THE INTERNATIONAL
C2 JOURNAL

VOLUME 3, NUMBER 1, 2009

SPECIAL ISSUE

Modeling and Simulation in Support of Network-Centric Approaches and Capabilities

GUEST EDITOR

Andreas Tolk
Old Dominion University

Understanding Information Uncertainty within the Context of a Net-Centric Data Model: A Mine Warfare Example

Megan A. Cramer
Jeffrey E. Beach
Thomas A. Mazzuchi
Shahram Sarkani

THE INTERNATIONAL C2 JOURNAL

About the Journal

The International C2 Journal was created in 2006 at the urging of an international group of command and control professionals including individuals from academia, industry, government, and the military. The Command and Control Research Program (CCRP, of the U.S. Office of the Assistant Secretary of Defense for Networks and Information Integration, or OASD-NII) responded to this need by bringing together interested professionals to shape the purpose and guide the execution of such a journal. Today, the Journal is overseen by an Editorial Board comprising representatives from many nations.

Opinions, conclusions, and recommendations expressed or implied within are solely those of the authors. They do not necessarily represent the views of the Department of Defense, or any other U.S. Government agency.

For more information

Visit us online at: www.dodccrp.org
Contact our staff at: publications@dodccrp.org

Understanding Information Uncertainty within the Context of a Net-Centric Data Model: A Mine Warfare Example

Megan A. Cramer (Mine Warfare Program Office – PMS495, USA)

Jeffrey E. Beach, Thomas A. Mazzuchi, and Shahram Sarkani (George Washington University, USA)

Abstract

This paper examines the challenge of assessing operational measures of effectiveness given incomplete and often imperfect information. With the migration towards Network Centric Warfare, the ability to capture, quantify, and aggregate uncertainty of information within a hierarchical framework will be integral to conveying the true operational picture. A potential way to represent uncertainty is through the incorporation of probabilistic information within a semantic data model. This paper establishes a notional framework for associating probabilities within a Command and Control construct and demonstrates this concept for the Mine Warfare mission. The management of multiple variable inputs and the improved bounding of uncertainty over time are developed within a Bayesian context. Finally, an information scoring approach is presented as a notional part of this "Network Centric Semantic Web."

Introduction

In his grand contribution to military theory, *On War*, military theorist General Carl von Clausewitz documented the important role that uncertainty plays in military decision making, a concept that has become known as the "fog of war." Consideration of the notion of uncertainty in a military context becomes all the more relevant with the emergence of information systems providing even greater access to operationally-relevant data. As new technologies become available, it is advantageous to examine these applicable information frameworks and understand how uncertainty can be represented within them.

Network centric technology has transformed communications, the business world, and even human social interactions. Similarly, the application of web-based technologies to the warfighting environment is expected to revolutionize military operations in the Information Age. There is vibrant debate in the literature as to how much the emergence of "Network Centric Warfare" (NCW) will affect the ways that battles are fought. A RAND report describes how information superiority will greatly reduce uncertainty and thereby change the way that military force is applied (Darilek et al., 2001). John Ferris from the University of Calgary notes that although the information revolution can enable military strengths, it does not address the fundamental uncertainty and reliance on intelligence (Ferris, 2008). Yet there is general consensus in the literature that expanded access to information brings with it the ability to reduce uncertainty and consequently gain military advantage. As described in the CCRP publication *Understanding C2*, "Data are facts that when put into context become information. Information, to have value, must reduce uncertainty" (Alberts and Hayes, 2006).

The vision of the Semantic Web was initiated to facilitate the exchange of data, information, and knowledge across the web. Extending this concept to the military arena, one could envision NCW enabled by semantic technologies, in other words a "Network

Centric Semantic Web." There is increasing discussion in research communities as to the requirement and methods for incorporating uncertainty within the Semantic Web. This discussion is especially applicable to a defense application, where understanding of information uncertainty is inherent to the mission objective.

This paper utilizes the Naval Mine Warfare (MIW) example to explore the notion of uncertainty within a semantic data model. The example is described within an operational Command and Control (C2) context. These principles could potentially be applied to other mission areas with other probabilistic measures of effectiveness (MOEs). The NATO Code of Best Practice recognizes the challenge of considering uncertainty within C2 models. "C2 issues have long been regarded as difficult to analyze. Many operational analysis (OA) studies have simply assumed perfect C2 in order to focus on other variables… . Uncertainty and risk associated with a lack of appropriate data need to be embraced as part of the analytical approach" (Stenbit et al., 2002). Within this example, methodologies are considered for presenting uncertainty to both a human decision maker as well as to an automated expert system, which may be providing recommendations for potential Courses of Action (COAs). Specifically, the theory explored is that including probabilistic information within a semantic data model can be a useful tool for managing uncertainty consistently in support of mission objectives. Uncertainty surrounding an operational MOE is shown to have a significant impact on both the variability of the overall metric calculation and the accurate communication of progress achieved towards the given metric.

