is equal to the union of the cores of Bel_1 and Bel_2.

Selecting a Combination Rule

Having these Conjunctive and Disjunctive rules for combining basic assignments/evidence clearly poses the question of what rule should be applied to a particular situation. Sentz & Ferson (2002) indicates that one helpful heuristic for choosing the appropriate combination rule is to determine the requirements of the situation as disjunctive pooling, conjunctive pooling or tradeoff - e.g. Dubois and Prade disjunctive combination rule, the Dempster-Shafer's combination rule, or the Yager's combination rule respectively. However, they also indicated that this is simplified somewhat and can be base on the level of development of the theories and their use in the particular situation.

Traditional applications of probabilistic methods to epistemic and subjective uncertainty are known as Bayesian probabilities (Sentz & Ferson, 2002). They continue to argue that 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, 1992, cited on p. 46). 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, p.194).

The literature has identified 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; Wu et al., 1996) as cited in (Sun & Farooq, 2004). Therefore, Yager (1987) proposed combination rule that is a modified version of Dempster-Shafer combination rule. It addresses the issue of counter-intuitive results and is considered to be the most prominent of the alternative combination rules based on the class of unbiased operators developed (Yager, 1987). To reflect the complete conflict between two sources, "Yager's rule provides the universal set or the real line as its answer" (Sentz & Ferson, 2002, p. 46), and "as the level of conflict increases, Yager's rule might be more appropriate as the conflict is not ignored" (ibid., pp. 48-49). It can be considered "as an epistemological honest interpretation of the evidence as it does not change the evidence by normalizing out the conflict" (ibid., p. 19). Therefore, "as there is no conflict, the rule provides the same answer as Dempster-Shafer's rule" (ibid. p. 45) although 'n' number of experts can be combined.

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 (the property that a given mathematical operation and set have when the result obtained using any two elements of the set with the operation does not differ with the order in which the elements are used (Merriam-

Webster Online Dictionary, 2006)):

$$m_1 \oplus m_2 = m_2 \oplus m_1 \tag{8}$$

(2) Associativity (the property of producing the same result no matter which pair of elements next to each other in a mathematical expression is used to perform a given operation first if the elements in the expression are listed in a fixed order (Merriam-Webster Online Dictionary, 2006)):

$$(m_1 \oplus m_2) \oplus m_3 = m_1 \oplus (m_2 \oplus m_3) \tag{9}$$

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

$$m = m_1 \oplus m_2 \oplus \ldots \oplus m_n \tag{10}$$

Yager's rule, find the updated arithmetic average (not itself associative) by adding the new "data points" to the sum of the pre-existing and divide by the total number of data points - the concept of *quasi-associative* operator (a non-associative operator is necessary for combination) (Sentz & Ferson, 2002). "Quasi-associativity means that the operator can be broken down into associative sub-operations" (p. 18) - on which operator Yager's general framework was developed, "by look at combination rules where associative operators are a proper subset" (ibid. p. 18). The combination of the assignment structure is defined as:

$$q(A) = \sum_{\bigcap_{i=1}^{n} A_i = A} m_1(A_1)\, m_2(A_2) \ldots m_n(A_n) \tag{11}$$

where: $q(A)$ can be used to include any number of evidence.
$m_1, m_{2,\ldots} m_n$ are the basic assignments.
A is the focal set.

The algebraic properties satisfied by this rule are commutativity and quasiassociativity, but not idempotence (when applied to itself under a given binary operation equals itself (Merriam-Webster Online Dictionary, 2006)) or continuity (any measure of uncertainty being a continuous functional) (ibid.).

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

Belief (lower) function:

$$Bel\,(A_i) = \sum_{all\,Aj \subseteq Ai} m(A_i) \tag{12}$$

Plausibility (upper) function:

$$Pl\,(A_i) = \sum_{all\,Aj \cap Ai \neq \emptyset} m(A_j) \tag{13}$$

The belief measure and plausibility measure as presented by Ayyub (2001, section on evidence theory) 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:

$$(Bel)\colon P_x \rightarrow [0,1] \tag{14}$$

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:

$$Pl(A) = \overline{1} - Bel(A) \tag{15}$$

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:

$$Pl(A) \geq Bel(A) \tag{16}$$

for each A in the power set.

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:

$$m: P_x \rightarrow [0,1] \tag{17}$$

A basic assignment must satisfy the following two conditions:

$$m(\varnothing) = 0 \tag{18}$$

$$\sum_{all\, A \subseteq Px} m(A) = 1 \tag{19}$$

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".

Reference	Contribution to Literature/Research
Ayyub, 2001	Contributes to the discussion on combination rules found in evidence theory - Dempster-Shafer's rule.
Bae et al., 2003	Identifies evidence theory as a generalized form of probability and possibility theory.
Bogler, 1992	Identifies that evidence theory combines 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.
Dezert, 2002	Contributes to the discussion on combination rules found in evidence theory - DSm's rule.
Dubois & Prade, 1998	Contributes to the discussion on combination rules found in evidence theory - Dubois and Prade's rule.

Klir, 2004	Addresses fuzzy measure theory in which evidence theory is instituted, and states that neither classical probability nor possibility theory fully recognizes ignorance without ignoring available data.
Sentz & Ferson, 2002	States that probability theory is not capable of capturing epistemic uncertainty. Also identifies that Yager's rule provides the universal set or the real line as its answer, and contains no conflict.
Sun & Farooq, 2004	Identifies fields in which evidence theory is used, and also contributes to the discussion on the combination rules found in evidence theory - Disjunctive rule.
Wu et al., 1996	Identifies limitations to the Dempster-Shafer's combination rule approach such as computational expenses and independent sources of information.
Yager, 1987	Identifies limitations to the Dempster-Shafer's combination rule approach such as computational expenses and independent sources of information. Also contributes to the discussion on the combination rules found in evidence theory – Yager's rule.
Zadeh, 1979, 1984, 1986	Identifies limitations to the Dempster-Shafer's combination rule approach such as counter-intuitive results for some pieces of evidence.

TABLE 16: REVIEW SUMMARY OF CONTRIBUTIONS TO EVIDENCE THEORY LITERATURE

PREVIOUS RESEARCH

There are various researches that motivated and set the foundation for this effort. Monroe (1997) developed, refined and demonstrated a synthesized methodology for eliciting expert judgment and was applied to a weight estimating relationship (WER) model for a 'single-stage-to-orbit vehicle concept'. This methodology used structured questions to anchor and assign levels to accomplish the estimation of uncertainty. The aim of his research was to develop a methodology that differed from others (Hammond, et al. (1987) and Mullin (1989) were identified) by the incorporation of a qualitative assessment as a starting point. These two studies, he indicated, did not deal with the level of complexity or the degree of uncertainty that his methodology entailed.

Monroe's (1997) methodology was adapted by Hampton (2001) as the mode of data collection. This research, in addition to examining risk associated to internal uncertainty, also extended these principles to external uncertainty. It incorporated research done by Du and Chen (1999) to address 'multidisciplinary design optimization (MDO)'. This included multiple input parameter distributions instead of one (work suggested by the author themselves), and integrated research done by Unal et al. (1998) that examines optimization of response surfaces for a launch vehicle.

There are other resent developments in this area of research, of interest, Conway (2003) and Chytka (2003). Conway (2003) developed a methodology to calibrate multiple expert judgments as part of the expert judgment elicitation process. A more robust system that includes expert judgment calibration, which efficiently handles a variety of conceptual design-related questions, was sought. Chytka (2003) concurrently developed a methodology for aggregating these uncertainties estimations of multiple experts. Both also adapted the questionnaire methodology of Monroe (1997).

LITERATURE SUMMARY

The following table summarizes the authors' contributions under their respective area of research:

T_1: High Consequence Conceptual Engineering
T_2: Risk and Uncertainty in Decision Making
T_3: Expert Judgment Elicitation
T_4: Heuristics and Biases
T_5: Estimation of Uncertainty
T_6: Evidence Theory

	T_1	T_2	T_3	T_4	T_5	T_6
Aase & Nybø (2002)	X					
Althaus (2005)		X				
Armor & Taylor (2002)	X				X	
Aven & Kristensen (2005)		X				
Ayyub (2001)			X	X		X
Bae & Grandhi. (2003)						X
Bolger (1992)						X
Booker et al. (2004)		X	X			
Booker et al. (2003)			X			
Booker & McNamara (2004-a)			X	X		
Booker & McNamara (2004-b)			X	X		
Booker & McNamara (2003)			X	X		
Booker & Meyer (1996)			X			
Cooke & Goossens (2004)			X			
Cvetkovich & Lofstedt (1999)		X				
Dalkey (1996)			X			
Dezert (2002)						X
Dietrich & Childress (2004)		X				
Dubois & Prade (1998)						X
Gigerenzer & Fieldler (2003)				X		
Gigerenzer (2003)				X		
Gilovich et al. (2002)				X		
Gustafon et al. (1973)			X			
Hammond (2000)				X		
Hampton (2001)			X			
Henrion & Fishoff (2002)					X	
Hoch (1984)				X		
Hood & Jones (1996)		X				
Hora & Iman (1989)			X			
Joffe (1999)		X				
Kahneman et al. (1982)				X	X	
Kahneman & Tversky (1972)				X		
Keeny & Von Windterfeldt (1991)			X			
Keeny & Von Windterfeldt (1989)			X	X		
Klir (2004)						X
Klir & Folger (1988)			X	X		
Knight (1921)		X				
Kogan & Wallach (1964)		X				

Lock (1987)			X			
Margolis (1996)		X				
McNeil et al. (1998)	X					
Meyer & Booker (2001)			X	X		
Meyer & Booker (1991)			X	X		
Monroe (1997)	X		X	X		
Morgan & Henrion (1990)				X	X	
Mullin (1986)			X	X		
Oberkampf (2005)		X				X
Perrow (1986)	X					
Reason (1997)	X					
Renooij (2001)			X	X		
Ross et al. (2002)			X			
Sentz & Ferson (2002)						X
Shanteau (1987)			X			
Shanteau (1992)			X			
Simons (1955, 1956)				X		
Slovic et al. (2002)					X	
Spetzler & Stael von Hestein (1975)				X		
Sun & Farooq (2004)						X
Szwed (2002)			X			
Takala (1989)	X					
Thompson (1986)		X				
Thys (1987)				X		
Trimpop (1994)		X				
Unal et al. (2005)		X	X			
Wang et al. (2002)	X					
Wright & Bolger (1992)			X	X		
Wu et al. (1996)						X
Yager (1987)						X
Zadeh (1979, 1984, 1986)						X
Barrows (2006)	X	X	X	X	X	X

TABLE 17: LITERATURE REVIEW SUMMARY

Although this table maps the various authors' contributions under their respective area of research, it does not contain all reference in this document, but represents a comprehensive list of the pertinent references.

RESEARCH CONTRIBUTION

Systems Engineering research has been modified and extended - including that of Monroe (1997); Hampton (2001); Chytka (2003); Conway (2003) to name a few - to using expert judgment elicitation as the mode for collecting data. Although this study also utilizes a similar modification compared to previous studies, one of the contributing elements is found in the evidence based (non-probabilistic) approach to risk analysis methods for elucidating the estimation of uncertainty bias within a related environment. Another contribution of this study is the significant for improvement in the quality of data obtain to support decision making in a real world setting. This is done by a developed, structured and methodological process for eliciting expert judgments in practice; i.e. the application in the aerospace industry, specifically Crew Launch Vehicles. A study of this nature is supported by Hampton (2001) who indicated that research should be "applied in other applications or problem domains in order to determine consistency of results between related environments" (p. 79). These contributions will be clearly identified and highlighted in preceding chapters.

No research was found within the literature that explicitly investigate a non-probabilistic handling of the under or overestimation of uncertainty bias found in expert judgment elicitation in High Consequence Conceptual Engineering Environments. It is important to identify how this bias affect these environments, in addition to the improvement in the quality of data, to better understand how experts structure problems; how they weigh and combine different sources of information in making decisions; and how they conceptualize uncertainty. Having this knowledge will elucidate the extent to which this estimation of uncertainty bias may degrade the quality, and increase the reliability of elicited data using expert judgment as the collection technique.

Research Question

How do we effectively elucidate the extent of the estimation of uncertainty bias in High Consequence Conceptual Engineering Environment?

Value of the Research

The goal of this research is to develop a methodology that will elucidate the existence of the estimation of uncertainty bias (under or overestimation) in High Consequence Conceptual Engineering Environments. In the effort to value this study in terms of usefulness of communicating, learning, understanding, and informing decision makers, the intended purpose of this investigation is:

- To be informed of the presence of bias (uncertainty estimation in particular) and develop means of addressing it.
- To clarify and present insights in a general area of uncertainty estimation in relationship to the decision making process.
- To provide documented arguments in support of one's view or to address criticism when expert judgment seen as an adversarial process.
- To assist in generating a justification for decision makers when justifying their action taken based on the scientific/technical specifics of a problem in question.
- To use a specific problem context as a medium to develop, demonstrate, and test a new methodology.

This allows for more informed decision making within these particular environments.

CHAPTER III

METHODOLOGY

Research Design

The focus of this study was to develop an approach to elucidate the estimation of uncertainty bias. The research was designed to elicit expert judgments on parameters associated with specified tasks at the design phase of a Crew Launch Vehicle (CLV). Placing the constraint of being in a high consequence conceptual design environment, the estimation of uncertainty was assessed to identify if there was under or overestimation in these judgments.

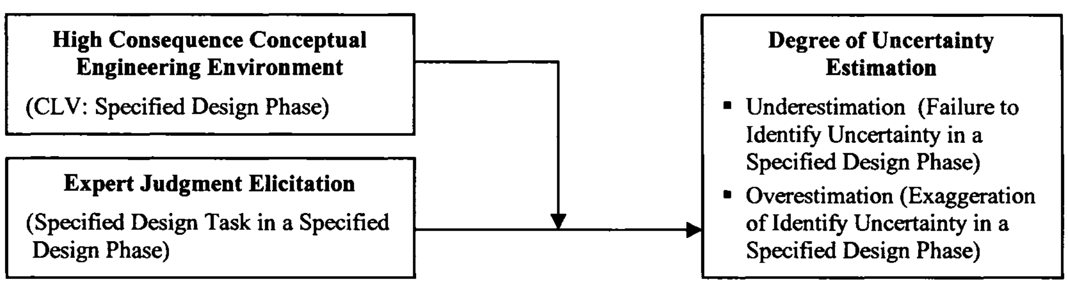


Figure 5: The Research Design

The elucidation of the estimation of uncertainty bias was conducted in two distinct phases. The intention (and a contribution of this study to previous research) was to have a structured method for the elicitation process coupled with the respective bias handling techniques as the initial phase (qualitatively). The data obtained was analyzed, using an evidence theory approach, to assess the remainder of the estimation of uncertainty bias (quantitatively) in the effort to elucidate the uncertainty estimations bias.

HANDLING BIASES DURING THE ELICITATION PROCESS (QUALITATIVELY)

The phases and steps of the structured elicitation process adapted for this study are presented in the following table:

Phases, Steps	Probability Example: Auto Reliability	Fuzzy Example: Radioisotopes	Modified Phases and Steps Adapted
Determine whether experts judgment can be feasibly elicited	Feasibility indicated by prior (informal) use of experts' judgment.	Feasibility indicated by prior (informal) use of experts' judgment.	Feasibility indicated by prior (informal) use of experts' judgment.
Determine the best framework for eliciting the expert judgment - in a probabilistic or alternative such as possibility, fuzzy, evidence etc.	Experts thought in terms of numeric likelihoods; the mathematical foundations of subjectivist probabilities were a plus.	Incoming information was imprecise; one lead expert preferred fuzzy for the quick creation of a robust expert system.	The experts think in terms of numeric likelihoods; this is a plus because evidence theory requires likelihood estimate.
Design the Elicitation			
1. Identify the Expert(s).	One self-identified lead expert identified additional advisors at the national and international levels.	One lead expert volunteered himself and identified another advisor.	The point of contact is the lead expert that assisted in the selection process for this study.
2. Construct representations of the way that the experts measure or forecast the phenomena of interest.	Representations included reliability success trees, and failure modes.	Representations focused on features evident in plots of gamma-ray spectrum and of the second derivative of the spectra.	A percentage value was elicited from the experts as a representation of the likelihood uncertainty estimation.
3. Draft the questions.	What is your expected, number of incidents per thousand vehicles to fail to meet specifications? Best-case number? Worst-cast number?	What are you fuzzy rules concerning a peak and these linguistic variables: low, medium, and high energy and very very good, or somewhat somewhat good?	The questions were drafted to obtain the likelihood estimation of each event in terms of low, medium or high based on a five point scale to which the percentages was assigned.
4. Plan the interview situation.	Team interviews because the experts worked in teams.	Separate interviews followed by structured joint interviews.	An individual elicitation situation was adapted.
5. Select the experts.	The advisor selected the auto products for reliability characterization, which determined the selection of teams, already composed of experts.	The advisor identified the two locally and recognized experts.	The lead expert selected recognized experts based on specified criteria identified in addition to availability.
6. Motivate participation by the experts.	The advisor carefully drafted the formal request for participation by cover memo and followed up with telephone calls.	The motivation of participation by the advisor was very informal because this was an in-house effort and therefore was only two experts.	The motivation of participation by the lead expert was very informal because this was an in-house effort and therefore only three experts' judgments were elicited.
7. Pilot test the questions and interview situation.	Extensive pilot tests of the sets of questions and the cover letter (for motivating participation) were performed via. teleconference calls.	Pilot tests of the questions were conducted on the lead expert and led to refinement in how the fuzzy rules were elicited.	Pilot tests of the questions were conducted on the lead expert and were refined in terms of the culture of the conceptual design environment.

Eliciting and documenting the expert judgment	Advisor and those he designated lead the team interviews, elicited and recorded the subjective probability estimates, assumptions, and failure modes.	The researchers elicited and documented the experts' fuzzy rules, membership functions, the information, and assumptions the experts considered.	**The lead expert assisted in eliciting and documenting the experts' estimates along with any additional information expressed by the expert relevant to the questions.**
Representing the expert judgment for the experts' review and refinement.	Teams' performance estimates were represented as probability distributions and updated their estimates as new information becomes available.	The researchers and the experts refined the fuzzy rules and membership functions. The experts refined their fuzzy rules, in structured joint interviews. The experts' reviews led to labels and caveats being placed on the expert judgment.	**The information was compiled and fed back to the experts for review and updating with additional information needed, assumption clarified etc. to ensure full understanding.**
Facilitating the comparison of multiple experts' judgments.	Comparisons were done between proposed designs and options for testing, instead of between experts' judgments.	We compared expert's fuzzy rules, assumptions, quantifications, and the difference to the bottom line in using one expert's judgment over another.	**The lead expert compared the judgments and ensured clarification of any differences etc.**

TABLE 18: ELICITATION PHASES AND STEPS TO BE CONDUCTED COMPARED TO ROSS (2002).

This tailored process was developed and adapted to this study. This approach was derived from the example elicitation tasks of previous research set forth by Ross et al. (2002), tailored to a high consequence conceptual engineering environment (aerospace).

Along with this modified structured elicitation process, the respective bias handling techniques were integrated to obtain a modification framework for handling biases and are presented in the following steps:

Step 1 - Anticipate Which Biases are Likely to Occur: Along with the lead expert, the component in which a particular bias can occur was identified.

Elicitation Process	-	Individual interview
Mode of Communication	-	Face to Face
Response Mode	-	Likelihood uncertainty measures

Having identified these components, the anticipated biases were identified - being aware and anticipating the biases facilitated a guidance session (approximately half a day) with the expert to explain some of the common heuristics that are found in making judgments under the related uncertainty conditions.

Step 2 - Redesign the Planned Elicitation to Make it Less Prone to the Anticipated Biases: Based on the anticipated biases, any relevant suggestions, definitions and additional information obtained from the experts pertaining to these biases was incorporated into the redesign of the elicitation.

Step 3 - Making the Experts Aware of the Potential Intrusion of Particular Biases and Familiarize Then to the Elicitation Procedures: Along with the guidance session, the experts were made aware of the potential causes of the biases and acquainted then to the elicitation procedures to reduce some of the inconsistencies that may have been encountered if they were not consciously attempting to address these factors.

Step 4 - Monitor the Elicitation for the Occurrence of Biases: The structure of the questionnaire required further disaggregating of selected questions by the experts, and estimates of the quantities in disaggregated sections were requested.

Step 5 – Analyze the Data for the Occurrence of Particular Biases: Based on steps 4, a mathematical analysis was conducted to determine the occurrence of the cognitive bias (uncertainty estimation); discussed in a later section.

HANDLING BIASES BY A MATHEMATICAL ANALYSIS (QUANTITATIVE)

An important factor to note is that the tailored elicitation process grounded in the research design was focused mainly on the estimation of uncertainty, and was the more complex and difficult bias to handle. Although this bias could be addressed during the elicitation process, as indicated in step 5 above, a mathematical analysis was conducted after the data was elicited to facilitate the elucidation of this bias. There were various steps involved in this analysis and were outline as follows:

Obtaining a Calibration Co-efficient (CC)

Conway (2003) developed a methodology and incorporated 'Fuzzy logic and Bayesian's statistical techniques that identified an "Expert Calibration Function (ECF) based on degree (level and time) of past experience and current philosophy" (Conway, 2002, p. 22). For this study, these techniques were adapted and integrated into the proposed methodology to obtain a Calibration Co-efficient (CC) that aided in the identification of under or overestimation of uncertainty. Questions were integrated into the questionnaire to obtain the necessary data for the following (Conway, 2003):

Expertise (E):

$$E = 5\,[\text{age}/60] + \text{sel} + \text{ecp} + 5\,[1/(1+(\text{dsk}-\text{act})/\text{act})] \tag{20}$$

where: age - is the expert's age in years.
sel - is the expert's self-designation of expertise in the discipline area being elicited, scale of 1 (least) through 5 (most).
ecp - is the expert's perception of expertise compared to peers in the discipline area being elicited, scale of 1 (least) through 5 (most).
dsk - is the expert's numerical response to questions involving discipline-specific knowledge.
act - is the actual (true) value of the response to the question involving discipline-specific knowledge.

Confidence/Risk Profile (CRP):

$$\text{CRP} = \sum\,[(\text{responses to 'crp' questions})/(\text{no. of 'crp' questions})] \tag{21}$$

where: CRP - is the confidence/risk profile of the expert.

These two values were substituted into the Δm equation and the CC factor was obtained.

Calibration Co-efficient (CC):

$$\Delta m = m\,(-\text{sign}\,(CRP)\,[1-(E/5)])\,A_1 \tag{22}$$

where: Δm - is the Calibration Co-efficient
m - is a basic assignment (likelihood estimate).
CRP - is the confidence/risk profile of the expert.
E - is the expertise of the expert
A_1 - an arbitrary constant (initially set at 1)

Representations of Uncertainty Regarding a Parameter "X"

The representation of epistemic uncertainties using a uniform probability distribution, or to obtain a combined quantity for both aleatory and epistemic uncertainty by using a 'second-order probability theory', can lead to the underestimation of uncertainty in (Oberkampf, 2005):

- Physical parameters
- Geometry of a system
- Initial conditions
- Scenarios and environments

Oberkampf (2005) argued that "evidence theory can correctly represent epistemic uncertainties from intervals, degrees of belief, and probabilistic information" (p. 8). Therefore, evidence theory was adapted to identify and represent the parameter "x".

In the literature review, we identified a belief function and plausibility function as being the lower and upper bounds of uncertainty:

Belief (lower) function:

$$Bel\,(A_i) = \sum_{all\,Aj \subseteq Ai} m(A_i) \tag{23}$$

Plausibility (upper) function:

$$Pl\,(A_i) = \sum_{all\ Aj \cap Ai \neq \varnothing} m(A_j) \tag{24}$$

A basic assignment (m) was identified as an assessment of the likelihood estimate of an element "x" of "X" to each set in the family of sets identified:

This basic assignment is characterized by:

$$m\colon P_x \rightarrow [0,1] \tag{25}$$

which must satisfy the following two conditions:

$$m(\varnothing) = 0 \tag{26}$$

$$\sum_{all\ A\ \subseteq\ Px} m(A) = 1 \tag{27}$$

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*":

- A Belief measure (strongest)
- A Plausibility measure (weakest)
- A basic assignment (collected evidence/likelihood)

The basic likelihood assignment was elicited from the selected experts. These assignments were 'calibrated' using the Calibration Co-efficient (CC) found and combined (aggregated) using Yagar's combination rule:

$$q\,(A) = \sum_{\bigcap_{i=1}^{n} Ai = A} m_1\,(A_1)\, m_2\,(A_2)\ \ldots\ m_n\,(A_n) \tag{28}$$

where: $q(A)$ can be used to include any number of evidence.
m_1, m_2,...m_n are the basic assignments.
A is the focal set.

Three of the main reasons for selecting this rule of combination (among others discussed earlier) were:

- It allows for the combination of 'n' number of experts vs. Dempster-Shafter's that only allows for two.
- It addresses the counter-intuitive results obtained from Dempster-Shafter's combination rule based on the integrated class of unbiased operators.
- This rule does not ignore any conflicts between the assignments, especially as the level of conflicts increase - better handling of biases.

It is important to note that three experts were selected for this study. According to Rantilla and Budescu (1999), "regardless of the aggregation method chosen, research indicates that combining the assignments of three experts yields the most advantage to aggregation" (as cited by Chytka, 2003, p. 18). She continued to argue that there is no empirical evidence that indicted by having more that three experts improves the "effectiveness or efficiency of model output" (ibid., p. 18), and referenced a study by Rantilla and Budescu (1999) which concluded that having more than three experts will produce less confidence in the estimates (counter-intuitive results). Clemen and Winkler (1997) and Hogarth (1990) were also cited as supporting this "three-expert postulate".

From the combination above, an aggregated value m_{123} was obtained that represented a calibrated and aggregated likelihood (estimate) of the elements "x" of "X" to each set in the family of sets identified which and was conflict free. The belief and plausibility functions were utilized with this m_{123} values to obtain the belief and plausibility measures, thus the upper and lower limits of uncertainty.

In elucidating the uncertainty estimation bias (including assessing the extent to which uncertainty is under or overestimated), the belief and plausibility measures of the basic assignment (*m*) were found for each expert. These measures were mapped against that of the calibrated and aggregated measures initially found: the control. This allowed for the identification of the extent to which uncertainty is under or overestimated based on the limits of the experts that falls outside of the limits of the calibrated and aggregated estimates - the portion outside of the belief limit identified underestimation and the portion outside of the plausibility limit identified overestimation. A Monte Carlo based tool, @RISK, was used to model the data thus appropriately represent these uncertainty estimates.

CHAPTER IV

APPLICATION & RESULTS

APPLICATION SETTING

Engineering and management teams from NASA Langley Research Center were the population from which the experts for this study were identified. Of interest to NASA officials, was to obtain uncertainty estimates associated with their Crew Launch Vehicle (CLV) designs; the designs of their existing Exploration Systems Architecture Study Crew Launch Vehicle (ESAS CLV) and the Parallel-Staged Crew Launch Vehicle (P-S CLV) which is currently being worked. This allowed for facilitating this study by applying the methodology described above and comparing the level of uncertainty in both designs by looking at the life cycle cost in three sections: development, production, and operational costs. An analysis was done to identify if the experts over or underestimated in their judgments by mapping the belief and plausibility functions for each expert against the 'aggregated and calibrated' belief and plausibility functions (limits of uncertainty that is considered the control) for both CLV's respectively. Additionally, a further investigation was done to see if the level of uncertainty estimation changed as a design matured.