Literature Review: Uncertainty within the Semantic Web

The World Wide Web Consortium (W3C) defines the Semantic Web as "a common framework that allows data to be shared and reused across applications, enterprise, and community boundaries" (www.w3.org). At its core the Semantic Web depends upon the *meaning* of information to enable information discovery, management, and automated exchange. The Semantic Web offers new potential to communicate information involving uncertainty within automated information systems connected to the network.

There is an active contingent of researchers working on various ways to integrate uncertainty within the vision of the Semantic Web. This is primarily accomplished through the incorporation of uncertainty into ontology efforts. Ontologies are a mechanism for realizing the vision of a Semantic Web. As defined by the W3C, an ontology defines the terms used to describe and represent an area of knowledge."

There have been several efforts to integrate uncertainty information within current ontological models. An example of this is research by Zhongli Ding, Yung Peng, and Rong Pan at the University of Maryland focuses on the extension of Ontology Web Language (OWL) to incorporate probabilistic information. Ding et al. also propose a framework, *BayesOWL*, to translate OWL to a Bayesian network framework, while maintaining the original semantics. OWL is the W3C endorsed standard for ontology language (Ding et al., 2005). The limit of such an approach is that a Bayesian network is inadequate in its ability to encompass all facets of an ontology. In response to this limitation, Paulo Costa in his dissertation attempts to address these constraints with the development of extensions for OWL given a probabilistic Bayesian framework. Costa calls these probabilistic extensions Probabilistic Ontology, or PR-OWL (Costa, 2005). From a C2 perspective, (Costa et al.) describes the potential of a probabilistic ontology in support of NCW. Specifically, the probabilistic basis that Costa uses for PR-OWL is Multi-Entity Bayesian Network Logic (MEBN) developed by Kathryn Laskey also at George Mason University (Laskey).

There are also opposing views to these efforts. In (Pool et al., 2005) the use of an ontology language is questioned given the complexity required to support adequate probabilistic structures. Kant and

Mamas from MIT argue that statistical metadata should be captured but that uncertainty should be determined separately rather than explicitly within an ontological construct. They argue that this statistical approach would be useful and complementary to the logic-based backbone of the Semantic Web (Kant and Mamas, 2005).

Other researchers agree that uncertainty needs to be represented within the Semantic Web but propose that extensions to ontology languages should be based on fuzzy logic to achieve this objective (Stoiles et al., 2006).

Despite various approaches, it is generally accepted in the literature that uncertainty should be addressed consistently within a semantic framework. This has also been acknowledged as a tenet of NCW as well. NATO's Code of Best Practice manual states "It is important to treat uncertainty consistently and explicitly. This allows information from two given sources or results to be fused… . Thus the resulting knowledge will be better than either of the two separate results" (Stenbit et al., 2002). This concept of fusion of uncertainty from multiple sources is stated many times in the literature and can be seen as a requirement for any approach to incorporating uncertainty within mission architectures (Stoutenburg et al., 2005). A data model is a specific subset of an ontology and will be utilized for the purposes of exploring these concepts in the described MIW example.

Literature Review: Quantifying Uncertainty

There is a tremendous amount of literature on the subject of uncertainty. (Halpern, 2005) provides a comprehensive overview on theories involving uncertainty. The most common way of representing uncertainty is with probability. Physicist Edwin T. Jaynes described the fundamental relationship between probability and uncertainty, "the purpose of any application of probability theory [is] simply to help us in forming reasonable judgments in situations where we do not have complete information" (Jaynes, 1957). Repeatedly in the literature, probability is used as the linkage between "qualitative thinking and quantitative calculations" as described in (Studer, 2006). (Clemens, 1996) considers probability within a decision-making context. Among other discussions, Clemens presents the concept of expected value of information using a Bayesian approach

A Bayesian perspective incorporates evidence from a subjective standpoint within the assessment and defines probability as a measure of belief. This description of probability as a measure of belief is found often in the literature and corresponds directly to the concept of uncertainty (Ross, 2006) (Halpern, 2005). Bayesian networks are useful in graphically showing conditional relationships and broadening the audience of Bayes concepts as an illustrative aid (Laskey et al., 2002). Researchers Don Koks and Subhash Challa from the Australian Defence Sciences and Technology Organisation propose a Bayesian approach to fuse information from multiple sensors. Koks and Challa iteratively update a Bayesian equation using a recursive method based upon a control theory approach of a Kalman filter (Koks and Challa, 2003).

Beyond probability, belief functions and Dempster-Shafer theory provide other ways to quantify uncertainty. Belief functions act as a lower bound on the likelihood function. An upper bound is also defined and this is called a Plausibility function (Halpern, 2005). Dempster-Shafer theory incorporates the level of belief regarding the state of a system. Several times in the literature is found comparison and analysis between the Dempster-Shafer theory of evidence and the well-established Bayes' theory (Laskey, 1989) (Koks and Challa, 2003).

It was the father of Information Theory, Claude Shannon, who initially applied the rules of probability theory to develop the concept of entropy to describe a measure of uncertainty. The equation for determining entropy for a random variable is $H(X) = -\sum_{i=1}^{n} p_i \log p_i$.

Maximum entropy can be equated to a situation in which uncertainty is maximized, such as when no prior information is available. Entropy is a concept that is explored extensively in the literature. Girardin applies entropy maximization for Markov and Semi-Markov processes, extending research that Shannon himself began in this area (Girardin, 2004). (Abbas, 2003) provides an extensive review of entropy methods in his dissertation on the subject. He explains the Kullback-Leibler divergence method of determining a measure for determining the distance between two probability distributions. The Kullback-Leibler distance formula is also useful for determining the relative entropy between two distributions. This formula has many uses for considering uncertainty. A Classical Expert Judgment Model for determining the informativeness of multiple experts providing input on a subject is very close to the Kullback-Leibler divergence and requires an empirical measure to determine a measure of relative information. This Relative Information Scoring approach is described in detail within (Bedford and Cooke, 2001).

Other methods for considering uncertainty include utility theory, fuzzy logic, Fisher information, and Probabilistic Information Content (PIC). Looking specifically at PIC, John Sudano proposes this concept to capture information content for a system in such a way that computationally complexity is reduced. This is accomplished by identifying mutually exclusive subsystems with uncorrelated informational components within the overall system (Sudano, 2002). The PIC variable is found by taking the normalized entropy of that subsystem. Sudano uses the term 'information fusion' to describe the aggregation of information content derived from a subsystem level.

In the CCRP publication *Complexity Theory and Network Centric Warfare*, (Moffat, 2003) describes several ways to quantify uncertainty within a military operational context and outlines a probabilistic framework at the command level. He defines a metric to denote "the degree of confidence the commander has that he possesses an accurate picture of the battlefield in his area of interest" (Moffat, 2003). This metric is based on a Bayesian update methodology within a wargame cycle. Moffat also proposes a 'knowledge metric' from this process to encompass the following information that is now known at the command level, "(1) the fact that his sensor suite detected a number of enemy units in his area of interest; (2) the refined probability distribution over the possible number of enemy units that might be in his area of interest based on the most recent sensor report" (Moffat, 2003). To develop this metric Moffat turns to information theory and the concept of entropy. Moffat also provides a measure for the total campaign entropy at an aggregate level.

Efforts to incorporate uncertainty to support models and simulations (M&S) include the following: (Park et al., 2005) proposes the design and implementation of a ProbabilisTic Programming Language that uses a sampling technique for determining probabilistic information. (Spiegel et al., 2008) extends this computer-science approach with the development of RiskModelica, a domain-specific programming language that incorporates both a front-end and back-end approach to collecting and generating probabilistic information to support uncertainty. Additional research includes the use of Bayesian techniques to incorporate uncertainty information within simulation models (Merrick et al., 2005).

Organization and Approach

This paper brings together concepts from the literature to consider the specific application of uncertainty within a "Network Centric Semantic Web." MIW is used as an example as it is a mission area in which uncertainty is at the center of the operational picture and fundamental to the mission MOEs. (Discenza et al., 1996) and (Mansell et al.) explore the concepts of uncertainty in context with MIW but stop short of addressing this information in support of NCW. This paper will extend these concepts to address uncertainty for this mission area within a NCW context.

The approach to this analysis is to briefly describe the MIW challenge and present a notional semantic framework. This semantic data framework is representative of a subset of an ontology, containing agreed upon definitions and hierarchical relationships to enable information exchange within a net-centric architecture. The example is based on the tactical contacts that may be found within the area of interest. These tactical contacts include all objects within the area of interest, both mines and non-mines. The number of total contacts in the area is a key assumption in the calculation of the primary MIW MOEs of the expected risk to a transiting ship and the expected time required to clear all of the mines. Such estimates, required for probabilistic calculations, are usually acquired via intelligence sources. The calculations required to arrive at these two metrics are then explained in detail. To convey the associated uncertainty, upper and lower bounds are formed around the key metrics to convey the associated uncertainty. Finally, a methodology for determining an information score is derived for each MOE by considering both the inherent uncertainty in the probability as well as the underlying assumptions. This probabilistic information and information scoring technique are then tied back within the semantic framework previously described.

The MIW Challenge

The strategic objective of the MIW mission is to prevent enemy mines from altering friendly force actions. At the operational level this objective becomes the reduction of risk of another ship hitting a mine while transiting through identified waterspace. Risk reduction is achieved through conducting mine countermeasures (MCM). The time to perform MCM is often limited and therefore becomes an important constraint when considering various COAs to employ MCM effort. Figure 1 illustrates the MIW challenge of reducing risk to a transiting ship by conducting MCM effort within a given area.