EXPERT SELECTION

There are several expert characteristics presented earlier from the literature by Wright & Bolger (1992) and Shanteau (1987). However, although expert diversity is sought, selected criteria are required to qualify the experts depending on the particular study (Meyer & Booker, 2001). They continue to argue that because of the limitations found in the number of available experts in most cases, logistics also plays an important role in this qualification process: i.e. "whether the experts are willing to participate, having the time to participate at the necessary level, and be allowed to do so by their employer" (as cited in Chytka, 2003, p.44). Ross et al. (2002) continues to argue that this also "varies more according to the circumstances of the elicitation…when few experts are available or the application is in-house, the process of selecting the experts can be informal" (p. 117).

The lead expert selected the recognized experts for this study based on specified criteria and availability. These criteria were adapted from previous research by Conway and Chytka both in 2003, which was conducted in a similar setting (a high consequence conceptual design environment), are presented in Table 19 below. The three experts were

Expert Characteristics
Domain Knowledge ▪ Years of experience ▪ Educational background
Cognitive Skills ▪ Ability to discern usefulness of data
Decision Strategies
Expert-task Congruence ▪ Appropriate expertise for discipline specific task

TABLE 19: CHARACTERISTIC FOR SELECTION OF THE EXPERT (ADAPTED FROM CHYTKA, 2003)

selected from engineering and management teams from NASA Langley Research Center. These three experts represent 20% of the total population (fifteen (15)) of recognized and eligible experts nationwide.

Expounding on the domain knowledge characteristics, according to Chytka (2003), "the literature does not support that "x" number of years of experience or "y" minimum educational background is used explicitly as selection criteria for the identification of the experts" (p. 44). This was supported by Conway (2003), indicating that "while there has been some positive correlation between years of experience or educational background, there is no evidence to support applying this standard universally" (as cited in Chytka, 2003, p.44). The experts selected are also recognized experts in their respective field by their peers with the cognitive skills, i.e. the ability to discern usefulness of data, and appropriate decision strategy ability. In addition, a key criterion in which contributes heavily on appropriateness is familiarity with multidisciplinary launch vehicle design and the task applications (Chytka, 2003); i.e. the appropriate expertise for discipline specific task.

THE QUESTIONNAIRE DESIGN

In 1997, Monroe developed a questionnaire that evolved through several iterations and provided ample feedback from the 'boarder domain of conceptual design engineering experts' [from five organizations - Boeing, Northrup Grumman, NASA LaRC, NASA Johnson Space Center, and the Naval Air Systems Command (NAVAIR)] as to the usefulness of the elements included in the questionnaire. This instrument also has selected features to optimize the task characteristics of the elicitation process advocated by Shanteau (1992).

The questionnaire has been the foundation for various research on which this study was built. The features of interest that were contained in this instrument are the:

- Rating of the parameters for uncertainty on a five point qualitative (Likert) scale (low, 2, moderate, 4, or high).

- Prompting of the experts to think of any additional cues (or triggers) that may further documenting the pattern of thinking affects the uncertainty rating.
- Anchoring of the three major points along the scales (documents the meaning of low, moderate and high uncertainty from the experts' perspective quantitatively as a percentage - used to interpret the 'true' meaning of the experts estimated).
- Careful structuring of the instrument in an open-ended format and to satisfying the Institutional Review Board (IRB) requirements.

This was supplemented by contributing studies of Conway and Chytka both in 2003 which was reflected mainly in the self-rating of expertise.

The experts were asked questions that allowed for self-rating of their expertise and a comparison to their peers (see Figure 6). The first allowed for predicting the performance… and allowed for the establishment of the level of expertise for the experts (Wright, Rowe, Bolger, & Gammack, 1994; Conway, 2003). The second provided a "second indicator of the expert's self-designated level of expertise related to a more absolute scale" (Conway, 2003, p. 34). Accordance to Crawford & Stankov (1996) and MacCrimmon & Wehring (1986) expertise can be related to age of an expert, thus age was requested as a background question (Conway, 2003).

Name or ID Code

Age

In this subject area, rate your own level of expertise on a scale of 1 (least) to 5 (most):

❍ 1 ❍ 2 ❍ 3 ❍ 4 ❍ 5

How do you rank yourself among your peers of similar experience with respect to expertise? 1 (much less) to 5 (much more):

❍ 1 ❍ 2 ❍ 3 ❍ 4 ❍ 5

FIGURE 6: QUESTIONS FOR SELF RATING OF EXPERTISE

Confidence level can be equated and interpreted as the risk tolerance (Miller & Byrnes, 1997; Wang, 2001), and "has been through the use of utility theory and the determination of an individual's utility function" (Conway, 2003, p. 23). Conway also highlighted that based of previous research, risk-takers tend to be overconfident, risk-averseness tend to be underconfidence (Wang, 2001; Simon, Houghton, & Aquino, 1999; and Miller & Byrnes, 1997), while risk propensity, although may always be cognizant, tend to be the result of overconfidence (Simon, Houghton, & Aquino, 1999). Thus the background questions attempting to obtain an expert's confidence level (see Figure 7).

Thinking about predicting the likelihood associate to a particular event, do you normally predict:

- More than what actually occur?
- Less than what actually occurs?
- About the amount/number of times that it actually occur?

In making estimates related to cost parameters, would you say you were:

- Very close with a high degree of confidence?
- Very close without a high degree of confidence?
- Not very close but within a high degree of confidence?
- Not very close and not much confidence?

In estimating in your subject area that has associated uncertainty, would you say it is better to:

- Be close to the actual value without a lot of confidence in your estimate?
- Not be very close to the actual value, but with a high degree of confidence in your estimate?

Do you think it is better for project success to:

- Set, in advance, the completion dates for a complex project.
- Establish, in advance, technical milestones for complex project.

Do you think it is better for project success to:

- Estimate, in advance, project budgets for a complex project?
- Identify, in advance, cost WBS for a complex project?

Do you think it is better to:

- Identify, at conceptual design review, scenarios for successful projects?
- Identify, at conceptual design review, technical performance characteristics of a successful project?

FIGURE 7: BACKGROUND QUESTIONS TO OBTAIN CONFIDENCE LEVEL

The uncertainty for various cost parameters were rated qualitatively using the 5-point (Likert) scale, Low, 2, Moderate, 4 and High; the "2" signified Low/ Moderate and the "4" signified Moderate/High (see example in Figure 8). In this section of the

Thinking of possible scenarios that could provide alternative assessments, what is the likelihood of the following combination(s) having the largest negative impact on these cost projections?

Development and production costs ONLY:

❍ Low ❍ 2 ❍ Moderate ❍ 4 ❍ High

FIGURE 8: EXAMPLE QUESTION FOR RATING COST PARAMETER

questionnaire, the structure the questions and rating of the various cost parameters produced values that were analyzed non-probabilistically. This is where, in addition

To further document your pattern of thinking, please provide any cues (or triggers) that influenced your thinking of these three cost parameters and record in the space provided:

The following questions attempt to anchor a quantitative value for Low, Moderate and High likelihood estimates. This is to ensure clarity in interpretation. What quantitative value would you assign to:

Low likelihood?

❍ Less ❍ 5% ❍ 7.5% ❍ 10% ❍ 12.5% ❍ 15% ❍ More

If more or less please indicate

Moderate likelihood?

❍ Less ❍ 10% ❍ 15% ❍ 20% ❍ 25% ❍ 30% ❍ More

If more or less please indicate

High likelihood?

❍ Less ❍ 20% ❍ 30% ❍ 40% ❍ 50% ❍ 60% ❍ More

If more or less please indicate

FIGURE 9: DOCUMENTING FURTHER THINKING PATTERNS OF THE EXPERTS AND QUANTIFYING THEIR QUALITATIVE RATINGS

the foundation elements adapted, most of the contributions in this study are entrenched.

This non-probabilistic approach included asking the experts to thick of any other cues or triggers that had not been documented, and record that information. This allowed for further documentation of the expert's thinking pattern of the cost parameters. They also anchored their Low, Moderate and High qualitative measures of uncertainty to a quantitative measure using the scales provided (see Figure 9) to ensure clarity in interpretation.

Institutional Review Board (IRB) Considerations

Addressing the Institutional Review Board (IRB) considerations, the questionnaire developed and utilized in support of NASA Crew Launch Vehicle (CLV) study was reported to the IRB representative at Old Dominion University. This study obtained 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 financially) to subject participants.

Data Collection

The questionnaire was developed using Adobe Acrobat as it medium, obtaining the instrument in a PDF format which included detailed instructions and directions. This facilitates, firstly, for electronically distributing, completing and returning of the questionnaire. Secondly, this also allows for data to be extracted from the instrument by linking it directly to a spreadsheet in MS Excel and @RISK for computations. Upon request, the experts' identities remained anonymous, and are identified in all reporting as expert numbers such as, Expert$_1$, Expert$_2$, etc. However, for tracking purposes each expert's Identifier Code (not reported), was the last four digits of their phone number in reversed order.

Data Analysis & Results

The formulas and mathematical operations used in the computation spreadsheets, as discussed earlier in the methodology, allowed the analysis of the obtained data in a scrupulous and methodical manner. The expertise values (see Equation 29) were obtained my eliciting the experts' self-assessment of his/her expertise (in accordance with Wright, Rowe, Bolger, & Gammack, 1994), and self-designation of this expertise in relation to peers in the discipline domain.

ESAS CLV					
Expert 1		Expert 2		Expert 3	
age:	37	age:	62	age:	54
sel:	0.55	sel:	0.55	sel:	0.65
ecp:	0.55	ecp:	0.55	ecp:	0.65
dsk:	0.65	dsk:	0.7	dsk:	0.5
act:	0.65	act:	0.65	act:	0.65
E=	9.18	E=	10.91	E=	12.30
P-S CLV					
Expert 1		Expert 2		Expert 3	
age:	37	age:	62	age:	54
sel:	0.55	sel:	0.55	sel:	0.65
ecp:	0.55	ecp:	0.55	ecp:	0.65
dsk:	0.7	dsk:	0.6	dsk:	0.9
act:	0.65	act:	0.65	act:	0.65
E=	8.83	E=	11.68	E=	9.41

Figure 10: Resulting Expertise Values

$$E = 5\ [age/60] + sel + ecp + 5\ [1/(1+(dsk-act)/act)] \tag{29}$$

This formula having considered the age of the experts (Crawford & Stankov, 1996; MacCrimmon & Wehring, 1986) and the experts response to a discipline-specific knowledge question versus the actual (true) response of the question, allowed for a comprehensive assessment of the expertise (see Figure 10). This preliminary assessment showed variations in the expertise values although the same expert made uncertainty estimations on two different applications (designs).

The responses to the experts' confidence level questions were mapped by using the chart in Figure 11. This was complied with the risk confidence/utility philosophy profiling (previously discussed in questionnaire design).

	Assigned Philosophy Profile For Response				
Question	**5**	**2.5**	**0**	**-2.5**	**-5**
3	(c)		(b)		(a)
4	(c)	(a)		(b)	(d)
5	(a)				(b)
6	(a)				(b)
7	(a)				(b)
8	(b)				(a)

FIGURE 11: RISK CONFIDENCE/UTILITY PHILOSOPHY PROFILING CHART (ADAPTED FROM CONWAY, 2003)

These values were then divided by the number of questions (see Equation 30).

$$\text{CRP} = \sum \left[(\text{responses to 'crp' questions})/(\text{no. of 'crp' questions})\right] \qquad (30)$$

This formula placed into a spreadsheet format produced the outputs values fruitfully (example in Figure 12). The results obtained were -2.92, -2.92, and -4.58 for Expert_1, Expert_2, and Expert_3 respectively. The values were substituted into the "Δm" Equation (31) to obtain the calibration co-efficient/adjustment factors.

The arbitrary constant "A_1" (initially set at 1) was also used to aide calibration, augmenting reliability among multiple experts, when the same questionnaire is used for the elicitation (James, Demaree, & Wolf, 1984 cited in Conway, 2003).

Expert 1							
Question		3	4	5	6	7	8
Risk Tolerant	5						X
	2.5						
Risk Neutral	0						
	-2.5		X				
Risk Adverse	-5	X		X	X	X	

Question	Topic	Response	Point Conversion
3	Predicted Discipline-Related Quantities	a	-5
4	Estimating Uncertainty Preference	b	-2.5
5	Estimating Trend in Discipline	b	-5
6	Completion vs. Milestones	b	-5
7	Total Outlays vs. Cost Elements	b	-5
8	Utilization Scenarios vs. Performance	b	5
CRP = -2.92	E = 8.83		

FIGURE 12: MAPPING AND CALCULATION FOR THE CONFIDENCE/RISK PROFILE (CRP)

$$\Delta m = m\,(-\text{sign}\,(CRP)\,[1-(E/5)])\,A_1 \qquad (31)$$

There are three measures that can be viewed as alternate representations of uncertainty regarding the same cost parameter; a Belief measure, a Plausibility measure, and a basic assignment, "m" (collected evidence/likelihood of the cost parameters). The calibration co-efficient/adjustment factors (shown in Figure 13) were used to calibrate each basic assignment for the cost parameters. These calibrated assignments were combined (aggregated) using Yagar's combination rule (defined in Equation 34).

The belief measure (Bel)

$$Bel\,(A_i) = \sum_{all\,A_j \subseteq A_i} m(A_i) \qquad (32)$$

The plausibility measure (Pl)

$$Pl\,(A_i) = \sum_{all\,A_j \cap A_i \neq \emptyset} m(A_j) \qquad (33)$$

Yagar's combination rule defined

$$q\,(A) = \sum_{\bigcap_{i=1}^{n} A_i = A} m_1\,(A_1)\, m_2\,(A_2) \ldots m_n\,(A_n) \qquad (34)$$

where: $q(A)$ can be used to include any number of evidence.
$m_1, m_2, \ldots m_n$ are the basic assignments.
A is the focal set.

EXPLORATION SYSTEMS ARCHITECTURE STUDY CREW LAUNCH VEHICLE

	EXPERT 1		EXPERT 2		EXPERT 3	
	Basic Assignment	Adjustment Factor	Basic Assignment	Adjustment Factor	Basic Assignment	Adjustment Factor
D = Development Cost	0.70	-0.59	0.25	-0.30	0.50	-0.73
P = Production Cost	0.25	-0.21	0.25	-0.30	0.50	-0.73
O = Operation Cost	0.70	-0.59	0.55	-0.65	0.80	-1.17
D U P	0.40	-0.33	0.25	-0.30	0.30	-0.44
D U O	0.70	-0.59	0.40	-0.47	0.50	-0.73
O U P	0.40	-0.33	0.40	-0.47	0.80	-1.17
D U P U O	0.70	-0.59	0.55	-0.65	0.80	-1.17

PARALLEL-STAGED CREW LAUNCH VEHICLE

	EXPERT 1		EXPERT 2		EXPERT 3	
	Basic Assignment	Adjustment Factor	Basic Assignment	Adjustment Factor	Basic Assignment	Adjustment Factor
D = Development Cost	0.40	-0.31	0.25	-0.33	0.30	-0.26
P = Production Cost	0.10	-0.08	0.40	-0.53	0.30	-0.26
O = Operation Cost	0.40	-0.31	0.55	-0.73	0.80	-0.71
D U P	0.25	-0.19	0.40	-0.53	0.30	-0.26
D U O	0.40	-0.31	0.55	-0.73	0.80	-0.71
O U P	0.40	-0.31	0.55	-0.73	0.65	-0.57
D U P U O	0.40	-0.31	0.70	-0.94	0.65	-0.57

FIGURE 13: CALCULATION FOR THE CALIBRATION CO-EFFICIENT/ADJUSTMENT FACTOR

BELIEF COMPUTATIONS						
SUBSET*	EXPERT 1		EXPERT 2		COMBINED JUDGMENT 1,2	
Costs Parameters	m_1	Bel_1	m_2	Bel_2	$m_{1,2}$	$Bel_{1,2}$
D = Development Cost	0.18	0.18	0.09	0.09	0.22	0.22
P = Production Cost	0.06	0.06	0.09	0.09	0.12	0.12
O = Operation Cost	0.18	0.18	0.21	0.21	0.34	0.34
D U P	0.10	0.35	0.09	0.28	0.06	0.41
D U O	0.18	0.55	0.15	0.45	0.12	0.68
O U P	0.10	0.35	0.15	0.45	0.08	0.55
D U P U O	0.18	1.00**	0.21	1.00**	0.05	1.00**
	1.00		1.00		1.00	

PLAUSIBILITY COMPUTATIONS						
SUBSET*	EXPERT 1		EXPERT 2		COMBINED JUDGMENT 1,2	
Costs Parameters	m_1	Pl_1	m_2	Pl_2	$m_{1,2}$	$Pl_{1,2}$
D = Development Cost	0.18	0.65	0.09	0.55	0.22	0.45
P = Production Cost	0.06	0.45	0.09	0.55	0.12	0.32
O = Operation Cost	0.18	0.65	0.21	0.72	0.34	0.59
D U P	0.10	0.82	0.09	0.79	0.06	0.66
D U O	0.18	0.94	0.15	0.91	0.12	0.88
O U P	0.10	0.82	0.15	0.91	0.08	0.78
D U P U O	0.18	1.00**	0.21	1.00**	0.05	1.00**
	1.00		1.00		1.00	

FIGURE 14: CALCULATION FOR THE BELIEF (BEL) AND PLAUSIBILITY (PL) FUNCTIONS

The belief and plausibility functions for each expert's normalized assignments and the experts' assignments combined of the cost parameters respectively (example in Figure 14) were calculated using Equations 32 and 33 in the spreadsheets. The Belief and

Plausibility functions (summary shown in Figure 15) are also recognized as the limits of uncertainty that identifies a solution space for the uncertainty of the cost parameters (Figures 16, 17 and 18).

Exploration Systems Architecture Study Crew Launch Vehicle (ESAS CLV)							
Expert $_1$		Expert $_2$		Expert $_3$		Combined	
Bel_1	Pl_1	Bel_2	Pl_2	Bel_3	Pl_3	$Bel_{1,2,3}$	$Pl_{1,2,3}$
0.18	0.65	0.09	0.55	0.12	0.50	0.22	0.33
0.06	0.45	0.09	0.55	0.12	0.57	0.16	0.26
0.18	0.65	0.21	0.72	0.19	0.69	0.46	0.59
0.35	0.82	0.28	0.79	0.31	0.81	0.41	0.54
0.55	0.94	0.45	0.91	0.43	0.88	0.74	0.84
0.35	0.82	0.45	0.91	0.50	0.88	0.67	0.78
1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Parallel-Staged Crew Launch Vehicle (P-S CLV)							
Expert $_1$		Expert $_2$		Expert $_3$		Combined	
Bel_1	Pl_1	Bel_2	Pl_2	Bel_3	Pl_3	$Bel_{1,2,3}$	$Pl_{1,2,3}$
0.17	0.62	0.07	0.56	0.08	0.54	0.21	0.32
0.04	0.49	0.12	0.60	0.08	0.50	0.15	0.25
0.17	0.68	0.16	0.69	0.21	0.76	0.47	0.61
0.32	0.83	0.31	0.84	0.24	0.79	0.39	0.53
0.51	0.96	0.40	0.88	0.50	0.92	0.75	0.85
0.38	0.83	0.44	0.93	0.46	0.92	0.68	0.79
1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

FIGURE 15: SUMMARY OF THE BELIEF (BEL) AND PLAUSIBILITY (PL) FUNCTIONS COMPUTATIONS

The resulting data was further analyzed and modeled using Monte Carlo simulation in ((@RISK; the data is taken through a selected series of iterations, simulated possible outcomes and presenting in a model. The models (data fitted to cumulative distribution functions) and reports generated are outputted in a spreadsheet format. The solution spaces obtained in Figure 16 is considered to be aggregated, calibrated, and without any assumptions: the control cost parameters' uncertainty solution space for this study. The resulting ranges of these solution spaces were found to be fairly diminutive at a few 'error-states' (y-axis). The wider limits of uncertainty-values (x-axis) found at various error-state-values depict the error-states where uncertainty is greater.

Overlay graphs of the cost parameters uncertainty solution spaces for each expert's uncalibrated assignments were mapped against the controls; for both the ESAS and P-S CLV's (Figure 17 & 18). These graphs exhibited cost parameters uncertainty solution spaces for the three experts and were, in contrast to the control, not diminutive at any point. These wider limits of uncertainty depicted that the cost parameters' uncertainty was greater with respect to the experts' limits to that of the controls. One of the observations made is all three experts in both applications have cost parameters uncertainty solution spaces that encompassed the cost parameters uncertainty solution spaces of the control (above the plausibility limit and below the belief limit).