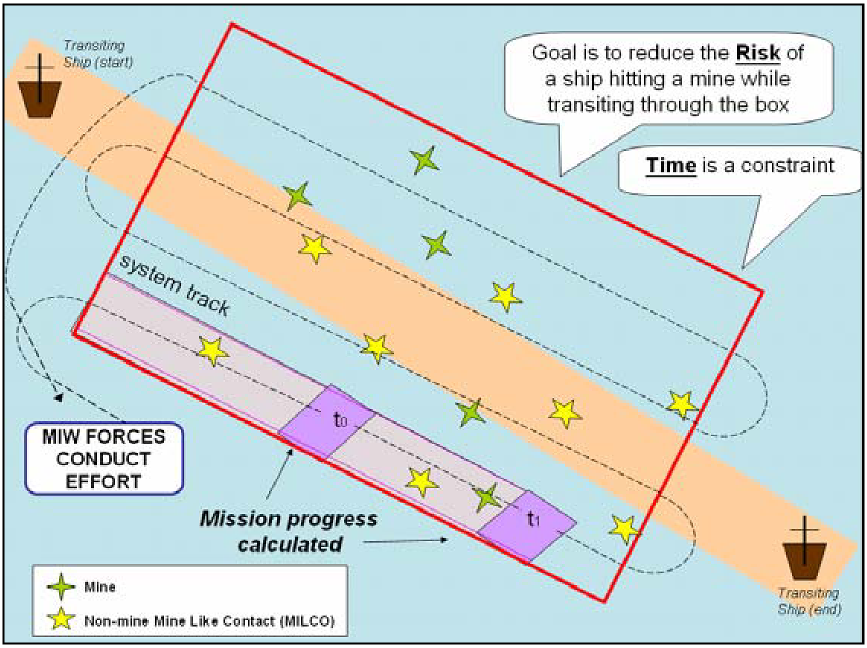

Figure 1. Mine Warfare Challenge.

In applying MCM effort, mines and non-mines are discovered and prosecuted. Risk is defined as the probability of damage to the transiting ship and can be reduced through MCM effort. The expected time required to perform the MCM mission can be calculated by the number of all mine-like contacts (MILCOs) in the area of interest. Note that MILCOs may be either mine or non-mine. The fraction of mines removed, more commonly known as Percent Clearance, is an important underlying factor in determining the likelihood for the number of mines in the area and is a measure of the estimated results of MCM effort conducted in the area of interest. Because it is a probabilistic measure, Percent Clearance can be calculated before any MCM effort has been conducted and with only an estimate of the number of mines in the area. This probability is updated as effort is applied throughout the mission.

Before delving into the technical details, it is helpful to provide an operational scenario of the MIW problem. For example, a MIW Mission Package onboard the new Littoral Combat Ship (LCS) may include some combination of hunting and sweeping MCM systems. The mission is to reduce risk to transiting ships in the area by applying MCM effort in the available period of time. An estimate of the number of mines in the area would be developed from intelligence sources. For example, a distribution of the number of mines can be said to be believed *a priori* in the area of interest. Once some MCM effort is applied, new information is available and can be factored into the process. An update of Percent Clearance, the estimated number of mines remaining, the expected time remaining until a certain Percent Clearance is achieved, and the expected risk can be determined. This process is iterative and MOEs are updated as new information becomes available. As would be expected, uncertainty should be reduced as information is obtained throughout the mission.

MIW Measures of Effectiveness (MOEs)

To calculate the risk to a transiting ship and determine the expected time to conduct the MCM mission, it is useful to consider the underlying tactical contact information that is essential to the determination of these operational objectives. The approach is to create a semantic data model for both the underlying tactical contacts and the overarching MOEs for the MIW mission. This semantic data model focuses on the incorporation of probabilistic information as a method for incorporating uncertainty information within a net-centric architecture. This concept builds upon existing approaches found in the literature.

To illustrate the making of a MIW data model, Figure 2 shows an abstraction of the contacts, both mine and non-mine, within the area. A contact is shown in the area whether or not it is a mine.

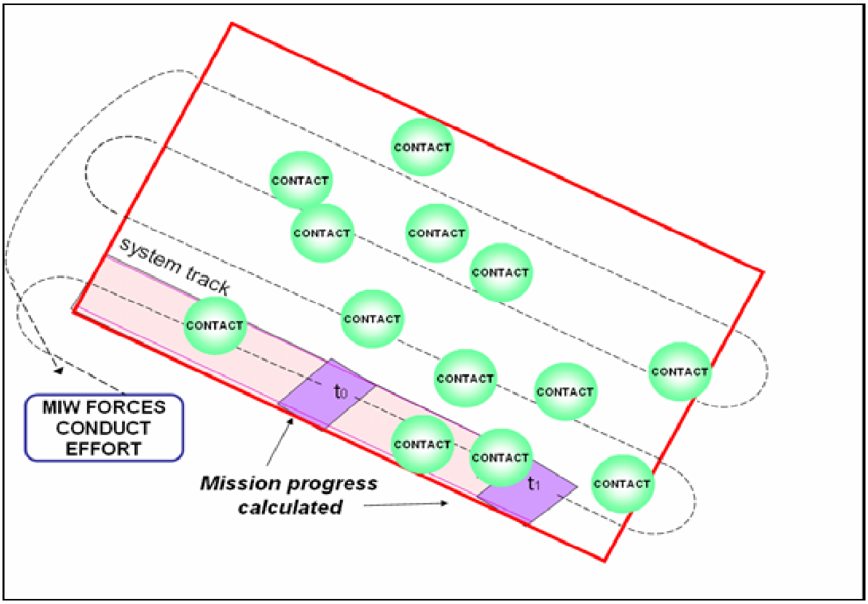

Figure 2. Making a MIW Data Model.

Figure 3 focuses on the tactical contact and provides some examples of the types of metadata that could be associated with a tactical contact. These categories are notional only and meant to be representative of the types of metadata that might be included in a semantic data model.

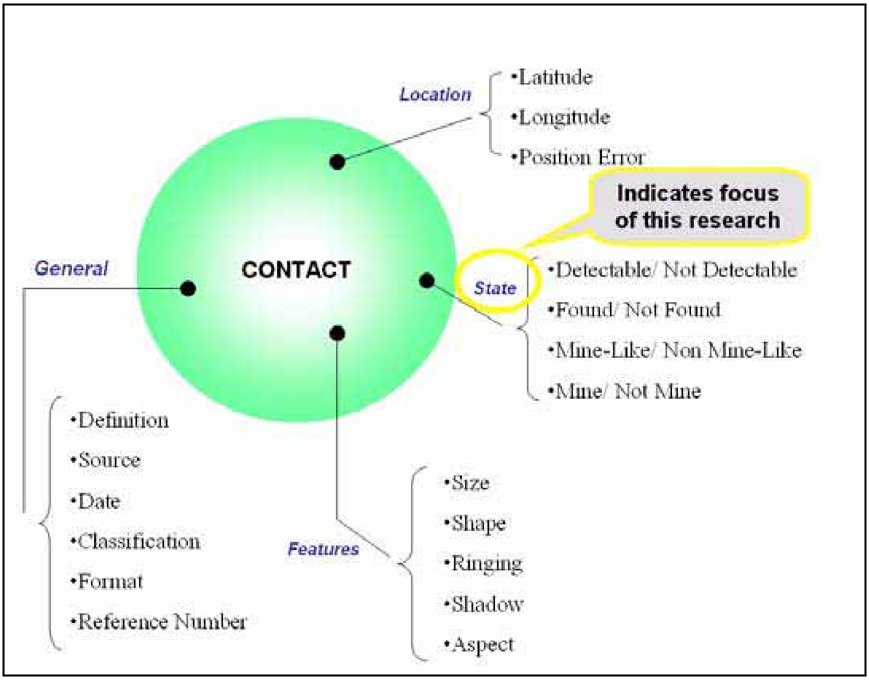

Figure 3. Making a MIW Contact Data Model.

For the purposes of incorporating probabilistic information within a semantic data framework for each MIW MOEs, it is necessary to provide state information as part of the data model for tactical contacts. A state is defined as the outcome of an event and can therefore be described by a random variable. The states that are important to determining the MIW MOEs are:

- *Whether or not a contact is detectable*
- *Whether or not a contact has been found*
- *Whether or not a contact is mine-like*
- *Whether or not a contact is a mine*

Figure 4 depicts the combination of these various states with respect to the entire set of tactical contacts that exist in the area. (The figure is intended to show relationships between the sets involved and is not drawn to scale. It would be typical to have more false alarms than actual mines, but again the level of clutter is very environment-dependent. Also, note that contacts that are non-mines and also not detectable are not included as they do not directly impact either MIW MOE.) All other combinations of the states are shown to be mutually exclusive within the sample space. The sample space as shown in the diagram is the total number of contacts estimated in the operational area of interest.