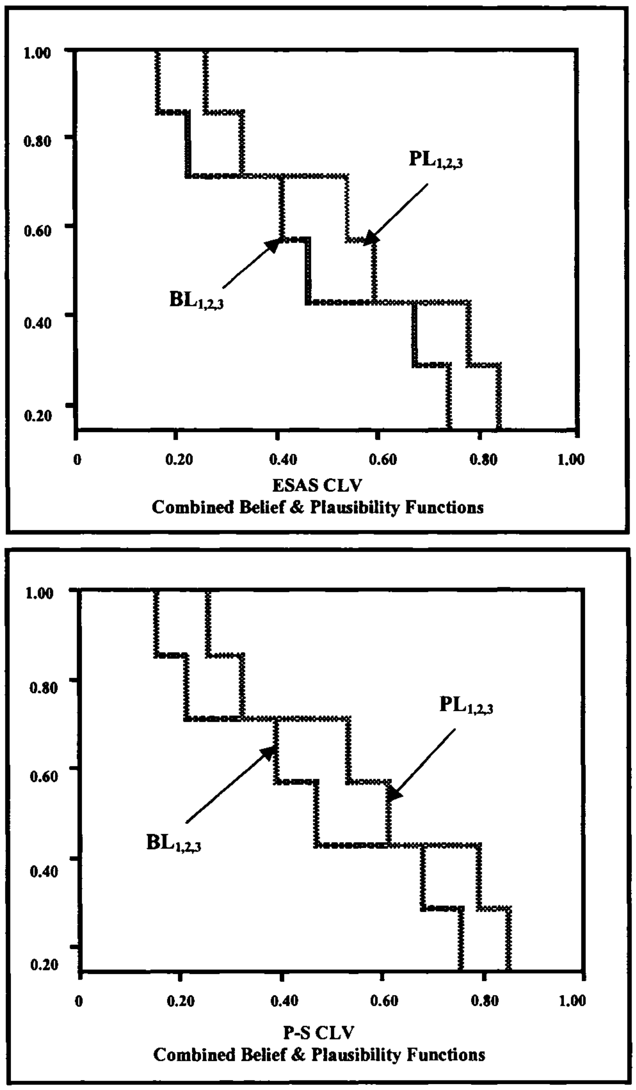


FIGURE 16: COMBINED BELIEF (BEL) AND PLAUSIBILITY (PL) FUNCTIONS FOR THE ESAS CLV & P-S CLV

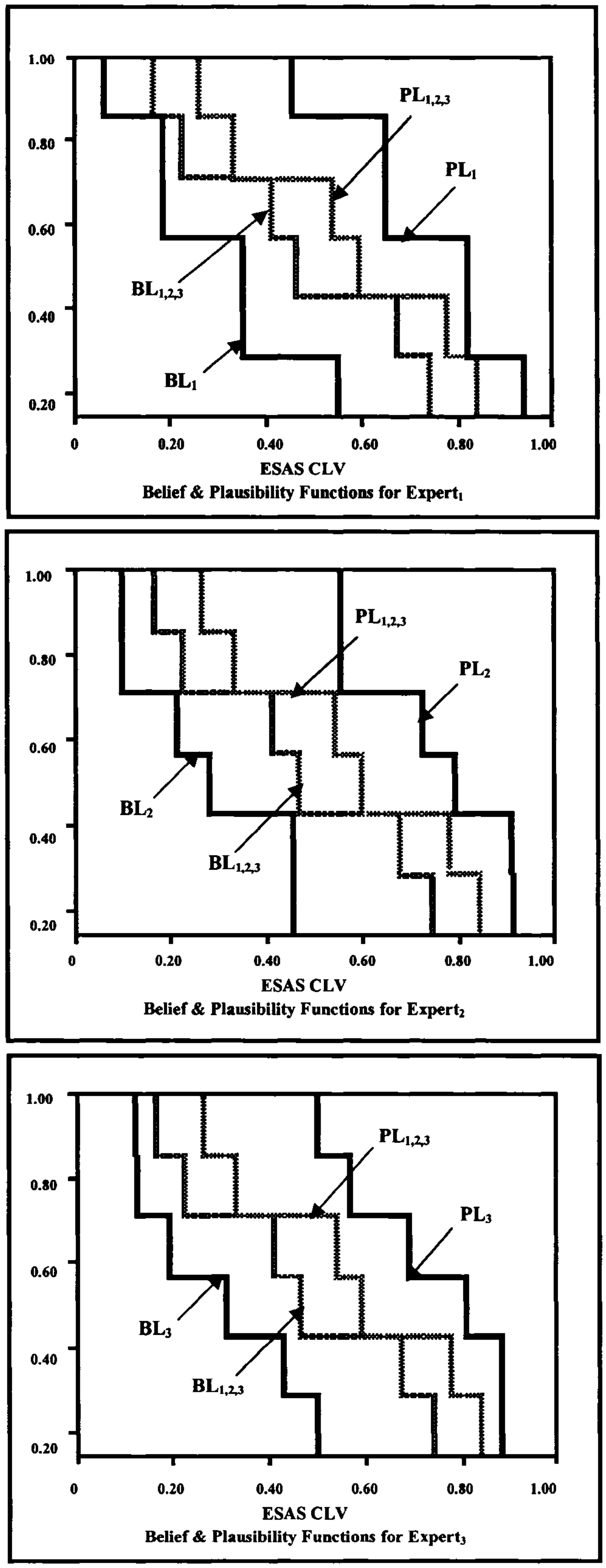


FIGURE 17: OVERLAY GRAPHS OF EXPERTS' UNCALIBRATED SOLUTION SPACE VS. THE CONTROL FOR THE ESAS CLV

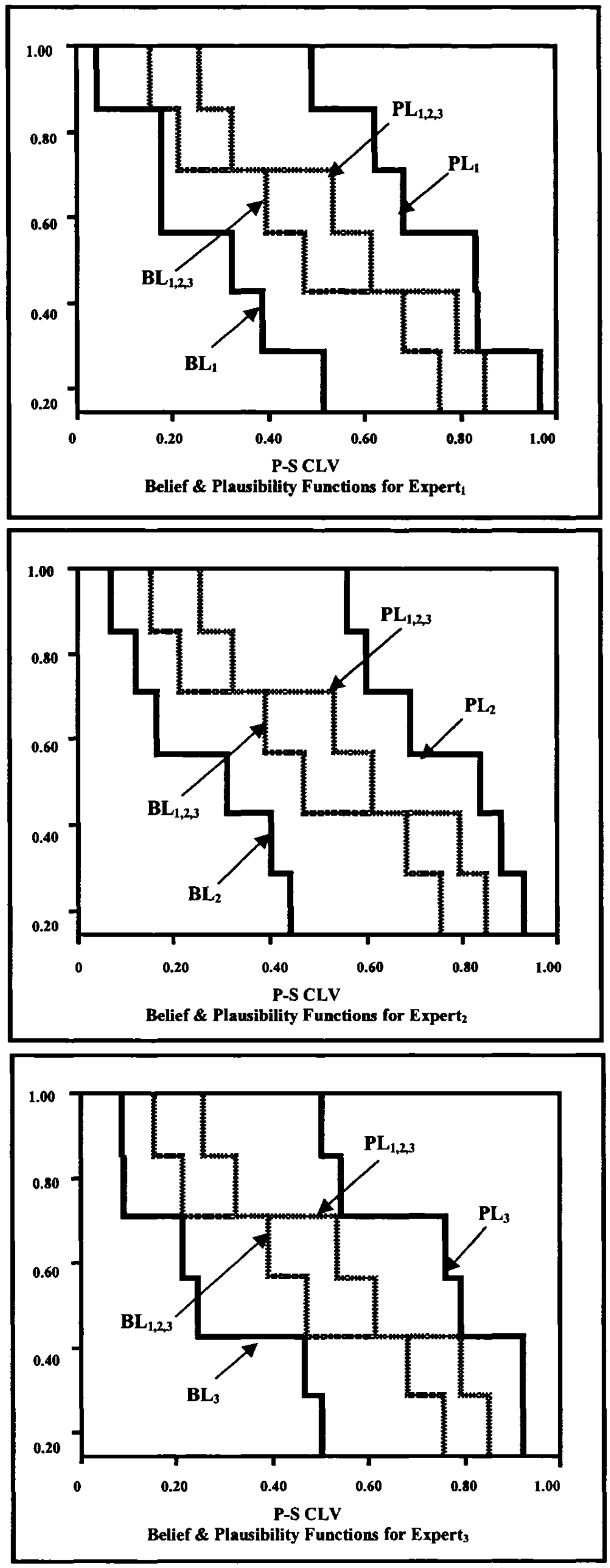


FIGURE 18: OVERLAY GRAPHS OF EXPERTS' UNCALIBRATED SOLUTION SPACE VS. THE CONTROL FOR THE P-S CLV

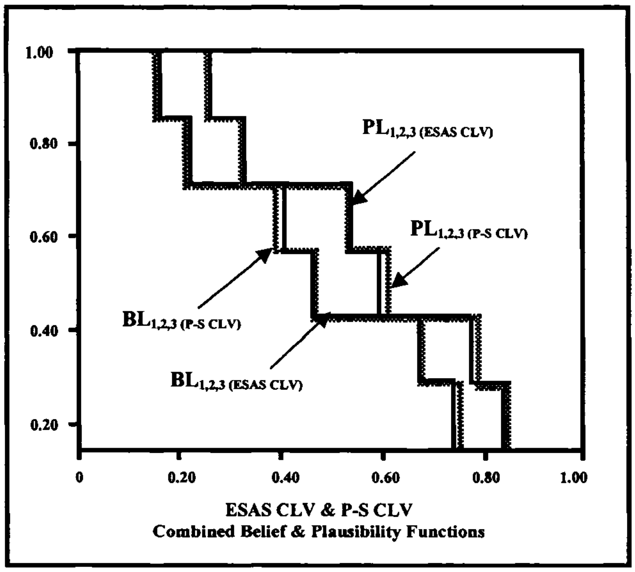


FIGURE 19: THE SOLUTION SPACE FOR THE COMBINED FUNCTIONS OF THE ESAS CLV AND THE P-S CLV COMPARED

Conducting a comparative analysis to identify if the level of cost parameters uncertainty changed as the designs mature, the cost parameters uncertainty solution spaces obtained for both Crew Launch Vehicle (CLV) designs were mapped against each other. The accompanying results are show in Figures 19 and 20. An observation was made that the solution spaces for the cost parameters uncertainty estimate for both the ESAS and P-S CLV's were fairly similar by the graphs showed both overlapping and interchanging limits at the various error-state-values. Analyzing each expert cost parameters uncertainty solution spaces for both applications plotted against each other, similar overlapping and interchanging limits observation were made. It is also noticeable that the ranges of each expert cost parameters uncertainty solution spaces varied when compared. However, further in-depth analysis was undertaken to clarify these observations and is discussed in the following section.

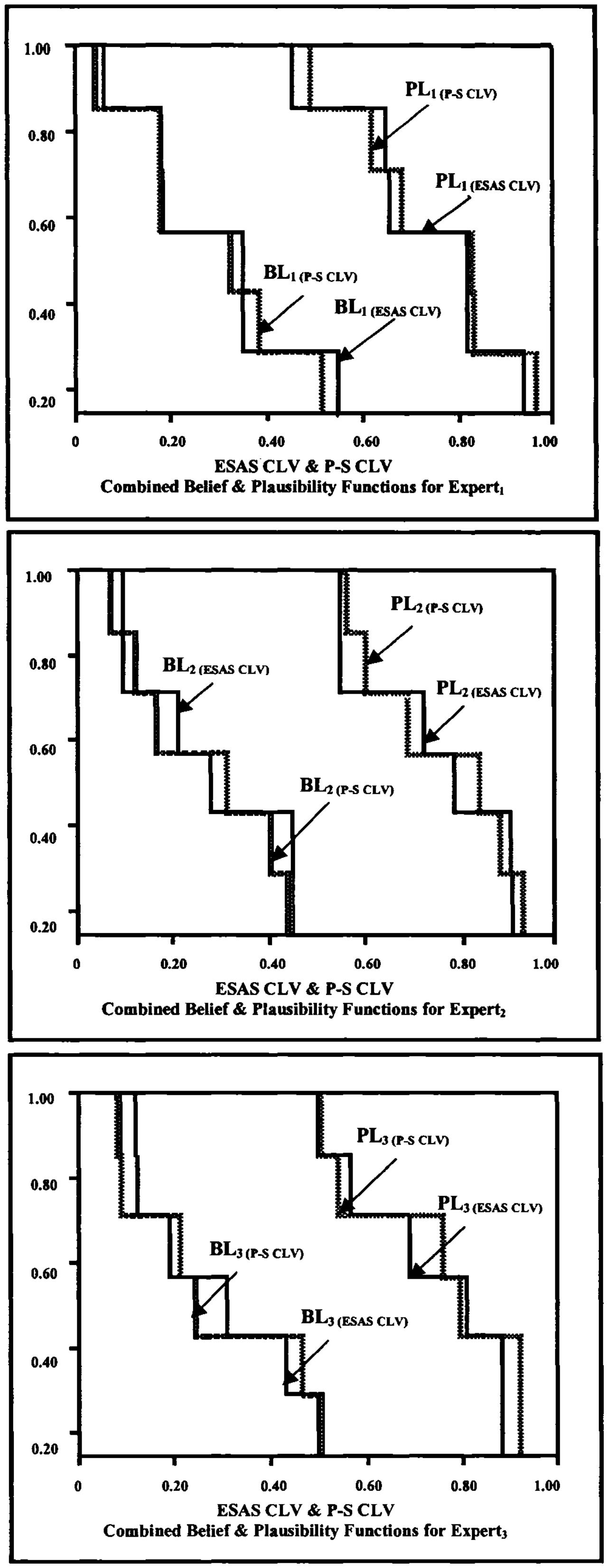


FIGURE 20: THE SOLUTION SPACE OF EXPERTS 1, 2 AND 3 FOR THE ESAS CLV AND THE P-S CLV COMPARED

CHAPTER V

DISCUSSION

OVERVIEW

The main purpose of this study is to provide an evidence based (non-probabilistic) approach for elucidating the estimation of uncertainty bias within High Consequence Conceptual Design Environments. The significance is to improve the quality of data obtained to support decision making in a real world setting. This is important for improving the quality of data, to better understand how experts structure problems and make judgments; how they weigh and combine different sources of information in making decisions; and how they conceptualize uncertainty.

In doing this, the proposed research question was: how do we effectively elucidate the extent of the estimation of uncertainty bias in High Consequence Conceptual Engineering Environment? This study was intended to provide an evidence-based approach to allow for this elucidation of the estimation of uncertainty bias when eliciting expert judgments within these environments.

From the literature, we can recall Henrion & Fishhoff (2002, p. 666) indicating that a "comprehensive assessment of uncertainty cannot rest solely on statistical analysis" (quantitatively) due to the presence of subjectivity in estimating uncertainty; subjective judgment is unavoidable in estimating uncertainty (Morgan & Henrion, 1990). In support, McNamara & Booker (2001) highlighted a few distinguishing features in their program for handling biases (qualitatively) which addresses this issue of subjectivity in uncertainty estimates.

This is the basis for contributions of this study to improve the quality of data obtain to support decision making in a real world setting. This is done by a developed, structured and methodological process for eliciting expert judgments in practice; i.e. the application in the aerospace industry, specifically Crew Launch Vehicles. This is in addition to the contribution of an evidence based (non-probabilistic) approach to risk analysis methods for elucidating the estimation of uncertainty bias within a related environment.

DISCUSSION

Real life situations and applications often have uncertainty with two or more dimensions and may have an uncertain number of events with associated values. These situations and applications may be suitably modeled using risk analysis. For this study, a risk analysis tool (@RISK) was used for this purpose.

The cost parameters uncertainty data obtained from the structured elicitation of experts at NASA Langley Research Center was transferred directly to MS Excel and @RISK spreadsheets by created links. The relevant belief and plausibility functions were modeled using Monte Carlo simulation in @RISK. This simulation involves repetitive recalculations "iteration". In each iteration:

- all distribution functions are sampled;
- sampled values are returned to the cells and formulas in the worksheet;
- the worksheet is recalculated; and
- values calculated for output cells are collected from the worksheet and stored.

This repetitive recalculation process can run hundreds or thousands of iterations if necessary. However, the iteration setting in this study was one hundred.

The models (data fitted to cumulative distribution functions) providing the upper and lower limits of the estimated cost parameters uncertainty defined the solution spaces for each expert and the experts combined respectively. This cost parameters data being considered as cumulative data is a set of (a,b) points that describe a continuous cumulative distribution function. To facilitate calculation of statistics and display graphs of this cumulative data, the input minimum and maximum points are explicitly defined (ie. the points with b=0 and b=1) in @RISK. The solution spaces obtained by combining all three experts' judgments were considered to be aggregated, calibrated, and without any assumptions; the control for this study. This control is the basis for developing reliability; i.e. to acquire and demonstrate logical consistency by having a reference for assessment the experts' bias of under or overestimation of uncertainty.

An absolute answer is not produced by @RISK, but rather identifies a distribution that most likely represents the input data. However, to best utilize these results, this discussion of the results from @RISK is evaluated both quantitatively and qualitatively (examining both the comparison graphs and the statistical fit results obtained).

Quantitatively

The estimation of cost parameters uncertainty solution space of the controls (Figure 16) was found to be fairly diminutive at a few 'error-states-values' (y-axis). This may be interpreted to be focal points at which the uncertainty estimates (x-axis) for the cost parameters are consistent; an outcome caused from the problem scenario making the associated errors explicit in these areas. The wider bounds of uncertainty estimates found at various error-state-values depict the error-states at which uncertainty estimates are greater and where most of the variation lies.

An analysis was done to identify the under or overestimation bias in the experts' judgments by mapping their uncalibrated belief and plausibility limits against the 'aggregated and calibrated' (control) limits for both CLV(s) respectively. These overlay graphs exhibited the estimation of cost parameters uncertainty solution spaces that were, in contrast to the controls, not diminutive at any point. Another observation made is all three experts in both applications have estimated cost parameters uncertainty solution spaces that encompassed the limits of the control (i.e. above the plausibility limit and below the belief limit). This is interpreted as experts' cost parameters uncertainty estimates generally increased in High Consequence Conceptual Engineering Environments. This is in contrast to the control which is 'aggregated', 'calibrated', and 'without any assumptions' bases on the theoretical grounding of Yager's rule for combining evidence. Therefore, it was concluded that there is more estimation of uncertainty bias present than being anticipated.

Examining further, the estimated cost parameters uncertainty solution spaces for both Crew Launch Vehicle (CLV) designs were mapped against each other; accompanying graphs are show in Figures 19 and 20. It was recognized that these solution spaces for both the ESAS and P-S CLV's were fairly similar. In addition, the graphs showed both overlapping and interchanging limits at the various error-state-values. Analyzing each expert solution spaces for both applications plotted against each other, a similar overlapping and interchanging limits conclusion was made. This indicated that comparing the two designs', the estimation of uncertainty bias ranges at a specified error-states may be greater than the others depending on that error-state-value. However, further in-depth analyses were undertaken to elucidate these overlapping and interchanging limits at the various error-state-values, and the variation noticed in the comparison of each expert's estimation of cost parameters uncertainty solution spaces.

Qualitatively

Non-parametric statistics is concerned with non-parametric statistical models and non-parametric statistic tests. The difference between non-parametric and parametric models is that 'the model structures are not specified by a priori but is instead determined from data'. The Fit Summary resulting statistics and test results from @RISK measured how well the models fits the input data and the confidence level that can be placed on these models. Of the three main inferential statistical methods @RISK performs, the Anderson-Darling (A-D) test, Chi-square (Chi-sq) test, and the Kolmogorov-Smimov (K-S) test, this study emphasized the K-S test as the basis for further analyses.

Exploration Systems Architecture Study Crew Launch Vehicle

	K-S- Test Values (Expon.)		
	BEL	PL	Range
Expert $_1$	0.260	0.401	0.141
Expert $_2$	0.192	0.306	0.114
Expert $_3$	0.164	0.307	0.143
Combined	0.279	0.316	0.037

Parallel-Staged Crew Launch Vehicle

	K-S- Test Values (Expon.)		
	BEL	PL	Range
Expert $_1$	0.273	0.311	0.038
Expert $_2$	0.196	0.321	0.125
Expert $_3$	0.198	0.377	0.179
Combined	0.260	0.306	0.046

FIGURE 21: THE KS-TEST RESULTING VALUES FOR EACH EXPERT AND EXPERTS COMBINED.

The focus of the K-S test is to determine the differences in two datasets. It has the advantage of making no assumption about the distribution of data; i.e. it is non-parametric and distribution free. Making the assumption of normal data, this enabled the viewing of the data graphically which helped to understand and interoperate the data. The K-S test results produced are shown in Figure 21. The estimation of cost parameters uncertainty values of Expert$_1$, Expert$_2$, Expert$_3$, and all three combined were plotted individually with respect to both CLV(s). The resulting graphs are shown in Figure 22.

Accessing this estimation of uncertainty ranges for the ESAS CLV, the values are 0.141 for Expert$_1$, 0.114 for Expert$_2$, 0.143 for Expert$_3$, and 0.037 for the control (experts combined). The graphical representations showed that Expert$_1$ range incorporated that of

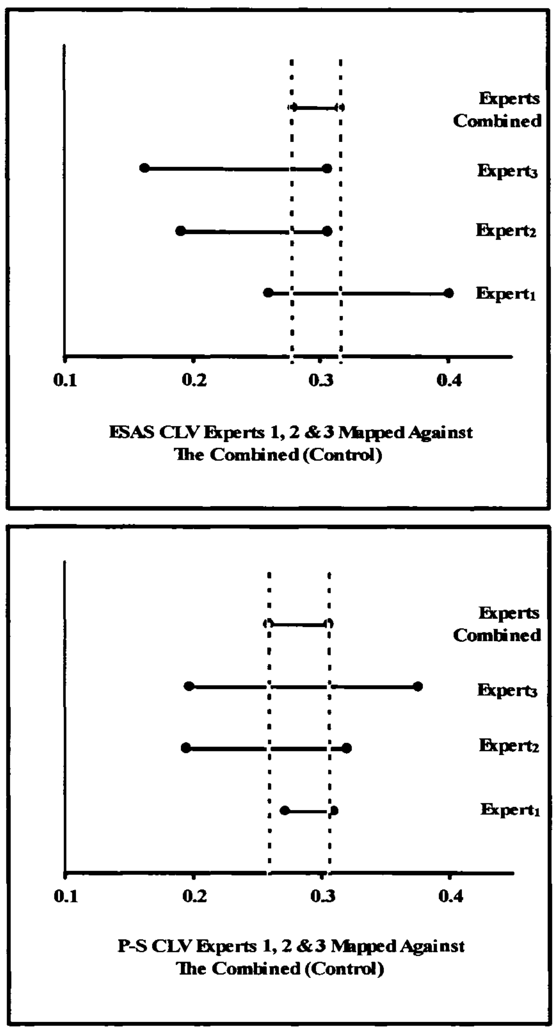


FIGURE 22: GRAPHS OF THE KS-TEST RESULTING VALUES FOR EACH EXPERT AND EXPERTS COMBINED

the control (identified the total range of estimated cost parameters uncertainty). This expert's estimated uncertainty range however, shifted further towards the plausibility limit (right) of this control signifying a perception of an overestimation bias. $Expert_2$ and $Expert_3$, incorporated only a fraction of the control range (i.e. identified only a fraction of

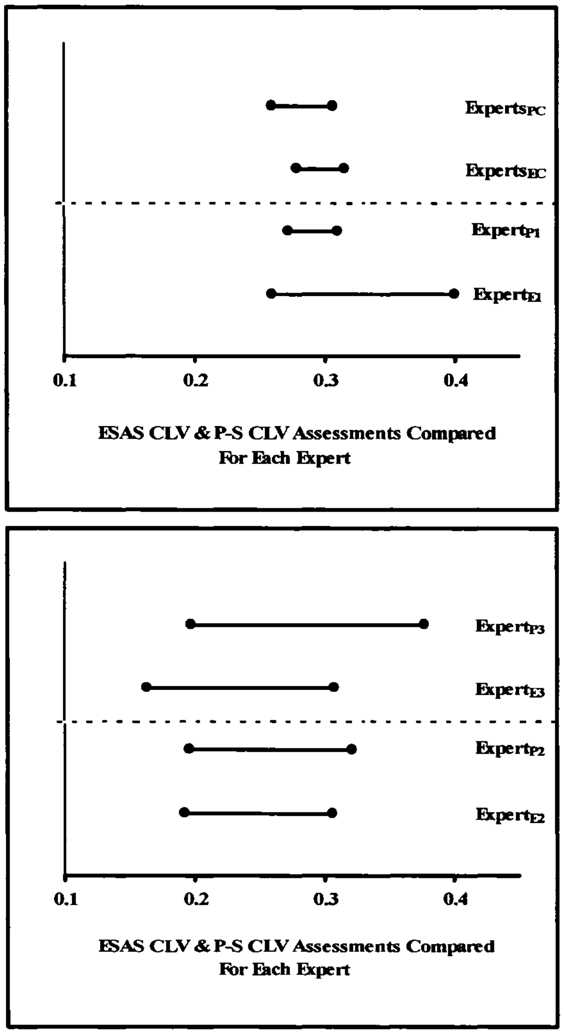


FIGURE 23: GRAPHS OF THE KS-TEST RESULTING VALUES FOR EACH EXPERT COMPARED FOR THE EASA & P-S CLV(S)

the associated estimated cost parameters uncertainty) and shifted towards the belief limits (left) of this control signifying a perception of an underestimation bias. It is noted that $Expert_2$ has a smaller range of 0.114 compared to $Expert_3$'s range of 0.143 although they appear to take the same fraction of the associated estimated cost parameters uncertainty. It is thus presumed that $Expert_3$ underestimation bias is greater than $Expert_2$.

Accessing each expert and experts combined for the P-S CLV, the range values are 0.038 for $Expert_1$, 0.125 for $Expert_2$, 0.179 for $Expert_3$, and 0.046 for the control. The graphical representations showed that $Expert_1$, unlike the ESAS CLV, the estimation of uncertainty range incorporated only a fraction of the control range. In addition, it is shown that $Expert_1$'s range (0.038) was less than that of the control range (0.046). Therefore, for the P-S CLV, the range of the estimated cost parameters uncertainty for $Expert_1$ was underestimated. However, it is important to note that this expert's estimation of uncertainty range shifted further towards and outside of the plausibility limit (right) of this control signifying a perception of an overestimation bias. This can be interpreted that this Expert by character exhibits an overestimation bias for cost parameters uncertainty but in this particular application the range of cost parameters uncertainty was underestimated.

$Expert_2$ and $Expert_3$, both in this case, incorporated the control range (i.e. identified the full range of estimated cost parameters uncertainty). $Expert_2$'s estimated of uncertainty range shifted towards and outside of the belief limits (left) of this control signifying a perception of an underestimation bias. $Expert_3$'s uncertainty range shifted further outside of the plausibility limits (right) compared to the portion outside of the belief limits (left), although by a minimal quantity, signifying a perception of an overestimation bias. Again $Expert_2$ had a smaller estimated cost parameters uncertainty range of 0.125 compared to $Expert_3$'s range of 0.179. It is thus presumed that $Expert_3$ underestimation bias is greater than $Expert_2$.

Focusing on the experts' comparison Graphs of the KS-test resulting, values (Figure 23) for the EASA & P-S CLV(s), the P-S CLV estimated cost parameters uncertainty ranges were greater than the ESAS CLV by 0.0111, 0.036 and 0.0094 for $Expert_2$, $Expert_3$, and the control respectively. Conversely, the estimated cost parameters uncertainty range for $Expert_1$ was much greater for the ESAS CLV than that of the P-S CLV by 0.1023. Expounding, the control range of estimated cost parameters uncertainty generally increased for the P-S CLV when compared to the ESAS CLV, with shifts indicating an overall tendency for an underestimated uncertainty bias of the associated cost parameters. $Expert_2$'s and $Expert_3$'s ranges of estimated cost parameters uncertainty increased for the P-S CLV and asserted shifts that indicates the tendency for these experts to display the overestimation uncertainty bias of the cost parameters in relation to the ESAS CLV. Uniquely, $Expert_1$'s range of estimated cost parameters uncertainty decreased for the P-S CLV and with this estimated cost parameter uncertainty range being underestimation. However, this expert asserted a shift indicating the tendency of the overestimation uncertainty bias for cost parameters in relation to the ESAS CLV.

CHAPTER VI

CONCLUSIONS

IN GENERAL

This study presented an approach that sought to identify cognitive bias in expert judgment elicitation to improve the quality of elicited data for uncertainty assessment. This was done by a developed, structured and methodological process for eliciting expert judgments in practice (i.e. the application in the aerospace industry, specifically Crew Launch Vehicles), in addition to the contribution of an evidence based (non-probabilistic) approach to risk analysis methods for elucidating the estimation of uncertainty bias within this environment. The results were also evaluated quantitatively and qualitatively (by modeling and statistical fit results). A further investigation was done to elucidate the level of estimated cost parameters uncertainty bias changed as conceptual designs mature.

The estimated cost parameters uncertainty solution spaces of the controls were fairly diminutive at a few error-states-values (y-axis), and wider at others. This concluded that in cost parameters uncertainty estimation there are focal points at which the body of evidence is consistent and at which the associated uncertainty bias was explicit. Conversely, the wider estimated cost parameters uncertainty solution spaces depict the error-states at which cost parameters uncertainty is greater and where most of the variation lies (the estimation of uncertainty bias was implicit). The experts' estimated cost parameters uncertainty solution spaces for the overlay graphs were not diminutive at any point and encompassed the limits of the controls in both applications. This was interpreted as the limits placed on cost parameters estimation of uncertainty bias in High

Consequence Conceptual Engineering Environments tended to increase thus concluded that there is more estimation of uncertainty bias present than what is being anticipated.

Further examination by comparing the control and each expert's solution spaces reveal that there were overlapping and interchanging limits at various error-state-values indicating that estimated cost parameters uncertainty is greater than others at different error-state even as the design matures. Further in-depth analyses were undertaken to elucidate these overlapping and interchanging limits and the variation noticed in the comparison of each experts' cost parameters uncertainty solution space by evaluating the Fit Summary results.

From the Fit Summary resulting statistics and the K-S test, $Expert_1$, $Expert_2$, $Expert_3$ and all three combined solution spaces were plotted individually with respect to the both CLV(s). $Expert_1$, $Expert_2$ and the combined estimated cost parameters uncertainty ranges increased for the P-S CLV when compared to the ESAS CLV. $Expert_1$, unlike the other experts' ranges, had estimated cost parameters uncertainty range that decreased. However, a shift of the limits for this expert towards the plausibility limit identified this expert as having the tendency to display the overestimation of uncertainty bias for cost parameters. A shift for $Experts_2$ and $Expert_3$ also indicated the tendency to also display the overestimation of uncertainty bias for cost parameters. Therefore, an overall conclusion was drawn that in a High Consequence Conceptual Engineering Environment, there tends to be the overestimation of uncertainty bias present for cost parameters.

This evidence based approach concluded that, in elucidation the estimation of uncertainty bias for cost parameters, uncertainty is not specifically over or under estimated in High Consequence Conceptual Engineering Environments. Rather, the limits placed around the uncertainty increases, indicating that there is more estimation of uncertainty bias present than what is being anticipated. From the perspective of maturing designs, it was concluded that when elucidating the estimation of cost parameters uncertainty at different error-state-values, it was interchangeably larger or smaller when compared to each other even as the design matures.

RELIABILITY AND VALIDITY

Reliability and validity typically determine the quality of a study. Traditionally, reliability and validity are concepts in classical test theory. "A reliable measure is measuring something consistently, while a valid measure is measuring what it is supposed to measure" (Wikipedia, 2006). In accessing the reliability and validity in this study, research findings presented by Bolger & Wright in 1992 were employed. They identified that to ideally know if a judgment is externally valid ("which deals with the ability of a study's results to generalize" (Wikipedia, 2006)), it is necessary to evaluate against an external, objective criterion ("gold standard" (Bolger & Wright, 1992, p. 48)).

Reliability

As indicated earlier, it is necessary to evaluate against an external, objective criterion ("gold standard" (Bolger & Wright, 1992, p. 48)). However, because this "gold standard" is not available where expert judgments is most valued, such as the environments of this study, it is usually possible to assess judgment in terms of its reliability which may be "intrajudge reliability over time (consistency), interjudge reliability (consensus), or logical consistency (coherence)" (ibid., p. 48).

Logical consistency (coherence) was identified as a realistic measure to aide validating the effectiveness of this methodology. The structured and methodological elicitation process developed and adapted was developed on a premise that included consideration of this measure. This methodological process is a step closer to assist in the repeatability of the process. In the mathematical analysis, as identified earlier, one of the reasons for selecting Yager's combination rule was its ability to address the issue of counter-intuitive results and also being considered to be the most prominent of the class of unbiased operators developed (Yager, 1987). This rule thus is considered an epistemologically honest interpretation of evidence that does not change the evidence by normalizing out the conflict and thus aides in coherence of mathematical operations.

In further assessing the judgments' reliability, there are three major questions put forth by Bolger & Wright (1992) that adequately address reliability (pp. 70-71):

- Who is truly an expert?
- How accurate and reliable is expert judgment?
- Can anything be done to assure the quality of judgment?