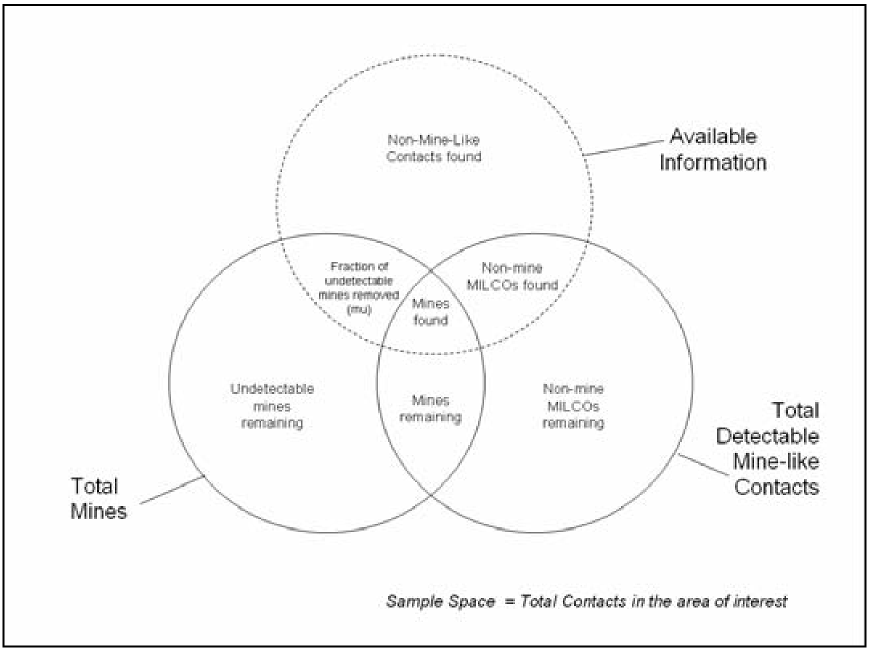

Figure 4. MIW Tactical Contact States.

The solid line circle on the left illustrates the total number of mines in the area, which are composed of detectable mines already found, detectable mines remaining, undetectable mines missed, and undetectable mines remaining. The solid line circle on the right describes the set of total mine-like contacts (MILCOs) that are detectable in the area, which is made up of both mines and mine-like non-mines in the area of interest. The total set of mine-like contacts in the area is composed of mines found, mines remaining, non-mine mine-like contacts, and non-mine mine-like contacts not yet found. The dotted lined circle at the top of the graphic represents available information. Available information includes mines found, non-mine mine-like contacts found, a fraction of undetectable mines that have been missed (estimated), and non-mine non-mine-like contacts that have been found. As might be expected, available information is influential in determining expected values for unknown information external to this circle within the sample space.

Calculation of the MIW mission objectives can be calculated within the context of this diagram. Percent clearance is typically a driver in the MCM effort and is calculated as the estimated fraction of mines removed. The primary MOE of risk, or probability of damage to a transiting ship, is calculated by using information in the highlighted circle on the left, to include both assumed prior information and new information gained throughout the mission. In Figure 5a, the determination of Percent Clearance (shaded in gray), based on knowledge of MCM effort applied in the area, is the common measure utilized by MCM forces to address the MCM problem. Percent Clearance will be described in more detail later in this discussion.

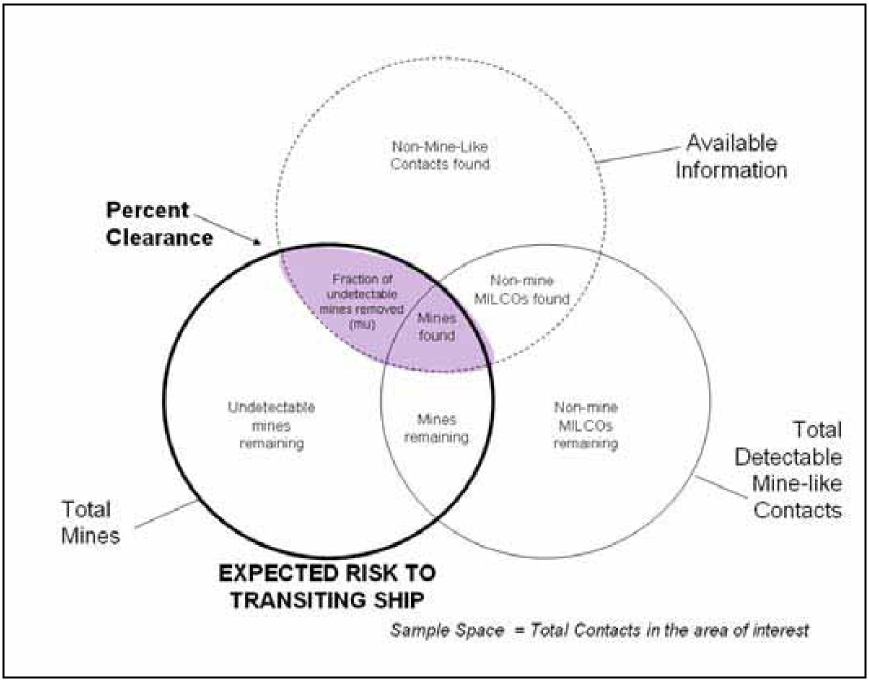

Figure 5a. Relationship to MIW MOE of Risk.

Similar to the calculation of risk, the set of information representing available information in Figure 5a can be utilized to calculate an expectation of the time remaining to complete the operation to the desired level of clearance. For example, the number of false alarms will drive the MCM timeline, if not directly impact the risk MOE. In the following section, a methodology is described for calculating an expectation for the time remaining in the MCM operation. A graphical representation of the information used to construct the estimated time for the mission is shown in Figure 5b. Upper and lower bounds are provided to qualify a range of uncertainty around this estimate.

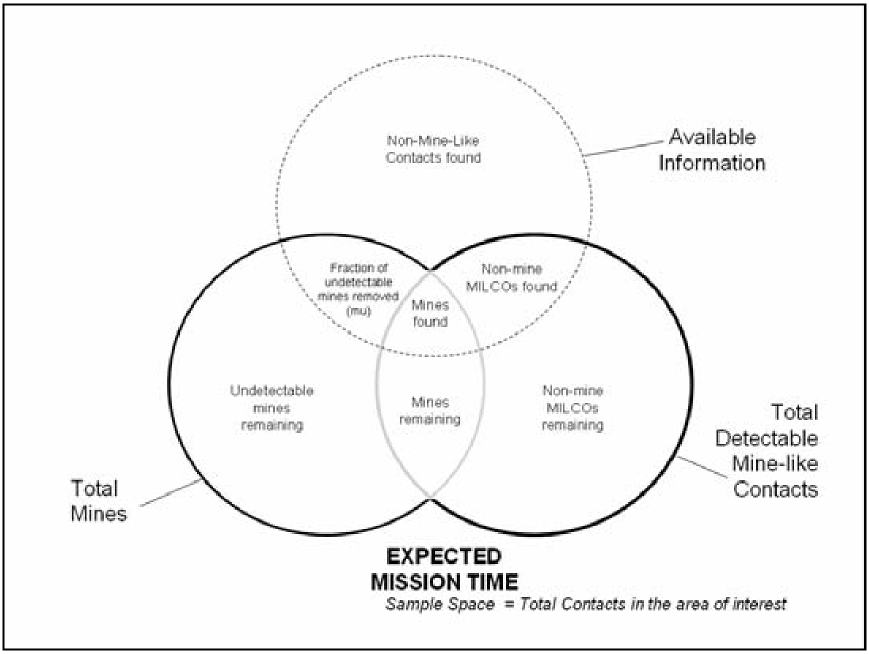

Figure 5b. Relationship to MIW MOE of Time.

As the mission progresses, the set of information that is available will become proportionally greater compared to the overall sample space. As this circle of available information expands throughout the mission, the amount of uncertainty surrounding progress towards the mission objectives is correspondingly reduced. This research will present a methodology for calculating an information score associated with both MOEs described above. This information score methodology could serve as a useful tool for conducting the ongoing trade-off analysis between MOEs, using uncertainty as the driving factor.

Expected Risk (Probability of Damage)

A significant amount of work in MIW research as been focused on the determination of expected risk, defined as the probability of damage to a transiting ship caused by a naval mine. The current approach to calculating risk will be discussed, followed by extensions to this work to elaborate upon the presentation of uncertainty information.

It can be observed that the concept of risk and its calculation as a probabilistic measure carries with it an inherent association with the notion of uncertainty. The approach can communicate to the operational commander an understanding of risk and its associated uncertainty, a more robust indication than simply providing a single risk value. This approach attempts to account for complexities found in a real operational situation such as the uncertainty associated with available data, accumulation of additional information, and the sensitivity of the metric to assumptions. Specifically, a Bayesian approach is utilized to incorporate prior information.

From an operational perspective there are two important points associated with utilizing the current approach. The first point is that there must be some information available about the presence of mines within the area (an *a priori* estimate) in order to conduct the Bayesian calculation. This information may be either information known with certainty (preferable) or else an estimate based on intelligence sources. The second point is that the number of mines assumed in the area is a key driver of the risk metric, although this sensitivity is less as the number of total mines is increased.

To address this sensitivity resulting from a key input variable, presentation of this risk metric to the operational user becomes very important. To enable the accurate communication of the metric and its sensitive to the assumptions by the operator, it is useful to calculate uncertainty bounds around the expectation of risk.

Calculating the Estimated Risk

The research in this arena of calculating the estimated risk to a transiting ship follows a Bayesian approach of determining the *a priori* distribution of mines and determining the likelihood function according to estimated information as to the number of mines found and clearance operations conducted in the area of interest. This Bayesian approach to calculating risk is described in detail in both the Decision Aid for Risk Evaluation (DARE) algorithm description document (Bryan, 2006) and a recent article published in Military Operations Research by Wagner Associates (Baker and Monach, 2006). Normalization is achieved by dividing by the sample space of all possibilities of the total number of mines in the area. The posterior distribution of mines remaining in the area is therefore determined from the number of total mines estimated.

The variables required to determine the probability of the number of total mines in the area given information about the number of mines found and the fraction of mines removed are provided below:

- n = total mines estimated in the area
- m = mines found
- p = Percent Clearance
- r = mines remaining.