Focusing on these questions, reliability is additionally addressed in this study by:

Who is truly an expert? – The literature indicated that the true expert is one that "demonstrates significantly more valid judgments" than one not accredited by expertise. In this study, the accreditation of expertise is addressed by the criteria as detailed earlier. By identifying and implementing the appropriate characteristics and criteria, these high consequence/risk experts selected as having the expertise within the context of this study; this qualification of the experts increases the level of coherence in the judgments obtained.

How accurate and reliable is expert judgment? - Experts being qualified and having the expertise, and their performance being assessed in a more "ecologically valid" manner ("the methods, material and setting of the experiment approximating the real-life situation" (Wikipedia, 2006) as in the context of this study), according to the literature, the expert judgments is considered highly reliable and accurate.

Can anything be done to assure the quality of judgment? - The developed structure methodological process incorporated bias handling techniques as presented by previous researchers as seen in the literature review. Highlighting one of the more relevant techniques, the experts were allowed to disaggregate selected questions and to provide more specific responses to these disaggregates; i.e. encouraging the experts to decompose the questions in their own way. These derived decompositions can be combined mechanically if "incoherence is suspected" (Bolger & Wright, 1992, p. 69). This corresponds to one of Bolger & Wright's proposed steps to reduce the potential for poor reliability.

Validity

Validity refers to getting results that accurately reflect the concept being measured and is defined in many ways. In psychometrics, criterion validity is 'to correlate measures with a criterion measure known to be valid' (Wikipedia, 2006). Concurrent validity is where the criterion measure relates to a measure of other concrete criteria assessed simultaneously; i.e. a test correlates well with a measure that has previously been validated (ibid.).

One of the motivation and foundation for this study stems from that of Monroe (1997) where he developed, refined and demonstrated a synthesized methodology for eliciting expert judgment. His methodology evolved through several iterations and was provided ample feedback from the 'boarder domain of conceptual design, high consequence engineering experts' (from five organizations - Boeing, Northrup Grumman, NASA LaRC, NASA Johnson Space Center, and the Naval Air Systems Command (NAVAIR)) to institute validity. In addition, excerpting a similar viewpoint that was presented by Clemen and Winker (1997), ["bases on previously developed and proven assessment techniques"], the methodology for this study encompasses a multitude of features that are contained in Monroe's synthesized methodology. It ensured that the grounding philosophies were enforced in all modifications of the questionnaire and in the associated application environment. Therefore, concurrent validity may be asserted by the correlation to this synthesized methodology.

Examining construct validity; where an investigator examines whether a measure is related to other variables as required by theory and whether the unnoticeable organization entity participants in a particular culture that agree to follow certain conventional rules (Wikipedia, 2006). This study enforced a meticulous selection process for the experts, and performed a structured and methodological elicitation process substantiated by and ensured the requirements by theory including:

- appropriate integration of bias handling techniques to obtain this modification framework;
- a pilot tests of the questions conducted on the lead expert and refined in terms of the culture agreeing to 'certain conventional rules' required in the conceptual design environments;
- the lead expert assisted in eliciting and documenting the experts' judgments along

with any additional information expressed by the expert relevant to the questions as required by theory;

- the information compiled and fed back to the experts for review and updating with additional information if needed, ensured the relationship of the respective cost parameters, and all assumption clarified etc. to obtain full understanding.

Feedback was obtained from the expert in reference to: (1) the userfriendliness and the ease of interpretating of the questionnaire, and (2) the usefulness and adaptability to the applications. The lead expert expressed a unitary response indicating that the methodology, inclusive of the questionnaire, was effective in terms of these qualities. It was also indicated that this methodology, having the ability to be developed into an automated (software or software like) instrument with the appropriate algorithms, would be of great value to, not only conceptual design enviroments, but also in environments in which expert judgments are used.

Limitations & Suggestions For Future Research

There are various limitations that that can be anticipated based on the literature. Within the context of this research, some of these limitations also apply. The first is the test application of this methodology will be on an average size application. The adaptability of this methodology to larger and more complex applications, depending of the situation, may be much more challenging and the effectiveness may be reduced.

There is a limitation to the availability of high risk experts. This is due to the uniqueness of conceptual CLV designs (the high consequence environment for application of this methodology) and the specific knowledge required in performing a CLV analysis that heavily constrains the acceptable population (Chytka, 2003).

There potential implications to the appropriateness and number of experts identified on the reliability and validity of the study. However, although the reliability and validity can be supported and justified, there is also some limitation in respect to that of real-world results. This is due to the conceptual nature of this environment; i.e. cannot be verified conclusively until and unless the design in question is built.

Many researchers have difficulty in accepting the fact that in domains such as in this study (a conceptual CLV design environment) exists and do not have precise and complete information, thus find it hard to give credibility to research based on subjective data (Chytka, 2003). However, qualitative expert judgment can be quantified and also be considered as data (subjective) (Booker et al., 2003), and is as credible with the same rigors of proving traceability and dependability (ibid.).

The modification of the questionnaire is also a possible limitation. Although a validated instrument was adapted from Monroe (1997), modification to elicit information of evidence was not validated with such rigor as Monroe's. However, this was addressed by ensuring that the grounding philosophies of his methodology were enforced in the modifications.

There is various extension of this study that could be pursed. However, only a few are set forth in this document. This methodology could be applied on a larger and more complex application to identify the challenges faced and its effectiveness. This could be facilitated by the development of the appropriate algorithms; i.e. a logical sequence of steps for solving a problem, often written out as a flow chart that can be translated into a computer program (Wikipedia, 2006) - to increase utility and reliability.

An investigation in a more extensive and rigorous approach for validation could be undertaken to address non-probabilistic studies in 'High Consequence Conceptual Engineering Environments'. In addition, this study obtained a solution space by combining all three experts' judgments, and was used as the control/reference for assessing the over or under estimation of the experts' uncertainty. Is this control/reference a "true" measure for developing reliability and/or validity?

The Calibration Co-efficient (CC) calculations in this study used an arbitrary constant "A_I" that was set initially at 1. This arbitrary constant "A_I" was used to aide calibration, augmenting reliability among multiple experts, when the same questionnaire is used for the elicitation. This arbitrary constant could be substituted with a weighting factor for each expert. Therefore, an extension to this research that would provide reinforcement is to identify an approach to recognize the true "high-risk" experts. This would facilitate the weight factor assignment for each expert to produce a more factual calibration factor.

REFERENCES

Aase, K. & Nybø, G. (2002). Organizational Knowledge in High-Risk Industries: What are the Alternatives to Model-Based Learning Approaches? *Proceedings of the Third European Conference on Organizational Knowledge, Learning, and Capabilities, April 5-6, 2002.* Athens.

Althaus, C. E. (2005). A Disciplinary Perspective on the Epistemological Status of Risk. *Risk Analysis*, 25 (3), pp. 567-588.

Armor, D. A., & Taylor, S. E. (2002). When Predictions Fail: The Dilemma of Unrealistic Optimism. In Gilovich, T., Griffin, D., & Kahneman D. (Eds.), *Heuristics and Biases: The Psychology of Intuitive Judgment* (pp. 334-347). Cambridge, UK: Cambridge University Press.

Aven, T., & Kristensen, V. (2005). Perspectives on Risk: Review and Discussion of the Basis for Establishing a Unified and Holistic Approach. *Reliability Engineering and System Safety.* 90, pp. 1-14.

Ayyub, B. (2001). *Elicitation of Expert Opinions for Uncertainty and Risks*. Boca Raton, FL: CRC Press.

Bae, H, & Grandhi, R. V. (2003). Uncertainty Quantification of Structural Response Using Evidence Theory, *American Institute of Aeronautics and Astronautics Journal*, October, 41 (10), pp. 2062-2068.

Bar-Hillel, M. (1973). On the Subjective Probability of Compound Events. *Organizational Behavior and Human Performance*, 9, pp. 396-406.

Bolger, F., & Wright G. (1992). Reliability and Validity in Expert Judgment. Cited In: Wright G., & Bolger, F (Eds.) *Expertise and Decision Support*. Plenum Press, New York and London.

Booker, J. M., Anderson, M. C., & Meyer, M. A. (2004). The Role of Expert Knowledge in Uncertainty Quantification: Are We Adding More Uncertainty or More Understanding? *Los Alamos National Laboratory*, pp. 1-7.

Booker, J. M., Bement, T. R., Meyer, M. A., & Kerscher, W. J. (2003). PREDICT: A New Approach to Product Development and Lifetime Assessment Using Information Integration Technology. *Handbook of Statistics: Statistics in Industry* 22 (11), May, pp. 1-31. Los Alamos National Laboratory report, LA-UR-00-4737.

Booker, J. M., & McNamara, L. A. (2003). Solving Black Box Computation Problems Using Expert Knowledge Theory and Methods. *Reliability Engineering and System Safety, Special Issue: Epistemic Uncertainty Workshop,* June, 1-25. Los Alamos National Laboratory report, LA-UR-03-3840.

Booker, J. M. & M,cNamara, L. A. (2004a). Solving Black Box Computation Problems Using Expert Knowledge Theory and Methods. *Reliability Engineering and System Safety*, 85, pp. 331–340.

Booker, J. M., & McNamara, L. A. (2004b). Expert Knowledge in Reliability Characterization: A Rigorous Approach to Eliciting, Documenting, and Analyzing Expert Knowledge. In: Nikolaidis, E., D. M. Ghiocel, & S. Singhal. (Eds.) *Engineering Design Reliability Handbook*, CRC Press, pp. 13-1 to 13-31.

Booker, J. M., & Meyer, M. A. (1996). Elicitation and Analysis of Expert Judgment. *Encyclopedia of Statistical Sciences*, pp. 1-4. Los Alamos National Laboratory report, LA-UR-99-1659.

Boose, J. H. & Gaines, B. R. (1988). Knowledge Acquisition for Knowledge-Based Systems: AAAI-88 Tutorial Notes. Cited in: Meyer, M.A., & Booker, J.M. (Eds.). *Eliciting and Analyzing Expert Judgment: A Practical Guide.* Society for Industrial and Applied Mathematics/American Statistical Association. Philadelphia, PA.

Boose, J. H. & Shaw, M. (1989). Knowledge Acquisition for Knowledge-Based Systems: AAAI-89 Tutorial Notes. Cited in: Meyer, M.A., & Booker, J.M. (2001). *Eliciting and Analyzing Expert Judgment: A Practical Guide.* Society for Industrial and Applied Mathematics/American Statistical Association. Philadelphia, PA.

Chytka, T. M. (2003). *Development of an Aggregation Methodology for Risk Analysis in Aerospace Conceptual Vehicle Design.* Ph.D. Dissertation, Old Dominion University, Norfolk, VA. U.M.I.

Cleaves, D. A. (1986). Cognitive Biases and Corrective Techniques: Proposals for Improving Elicitation Procedures fro Knowledge-Base Systems. *Proceedings from the AAAI Sponsored 2nd Annual Knowledge Acquisition for Knowledge-Based Systems Workshop*, Banff, Canada, pp. 9-0 to 9-11.

Clemen, R. T., & Winkler, R. L. (1997). Combining Probability Distributions from Expert in Risk Analysis. Cited In: Chytka, T. M. (2003). *Development of an Aggregation Methodology for Risk Analysis in Aerospace Conceptual Vehicle Design.* Ph.D. Dissertation, Old Dominion University, Norfolk, VA. U.M.I.

Conway, B. A. (2003). *Calibrating Expert Assessment of Advance Areospace Technology Adoption Impact.* Ph.D. Dissertation, Old Dominion University, Norfolk, VA. U.M.I.

Cook, R. M., (1991). *Experts in Uncertainty.* New York: Oxford University Press.

Cooke, R. M., Goossens, L. H. J. (2004). Expert Judgement Elicitation for Risk Assessments of Critical Infrastructures. *Journal of Risk Research*, 7 (6), pp. 643-656.

Crawford, J. D., & Stankov, L. (1996). Age Differences in The Realism of Confidence Judgements: A Calibration Study Using Tests of Fluid and Crystallized. Cited in: Conway, B. A. (2003). *Calibrating Expert Assessment of Advance Areospace Technology Adoption Impact*. Ph.D. Dissertation, Old Dominion University, Norfolk, VA. U.M.I.

Cvetkovich,G. & Lofstedt, R. E. (1999). Social Trust and the Management of Risk. London: Earthscan Publications Ltd. Cited In: Althaus, C. E. (2005). A Disciplinary Perspective on the Epistemological Status of Risk. *Risk Analysis*, 25 (3), pp. 567-588.

Dalkey, N. C. (1969). *The Delphi Method: An Experimental Study of Group Opinion*. Santa Monica, CA: RAND Corporation.

Dezert J., (2002). Foundations for a New Theory of Plausible and Paradoxical Reasoning. *Information and Security Journal*, Edited by Tz. Semerdjiev, ProCon Ltd., Sofia, Bulgaria, 9, pp. 13-57.

Dubois D., & Prade, H., (1988). Representation and Combination of Uncertainty with Belief Functions and Possibility Measures. *Computational Intelligence*, 4, pp.244-264.

Dietrich, R. & Childress, T. M. (2004). *Group Interaction in High Risk Environments*. MPG Books Ltd., Bodmin, Cornwall.

Du, X. & Chen, W. (1999). An Integrated Methodology for Uncertainty Propagation and Management in Simulation Based Systems Design. American Institute of Aeronautics and Astronautics Journal, July.

Gigerenzer, G. (2003). The Irrationality Paradox. In Krueger, J. (Ed.), Towards a Balanced Social Psychology: Causes, Consequences and Cures for the Problem-Seeking Approach to Social Behavior and Cognition. (pp. 62-67) To be published in *Behavioral and Brain Sciences* (in press) Cambridge University Press.

Gigerenzer, G., & Fiedler, K. (2003). *Minds in Environments: The Potential of an Ecological Approach to Cognition*. Manuscript submitted for publication.

Gilovich, T., Griffin, D., & Kahneman, D. (Eds.). (2002). *Heuristics and Biases: The Psychology of Intuitive Judgment*. Cambridge University Press, Cambridge.

Gustafson, D. H., Shukla, R. K., Delbecq, A., & Walster, G. W. (1973). A Comparative Study of Differences in Subjective Likelihood Estimates Made by Individuals, Interactive Groups, Delhi Groups, and Nominal Groups. *Organizational Behavior and Human Performance*, 9, pp. 200-291.

Hammond, K. R., Hamm, R. M., Grassia, J., & Pearson, T. (1987). *IEEE Transactions on Systems, Man, and Cybernetics*, SMC-17 (5), pp.753-770.

Hammond, K. R. (2000). *Judgment under Stress*. New York: Oxford University Press.

Hampton, K. R. (2001). *An Integrated Risk Analysis Methodology in a Multidisciplinary Design Environment*. Ph.D. Dissertation, Old Dominion University, Norfolk, VA. U.M.I.

Hawkins, S. A., & Hastie, R. (1990). Hindsight: Biases Judgment of Past Events after Outcomes are Known. *Psychological Bulletin*, 107, pp. 311-327.

Henrion, M., & Fishhoff, B. (2002). Assessing Uncertainty in Physical Constants. In: Gilovich, T., Griffin, D., & Kahneman, D. (Eds.), *Heuristics and Biases: The Psychology of Intuitive Judgment*. Cambridge University Press, Cambridge.

Hogarth, R. M. (1990). Decision-Making under Uncertainty: The Effects of Role and Amiguity. Cited In: Chytka, T. M. (2003). *Development of an Aggregation Methodology for Risk Analysis in Aerospace Conceptual Vehicle Design*. Ph.D. Dissertation, Old Dominion University, Norfolk, VA. U.M.I.

Hood, C., & Jones, D. K. (1996). Accident and Design: Contemporary Debates in Risk Management. Cited In: Althaus, C. E. (2005). A Disciplinary Perspective on the Epistemological Status of Risk. *Risk Analysis*, 25 (3), pp. 567-588.

Hoch, S. J. (1984). Availability and Inference in Predictive Judgment. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 10, pp. 649-662.

Hora, S. C., & Iman, R. L. (1989). Expert Opinion in Risk Analysis: The NUREG 1150 Methodology. *Nuclear Science and Engineering*, 102 (4), pp. 323–31.

James, L., Demaree, R. D., & Wolf G. (1984). Estimating Within-Group Interrater Reliability With and Without Response Bias. *Journal of Applied Psychology*, 69 (1), pp. 85-98.

Joffe, H. (1999). Risk and "The Other." In: Althaus, C. E. (2005). A Disciplinary Perspective on the Epistemological Status of Risk. *Risk Analysis*, 25 (3), pp. 567-588.

Kahneman, D., Slovic, P., & Tversky, A. (Eds.). (1982). *Judgment under Uncertainty: Heuristics and Biases*. Cambridge University Press, Cambridge.

Kahneman, D., & Tversky, A. (1972). Subjective Probability: A Judgment of Representativeness. *Cognitive Psychology*, 3, pp. 430-454.

Keeney, R. L., & Von Windterfeldt, D. (1989). On the Uses of Expert Judgment on Complex Technical Problems, *IEEE Transactions on Engineering Management*, 36 (2), pp. 83-86.

Keeney, R. L., & Von Windterfeldt, D. (1991). Eliciting Probabilities from Experts in Complex Technical Problems, *IEEE Transactions on Engineering Management*, 38 (3), pp. 191-201.

Klir, G. (2004). Generalized Information Theory: Aims, Results, and Open Problems. *Reliability Engineering and System Safety*, 85, pp. 21-38.

Klir, G. & Folger, T. (1988). *Fuzzy Sets, Uncertainty, and Information*. Prentice Hall, Englewood Cliffs, NJ.

Knight, F. (1921). Risk, Uncertainty and Profit. Boston: Houghton Mifflin Company. Cited In: Althaus, C. E. (2005). A Disciplinary Perspective on the Epistemological Status of Risk. *Risk Analysis*, 25 (3), pp. 567-588.

Kogan, N., & Wallach, M. A. (1964). Risk Taking: A Study in Cognition and Personality. Cited In: Althaus, C. E. (2005). A Disciplinary Perspective on the Epistemological Status of Risk. *Risk Analysis*, 25 (3), pp. 567-588.

Linstone, H. A., & Turot, M. (1975). *The Delphi Method, Technique and Applications*. Addison Wesley, MA.

Lock, A. (1987). Integrating Group Judgments in Subjective Forecasts. In *Judgmental Forecasting*, Wright, G., & P. Ayton (Eds.). John Wiley and Sons: Chichester.

Lupton, D. (1999). Introduction: Risk and Sociocultural Theory. In: *Risk and Sociocultural Theory: New Directions and Perspectives*. Cambridge University Press.

MacCrimmon, K. R. & Wehrung, D. A. (1986). Taking Risks: The Management of Uncertainty. Cited in: Conway, B. A. (2003). *Calibrating Expert Assessment of Advance Areospace Technology Adoption Impact*. Ph.D. Dissertation, Old Dominion University, Norfolk, VA. U.M.I.

Margolis, H. (1996). Dealing with Risk: Why the Public and the Experts Disagree on Environmental Issues. In: Althaus, C. E. (2005). A Disciplinary Perspective on the Epistemological Status of Risk. *Risk Analysis*, 25 (3), pp. 567-588.

McNeil, T., Gero, J. S., & Warren, J. (1998). Understanding Conceptual Electronic Design using Protocol Analysis. *Research in Engineering Design*, 10, pp. 129-140.

Merriam-Webster (2006). *Merriam-Webster Online Dictionary*. Accessed at http://www.m-w.com/cgi-bin/dictionary?va=idempotent. Accessed on February 14th, 2006

Meyer, M. A. (1986). Human Factors Affecting Subjective Judgments. Cited in: Meyer, M.A., & Booker, J.M. (2001). *Eliciting and Analyzing Expert Judgment: A Practical Guide*. Society for Industrial and Applied Mathematics/American Statistical Association. Philadelphia, PA.

Meyer, M. A. & Booker, J. M. (1987). Sourses of Correlation between Experts: Empirical Results from Two Extremes. Cited in: Meyer, M.A., & Booker, J.M. (2001). *Eliciting and Analyzing Expert Judgment: A Practical Guide.* Society for Industrial and Applied Mathematics/American Statistical Association. Philadelphia, PA.

Meyer, M. A., Peaslee, A. T., Jr. & Booker, J. M. (1982).Group Consensus Methods and Results. Cited in: Meyer, M.A., & Booker, J.M. (2001). *Eliciting and Analyzing Expert Judgment: A Practical Guide.* Society for Industrial and Applied Mathematics/American Statistical Association. Philadelphia, PA.

Meyer, M.A., & Booker, J.M. (2001). *Eliciting and Analyzing Expert Judgment: A Practical Guide.* Society for Industrial and Applied Mathematics/American Statistical Association. Philadelphia, PA.

Meyer, M. A., & Booker, J. M. (1991). *Eliciting and Analyzing Expert Judgment: A Practical Guide.* Academic Press, London, UK.

Miller, D. C. & Byrnes, J. M. (1997). The Role of Contextual and Personal Factors in Children's Risk Taking. Cited in: Conway, B. A. (2003). *Calibrating Expert Assessment of Advance Areospace Technology Adoption Impact.* Ph.D. Dissertation, Old Dominion University, Norfolk, VA. U.M.I.

Monroe, R. W. (1997). *A Synthesized Methodology for Eliciting Expert Judgment for Addressing Uncertainty in Decision Analysis.* Ph.D. Dissertation, Old Dominion Umiversity, Norfolk, VA, U.M.I.

Morgan, M. G., & Henrion, M. (1990). *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis.* Cambridge University Press, Cambridge.

Morris, P. (2003). Personal Conversation, October 28, 2003 11:00am. Cited In: Chytka, T. M. (2003). *Development of an Aggregation Methodology for Risk Analysis in Aerospace Conceptual Vehicle Design.* Ph.D. Dissertation, Old Dominion University, Norfolk, VA. U.M.I.

Mullin, T. M. (1986). *Understanding and Supporting the Process of Probabilistic Estimation.* Ph.D. Dissertation, Carnegie Mellon University, Pittsburg, U.M.I.

Mullin, T. M. (1989). Experts' Estimation of Uncertainty Quantities and its Implications for Knowledge Acquisition. *IEEE Transactions on Systems, Man, and Cybernetics*, 19 (3), pp. 616-625.

Oberkampf, W. L. (2005). Uncertainty Quantification Using Evidence Theory. *Proceedings from the Advanced Simulation & Computing Workshop; Error Estimation, Uncertainty Quantification, and Reliability in Numerical Simulations. August 22-23, 2005*, Sandia National Laboratories Albuquerque, New Mexico.

Pahl, G., & Beitz, W. (1996). *Engineering Design - A Systematic Approach*. Springer-Verlag, London.

Perrow, C. (1986). *Complex Organizations*. A Critical Essay. Third edition, McGraw-Hill.

Rantilla. A. H. & Budescu, D. V. (1999). Aggregation of Expert Opinion. Cited In: Chytka, T. M. (2003). *Development of an Aggregation Methodology for Risk Analysis in Aerospace Conceptual Vehicle Design*. Ph.D. Dissertation, Old Dominion University, Norfolk, VA. U.M.I.

Reason, J. (1997). *Managing the Risk of Organizational Accidents*. Aldershot: Ashgate.

Renooij, S. (2001). Probability Elicitation for Belief Networks: Issues to Consider. *The Knowledge Engineering Review*, 16 (3), pp. 255-269.

Ross, T. J., Booker, J. M. & Parkinson, W. J. (2002). *Fuzzy Logic and Probability Applications: Bridging the Gap*. American Statistical Association, Alexandria, VA.

Sentz, K. & Ferson, S. (2002). *Combination of Evidence in Demspter-Shafer Theory*. SANDIA Tech. Report, SAND2002-0835, 96 pages, April 2002.

Shafer G., (1976). *A Mathematical Theory of Evidence*. Princeton University Press, Princeton, New Jersey.

Shanteau, J. (1987). Psychological Aspects of Expert Decision Makers. Expert Judgment and Expert Systems. Cited In: Hutton, R. B. J., & Klein, G. (Eds.), Expert Decision Making: *Systems Engineering*, 2, pp. 32-45, John Wiley & Sons, Inc.

Shanteau, J. (1992). Competence in Experts: The Role of Task Characteristics. Cited In: Shanteau, J., Mellers, B. A., & D. A. Schum, (Eds.), *Decision science and Technology: Reflections on the contributions of Ward Edwards*, Boston: Kluwer. pp. 105-130.

Simon, H. A. (1955). A behavioral Model of Rational Choice. *Quarterly Journal of Economics*, 66, pp. 99-118.

Simon, H. A. (1956). Rational Choice and the Structure of the Environment. *Psychological Review*, 63, pp. 129-138.

Simon, M., Houghton, S. M., & Aquino, K. (1999). Cognitive Biases, Risk Perception, and Venture Formation: How Individuals Decide to Start Companies. Cited in: Conway, B. A. (2003). *Calibrating Expert Assessment of Advance Areospace Technology Adoption Impact*. Ph.D. Dissertation, Old Dominion University, Norfolk, VA. U.M.I.

Slovic, P., Finucane. M., Peters. E., & MacGregor, D. G. (2002). The Affect Heuristic. In Gilovich, T., Griffin, D., & Kahneman D. (Eds.), *Heuristics and Biases: The Psychology of Intuitive Judgment* (pp. 397–420). Cambridge, UK: Cambridge University Press.

Slovic, P., Fischhoff, B., & Lichtenstein, S. (1982). Facts versus Fears: Understanding Perceived Risk. In Kahneman, D., Slovic, P., & Tversky, A. (Eds.), *Judgment under Uncertainty: Heuristics and Biases* (pp. 463-489). Cambridge, UK: Cambridge University Press.

Spetzler, C. S., & Stael Von Holstein, C. A. S. (1975). Probability Encoding in Decision Analysis. *Management Science*, 22 (3), pp. 340-358.

Sun H., Majdi F., Farooq M. (Eds.). (2002). Dempster-Shafer Combination Rule Induced by Multi-valued Mapping. *Proceedings of SPIE, April, 2002*. Orlando, FL, USA.

Sun H., Farooq M., (2003). A Novel Justification of the Disjunctive Combination Rule. *Proceedings of the Sixth International Conference on Information Fusion, July, 2003*. Cairns, Queensland, Australia.

Sun, H. & Farooq, M. (2004). On Conjunctive and Disjunctive Combination Rules of Evidence. In Smarandache, F., & Dezert, J. (Eds.), *Advances and Applications of DSmT for Information Fusion* (pp. 193-221). American Research Press: Rehoboth.

Szwed, P. S. (2002). *A Bayesian Model for Assessing Risk using Expert Judgment about Paired Scenario Comparisons*. Ph.D. Dissertation, The George Washington University, Washington, DC. U.M.I.

Takala, T. (1989). Design Transactions and Retrospective Planning Tools for Conceptual Design. In: Akman, V., Ten Hagen, P. j. W. Veerkamp, P. J. (Eds.), *Intelligent CAD Systems II*, Spring Verlag, pp. 262-272.

Thompson, P. B. (1986). The Philosophical Foundations of Risk. Quoted in: Althaus, C. E. (2005). A Disciplinary Perspective on the Epistemological Status of Risk. *Risk Analysis*, 25 (3), pp. 567-588.

Thys, W. (1987). *Fault Management*. Ph.D. Dissertation, Delft University of Technology, Delft. U.M.I.

Unal, R., Lepsch, R., & McMillin, M. (1998). Response Surface Model Building and Multidisciplinary Optimization using D-OptimalDesign. *American Institute of Aeronautics and Astronautics Journal*; AIAA-98-4759.

Wang, F. A. (2001). Overconfidence, Investor Sentiment, and Evolution. Cited in: Conway, B. A. (2003). *Calibrating Expert Assessment of Advance Areospace Technology Adoption Impact*. Ph.D. Dissertation, Old Dominion University, Norfolk, VA. U.M.I.

Wang, L., Shen, W., Xie, H., Neelamkavil, J., & Pardasani, A. (2002). Collaborative Conceptual Design - State of the Art and Future Trends. *Computer-Aided Design*, 34, pp. 981-996.

Wikipedia (2006). *Wikipedia, The Free Encyclopedia Online.* Accessed at http://en.wikipedia.org/wiki/Ecological_validity. Accessed on April 21st, 2006.

Wright G., & Bolger, F. (1992). *Expertise and Decision Support.* Plenum Press, New York and London.

Wright G., Rowe, F., Bolger, F., & Gammack, J. (1994). Coherence, Calibration, and Expertise in Judgmental Probability Forecasting. Cited in: Conway, B. A. (2003). *Calibrating Expert Assessment of Advance Areospace Technology Adoption Impact.* Ph.D. Dissertation, Old Dominion University, Norfolk, VA. U.M.I.

Yager R.R., (1987). On the Dempster-Shafer Framework and New Combination Rules. *Information Sciences*, 41, pp.93-137.

Zadeh L.A., (1979).Validity of Dempster's Rule of Combination of Evidence. *ERL Memo M 79/24*, University of California, Berkeley.

Zadeh L.A., (1984). Review of Shafer's A Mathematical Theory of Evidence, *AI Magazine*, 5 (3), pp.81-83.

Zadeh L.A., (1986). A Simple View of the Dempster-Shafer Theory of Evidence and its Implications for the Rule of Combination, *AI Magazine*, 7 (2), pp. 85-90.

APPENDIX A

EXPERT JUDGMENT ELICITATION QUESTIONNAIRE OF COST PARAMETERS FOR THE PARALLEL-STAGED CREW LAUNCH VEHICLE (P-S CLV) AND THE EXPLORATION SYSTEM ARCHITECTURE STUDY CREW LAUNCH VEHICLE (ESAS-CLV)

QUESTIONS FOR SELF RATING OF EXPERTISE

Name or ID Code

Age

In this subject area, rate your own level of expertise on a scale of 1 (least) to 5 (most):

❍ 1 ❍ 2 ❍ 3 ❍ 4 ❍ 5

How do you rank yourself among your peers of similar experience with respect to expertise? 1 (much less) to 5 (much more):

❍ 1 ❍ 2 ❍ 3 ❍ 4 ❍ 5

BACKGROUND QUESTIONS TO OBTAIN CONFIDENCE LEVEL

Thinking about predicting the likelihood associate to a particular event, do you normally predict:

- ❍ More than what actually occur?
- ❍ Less than what actually occurs?
- ❍ About the amount/number of times that it actually occur?

In making estimates related to cost parameters, would you say you were:

- ❍ Very close with a high degree of confidence?
- ❍ Very close without a high degree of confidence?
- ❍ Not very close but within a high degree of confidence?
- ❍ Not very close and not much confidence?

In estimating in your subject area that has associated uncertainty, would you say it is better to:

- ❍ Be close to the actual value without a lot of confidence in your estimate?
- ❍ Not be very close to the actual value, but with a high degree of confidence in your estimate?

Do you think it is better for project success to:

- ❍ Set, in advance, the completion dates for a complex project.
- ❍ Establish, in advance, technical milestones for complex project.

Do you think it is better for project success to:

- ❍ Estimate, in advance, project budgets for a complex project?
- ❍ Identify, in advance, cost WBS for a complex project?

Do you think it is better to:

- ❍ Identify, at conceptual design review, scenarios for successful projects?
- ❍ Identify, at conceptual design review, technical performance characteristics of a successful project?

EXAMPLE QUESTION FOR RATING COST PARAMETER

Thinking of possible scenarios that could provide alternative assessments, what is the likelihood of the following combination(s) having the largest negative impact on these cost projections?

Development and production costs ONLY:

❍ Low ❍ 2 ❍ Moderate ❍ 4 ❍ High

FIGURE 8: EXAMPLE QUESTION FOR RATING COST PARAMETER

DOCUMENTING FURTHER THINKING PATTERNS OF THE EXPERTS AND QUANTIFYING THEIR QUALITATIVE RATINGS

To further document your pattern of thinking, please provide any cues (or triggers) that influenced your thinking of these three cost parameters and record in the space provided:

The following questions attempt to anchor a quantitative value for Low, Moderate and High likelihood estimates. This is to ensure clarity in interpretation. What quantitative value would you assign to:

Low likelihood?

❍ Less ❍ 5% ❍ 7.5% ❍ 10% ❍ 12.5% ❍ 15% ❍ More

If more or less please indicate

Moderate likelihood?

❍ Less ❍ 10% ❍ 15% ❍ 20% ❍ 25% ❍ 30% ❍ More

If more or less please indicate

High likelihood?

❍ Less ❍ 20% ❍ 30% ❍ 40% ❍ 50% ❍ 60% ❍ More

If more or less please indicate

APPENDIX B

The Experts' Expertise Computations For The Parallel-Staged Crew Launch Vehicle And The Exploration System Architecture Study Crew Launch Vehicle

EXPLORATION SYSTEMS ARCHITECTURE STUDY CREW LAUNCH VEHICLE

ESAS CLV					
Expert 1		Expert 2		Expert 3	
age:	37	age:	62	age:	54
sel:	0.55	sel:	0.55	sel:	0.65
ecp:	0.55	ecp:	0.55	ecp:	0.65
dsk:	0.65	dsk:	0.7	dsk:	0.5
act:	0.65	act:	0.65	act:	0.65
E=	9.18	E=	10.91	E=	12.30

	EXPERT 1		EXPERT 2		EXPERT 3	
	Basic Assignment	Adjustment Factor	Basic Assignment	Adjustment Factor	Basic Assignment	Adjustment Factor
D = Development Cost	0.70	-0.59	0.25	-0.30	0.50	-0.73
P = Production Cost	0.25	-0.21	0.25	-0.30	0.50	-0.73
O = Operation Cost	0.70	-0.59	0.55	-0.65	0.80	-1.17
D U P	0.40	-0.33	0.25	-0.30	0.30	-0.44
D U O	0.70	-0.59	0.40	-0.47	0.50	-0.73
O U P	0.40	-0.33	0.40	-0.47	0.80	-1.17
D U P U O	0.70	-0.59	0.55	-0.65	0.80	-1.17

PARALLEL-STAGED CREW LAUNCH VEHICLE

P-S CLV					
Expert 1		Expert 2		Expert 3	
age:	37	age:	62	age:	54
sel:	0.55	sel:	0.55	sel:	0.65
ecp:	0.55	ecp:	0.55	ecp:	0.65
dsk:	0.7	dsk:	0.6	dsk:	0.9
act:	0.65	act:	0.65	act:	0.65
E=	8.83	E=	11.68	E=	9.41

	EXPERT 1		EXPERT 2		EXPERT 3	
	Basic Assignment	Adjustment Factor	Basic Assignment	Adjustment Factor	Basic Assignment	Adjustment Factor
D = Development Cost	0.40	-0.31	0.25	-0.33	0.30	-0.26
P = Production Cost	0.10	-0.08	0.40	-0.53	0.30	-0.26
O = Operation Cost	0.40	-0.31	0.55	-0.73	0.80	-0.71
D U P	0.25	-0.19	0.40	-0.53	0.30	-0.26
D U O	0.40	-0.31	0.55	-0.73	0.80	-0.71
O U P	0.40	-0.31	0.55	-0.73	0.65	-0.57
D U P U O	0.40	-0.31	0.70	-0.94	0.65	-0.57

APPENDIX C

THE EXPERTS' CONFIDENCE / RISK PROFILE COMPUTATIONS FOR THE PARALLEL-STAGED CREW LAUNCH VEHICLE AND THE EXPLORATION SYSTEM ARCHITECTURE STUDY CREW LAUNCH VEHICLE

EXPLORATION SYSTEMS ARCHITECTURE STUDY CREW LAUNCH VEHICLE

Expert 1							
Question		3	4	5	6	7	8
Risk Tolerant	5						X
	2.5						
Risk Neutral	0						
	-2.5		X				
Risk Adverse	-5	X		X	X	X	

Question	Topic	Response	Point Conversion
3	Predicted Discipline-Related Quantities	a	-5
4	Estimating Uncertainty Preference	b	-2.5
5	Estimating Trend in Discipline	b	-5
6	Completion vs. Milestones	b	-5
7	Total Outlays vs. Cost Elements	b	-5
8	Utilization Scenarios vs. Performance	b	5
CRP = -2.92	E = 9.18		

Expert 2							
Question		3	4	5	6	7	8
Risk Tolerant	5						X
	2.5						
Risk Neutral	0						
	-2.5		X				
Risk Adverse	-5	X		X	X	X	

Question	Topic	Response	Point Conversion
3	Predicted Discipline-Related Quantities	a	-5
4	Estimating Uncertainty Preference	b	-2.5
5	Estimating Trend in Discipline	b	-5
6	Completion vs. Milestones	b	-5
7	Total Outlays vs. Cost Elements	b	-5
8	Utilization Scenarios vs. Performance	b	5
CRP = -2.92	E = 10.91		

Expert 3							
Question		3	4	5	6	7	8
Risk Tolerant	5						
	2.5						
Risk Neutral	0						
	-2.5		X				
Risk Adverse	-5	X		X	X	X	X

Question	Topic	Response	Point Conversion
3	Predicted Discipline-Related Quantities	a	-5
4	Estimating Uncertainty Preference	b	-2.5
5	Estimating Trend in Discipline	b	-5
6	Completion vs. Milestones	b	-5
7	Total Outlays vs. Cost Elements	b	-5
8	Utilization Scenarios vs. Performance	a	-5
CRP = -4.58	E = 12.30		

PARALLEL-STAGED CREW LAUNCH VEHICLE

Expert 1							
Question		**3**	**4**	**5**	**6**	**7**	**8**
Risk Tolerant	5						X
	2.5						
Risk Neutral	0						
	-2.5		X				
Risk Adverse	-5	X		X	X	X	

Question	Topic	Response	Point Conversion
3	Predicted Discipline-Related Quantities	a	-5
4	Estimating Uncertainty Preference	b	-2.5
5	Estimating Trend in Discipline	b	-5
6	Completion vs. Milestones	b	-5
7	Total Outlays vs. Cost Elements	b	-5
8	Utilization Scenarios vs. Performance	b	5
CRP = -2.92	E = 8.83		

Expert 2							
Question		**3**	**4**	**5**	**6**	**7**	**8**
Risk Tolerant	5						X
	2.5						
Risk Neutral	0						
	-2.5		X				
Risk Adverse	-5	X		X	X	X	

Question	Topic	Response	Point Conversion
3	Predicted Discipline-Related Quantities	a	-5
4	Estimating Uncertainty Preference	b	-2.5
5	Estimating Trend in Discipline	b	-5
6	Completion vs. Milestones	b	-5
7	Total Outlays vs. Cost Elements	b	-5
8	Utilization Scenarios vs. Performance	b	5
CRP = -2.92	E = 11.68		

Expert 3							
Question		**3**	**4**	**5**	**6**	**7**	**8**
Risk Tolerant	5						
	2.5						
Risk Neutral	0						
	-2.5		X				
Risk Adverse	-5	X		X	X	X	X

Question	Topic	Response	Point Conversion
3	Predicted Discipline-Related Quantities	a	-5
4	Estimating Uncertainty Preference	b	-2.5
5	Estimating Trend in Discipline	b	-5
6	Completion vs. Milestones	b	-5
7	Total Outlays vs. Cost Elements	b	-5
8	Utilization Scenarios vs. Performance	a	-5
CRP = -4.58	E = 9.41		

APPENDIX D

THE EXPERTS' BELIEF AND PLAUSIBILITY FUNCTIONS COMPUTATIONS FOR THE PARALLEL-STAGED CREW LAUNCH VEHICLE AND THE EXPLORATION SYSTEM ARCHITECTURE STUDY CREW LAUNCH VEHICLE

EXPLORATION SYSTEMS ARCHITECTURE STUDY CREW LAUNCH VEHICLE

	EXPERT 1		EXPERT 2		EXPERT 3	
	Basic Assignment	Normalize	Basic Assignment	Normalize	Basic Assignment	Normalize
D = Development Cost	0.70	0.18	0.25	0.09	0.50	0.12
P = Production Cost	0.25	0.06	0.25	0.09	0.50	0.12
O = Operation Cost	0.70	0.18	0.55	0.21	0.80	0.19
D U P	0.40	0.10	0.25	0.09	0.30	0.07
D U O	0.70	0.18	0.40	0.15	0.50	0.12
O U P	0.40	0.10	0.40	0.15	0.80	0.19
D U P U O	0.70	0.18	0.55	0.21	0.80	0.19
	3.85	1.00	2.65	1.00	4.20	1.00

BELIEF COMPUTATIONS						
SUBSET*	EXPERT 1		EXPERT 2		COMBINED JUDGMENT 1,2	
Costs Parameters	m_1	Bel_1	m_2	Bel_2	$m_{1,2}$	$Bel_{1,2}$
D = Development Cost	0.18	0.18	0.09	0.09	0.22	0.22
P = Production Cost	0.06	0.06	0.09	0.09	0.12	0.12
O = Operation Cost	0.18	0.18	0.21	0.21	0.34	0.34
D U P	0.10	0.35	0.09	0.28	0.06	0.41
D U O	0.18	0.55	0.15	0.45	0.12	0.68
O U P	0.10	0.35	0.15	0.45	0.08	0.55
D U P U O	0.18	1.00**	0.21	1.00**	0.05	1.00**
	1.00		1.00		1.00	

PLAUSIBILITY COMPUTATIONS						
SUBSET*	EXPERT 1		EXPERT 2		COMBINED JUDGMENT 1,2	
Costs Parameters	m_1	Pl_1	m_2	Pl_2	$m_{1,2}$	$Pl_{1,2}$
D = Development Cost	0.18	0.65	0.09	0.55	0.22	0.45
P = Production Cost	0.06	0.45	0.09	0.55	0.12	0.32
O = Operation Cost	0.18	0.65	0.21	0.72	0.34	0.59
D U P	0.10	0.82	0.09	0.79	0.06	0.66
D U O	0.18	0.94	0.15	0.91	0.12	0.88
O U P	0.10	0.82	0.15	0.91	0.08	0.78
D U P U O	0.18	1.00**	0.21	1.00**	0.05	1.00**
	1.00		1.00		1.00	

BELIEF COMPUTATIONS						
SUBSET*	EXPERT 1,2		EXPERT 3		COMBINED JUDGMENT 1,2,3	
Costs Parameters	$m_{1,2}$	$Bel_{1,2}$	m_3	Bel_3	$m_{1,2,3}$	$Bel_{1,2,3}$
D = Development Cost	0.22	0.22	0.12	0.12	0.22	0.22
P = Production Cost	0.12	0.12	0.12	0.12	0.16	0.16
O = Operation Cost	0.34	0.34	0.19	0.19	0.46	0.46
D U P	0.06	0.41	0.07	0.31	0.03	0.41
D U O	0.12	0.68	0.12	0.43	0.06	0.74
O U P	0.08	0.55	0.19	0.50	0.06	0.67
D U P U O	0.05	1.00**	0.19	1.00**	0.01	1.00**
	1.00		1.00		1.00	

PLAUSIBILITY COMPUTATIONS						
SUBSET*	EXPERT 1,2		EXPERT 3		COMBINED JUDGMENT 1,2,3	
Costs Parameters	$m_{1,2}$	$Pl_{1,2}$	m_3	Pl_3	$m_{1,2,3}$	$Pl_{1,2,3}$
D = Development Cost	0.22	0.45	0.12	0.50	0.22	0.33
P = Production Cost	0.12	0.32	0.12	0.57	0.16	0.26
O = Operation Cost	0.34	0.59	0.19	0.69	0.46	0.59
D U P	0.06	0.66	0.07	0.81	0.03	0.54
D U O	0.12	0.88	0.12	0.88	0.06	0.84
O U P	0.08	0.78	0.19	0.88	0.06	0.78
D U P U O	0.05	1.00**	0.19	1.00**	0.01	1.00**
	1.00		1.00		1.00	

	EXPERT 1		EXPERT 2		EXPERT 3	
	Calibrated Assignment	Normalize	Calibrated Assignment	Normalize	Calibrated Assignment	Normalize
D = Development Cost	0.11	0.18	-0.05	0.09	-0.23	0.12
P = Production Cost	0.04	0.06	-0.05	0.09	-0.23	0.12
O = Operation Cost	0.11	0.18	-0.10	0.21	-0.37	0.19
D U P	0.07	0.10	-0.05	0.09	-0.14	0.07
D U O	0.11	0.18	-0.07	0.15	-0.23	0.12
O U P	0.07	0.10	-0.07	0.15	-0.37	0.19
D U P U O	0.11	0.18	-0.10	0.21	-0.37	0.19
	0.63	1.00	-0.48	1.00	-1.93	1.00

BELIEF COMPUTATIONS						
SUBSET*	EXPERT 1		EXPERT 2		COMBINED JUDGMENT 1,2	
Costs Parameters	m_1	Bel_1	m_2	Bel_2	$m_{1,2}$	$Bel_{1,2}$
D = Development Cost	0.18	0.18	0.09	0.09	0.22	0.22
P = Production Cost	0.06	0.06	0.09	0.09	0.12	0.12
O = Operation Cost	0.18	0.18	0.21	0.21	0.34	0.34
D U P	0.10	0.35	0.09	0.28	0.06	0.41
D U O	0.18	0.55	0.15	0.45	0.12	0.68
O U P	0.10	0.35	0.15	0.45	0.08	0.55
D U P U O	0.18	1.00**	0.21	1.00**	0.05	1.00**
	1.00		1.00		1.00	

PLAUSIBILITY COMPUTATIONS						
SUBSET*	EXPERT 1		EXPERT 2		COMBINED JUDGMENT 1,2	
Costs Parameters	m_1	Pl_1	m_2	Pl_2	$m_{1,2}$	$Pl_{1,2}$
D = Development Cost	0.18	0.65	0.09	0.55	0.22	0.45
P = Production Cost	0.06	0.45	0.09	0.55	0.12	0.32
O = Operation Cost	0.18	0.65	0.21	0.72	0.34	0.59
D U P	0.10	0.82	0.09	0.79	0.06	0.66
D U O	0.18	0.94	0.15	0.91	0.12	0.88
O U P	0.10	0.82	0.15	0.91	0.08	0.78
D U P U O	0.18	1.00**	0.21	1.00**	0.05	1.00**
	1.00		1.00		1.00	

BELIEF COMPUTATIONS						
SUBSET*	EXPERT 1,2		EXPERT 3		COMBINED JUDGMENT 1,2,3	
Costs Parameters	$m_{1,2}$	$Bel_{1,2}$	m_3	Bel_3	$m_{1,2,3}$	$Bel_{1,2,3}$
D = Development Cost	0.22	0.22	0.12	0.12	0.22	0.22
P = Production Cost	0.12	0.12	0.12	0.12	0.16	0.16
O = Operation Cost	0.34	0.34	0.19	0.19	0.46	0.46
D U P	0.06	0.41	0.07	0.31	0.03	0.41
D U O	0.12	0.68	0.12	0.43	0.06	0.74
O U P	0.08	0.55	0.19	0.50	0.06	0.67
D U P U O	0.05	1.00**	0.19	1.00**	0.01	1.00**
	1.00		1.00		1.00	

PLAUSIBILITY COMPUTATIONS						
SUBSET*	EXPERT 1,2		EXPERT 3		COMBINED JUDGMENT 1,2,3	
Costs Parameters	$m_{1,2}$	$Pl_{1,2}$	m_3	Pl_3	$m_{1,2,3}$	$Pl_{1,2,3}$
D = Development Cost	0.22	0.45	0.12	0.50	0.22	0.33
P = Production Cost	0.12	0.32	0.12	0.57	0.16	0.26
O = Operation Cost	0.34	0.59	0.19	0.69	0.46	0.59
D U P	0.06	0.66	0.07	0.81	0.03	0.54
D U O	0.12	0.88	0.12	0.88	0.06	0.84
O U P	0.08	0.78	0.19	0.88	0.06	0.78
D U P U O	0.05	1.00**	0.19	1.00**	0.01	1.00**
	1.00		1.00		1.00	

PARALLEL-STAGED CREW LAUNCH VEHICLE

	EXPERT 1		EXPERT 2		EXPERT 3	
	Basic Assignment	Normalize	Basic Assignment	Normalize	Basic Assignment	Normalize
D = Development Cost	0.40	0.17	0.25	0.07	0.30	0.08
P = Production Cost	0.10	0.04	0.40	0.12	0.30	0.08
O = Operation Cost	0.40	0.17	0.55	0.16	0.80	0.21
D U P	0.25	0.11	0.40	0.12	0.30	0.08
D U O	0.40	0.17	0.55	0.16	0.80	0.21
O U P	0.40	0.17	0.55	0.16	0.65	0.17
D U P U O	0.40	0.17	0.70	0.21	0.65	0.17
	2.35	1.00	3.40	1.00	3.80	1.00

BELIEF COMPUTATIONS						
SUBSET*	EXPERT 1		EXPERT 2		COMBINED JUDGMENT 1,2	
Costs Parameters	m_1	Bel_1	m_2	Bel_2	$m_{1,2}$	$Bel_{1,2}$
D = Development Cost	0.17	0.17	0.07	0.07	0.21	0.21
P = Production Cost	0.04	0.04	0.12	0.12	0.14	0.14
O = Operation Cost	0.17	0.17	0.16	0.16	0.32	0.32
D U P	0.11	0.32	0.12	0.31	0.07	0.42
D U O	0.17	0.51	0.16	0.40	0.11	0.63
O U P	0.17	0.38	0.16	0.44	0.11	0.57
D U P U O	0.17	1.00**	0.21	1.00**	0.04	1.00**
	1.00		1.00		1.00	

PLAUSIBILITY COMPUTATIONS						
SUBSET*	EXPERT 1		EXPERT 2		COMBINED JUDGMENT 1,2	
Costs Parameters	m_1	Pl_1	m_2	Pl_2	$m_{1,2}$	$Pl_{1,2}$
D = Development Cost	0.17	0.62	0.07	0.56	0.21	0.43
P = Production Cost	0.04	0.49	0.12	0.60	0.14	0.37
O = Operation Cost	0.17	0.68	0.16	0.69	0.32	0.58
D U P	0.11	0.83	0.12	0.84	0.07	0.68
D U O	0.17	0.96	0.16	0.88	0.11	0.86
O U P	0.17	0.83	0.16	0.93	0.11	0.79
D U P U O	0.17	1.00**	0.21	1.00**	0.04	1.00**
	1.00		1.00		1.00	

BELIEF COMPUTATIONS						
SUBSET*	EXPERT 1,2		EXPERT 3		COMBINED JUDGMENT 1,2,3	
Costs Parameters	$m_{1,2}$	$Bel_{1,2}$	m_3	Bel_3	$m_{1,2,3}$	$Bel_{1,2,3}$
D = Development Cost	0.21	0.21	0.08	0.08	0.21	0.21
P = Production Cost	0.14	0.14	0.08	0.08	0.15	0.15
O = Operation Cost	0.32	0.32	0.21	0.21	0.47	0.47
D U P	0.07	0.42	0.08	0.24	0.03	0.39
D U O	0.11	0.63	0.21	0.50	0.07	0.75
O U P	0.11	0.57	0.17	0.46	0.06	0.68
D U P U O	0.04	1.00**	0.17	1.00**	0.01	1.00**
	1.00		1.00		1.00	

PLAUSIBILITY COMPUTATIONS						
SUBSET*	EXPERT 1,2		EXPERT 3		COMBINED JUDGMENT 1,2,3	
Costs Parameters	$m_{1,2}$	$Pl_{1,2}$	m_3	Pl_3	$m_{1,2,3}$	$Pl_{1,2,3}$
D = Development Cost	0.21	0.43	0.08	0.54	0.21	0.32
P = Production Cost	0.14	0.37	0.08	0.50	0.15	0.25
O = Operation Cost	0.32	0.58	0.21	0.76	0.47	0.61
D U P	0.07	0.68	0.08	0.79	0.03	0.53
D U O	0.11	0.86	0.21	0.92	0.07	0.85
O U P	0.11	0.79	0.17	0.92	0.06	0.79
D U P U O	0.04	1.00**	0.17	1.00**	0.01	1.00**
	1.00		1.00		1.00	

	EXPERT 1		EXPERT 2		EXPERT 3	
	Calibrated Assignment	Normalize	Calibrated Assignment	Normalize	Calibrated Assignment	Normalize
D = Development Cost	0.09	0.17	-0.08	0.07	0.04	0.08
P = Production Cost	0.02	0.04	-0.13	0.12	0.04	0.08
O = Operation Cost	0.09	0.17	-0.18	0.16	0.09	0.21
D U P	0.06	0.11	-0.13	0.12	0.04	0.08
D U O	0.09	0.17	-0.18	0.16	0.09	0.21
O U P	0.09	0.17	-0.18	0.16	0.08	0.17
D U P U O	0.09	0.17	-0.24	0.21	0.08	0.17
	0.55	1.00	-1.14	1.00	0.45	1.00

BELIEF COMPUTATIONS						
SUBSET*	EXPERT 1		EXPERT 2		COMBINED JUDGMENT 1,2	
Costs Parameters	m_1	Bel_1	m_2	Bel_2	$m_{1,2}$	$Bel_{1,2}$
D = Development Cost	0.17	0.17	0.07	0.07	0.21	0.21
P = Production Cost	0.04	0.04	0.12	0.12	0.14	0.14
O = Operation Cost	0.17	0.17	0.16	0.16	0.32	0.32
D U P	0.11	0.32	0.12	0.31	0.07	0.42
D U O	0.17	0.51	0.16	0.40	0.11	0.63
O U P	0.17	0.38	0.16	0.44	0.11	0.57
D U P U O	0.17	1.00**	0.21	1.00**	0.04	1.00**
	1.00		1.00		1.00	

PLAUSIBILITY COMPUTATIONS						
SUBSET*	EXPERT 1		EXPERT 2		COMBINED JUDGMENT 1,2	
Costs Parameters	m_1	Pl_1	m_2	Pl_2	$m_{1,2}$	$Pl_{1,2}$
D = Development Cost	0.17	0.62	0.07	0.56	0.21	0.43
P = Production Cost	0.04	0.49	0.12	0.60	0.14	0.37
O = Operation Cost	0.17	0.68	0.16	0.69	0.32	0.58
D U P	0.11	0.83	0.12	0.84	0.07	0.68
D U O	0.17	0.96	0.16	0.88	0.11	0.86
O U P	0.17	0.83	0.16	0.93	0.11	0.79
D U P U O	0.17	1.00**	0.21	1.00**	0.04	1.00**
	1.00		1.00		1.00	

BELIEF COMPUTATIONS						
SUBSET*	EXPERT 1,2		EXPERT 3		COMBINED JUDGMENT 1,2,3	
Costs Parameters	$m_{1,2}$	$Bel_{1,2}$	m_3	Bel_3	$m_{1,2,3}$	$Bel_{1,2,3}$
D = Development Cost	0.21	0.21	0.08	0.08	0.21	0.21
P = Production Cost	0.14	0.14	0.08	0.08	0.15	0.15
O = Operation Cost	0.32	0.32	0.21	0.21	0.47	0.47
D U P	0.07	0.42	0.08	0.24	0.03	0.39
D U O	0.11	0.63	0.21	0.50	0.07	0.75
O U P	0.11	0.57	0.17	0.46	0.06	0.68
D U P U O	0.04	1.00**	0.17	1.00**	0.01	1.00**
	1.00		1.00		1.00	

PLAUSIBILITY COMPUTATIONS						
SUBSET*	EXPERT 1,2		EXPERT 3		COMBINED JUDGMENT 1,2,3	
Costs Parameters	$m_{1,2}$	$Pl_{1,2}$	m_3	Pl_3	$m_{1,2,3}$	$Pl_{1,2,3}$
D = Development Cost	0.21	0.43	0.08	0.54	0.21	0.32
P = Production Cost	0.14	0.37	0.08	0.50	0.15	0.25
O = Operation Cost	0.32	0.58	0.21	0.76	0.47	0.61
D U P	0.07	0.68	0.08	0.79	0.03	0.53
D U O	0.11	0.86	0.21	0.92	0.07	0.85
O U P	0.11	0.79	0.17	0.92	0.06	0.79
D U P U O	0.04	1.00**	0.17	1.00**	0.01	1.00**
	1.00		1.00		1.00	

* The subsets could also be written as {D}, {P}, {O}, {D,P}, {D,O}, {O,P}, and {D,P,O}, respectively.
** Complete Ignorance

APPENDIX E

SUMMARY OF THE BELIEF AND PLAUSIBILITY FUNCTIONS COMPUTATIONS FOR THE PARALLEL-STAGED CREW LAUNCH VEHICLE AND THE EXPLORATION SYSTEM ARCHITECTURE STUDY CREW LAUNCH VEHICLE

EXPLORATION SYSTEMS ARCHITECTURE STUDY CREW LAUNCH VEHICLE

Exploration Systems Architecture Study Crew Launch Vehicle (ESAS CLV)							
Expert $_1$		Expert $_2$		Expert $_3$		Combined	
Bel_1	Pl_1	Bel_2	Pl_2	Bel_3	Pl_3	$Bel_{1,2,3}$	$Pl_{1,2,3}$
0.18	0.65	0.09	0.55	0.12	0.50	0.22	0.33
0.06	0.45	0.09	0.55	0.12	0.57	0.16	0.26
0.18	0.65	0.21	0.72	0.19	0.69	0.46	0.59
0.35	0.82	0.28	0.79	0.31	0.81	0.41	0.54
0.55	0.94	0.45	0.91	0.43	0.88	0.74	0.84
0.35	0.82	0.45	0.91	0.50	0.88	0.67	0.78
1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

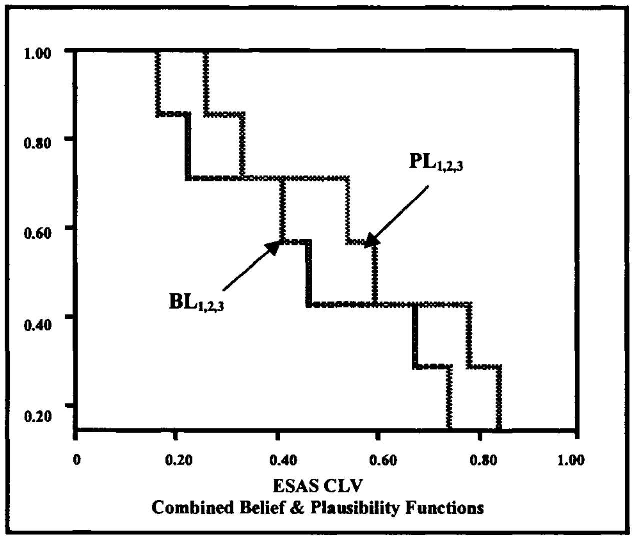
PARALLEL-STAGED CREW LAUNCH VEHICLE

Parallel-Staged Crew Launch Vehicle (P-S CLV)							
Expert $_1$		Expert $_2$		Expert $_3$		Combined	
Bel_1	Pl_1	Bel_2	Pl_2	Bel_3	Pl_3	$Bel_{1,2,3}$	$Pl_{1,2,3}$
0.17	0.62	0.07	0.56	0.08	0.54	0.21	0.32
0.04	0.49	0.12	0.60	0.08	0.50	0.15	0.25
0.17	0.68	0.16	0.69	0.21	0.76	0.47	0.61
0.32	0.83	0.31	0.84	0.24	0.79	0.39	0.53
0.51	0.96	0.40	0.88	0.50	0.92	0.75	0.85
0.38	0.83	0.44	0.93	0.46	0.92	0.68	0.79
1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

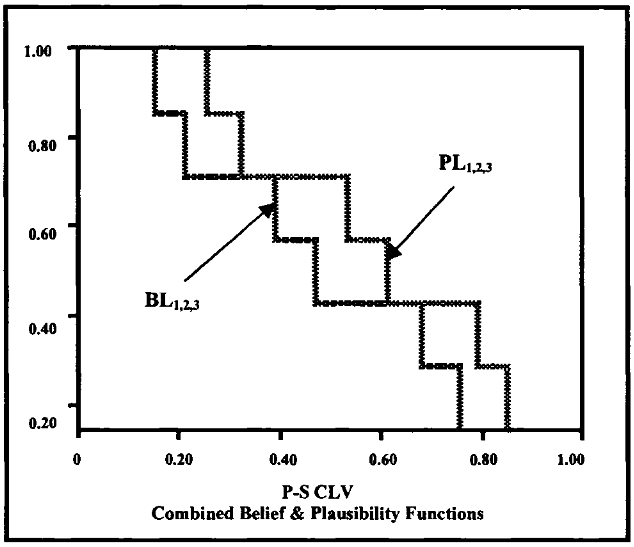
APPENDIX F

GRAPHS OF THE COMBINED BELIEF AND PLAUSIBILITY FUNCTIONS FOR THE PARALLEL-STAGED CREW LAUNCH VEHICLE AND THE EXPLORATION SYSTEM ARCHITECTURE STUDY CREW LAUNCH VEHICLE

EXPLORATION SYSTEMS ARCHITECTURE STUDY CREW LAUNCH VEHICLE



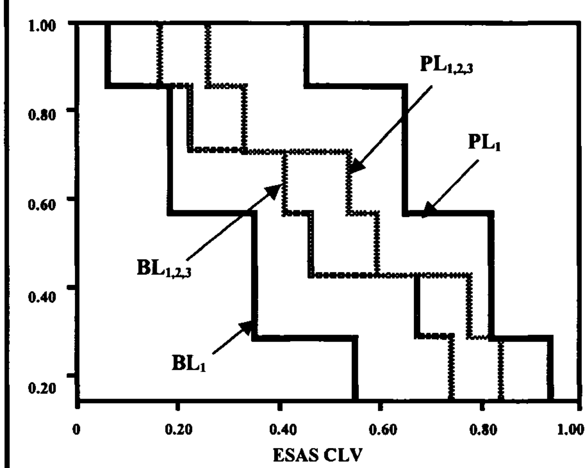
PARALLEL-STAGED CREW LAUNCH VEHICLE



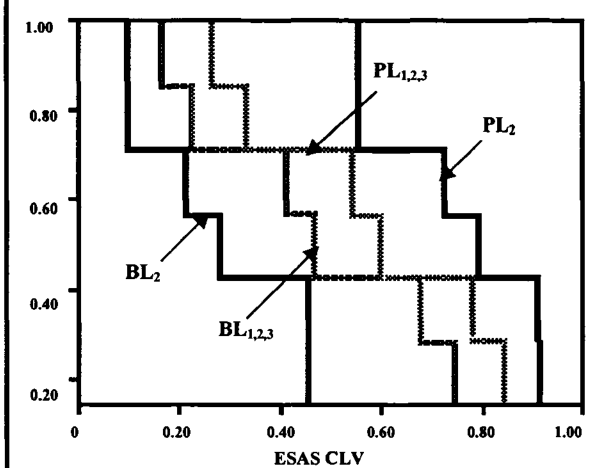
APPENDIX G

Graphs Of Each Experts' Belief And Plausibility Functions Verses The Combined Belief And Plausibility Functions For The Parallel-Staged Crew Launch Vehicle And The EXPLORATION SYSTEM ARCHITECTURE STUDY CREW LAUNCH VEHICLE

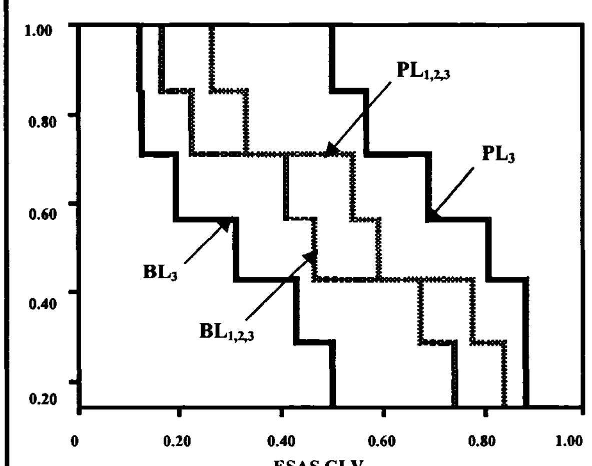
EXPLORATION SYSTEMS ARCHITECTURE STUDY CREW LAUNCH VEHICLE



Belief & Plausibility Functions for Expert$_1$

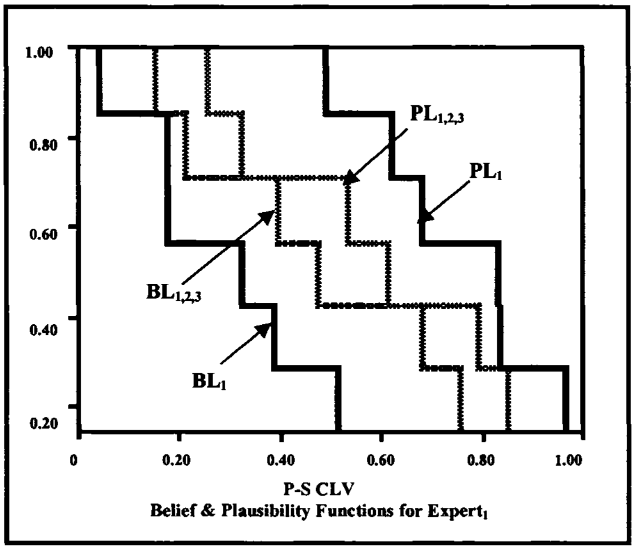


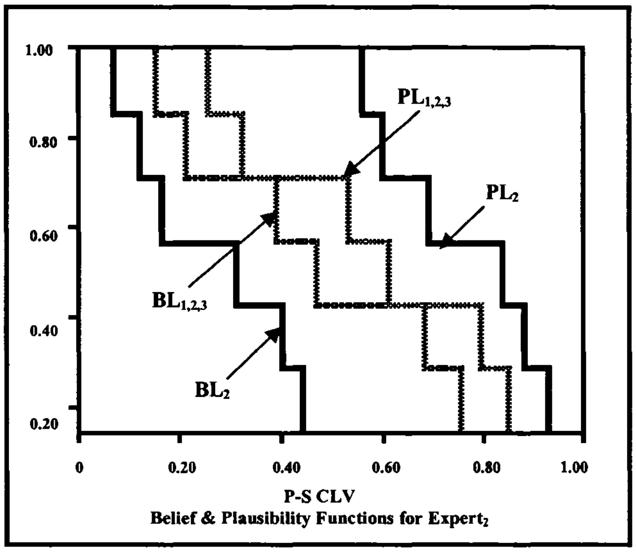
Belief & Plausibility Functions for Expert$_2$

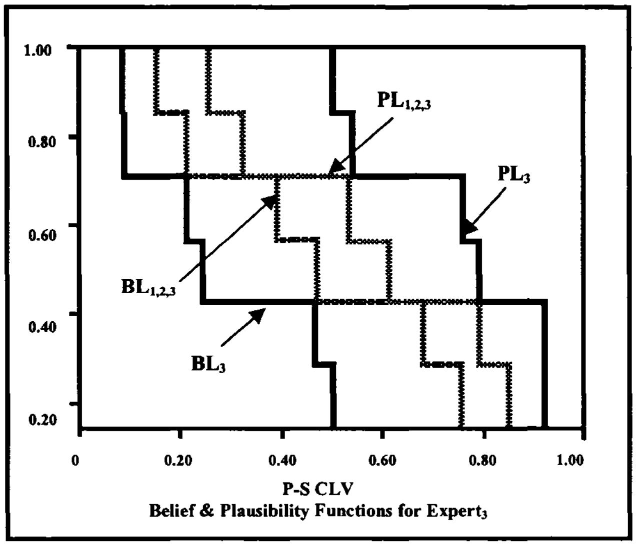


Belief & Plausibility Functions for Expert$_3$

PARALLEL-STAGED CREW LAUNCH VEHICLE

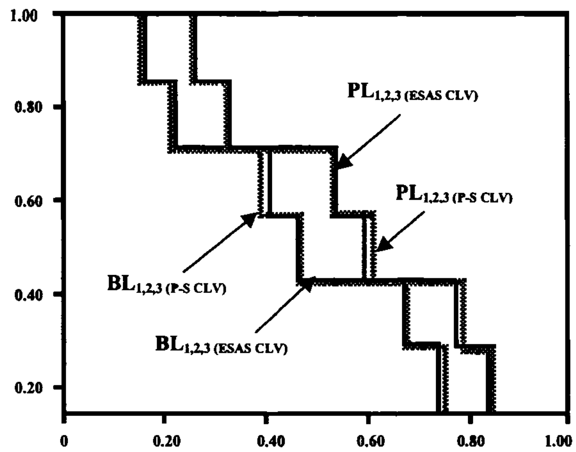




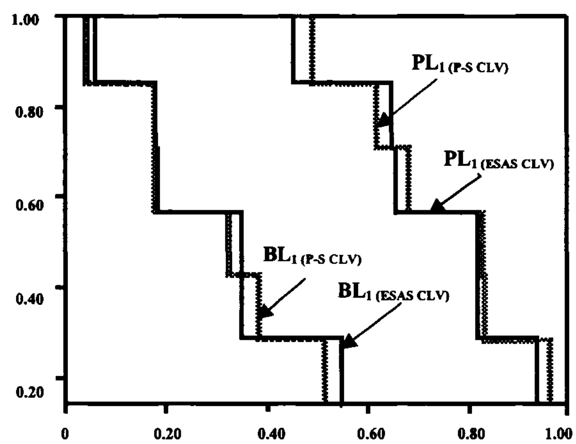


APPENDIX H

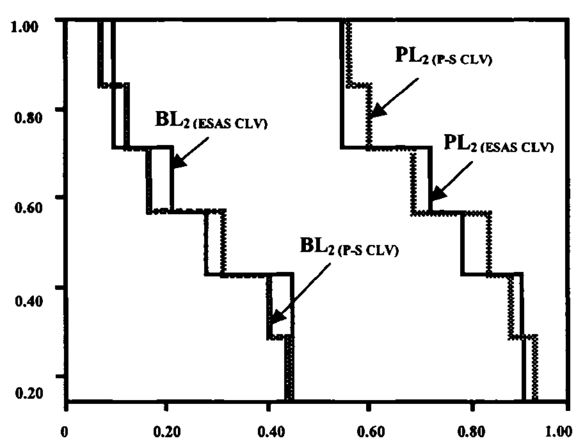
GRAPHS COMPARING THE BELIEF AND PLAUSIBILITY FUNCTIONS OF THE PARALLEL-STAGED CREW LAUNCH VEHICLE VERSE THE EXPLORATION SYSTEM ARCHITECTURE STUDY CREW LAUNCH VEHICLE



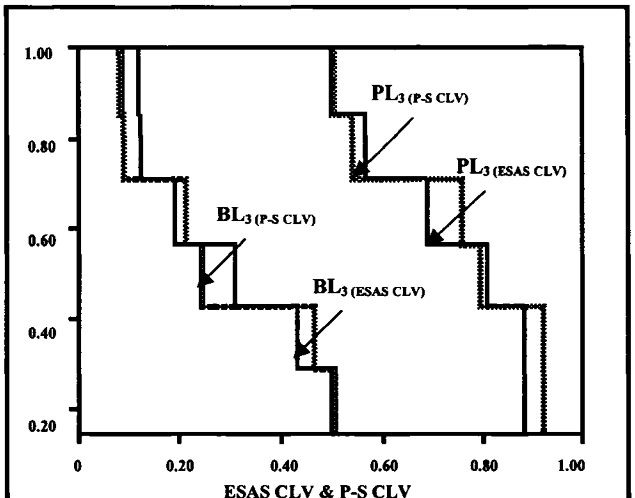
ESAS CLV & P-S CLV
Combined Belief & Plausibility Functions



ESAS CLV & P-S CLV
Combined Belief & Plausibility Functions for Expert$_1$



ESAS CLV & P-S CLV
Combined Belief & Plausibility Functions for Expert$_2$



Combined Belief & Plausibility Functions for Expert$_3$

APPENDIX I

Fit Result Summary For The Belief And Plausibility Functions Of The Parallel-Staged Crew Launch Vehicle And The Exploration System Architecture Study Crew Launch Vehicle

Exploration Systems Architecture Study Crew Launch Vehicle - E1, 2, 3 - B1, 2, 3						
	Input	**Expon**	**ExtValue**	**Logistic**	**Normal**	**Uniform**
Function	N/A	0.47102	0.52324639	0.51152	0.52286	0.58
Variance	0.076649	0.13167	0.088661	0.091067	0.089424	0.10453
Kurtosis	1.9562	9	5.4	4.2	3	1.8
Target #1 (%)	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
Target #1 (X)	0.16	0.14639	0.19561	0.14595	0.13962	0.132
Target #2 (%)	20.00%	20.00%	20.00%	20.00%	20.00%	20.00%
Target #2 (X)	0.22	0.18913	0.27875	0.28087	0.27118	0.244
Target #3 (%)	30.00%	30.00%	30.00%	30.00%	30.00%	30.00%
Target #3 (X)	0.41	0.23759	0.34614	0.37055	0.36604	0.356
Target #4 (%)	40.00%	40.00%	40.00%	40.00%	40.00%	40.00%
Target #4 (X)	0.41	0.29352	0.40953	0.44406	0.4471	0.468
Target #5 (%)	50.00%	50.00%	50.00%	50.00%	50.00%	50.00%
Target #5 (X)	0.46	0.35968	0.47433	0.51152	0.52286	0.58
Target #6 (%)	60.00%	60.00%	60.00%	60.00%	60.00%	60.00%
Target #6 (X)	0.67	0.44065	0.54519	0.57898	0.59862	0.692
Target #7 (%)	70.00%	70.00%	70.00%	70.00%	70.00%	70.00%
Target #7 (X)	0.67	0.54503	0.62858	0.65249	0.67967	0.804
Target #8 (%)	80.00%	80.00%	80.00%	80.00%	80.00%	80.00%
Target #8 (X)	0.74	0.69216	0.73747	0.74216	0.77453	0.916
Target #9 (%)	90.00%	90.00%	90.00%	90.00%	90.00%	90.00%
Target #9 (X)	1	0.94367	0.91169	0.87708	0.90609	1.028
Target #10 (%)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
A-D Test Value	N/A	0.5103	0.221	0.2104	0.1885	0.3301
Rank	N/A	8	3	2	1	7
K-S Test Value	N/A	0.279	0.1706	0.1502	0.1547	0.2143
Rank	N/A	10	4	1	2	8
Chi-Sq Test Value	N/A	1.286	0.1429	0.1429	0.1429	0.1429
Rank	N/A	10	2	4	7	9
C.Val @ 0.75	N/A	0.1015	0.1015	0.1015	0.1015	0.1015
C.Val @ 0.5	N/A	0.4549	0.4549	0.4549	0.4549	0.4549
C.Val @ 0.25	N/A	1.3233	1.3233	1.3233	1.3233	1.3233
C.Val @ 0.15	N/A	2.0723	2.0723	2.0723	2.0723	2.0723
C.Val @ 0.1	N/A	2.7055	2.7055	2.7055	2.7055	2.7055
C.Val @ 0.05	N/A	3.8415	3.8415	3.8415	3.8415	3.8415
C.Val @ 0.025	N/A	5.0239	5.0239	5.0239	5.0239	5.0239
C.Val @ 0.01	N/A	6.6349	6.6349	6.6349	6.6349	6.6349
C.Val @ 0.005	N/A	7.8794	7.8794	7.8794	7.8794	7.8794
C.Val @ 0.001	N/A	10.8276	10.8276	10.8276	10.8276	10.8276
# Bins	N/A	2	2	2	2	2
Bin #1 Input	N/A	2	4	4	4	4
Bin #1 Fit	N/A	3.5	3.5	3.5	3.5	3.5
Bin #2 Input	N/A	5	3	3	3	3
Bin #2 Fit	N/A	3.5	3.5	3.5	3.5	3.5

Exploration Systems Architecture Study Crew Launch Vehicle - E1, 2, 3 - P1, 2, 3						
	Input	Expon	ExtValue	Logistic	Normal	Uniform
Function	N/A	0.56857	0.62515401	0.62166	0.62	0.63
Variance	0.062771	0.1296	0.083519	0.07681	0.073233	0.081126
Kurtosis	1.7316	9	5.4	4.2	3	1.8
Target #1 (%)	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
Target #1 (X)	0.26	0.2465	0.30716	0.28593	0.27319	0.23533
Target #2 (%)	20.00%	20.00%	20.00%	20.00%	20.00%	20.00%
Target #2 (X)	0.33	0.2889	0.38786	0.40984	0.39224	0.334
Target #3 (%)	30.00%	30.00%	30.00%	30.00%	30.00%	30.00%
Target #3 (X)	0.54	0.33697	0.45326	0.4922	0.47809	0.43267
Target #4 (%)	40.00%	40.00%	40.00%	40.00%	40.00%	40.00%
Target #4 (X)	0.54	0.39247	0.51479	0.55971	0.55144	0.53133
Target #5 (%)	50.00%	50.00%	50.00%	50.00%	50.00%	50.00%
Target #5 (X)	0.59	0.4581	0.57768	0.62166	0.62	0.63
Target #6 (%)	60.00%	60.00%	60.00%	60.00%	60.00%	60.00%
Target #6 (X)	0.78	0.53844	0.64645	0.68362	0.68856	0.72867
Target #7 (%)	70.00%	70.00%	70.00%	70.00%	70.00%	70.00%
Target #7 (X)	0.78	0.642	0.72739	0.75113	0.76191	0.82733
Target #8 (%)	80.00%	80.00%	80.00%	80.00%	80.00%	80.00%
Target #8 (X)	0.84	0.78797	0.83307	0.83349	0.84776	0.926
Target #9 (%)	90.00%	90.00%	90.00%	90.00%	90.00%	90.00%
Target #9 (X)	1	1.0375	1.00217	0.9574	0.96681	1.02467
Target #10 (%)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
A-D Test Value	N/A	0.6618	0.2704	0.2177	0.1868	0.2095
Rank	N/A	5	4	3	1	2
K-S Test Value	N/A	0.316	0.1825	0.1667	0.1514	0.1443
Rank	N/A	7	4	3	2	1
Chi-Sq Test Value	N/A	1.286	0.1429	0.1429	0.1429	0.1429
Rank	N/A	7	2	3	4	6
C.Val @ 0.75	N/A	0.1015	0.1015	0.1015	0.1015	0.1015
C.Val @ 0.5	N/A	0.4549	0.4549	0.4549	0.4549	0.4549
C.Val @ 0.25	N/A	1.3233	1.3233	1.3233	1.3233	1.3233
C.Val @ 0.15	N/A	2.0723	2.0723	2.0723	2.0723	2.0723
C.Val @ 0.1	N/A	2.7055	2.7055	2.7055	2.7055	2.7055
C.Val @ 0.05	N/A	3.8415	3.8415	3.8415	3.8415	3.8415
C.Val @ 0.025	N/A	5.0239	5.0239	5.0239	5.0239	5.0239
C.Val @ 0.01	N/A	6.6349	6.6349	6.6349	6.6349	6.6349
C.Val @ 0.005	N/A	7.8794	7.8794	7.8794	7.8794	7.8794
C.Val @ 0.001	N/A	10.8276	10.8276	10.8276	10.8276	10.8276
# Bins	N/A	2	2	2	2	2
Bin #1 Input	N/A	2	3	4	4	4
Bin #1 Fit	N/A	3.5	3.5	3.5	3.5	3.5
Bin #2 Input	N/A	5	4	3	3	3
Bin #2 Fit	N/A	3.5	3.5	3.5	3.5	3.5

Exploration Systems Architecture Study Crew Launch Vehicle - E1 - B1						
	Input	**Expon**	**ExtValue**	**Logistic**	**Normal**	**Uniform**
Function	N/A	0.335512	0.36994734	0.33817	0.38143	0.5300165
Variance	0.085355	0.10332	0.066606	0.082534	0.099581	0.1309
Kurtosis	3.1605	9	5.4	4.2	3	1.8
Target #1 (%)	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
Target #1 (X)	0.06	0.047948	0.085977	-0.0098493	-0.022984	0.028667
Target #2 (%)	20.00%	20.00%	20.00%	20.00%	20.00%	20.00%
Target #2 (X)	0.18	0.085806	0.15804	0.11859	0.11584	0.154
Target #3 (%)	30.00%	30.00%	30.00%	30.00%	30.00%	30.00%
Target #3 (X)	0.18	0.12873	0.21645	0.20397	0.21595	0.27933
Target #4 (%)	40.00%	40.00%	40.00%	40.00%	40.00%	40.00%
Target #4 (X)	0.18	0.17828	0.2714	0.27395	0.30148	0.40467
Target #5 (%)	50.00%	50.00%	50.00%	50.00%	50.00%	50.00%
Target #5 (X)	0.35	0.23688	0.32756	0.33817	0.38143	0.53
Target #6 (%)	60.00%	60.00%	60.00%	60.00%	60.00%	60.00%
Target #6 (X)	0.35	0.3086	0.38897	0.40239	0.46138	0.65533
Target #7 (%)	70.00%	70.00%	70.00%	70.00%	70.00%	70.00%
Target #7 (X)	0.35	0.40107	0.46125	0.47237	0.54691	0.78067
Target #8 (%)	80.00%	80.00%	80.00%	80.00%	80.00%	80.00%
Target #8 (X)	0.55	0.5314	0.55563	0.55774	0.64701	0.906
Target #9 (%)	90.00%	90.00%	90.00%	90.00%	90.00%	90.00%
Target #9 (X)	1	0.7542	0.70663	0.68619	0.78584	1.03133
Target #10 (%)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
A-D Test Value	N/A	0.4183	0.2912	0.3861	0.4555	0.9938
Rank	N/A	5	3	4	6	7
K-S Test Value	N/A	0.2604	0.1924	0.1956	0.254	0.3579
Rank	N/A	6	3	4	5	9
Chi-Sq Test Value	N/A	0.1429	0.1429	0.1429	1.286	1.286
Rank	N/A	1	2	4	7	9
C.Val @ 0.75	N/A	0.1015	0.1015	0.1015	0.1015	0.1015
C.Val @ 0.5	N/A	0.4549	0.4549	0.4549	0.4549	0.4549
C.Val @ 0.25	N/A	1.3233	1.3233	1.3233	1.3233	1.3233
C.Val @ 0.15	N/A	2.0723	2.0723	2.0723	2.0723	2.0723
C.Val @ 0.1	N/A	2.7055	2.7055	2.7055	2.7055	2.7055
C.Val @ 0.05	N/A	3.8415	3.8415	3.8415	3.8415	3.8415
C.Val @ 0.025	N/A	5.0239	5.0239	5.0239	5.0239	5.0239
C.Val @ 0.01	N/A	6.6349	6.6349	6.6349	6.6349	6.6349
C.Val @ 0.005	N/A	7.8794	7.8794	7.8794	7.8794	7.8794
C.Val @ 0.001	N/A	10.8276	10.8276	10.8276	10.8276	10.8276
# Bins	N/A	2	2	2	2	2
Bin #1 Input	N/A	3	3	3	5	5
Bin #1 Fit	N/A	3.5	3.5	3.5	3.5	3.5
Bin #2 Input	N/A	4	4	4	2	2
Bin #2 Fit	N/A	3.5	3.5	3.5	3.5	3.5

Exploration Systems Architecture Study Crew Launch Vehicle - E1 - P1						
	Input	Expon	ExtValue	Logistic	Normal	Uniform
Function	N/A	0.71694	0.77176583	0.76968	0.76143	0.725
Variance	0.031069	0.096988	0.050398	0.036328	0.036248	0.044815
Kurtosis	2.0711	9	5.4	4.2	3	1.8
Target #1 (%)	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
Target #1 (X)	0.45	0.43832	0.52474	0.53879	0.51744	0.43167
Target #2 (%)	20.00%	20.00%	20.00%	20.00%	20.00%	20.00%
Target #2 (X)	0.65	0.475	0.58743	0.624	0.60119	0.505
Target #3 (%)	30.00%	30.00%	30.00%	30.00%	30.00%	30.00%
Target #3 (X)	0.65	0.51659	0.63823	0.68064	0.66159	0.57833
Target #4 (%)	40.00%	40.00%	40.00%	40.00%	40.00%	40.00%
Target #4 (X)	0.65	0.5646	0.68603	0.72707	0.71319	0.65167
Target #5 (%)	50.00%	50.00%	50.00%	50.00%	50.00%	50.00%
Target #5 (X)	0.82	0.62138	0.73488	0.76968	0.76143	0.725
Target #6 (%)	60.00%	60.00%	60.00%	60.00%	60.00%	60.00%
Target #6 (X)	0.82	0.69087	0.7883	0.81228	0.80966	0.79833
Target #7 (%)	70.00%	70.00%	70.00%	70.00%	70.00%	70.00%
Target #7 (X)	0.82	0.78046	0.85118	0.85871	0.86127	0.87167
Target #8 (%)	80.00%	80.00%	80.00%	80.00%	80.00%	80.00%
Target #8 (X)	0.94	0.90674	0.93327	0.91535	0.92166	0.945
Target #9 (%)	90.00%	90.00%	90.00%	90.00%	90.00%	90.00%
Target #9 (X)	1	1.1226	1.06463	1.00057	1.00542	1.01833
Target #10 (%)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
A-D Test Value	N/A	1.093	0.3595	0.2703	0.2458	0.3921
Rank	N/A	6	4	3	1	5
K-S Test Value	N/A	0.4011	0.2244	0.1889	0.1923	0.2549
Rank	N/A	9	5	1	4	6
Chi-Sq Test Value	N/A	3.571	0.1429	0.1429	0.1429	0.1429
Rank	N/A	8	2	3	4	6
C.Val @ 0.75	N/A	0.1015	0.1015	0.1015	0.1015	0.1015
C.Val @ 0.5	N/A	0.4549	0.4549	0.4549	0.4549	0.4549
C.Val @ 0.25	N/A	1.3233	1.3233	1.3233	1.3233	1.3233
C.Val @ 0.15	N/A	2.0723	2.0723	2.0723	2.0723	2.0723
C.Val @ 0.1	N/A	2.7055	2.7055	2.7055	2.7055	2.7055
C.Val @ 0.05	N/A	3.8415	3.8415	3.8415	3.8415	3.8415
C.Val @ 0.025	N/A	5.0239	5.0239	5.0239	5.0239	5.0239
C.Val @ 0.01	N/A	6.6349	6.6349	6.6349	6.6349	6.6349
C.Val @ 0.005	N/A	7.8794	7.8794	7.8794	7.8794	7.8794
C.Val @ 0.001	N/A	10.8276	10.8276	10.8276	10.8276	10.8276
# Bins	N/A	2	2	2	2	2
Bin #1 Input	N/A	1	3	3	3	3
Bin #1 Fit	N/A	3.5	3.5	3.5	3.5	3.5
Bin #2 Input	N/A	6	4	4	4	4
Bin #2 Fit	N/A	3.5	3.5	3.5	3.5	3.5

Exploration Systems Architecture Study Crew Launch Vehicle - E2 - B2						
	Input	**Expon**	**ExtValue**	**Logistic**	**Normal**	**Uniform**
Function	N/A	0.327548	0.35416678	0.32285	0.36714	0.5450165
Variance	0.085735	0.076808	0.06363	0.080673	0.10002	0.12268
Kurtosis	3.3617	9	5.4	4.2	3	1.8
Target #1 (%)	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
Target #1 (X)	0.09	0.079608	0.076604	-0.021221	-0.038168	0.059667
Target #2 (%)	20.00%	20.00%	20.00%	20.00%	20.00%	20.00%
Target #2 (X)	0.09	0.11225	0.14704	0.10577	0.10097	0.181
Target #3 (%)	30.00%	30.00%	30.00%	30.00%	30.00%	30.00%
Target #3 (X)	0.21	0.14926	0.20413	0.19017	0.20129	0.30233
Target #4 (%)	40.00%	40.00%	40.00%	40.00%	40.00%	40.00%
Target #4 (X)	0.21	0.19198	0.25783	0.25936	0.28702	0.42367
Target #5 (%)	50.00%	50.00%	50.00%	50.00%	50.00%	50.00%
Target #5 (X)	0.28	0.24251	0.31272	0.32285	0.36714	0.545
Target #6 (%)	60.00%	60.00%	60.00%	60.00%	60.00%	60.00%
Target #6 (X)	0.45	0.30435	0.37275	0.38634	0.44727	0.66633
Target #7 (%)	70.00%	70.00%	70.00%	70.00%	70.00%	70.00%
Target #7 (X)	0.45	0.38408	0.4434	0.45553	0.53299	0.78767
Target #8 (%)	80.00%	80.00%	80.00%	80.00%	80.00%	80.00%
Target #8 (X)	0.45	0.49645	0.53564	0.53994	0.63332	0.909
Target #9 (%)	90.00%	90.00%	90.00%	90.00%	90.00%	90.00%
Target #9 (X)	1	0.68855	0.68324	0.66692	0.77245	1.03033
Target #10 (%)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
A-D Test Value	N/A	0.3445	0.3525	0.419	0.5042	1.277
Rank	N/A	1	2	3	4	8
K-S Test Value	N/A	0.1921	0.1693	0.1844	0.2538	0.4354
Rank	N/A	3	1	2	6	11
Chi-Sq Test Value	N/A	0.1429	0.1429	0.1429	0.1429	3.571
Rank	N/A	2	3	4	6	11
C.Val @ 0.75	N/A	0.1015	0.1015	0.1015	0.1015	0.1015
C.Val @ 0.5	N/A	0.4549	0.4549	0.4549	0.4549	0.4549
C.Val @ 0.25	N/A	1.3233	1.3233	1.3233	1.3233	1.3233
C.Val @ 0.15	N/A	2.0723	2.0723	2.0723	2.0723	2.0723
C.Val @ 0.1	N/A	2.7055	2.7055	2.7055	2.7055	2.7055
C.Val @ 0.05	N/A	3.8415	3.8415	3.8415	3.8415	3.8415
C.Val @ 0.025	N/A	5.0239	5.0239	5.0239	5.0239	5.0239
C.Val @ 0.01	N/A	6.6349	6.6349	6.6349	6.6349	6.6349
C.Val @ 0.005	N/A	7.8794	7.8794	7.8794	7.8794	7.8794
C.Val @ 0.001	N/A	10.8276	10.8276	10.8276	10.8276	10.8276
# Bins	N/A	2	2	2	2	2
Bin #1 Input	N/A	3	4	4	4	6
Bin #1 Fit	N/A	3.5	3.5	3.5	3.5	3.5
Bin #2 Input	N/A	4	3	3	3	1
Bin #2 Fit	N/A	3.5	3.5	3.5	3.5	3.5

Exploration Systems Architecture Study Crew Launch Vehicle - E2 - P2						
	Input	Expon	ExtValue	Logistic	Normal	Uniform
Function	N/A	0.74347	0.78047617	0.78293	0.77571	0.775
Variance	0.027367	0.050947	0.038944	0.033994	0.031929	0.03
Kurtosis	1.5987	9	5.4	4.2	3	1.8
Target #1 (%)	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
Target #1 (X)	0.55	0.54154	0.56333	0.55958	0.54672	0.535
Target #2 (%)	20.00%	20.00%	20.00%	20.00%	20.00%	20.00%
Target #2 (X)	0.55	0.56812	0.61843	0.64201	0.62533	0.595
Target #3 (%)	30.00%	30.00%	30.00%	30.00%	30.00%	30.00%
Target #3 (X)	0.72	0.59826	0.66309	0.6968	0.68201	0.655
Target #4 (%)	40.00%	40.00%	40.00%	40.00%	40.00%	40.00%
Target #4 (X)	0.72	0.63306	0.70511	0.74171	0.73044	0.715
Target #5 (%)	50.00%	50.00%	50.00%	50.00%	50.00%	50.00%
Target #5 (X)	0.79	0.67421	0.74805	0.78293	0.77571	0.775
Target #6 (%)	60.00%	60.00%	60.00%	60.00%	60.00%	60.00%
Target #6 (X)	0.91	0.72458	0.79501	0.82414	0.82098	0.835
Target #7 (%)	70.00%	70.00%	70.00%	70.00%	70.00%	70.00%
Target #7 (X)	0.91	0.78951	0.85028	0.86905	0.86942	0.895
Target #8 (%)	80.00%	80.00%	80.00%	80.00%	80.00%	80.00%
Target #8 (X)	0.91	0.88103	0.92245	0.92384	0.9261	0.955
Target #9 (%)	90.00%	90.00%	90.00%	90.00%	90.00%	90.00%
Target #9 (X)	1	1.03748	1.03792	1.00628	1.00471	1.015
Target #10 (%)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
A-D Test Value	N/A	0.8081	0.4678	0.3507	0.326	0.2887
Rank	N/A	5	4	3	2	1
K-S Test Value	N/A	0.3061	0.2137	0.2059	0.2024	0.1607
Rank	N/A	8	4	3	2	1
Chi-Sq Test Value	N/A	1.286	0.1429	0.1429	0.1429	0.1429
Rank	N/A	7	1	2	3	5
C.Val @ 0.75	N/A	0.1015	0.1015	0.1015	0.1015	0.1015
C.Val @ 0.5	N/A	0.4549	0.4549	0.4549	0.4549	0.4549
C.Val @ 0.25	N/A	1.3233	1.3233	1.3233	1.3233	1.3233
C.Val @ 0.15	N/A	2.0723	2.0723	2.0723	2.0723	2.0723
C.Val @ 0.1	N/A	2.7055	2.7055	2.7055	2.7055	2.7055
C.Val @ 0.05	N/A	3.8415	3.8415	3.8415	3.8415	3.8415
C.Val @ 0.025	N/A	5.0239	5.0239	5.0239	5.0239	5.0239
C.Val @ 0.01	N/A	6.6349	6.6349	6.6349	6.6349	6.6349
C.Val @ 0.005	N/A	7.8794	7.8794	7.8794	7.8794	7.8794
C.Val @ 0.001	N/A	10.8276	10.8276	10.8276	10.8276	10.8276
# Bins	N/A	2	2	2	2	2
Bin #1 Input	N/A	2	3	3	3	3
Bin #1 Fit	N/A	3.5	3.5	3.5	3.5	3.5
Bin #2 Input	N/A	5	4	4	4	4
Bin #2 Fit	N/A	3.5	3.5	3.5	3.5	3.5

Exploration Systems Architecture Study Crew Launch Vehicle - E3 - B3						
	Input	Expon	ExtValue	Logistic	Normal	Uniform
Function	N/A	0.344083	0.36763584	0.33746	0.38143	0.5600165
Variance	0.082498	0.068345	0.059908	0.078551	0.096248	0.11473
Kurtosis	3.3022	9	5.4	4.2	3	1.8
Target #1 (%)	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
Target #1 (X)	0.12	0.1102	0.098312	-0.0020552	-0.016157	0.090667
Target #2 (%)	20.00%	20.00%	20.00%	20.00%	20.00%	20.00%
Target #2 (X)	0.12	0.14099	0.16666	0.12325	0.12033	0.208
Target #3 (%)	30.00%	30.00%	30.00%	30.00%	30.00%	30.00%
Target #3 (X)	0.19	0.1759	0.22205	0.20654	0.21874	0.32533
Target #4 (%)	40.00%	40.00%	40.00%	40.00%	40.00%	40.00%
Target #4 (X)	0.19	0.2162	0.27416	0.27481	0.30283	0.44267
Target #5 (%)	50.00%	50.00%	50.00%	50.00%	50.00%	50.00%
Target #5 (X)	0.31	0.26386	0.32742	0.33746	0.38143	0.56
Target #6 (%)	60.00%	60.00%	60.00%	60.00%	60.00%	60.00%
Target #6 (X)	0.43	0.3222	0.38567	0.40011	0.46003	0.67733
Target #7 (%)	70.00%	70.00%	70.00%	70.00%	70.00%	70.00%
Target #7 (X)	0.43	0.39741	0.45422	0.46839	0.54412	0.79467
Target #8 (%)	80.00%	80.00%	80.00%	80.00%	80.00%	80.00%
Target #8 (X)	0.5	0.50341	0.54373	0.55167	0.64253	0.912
Target #9 (%)	90.00%	90.00%	90.00%	90.00%	90.00%	90.00%
Target #9 (X)	1	0.68461	0.68694	0.67698	0.77901	1.02933
Target #10 (%)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
A-D Test Value	N/A	0.3025	0.3516	0.4007	0.4859	1.326
Rank	N/A	1	2	3	4	7
K-S Test Value	N/A	0.1637	0.1879	0.1967	0.2083	0.4083
Rank	N/A	1	2	3	5	10
Chi-Sq Test Value	N/A	0.1429	0.1429	0.1429	0.1429	3.571
Rank	N/A	2	3	5	7	10
C.Val @ 0.75	N/A	0.1015	0.1015	0.1015	0.1015	0.1015
C.Val @ 0.5	N/A	0.4549	0.4549	0.4549	0.4549	0.4549
C.Val @ 0.25	N/A	1.3233	1.3233	1.3233	1.3233	1.3233
C.Val @ 0.15	N/A	2.0723	2.0723	2.0723	2.0723	2.0723
C.Val @ 0.1	N/A	2.7055	2.7055	2.7055	2.7055	2.7055
C.Val @ 0.05	N/A	3.8415	3.8415	3.8415	3.8415	3.8415
C.Val @ 0.025	N/A	5.0239	5.0239	5.0239	5.0239	5.0239
C.Val @ 0.01	N/A	6.6349	6.6349	6.6349	6.6349	6.6349
C.Val @ 0.005	N/A	7.8794	7.8794	7.8794	7.8794	7.8794
C.Val @ 0.001	N/A	10.8276	10.8276	10.8276	10.8276	10.8276
# Bins	N/A	2	2	2	2	2
Bin #1 Input	N/A	3	4	4	4	6
Bin #1 Fit	N/A	3.5	3.5	3.5	3.5	3.5
Bin #2 Input	N/A	4	3	3	3	1
Bin #2 Fit	N/A	3.5	3.5	3.5	3.5	3.5

Exploration Systems Architecture Study Crew Launch Vehicle - E3 - P3						
	Input	**Expon**	**ExtValue**	**Logistic**	**Normal**	**Uniform**
Function	N/A	0.72408	0.76749762	0.7697	0.76143	0.75
Variance	0.028212	0.068345	0.041487	0.034431	0.032914	0.037037
Kurtosis	1.7375	9	5.4	4.2	3	1.8
Target #1 (%)	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
Target #1 (X)	0.5	0.4902	0.54338	0.54491	0.52893	0.48333
Target #2 (%)	20.00%	20.00%	20.00%	20.00%	20.00%	20.00%
Target #2 (X)	0.57	0.52099	0.60025	0.62787	0.60874	0.55
Target #3 (%)	30.00%	30.00%	30.00%	30.00%	30.00%	30.00%
Target #3 (X)	0.69	0.5559	0.64635	0.68302	0.66629	0.61667
Target #4 (%)	40.00%	40.00%	40.00%	40.00%	40.00%	40.00%
Target #4 (X)	0.69	0.5962	0.68971	0.72822	0.71547	0.68333
Target #5 (%)	50.00%	50.00%	50.00%	50.00%	50.00%	50.00%
Target #5 (X)	0.81	0.64386	0.73404	0.7697	0.76143	0.75
Target #6 (%)	60.00%	60.00%	60.00%	60.00%	60.00%	60.00%
Target #6 (X)	0.88	0.7022	0.78251	0.81118	0.80739	0.81667
Target #7 (%)	70.00%	70.00%	70.00%	70.00%	70.00%	70.00%
Target #7 (X)	0.88	0.77741	0.83955	0.85638	0.85657	0.88333
Target #8 (%)	80.00%	80.00%	80.00%	80.00%	80.00%	80.00%
Target #8 (X)	0.88	0.88341	0.91404	0.91152	0.91412	0.95
Target #9 (%)	90.00%	90.00%	90.00%	90.00%	90.00%	90.00%
Target #9 (X)	1	1.06461	1.03321	0.99448	0.99393	1.01667
Target #10 (%)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
A-D Test Value	N/A	0.827	0.3497	0.279	0.2466	0.2618
Rank	N/A	6	5	4	1	2
K-S Test Value	N/A	0.3066	0.2222	0.1747	0.177	0.1621
Rank	N/A	9	6	2	3	1
Chi-Sq Test Value	N/A	1.286	0.1429	0.1429	0.1429	0.1429
Rank	N/A	8	2	3	4	6
C.Val @ 0.75	N/A	0.1015	0.1015	0.1015	0.1015	0.1015
C.Val @ 0.5	N/A	0.4549	0.4549	0.4549	0.4549	0.4549
C.Val @ 0.25	N/A	1.3233	1.3233	1.3233	1.3233	1.3233
C.Val @ 0.15	N/A	2.0723	2.0723	2.0723	2.0723	2.0723
C.Val @ 0.1	N/A	2.7055	2.7055	2.7055	2.7055	2.7055
C.Val @ 0.05	N/A	3.8415	3.8415	3.8415	3.8415	3.8415
C.Val @ 0.025	N/A	5.0239	5.0239	5.0239	5.0239	5.0239
C.Val @ 0.01	N/A	6.6349	6.6349	6.6349	6.6349	6.6349
C.Val @ 0.005	N/A	7.8794	7.8794	7.8794	7.8794	7.8794
C.Val @ 0.001	N/A	10.8276	10.8276	10.8276	10.8276	10.8276
# Bins	N/A	2	2	2	2	2
Bin #1 Input	N/A	2	3	3	3	3
Bin #1 Fit	N/A	3.5	3.5	3.5	3.5	3.5
Bin #2 Input	N/A	5	4	4	4	4
Bin #2 Fit	N/A	3.5	3.5	3.5	3.5	3.5

Parallel-Staged Crew Launch Vehicle - E1, 2, 3 - B1, 2, 3						
	Input	**Expon**	**ExtValue**	**Logistic**	**Normal**	**Uniform**
Function	N/A	0.468369	0.5219852	0.51127	0.52143	0.57501665
Variance	0.080184	0.13796	0.093665	0.096439	0.093548	0.10704
Kurtosis	1.8789	9	5.4	4.2	3	1.8
Target #1 (%)	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
Target #1 (X)	0.15	0.13607	0.18523	0.13508	0.12946	0.12167
Target #2 (%)	20.00%	20.00%	20.00%	20.00%	20.00%	20.00%
Target #2 (X)	0.21	0.17982	0.27069	0.27392	0.26401	0.235
Target #3 (%)	30.00%	30.00%	30.00%	30.00%	30.00%	30.00%
Target #3 (X)	0.39	0.22942	0.33995	0.3662	0.36104	0.34833
Target #4 (%)	40.00%	40.00%	40.00%	40.00%	40.00%	40.00%
Target #4 (X)	0.39	0.28667	0.40511	0.44185	0.44394	0.46167
Target #5 (%)	50.00%	50.00%	50.00%	50.00%	50.00%	50.00%
Target #5 (X)	0.47	0.35439	0.47171	0.51127	0.52143	0.575
Target #6 (%)	60.00%	60.00%	60.00%	60.00%	60.00%	60.00%
Target #6 (X)	0.68	0.43728	0.54454	0.58069	0.59892	0.68833
Target #7 (%)	70.00%	70.00%	70.00%	70.00%	70.00%	70.00%
Target #7 (X)	0.68	0.54413	0.63025	0.65634	0.68182	0.80167
Target #8 (%)	80.00%	80.00%	80.00%	80.00%	80.00%	80.00%
Target #8 (X)	0.75	0.69473	0.74217	0.74862	0.77884	0.915
Target #9 (%)	90.00%	90.00%	90.00%	90.00%	90.00%	90.00%
Target #9 (X)	1	0.95218	0.92124	0.88746	0.9134	1.02833
Target #10 (%)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
A-D Test Value	N/A	0.5029	0.2213	0.2083	0.1831	0.3002
Rank	N/A	8	3	2	1	7
K-S Test Value	N/A	0.26	0.1772	0.1568	0.1382	0.2027
Rank	N/A	10	5	2	1	8
Chi-Sq Test Value	N/A	1.286	0.1429	0.1429	0.1429	0.1429
Rank	N/A	10	2	4	7	9
C.Val @ 0.75	N/A	0.1015	0.1015	0.1015	0.1015	0.1015
C.Val @ 0.5	N/A	0.4549	0.4549	0.4549	0.4549	0.4549
C.Val @ 0.25	N/A	1.3233	1.3233	1.3233	1.3233	1.3233
C.Val @ 0.15	N/A	2.0723	2.0723	2.0723	2.0723	2.0723
C.Val @ 0.1	N/A	2.7055	2.7055	2.7055	2.7055	2.7055
C.Val @ 0.05	N/A	3.8415	3.8415	3.8415	3.8415	3.8415
C.Val @ 0.025	N/A	5.0239	5.0239	5.0239	5.0239	5.0239
C.Val @ 0.01	N/A	6.6349	6.6349	6.6349	6.6349	6.6349
C.Val @ 0.005	N/A	7.8794	7.8794	7.8794	7.8794	7.8794
C.Val @ 0.001	N/A	10.8276	10.8276	10.8276	10.8276	10.8276
# Bins	N/A	2	2	2	2	2
Bin #1 Input	N/A	2	4	4	4	4
Bin #1 Fit	N/A	3.5	3.5	3.5	3.5	3.5
Bin #2 Input	N/A	5	3	3	3	3
Bin #2 Fit	N/A	3.5	3.5	3.5	3.5	3.5

Parallel-Staged Crew Launch Vehicle - E1, 2, 3 - P1, 2, 3						
	Input	Expon	ExtValue	Logistic	Normal	Uniform
Function	N/A	0.56837	0.62731857	0.62543	0.62143	0.625
Variance	0.065898	0.13796	0.089321	0.081079	0.076881	0.083333
Kurtosis	1.6921	9	5.4	4.2	3	1.8
Target #1 (%)	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
Target #1 (X)	0.25	0.23607	0.29846	0.2805	0.26609	0.225
Target #2 (%)	20.00%	20.00%	20.00%	20.00%	20.00%	20.00%
Target #2 (X)	0.32	0.27982	0.38191	0.4078	0.38807	0.325
Target #3 (%)	30.00%	30.00%	30.00%	30.00%	30.00%	30.00%
Target #3 (X)	0.53	0.32942	0.44955	0.49242	0.47603	0.425
Target #4 (%)	40.00%	40.00%	40.00%	40.00%	40.00%	40.00%
Target #4 (X)	0.53	0.38667	0.51318	0.56178	0.55118	0.525
Target #5 (%)	50.00%	50.00%	50.00%	50.00%	50.00%	50.00%
Target #5 (X)	0.61	0.45439	0.57821	0.62543	0.62143	0.625
Target #6 (%)	60.00%	60.00%	60.00%	60.00%	60.00%	60.00%
Target #6 (X)	0.79	0.53728	0.64934	0.68909	0.69168	0.725
Target #7 (%)	70.00%	70.00%	70.00%	70.00%	70.00%	70.00%
Target #7 (X)	0.79	0.64413	0.73304	0.75845	0.76683	0.825
Target #8 (%)	80.00%	80.00%	80.00%	80.00%	80.00%	80.00%
Target #8 (X)	0.85	0.79473	0.84233	0.84307	0.85479	0.925
Target #9 (%)	90.00%	90.00%	90.00%	90.00%	90.00%	90.00%
Target #9 (X)	1	1.05218	1.0172	0.97037	0.97677	1.025
Target #10 (%)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
A-D Test Value	N/A	0.6729	0.2797	0.2187	0.1881	0.1962
Rank	N/A	6	4	3	1	2
K-S Test Value	N/A	0.3064	0.1849	0.169	0.157	0.1321
Rank	N/A	8	4	3	2	1
Chi-Sq Test Value	N/A	1.286	0.1429	0.1429	0.1429	0.1429
Rank	N/A	8	2	3	4	6
C.Val @ 0.75	N/A	0.1015	0.1015	0.1015	0.1015	0.1015
C.Val @ 0.5	N/A	0.4549	0.4549	0.4549	0.4549	0.4549
C.Val @ 0.25	N/A	1.3233	1.3233	1.3233	1.3233	1.3233
C.Val @ 0.15	N/A	2.0723	2.0723	2.0723	2.0723	2.0723
C.Val @ 0.1	N/A	2.7055	2.7055	2.7055	2.7055	2.7055
C.Val @ 0.05	N/A	3.8415	3.8415	3.8415	3.8415	3.8415
C.Val @ 0.025	N/A	5.0239	5.0239	5.0239	5.0239	5.0239
C.Val @ 0.01	N/A	6.6349	6.6349	6.6349	6.6349	6.6349
C.Val @ 0.005	N/A	7.8794	7.8794	7.8794	7.8794	7.8794
C.Val @ 0.001	N/A	10.8276	10.8276	10.8276	10.8276	10.8276
# Bins	N/A	2	2	2	2	2
Bin #1 Input	N/A	2	3	4	4	4
Bin #1 Fit	N/A	3.5	3.5	3.5	3.5	3.5
Bin #2 Input	N/A	5	4	3	3	3
Bin #2 Fit	N/A	3.5	3.5	3.5	3.5	3.5

Parallel-Staged Crew Launch Vehicle - E1 - B1						
	Input	Expon	ExtValue	Logistic	Normal	Uniform
Function	N/A	0.3228571	0.35921549	0.327	0.37	0.52
Variance	0.086857	0.1089	0.068531	0.082538	0.10133	0.13653
Kurtosis	3.2756	9	5.4	4.2	3	1.8
Target #1 (%)	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
Target #1 (X)	0.04	0.027626	0.071163	-0.021026	-0.037955	0.008
Target #2 (%)	20.00%	20.00%	20.00%	20.00%	20.00%	20.00%
Target #2 (X)	0.17	0.066495	0.14427	0.10742	0.10209	0.136
Target #3 (%)	30.00%	30.00%	30.00%	30.00%	30.00%	30.00%
Target #3 (X)	0.17	0.11056	0.20351	0.19279	0.20307	0.264
Target #4 (%)	40.00%	40.00%	40.00%	40.00%	40.00%	40.00%
Target #4 (X)	0.17	0.16143	0.25924	0.26278	0.28935	0.392
Target #5 (%)	50.00%	50.00%	50.00%	50.00%	50.00%	50.00%
Target #5 (X)	0.32	0.2216	0.31621	0.327	0.37	0.52
Target #6 (%)	60.00%	60.00%	60.00%	60.00%	60.00%	60.00%
Target #6 (X)	0.38	0.29523	0.37851	0.39122	0.45065	0.648
Target #7 (%)	70.00%	70.00%	70.00%	70.00%	70.00%	70.00%
Target #7 (X)	0.38	0.39017	0.45182	0.46121	0.53693	0.776
Target #8 (%)	80.00%	80.00%	80.00%	80.00%	80.00%	80.00%
Target #8 (X)	0.51	0.52397	0.54755	0.54658	0.63791	0.904
Target #9 (%)	90.00%	90.00%	90.00%	90.00%	90.00%	90.00%
Target #9 (X)	1	0.75271	0.70073	0.67502	0.77795	1.032
Target #10 (%)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
A-D Test Value	N/A	0.4254	0.2444	0.3402	0.4276	0.9768
Rank	N/A	5	3	4	6	8
K-S Test Value	N/A	0.2725	0.1866	0.1579	0.2018	0.365
Rank	N/A	8	4	3	6	10
Chi-Sq Test Value	N/A	0.1429	0.1429	0.1429	0.1429	3.571
Rank	N/A	1	2	4	7	12
C.Val @ 0.75	N/A	0.1015	0.1015	0.1015	0.1015	0.1015
C.Val @ 0.5	N/A	0.4549	0.4549	0.4549	0.4549	0.4549
C.Val @ 0.25	N/A	1.3233	1.3233	1.3233	1.3233	1.3233
C.Val @ 0.15	N/A	2.0723	2.0723	2.0723	2.0723	2.0723
C.Val @ 0.1	N/A	2.7055	2.7055	2.7055	2.7055	2.7055
C.Val @ 0.05	N/A	3.8415	3.8415	3.8415	3.8415	3.8415
C.Val @ 0.025	N/A	5.0239	5.0239	5.0239	5.0239	5.0239
C.Val @ 0.01	N/A	6.6349	6.6349	6.6349	6.6349	6.6349
C.Val @ 0.005	N/A	7.8794	7.8794	7.8794	7.8794	7.8794
C.Val @ 0.001	N/A	10.8276	10.8276	10.8276	10.8276	10.8276
# Bins	N/A	2	2	2	2	2
Bin #1 Input	N/A	3	3	4	4	6
Bin #1 Fit	N/A	3.5	3.5	3.5	3.5	3.5
Bin #2 Input	N/A	4	4	3	3	1
Bin #2 Fit	N/A	3.5	3.5	3.5	3.5	3.5

Parallel-Staged Crew Launch Vehicle - E1 - P1						
	Input	Expon	ExtValue	Logistic	Normal	Uniform
Function	N/A	0.73245	0.78013517	0.77897	0.77286	0.745
Variance	0.029306	0.080008	0.044008	0.035503	0.03419	0.038533
Kurtosis	1.8183	9	5.4	4.2	3	1.8
Target #1 (%)	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
Target #1 (X)	0.49	0.47939	0.5493	0.55072	0.53589	0.473
Target #2 (%)	20.00%	20.00%	20.00%	20.00%	20.00%	20.00%
Target #2 (X)	0.62	0.51271	0.60788	0.63496	0.61724	0.541
Target #3 (%)	30.00%	30.00%	30.00%	30.00%	30.00%	30.00%
Target #3 (X)	0.68	0.55048	0.65536	0.69095	0.67589	0.609
Target #4 (%)	40.00%	40.00%	40.00%	40.00%	40.00%	40.00%
Target #4 (X)	0.68	0.59408	0.70002	0.73685	0.72601	0.677
Target #5 (%)	50.00%	50.00%	50.00%	50.00%	50.00%	50.00%
Target #5 (X)	0.83	0.64565	0.74567	0.77897	0.77286	0.745
Target #6 (%)	60.00%	60.00%	60.00%	60.00%	60.00%	60.00%
Target #6 (X)	0.83	0.70877	0.79559	0.82109	0.8197	0.813
Target #7 (%)	70.00%	70.00%	70.00%	70.00%	70.00%	70.00%
Target #7 (X)	0.83	0.79014	0.85434	0.86699	0.86982	0.881
Target #8 (%)	80.00%	80.00%	80.00%	80.00%	80.00%	80.00%
Target #8 (X)	0.96	0.90483	0.93106	0.92298	0.92848	0.949
Target #9 (%)	90.00%	90.00%	90.00%	90.00%	90.00%	90.00%
Target #9 (X)	1	1.10089	1.0538	1.00722	1.00982	1.017
Target #10 (%)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
A-D Test Value	N/A	0.9206	0.2945	0.2484	0.2172	0.2946
Rank	N/A	6	4	2	1	5
K-S Test Value	N/A	0.3109	0.2325	0.1918	0.1928	0.1964
Rank	N/A	9	7	3	4	5
Chi-Sq Test Value	N/A	1.286	0.1429	0.1429	0.1429	0.1429
Rank	N/A	8	2	3	4	6
C.Val @ 0.75	N/A	0.1015	0.1015	0.1015	0.1015	0.1015
C.Val @ 0.5	N/A	0.4549	0.4549	0.4549	0.4549	0.4549
C.Val @ 0.25	N/A	1.3233	1.3233	1.3233	1.3233	1.3233
C.Val @ 0.15	N/A	2.0723	2.0723	2.0723	2.0723	2.0723
C.Val @ 0.1	N/A	2.7055	2.7055	2.7055	2.7055	2.7055
C.Val @ 0.05	N/A	3.8415	3.8415	3.8415	3.8415	3.8415
C.Val @ 0.025	N/A	5.0239	5.0239	5.0239	5.0239	5.0239
C.Val @ 0.01	N/A	6.6349	6.6349	6.6349	6.6349	6.6349
C.Val @ 0.005	N/A	7.8794	7.8794	7.8794	7.8794	7.8794
C.Val @ 0.001	N/A	10.8276	10.8276	10.8276	10.8276	10.8276
# Bins	N/A	2	2	2	2	2
Bin #1 Input	N/A	2	3	3	3	3
Bin #1 Fit	N/A	3.5	3.5	3.5	3.5	3.5
Bin #2 Input	N/A	5	4	4	4	4
Bin #2 Fit	N/A	3.5	3.5	3.5	3.5	3.5

Parallel-Staged Crew Launch Vehicle - E2 - B2						
	Input	Expon	ExtValue	Logistic	Normal	Uniform
Function	N/A	0.31612	0.34315523	0.31053	0.35714	0.535
Variance	0.085963	0.082451	0.061086	0.078327	0.10029	0.12813
Kurtosis	3.5245	9	5.4	4.2	3	1.8
Target #1 (%)	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
Target #1 (X)	0.07	0.059233	0.071199	-0.028498	-0.048707	0.039
Target #2 (%)	20.00%	20.00%	20.00%	20.00%	20.00%	20.00%
Target #2 (X)	0.12	0.093054	0.14022	0.096629	0.090613	0.163
Target #3 (%)	30.00%	30.00%	30.00%	30.00%	30.00%	30.00%
Target #3 (X)	0.16	0.1314	0.19615	0.1798	0.19107	0.287
Target #4 (%)	40.00%	40.00%	40.00%	40.00%	40.00%	40.00%
Target #4 (X)	0.16	0.17566	0.24877	0.24797	0.27691	0.411
Target #5 (%)	50.00%	50.00%	50.00%	50.00%	50.00%	50.00%
Target #5 (X)	0.31	0.22801	0.30255	0.31053	0.35714	0.535
Target #6 (%)	60.00%	60.00%	60.00%	60.00%	60.00%	60.00%
Target #6 (X)	0.4	0.29209	0.36137	0.3731	0.43737	0.659
Target #7 (%)	70.00%	70.00%	70.00%	70.00%	70.00%	70.00%
Target #7 (X)	0.4	0.37469	0.43059	0.44127	0.52321	0.783
Target #8 (%)	80.00%	80.00%	80.00%	80.00%	80.00%	80.00%
Target #8 (X)	0.44	0.49112	0.52097	0.52444	0.62367	0.907
Target #9 (%)	90.00%	90.00%	90.00%	90.00%	90.00%	90.00%
Target #9 (X)	1	0.69015	0.66558	0.64957	0.76299	1.031
Target #10 (%)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
A-D Test Value	N/A	0.2896	0.3219	0.4099	0.5173	1.262
Rank	N/A	2	3	4	5	7
K-S Test Value	N/A	0.1956	0.1946	0.1738	0.2539	0.4338
Rank	N/A	3	2	1	7	10
Chi-Sq Test Value	N/A	0.1429	0.1429	0.1429	0.1429	3.571
Rank	N/A	2	3	5	7	11
C.Val @ 0.75	N/A	0.1015	0.1015	0.1015	0.1015	0.1015
C.Val @ 0.5	N/A	0.4549	0.4549	0.4549	0.4549	0.4549
C.Val @ 0.25	N/A	1.3233	1.3233	1.3233	1.3233	1.3233
C.Val @ 0.15	N/A	2.0723	2.0723	2.0723	2.0723	2.0723
C.Val @ 0.1	N/A	2.7055	2.7055	2.7055	2.7055	2.7055
C.Val @ 0.05	N/A	3.8415	3.8415	3.8415	3.8415	3.8415
C.Val @ 0.025	N/A	5.0239	5.0239	5.0239	5.0239	5.0239
C.Val @ 0.01	N/A	6.6349	6.6349	6.6349	6.6349	6.6349
C.Val @ 0.005	N/A	7.8794	7.8794	7.8794	7.8794	7.8794
C.Val @ 0.001	N/A	10.8276	10.8276	10.8276	10.8276	10.8276
# Bins	N/A	2	2	2	2	2
Bin #1 Input	N/A	3	3	4	4	6
Bin #1 Fit	N/A	3.5	3.5	3.5	3.5	3.5
Bin #2 Input	N/A	4	4	3	3	1
Bin #2 Fit	N/A	3.5	3.5	3.5	3.5	3.5

Parallel-Staged Crew Launch Vehicle - E2 - P2						
	Input	Expon	ExtValue	Logistic	Normal	Uniform
Function	N/A	0.75347	0.78935987	0.79181	0.78571	0.78
Variance	0.024739	0.050947	0.034177	0.031331	0.028862	0.028681
Kurtosis	1.5169	9	5.4	4.2	3	1.8
Target #1 (%)	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
Target #1 (X)	0.56	0.55154	0.58594	0.57738	0.56799	0.54533
Target #2 (%)	20.00%	20.00%	20.00%	20.00%	20.00%	20.00%
Target #2 (X)	0.6	0.57812	0.63756	0.65652	0.64273	0.604
Target #3 (%)	30.00%	30.00%	30.00%	30.00%	30.00%	30.00%
Target #3 (X)	0.69	0.60826	0.6794	0.70912	0.69662	0.66267
Target #4 (%)	40.00%	40.00%	40.00%	40.00%	40.00%	40.00%
Target #4 (X)	0.69	0.64306	0.71876	0.75224	0.74267	0.72133
Target #5 (%)	50.00%	50.00%	50.00%	50.00%	50.00%	50.00%
Target #5 (X)	0.84	0.68421	0.75899	0.79181	0.78571	0.78
Target #6 (%)	60.00%	60.00%	60.00%	60.00%	60.00%	60.00%
Target #6 (X)	0.88	0.73458	0.80298	0.83138	0.82875	0.83867
Target #7 (%)	70.00%	70.00%	70.00%	70.00%	70.00%	70.00%
Target #7 (X)	0.88	0.79951	0.85476	0.8745	0.8748	0.89733
Target #8 (%)	80.00%	80.00%	80.00%	80.00%	80.00%	80.00%
Target #8 (X)	0.93	0.89103	0.92236	0.9271	0.9287	0.956
Target #9 (%)	90.00%	90.00%	90.00%	90.00%	90.00%	90.00%
Target #9 (X)	1	1.04748	1.03053	1.00623	1.00343	1.01467
Target #10 (%)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
A-D Test Value	N/A	0.6994	0.3765	0.3129	0.2741	0.2162
Rank	N/A	5	4	3	2	1
K-S Test Value	N/A	0.3207	0.245	0.1924	0.1968	0.1737
Rank	N/A	8	6	2	3	1
Chi-Sq Test Value	N/A	1.286	0.1429	0.1429	0.1429	0.1429
Rank	N/A	8	2	3	4	7
C.Val @ 0.75	N/A	0.1015	0.1015	0.1015	0.1015	0.1015
C.Val @ 0.5	N/A	0.4549	0.4549	0.4549	0.4549	0.4549
C.Val @ 0.25	N/A	1.3233	1.3233	1.3233	1.3233	1.3233
C.Val @ 0.15	N/A	2.0723	2.0723	2.0723	2.0723	2.0723
C.Val @ 0.1	N/A	2.7055	2.7055	2.7055	2.7055	2.7055
C.Val @ 0.05	N/A	3.8415	3.8415	3.8415	3.8415	3.8415
C.Val @ 0.025	N/A	5.0239	5.0239	5.0239	5.0239	5.0239
C.Val @ 0.01	N/A	6.6349	6.6349	6.6349	6.6349	6.6349
C.Val @ 0.005	N/A	7.8794	7.8794	7.8794	7.8794	7.8794
C.Val @ 0.001	N/A	10.8276	10.8276	10.8276	10.8276	10.8276
# Bins	N/A	2	2	2	2	2
Bin #1 Input	N/A	2	3	3	3	3
Bin #1 Fit	N/A	3.5	3.5	3.5	3.5	3.5
Bin #2 Input	N/A	5	4	4	4	4
Bin #2 Fit	N/A	3.5	3.5	3.5	3.5	3.5

Parallel-Staged Crew Launch Vehicle - E3 - B3						
	Input	Expon	ExtValue	Logistic	Normal	Uniform
Function	N/A	0.32612	0.35413521	0.32454	0.36714	0.5399835
Variance	0.090363	0.082451	0.069661	0.089984	0.10542	0.12539
Kurtosis	3.0662	9	5.4	4.2	3	1.8
Target #1 (%)	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
Target #1 (X)	0.08	0.069233	0.063719	-0.038845	-0.048965	0.049333
Target #2 (%)	20.00%	20.00%	20.00%	20.00%	20.00%	20.00%
Target #2 (X)	0.08	0.10305	0.13742	0.095269	0.093877	0.172
Target #3 (%)	30.00%	30.00%	30.00%	30.00%	30.00%	30.00%
Target #3 (X)	0.21	0.1414	0.19715	0.18441	0.19688	0.29467
Target #4 (%)	40.00%	40.00%	40.00%	40.00%	40.00%	40.00%
Target #4 (X)	0.21	0.18566	0.25334	0.25748	0.28488	0.41733
Target #5 (%)	50.00%	50.00%	50.00%	50.00%	50.00%	50.00%
Target #5 (X)	0.24	0.23801	0.31078	0.32454	0.36714	0.54
Target #6 (%)	60.00%	60.00%	60.00%	60.00%	60.00%	60.00%
Target #6 (X)	0.46	0.30209	0.37359	0.3916	0.4494	0.66267
Target #7 (%)	70.00%	70.00%	70.00%	70.00%	70.00%	70.00%
Target #7 (X)	0.46	0.38469	0.4475	0.46467	0.53741	0.78533
Target #8 (%)	80.00%	80.00%	80.00%	80.00%	80.00%	80.00%
Target #8 (X)	0.5	0.50112	0.54402	0.55381	0.64041	0.908
Target #9 (%)	90.00%	90.00%	90.00%	90.00%	90.00%	90.00%
Target #9 (X)	1	0.70015	0.69845	0.68792	0.78325	1.03067
Target #10 (%)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
A-D Test Value	N/A	0.3361	0.3579	0.4048	0.4606	1.179
Rank	N/A	1	2	3	4	8
K-S Test Value	N/A	0.1978	0.1952	0.1965	0.2237	0.3898
Rank	N/A	3	1	2	4	11
Chi-Sq Test Value	N/A	0.1429	0.1429	0.1429	0.1429	3.571
Rank	N/A	2	3	4	6	11
C.Val @ 0.75	N/A	0.1015	0.1015	0.1015	0.1015	0.1015
C.Val @ 0.5	N/A	0.4549	0.4549	0.4549	0.4549	0.4549
C.Val @ 0.25	N/A	1.3233	1.3233	1.3233	1.3233	1.3233
C.Val @ 0.15	N/A	2.0723	2.0723	2.0723	2.0723	2.0723
C.Val @ 0.1	N/A	2.7055	2.7055	2.7055	2.7055	2.7055
C.Val @ 0.05	N/A	3.8415	3.8415	3.8415	3.8415	3.8415
C.Val @ 0.025	N/A	5.0239	5.0239	5.0239	5.0239	5.0239
C.Val @ 0.01	N/A	6.6349	6.6349	6.6349	6.6349	6.6349
C.Val @ 0.005	N/A	7.8794	7.8794	7.8794	7.8794	7.8794
C.Val @ 0.001	N/A	10.8276	10.8276	10.8276	10.8276	10.8276
# Bins	N/A	2	2	2	2	2
Bin #1 Input	N/A	3	4	4	4	6
Bin #1 Fit	N/A	3.5	3.5	3.5	3.5	3.5
Bin #2 Input	N/A	4	3	3	3	1
Bin #2 Fit	N/A	3.5	3.5	3.5	3.5	3.5

Parallel-Staged Crew Launch Vehicle - E3 - P3						
	Input	Expon	ExtValue	Logistic	Normal	Uniform
Function	N/A	0.73632	0.78362439	0.78973	0.77571	0.75
Variance	0.031996	0.076018	0.049831	0.038619	0.037329	0.037037
Kurtosis	1.7113	9	5.4	4.2	3	1.8
Target #1 (%)	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
Target #1 (X)	0.5	0.48966	0.538	0.55167	0.52811	0.48333
Target #2 (%)	20.00%	20.00%	20.00%	20.00%	20.00%	20.00%
Target #2 (X)	0.54	0.52214	0.60034	0.63953	0.61311	0.55
Target #3 (%)	30.00%	30.00%	30.00%	30.00%	30.00%	30.00%
Target #3 (X)	0.76	0.55895	0.65086	0.69793	0.6744	0.61667
Target #4 (%)	40.00%	40.00%	40.00%	40.00%	40.00%	40.00%
Target #4 (X)	0.76	0.60145	0.69838	0.7458	0.72677	0.68333
Target #5 (%)	50.00%	50.00%	50.00%	50.00%	50.00%	50.00%
Target #5 (X)	0.79	0.65172	0.74696	0.78973	0.77571	0.75
Target #6 (%)	60.00%	60.00%	60.00%	60.00%	60.00%	60.00%
Target #6 (X)	0.92	0.71325	0.80008	0.83366	0.82466	0.81667
Target #7 (%)	70.00%	70.00%	70.00%	70.00%	70.00%	70.00%
Target #7 (X)	0.92	0.79256	0.8626	0.88153	0.87703	0.88333
Target #8 (%)	80.00%	80.00%	80.00%	80.00%	80.00%	80.00%
Target #8 (X)	0.92	0.90436	0.94423	0.93993	0.93832	0.95
Target #9 (%)	90.00%	90.00%	90.00%	90.00%	90.00%	90.00%
Target #9 (X)	1	1.09547	1.07484	1.02779	1.02332	1.01667
Target #10 (%)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
A-D Test Value	N/A	0.9105	0.4994	0.3771	0.3572	0.3503
Rank	N/A	5	4	3	2	1
K-S Test Value	N/A	0.3767	0.2399	0.1975	0.201	0.2293
Rank	N/A	8	6	1	3	5
Chi-Sq Test Value	N/A	1.286	1.286	0.1429	0.1429	1.286
Rank	N/A	5	6	2	3	8
C.Val @ 0.75	N/A	0.1015	0.1015	0.1015	0.1015	0.1015
C.Val @ 0.5	N/A	0.4549	0.4549	0.4549	0.4549	0.4549
C.Val @ 0.25	N/A	1.3233	1.3233	1.3233	1.3233	1.3233
C.Val @ 0.15	N/A	2.0723	2.0723	2.0723	2.0723	2.0723
C.Val @ 0.1	N/A	2.7055	2.7055	2.7055	2.7055	2.7055
C.Val @ 0.05	N/A	3.8415	3.8415	3.8415	3.8415	3.8415
C.Val @ 0.025	N/A	5.0239	5.0239	5.0239	5.0239	5.0239
C.Val @ 0.01	N/A	6.6349	6.6349	6.6349	6.6349	6.6349
C.Val @ 0.005	N/A	7.8794	7.8794	7.8794	7.8794	7.8794
C.Val @ 0.001	N/A	10.8276	10.8276	10.8276	10.8276	10.8276
# Bins	N/A	2	2	2	2	2
Bin #1 Input	N/A	2	2	3	3	2
Bin #1 Fit	N/A	3.5	3.5	3.5	3.5	3.5
Bin #2 Input	N/A	5	5	4	4	5
Bin #2 Fit	N/A	3.5	3.5	3.5	3.5	3.5

APPENDIX J

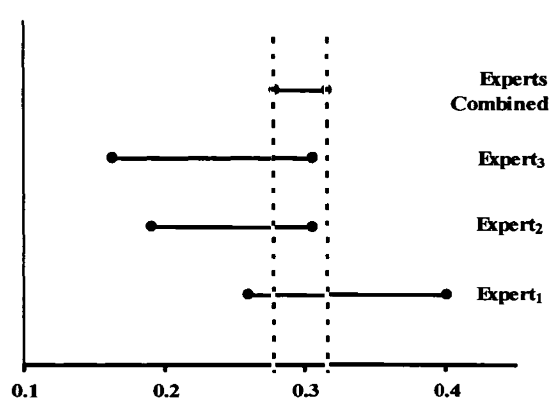
KS - TEST RESULT COMPARISONS OF THE EXPERTS AND EXPERTS COMBINED FOR THE PARALLEL-STAGED CREW LAUNCH VEHICLE AND THE EXPLORATION SYSTEM ARCHITECTURE STUDY CREW LAUNCH VEHICLE

Exploration Systems Architecture Study Crew Launch Vehicle

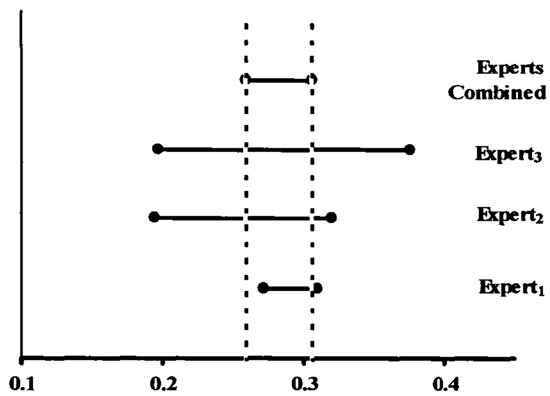
	K-S- Test Values (Expon.)		
	BEL	PL	Range
Expert $_1$	0.260	0.401	0.141
Expert $_2$	0.192	0.306	0.114
Expert $_3$	0.164	0.307	0.143
Combined	0.279	0.316	0.037

Parallel-Staged Crew Launch Vehicle

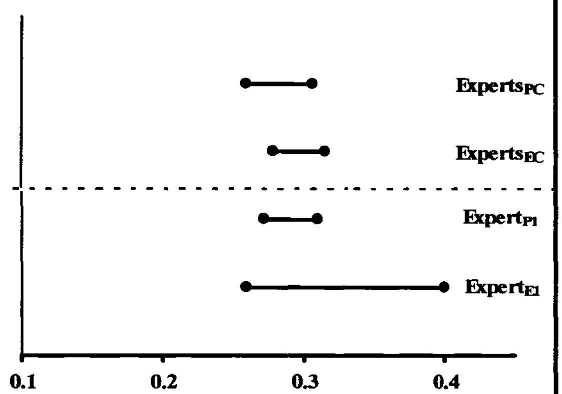
	K-S- Test Values (Expon.)		
	BEL	PL	Range
Expert $_1$	0.273	0.311	0.038
Expert $_2$	0.196	0.321	0.125
Expert $_3$	0.198	0.377	0.179
Combined	0.260	0.306	0.046



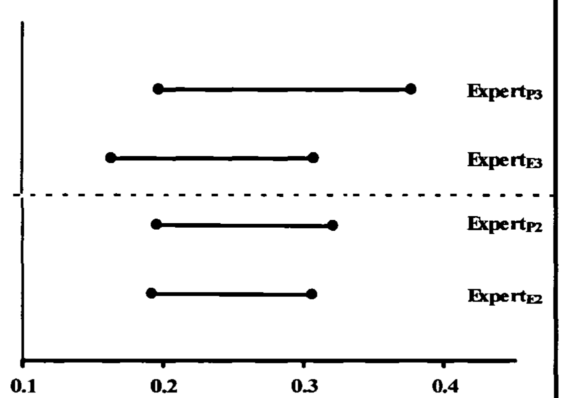
ESAS CLV Experts 1, 2 & 3 Mapped Against The Combined (Control)



P-S CLV Experts 1, 2 & 3 Mapped Against
The Combined (Control)



ESAS CLV & P-S CLV Assessments Compared
For Each Expert



ESAS CLV & P-S CLV Assessments Compared
For Each Expert