The inputs into the calculation include $\Pr(n)$ for the prior distribution, $\Pr(m \mid n,p)$ as the likelihood function, and $\Pr(n \mid m,p)$ as the posterior distribution. [1]

1. A research focus for the mine warfare research community has been to determine the appropriate *a prior* distribution to use for the probability mass function of mines assumed in the area. The authors of (Bryan, 2006) and (Baker and Monach, 2006) have improved upon solutions for calculating the prior, including implementation of a Dirchelet approach to the prior that is considered superior

$$\Pr(n \mid m, p) = \frac{\Pr(m \mid n, p) \times \Pr(n)}{\sum_{n=1}^{n=N} \Pr(m \mid n, p) \times \Pr(n)}$$

Equation 1

The likelihood function is given by $\Pr(m \mid n, p) = \binom{n}{m} P^m (1-P)^{n-m}$. It should be noted that this function includes the assumption (potentially worthy of reconsideration) that mines in an area are treated with independence. One adjustment that is often made in practice for the number of mines found *m* is to adjust upwards to $m+1$ to error on the conservative side. The normalization function in the denominator is determined by the total probability (sum) for all possible values of *n*. $\Pr(r \mid m,p)$ can be inferred directly from the posterior given $r = n\text{-}m$.

Once $\Pr(r \mid m,p)$ is derived, the expected number of mines remaining in the area is the expectation for *r* given *m* mines are found and *p* Percent Clearance achieved.

$$\mathrm{E}(r) = \sum_{r=0}^{\infty} r \Pr(r \mid m, p)$$

Equation 2

to using solely a straight multinomial prior. The discussion surrounding the appropriate prior has revolved around the importance that the 'learned' information of the likelihood function should play within the Bayesian update. Because this area is not the focus of this research and for the purposes of simplicity, a uniform prior distribution is utilized throughout this research. Therefore, $\Pr(n)$ assumes mines are distributed randomly across the entire operational area.

Risk can be calculated for each transiting ship given the expected number of mines. The required information for this calculation is the probability of mission abort for each transiting ship. Probability of damage, *D*, can therefore be calculated for multiple mine types and area segments in addition to multiple transiting ships moving through the area.

$$\Pr(D) = \mathrm{E}[\Pr(D \mid r)]$$

Equation 3

Probability of damage, or estimated risk, is therefore the expected value of the probability of damage given a certain number of mines remaining in the area.

Expounding on Uncertainty

Uncertainty bounds, *a* and *b*, are determined on the posterior using a standard Bayesian credibility interval approach. An input ε is used to calculate the range values for the integral for the posterior probability determined above for $\Pr(r \mid m,p)$. Note that a Bayesian uncertainty bound is analogous to a confidence interval in traditional statistics.

$$\Pr(a(m,p) < r < b(m,p) \mid m,p) = \int_{a(m,p)}^{b(m,p)} \Pr(r \mid m,p)\,dr = 1 - \varepsilon$$

Equation 4

By drawing a range around the probability of damage (risk) MOE, the uncertainty associated with this metric can be communicated to the operational user. Additionally, the objective then becomes the reduction of uncertainty around the MOE. As uncertainty is reduced, the bounds can be narrowed around the risk MOE metric thereby communicating to the user a level of confidence in that information.

Expected Time Remaining

Expected time remaining to accomplish the mission is an important parameter for MIW operations. Inputs into this expectation must include the number of non-mine MILCOs in addition to the number of actual mines in the area of interest. Expected time is defined as the long-term average time required to identify every remaining MILCO in the area as either a mine or a non-mine.

A similar methodology that has been used in determining the number of mines remaining in an area can be applied to determine the number of detectable mine-like contacts in a given area. As described before, the number of detectable MILCOs is an important consideration in an operation even if it does not directly impact the calculation of risk MOE or the fraction of mines removed (Percent Clearance). The reason for its importance is because the number of MILCOs in an operational area is a tremendous driver in both the timeline to accomplish the mission objectives and the systems that should be utilized to counter the mine threat.

A short discussion on Percent Clearance is warranted here to provide some context to the above:

A measure of success in removing the mines in an area is Percent Clearance, p, is the average cumulative probability that a mine located at any given point within the area has been removed. (Removal implies that the mine was either swept with an MCM sweeping system or removed by a mine-hunting system.) Before the first mine is found, Percent Clearance is estimated according to a level of confidence using a negative binomial approach. Once the first mine is discovered, the required Percent Clearance increases to 0.95 from 0.64 to account for effort applied towards reducing the number of mines in the area. Cumulative effort of Percent Clearance, p_{cum}, towards removing the mines includes the probability of success in using the two kinds of MCM techniques, mine-hunting, p_{hunt}, and mine-sweeping, p_{sweep}. This can be determined by $p_{cum} = 1-(1-p_{hunt})(1-p_{sweep})$.

The calculation of Percent Clearance for an MCM sweep system, p_{sweep}, is $p_{sweep} = (1 - e^{-x})$ where x denotes the efficiency of the MCM system used. The calculation of the probability of success in utilizing mine-hunting techniques, p_{hunt}, also includes the fraction of undetectable mines, *mu*, the probability of correctly classifying a mine as a mine-like object, p_c, the efficiency of the hunting system, p_h, and the probability of identification and removal techniques succeeding once the mine has been identified as a mine-like contact *Bn*. (Terminology such as *mu* and *Bn* is common in the field of MCM and is used here for convenience.) For purposes of this discussion, *Bn* described here is decomposed into probability of identification, p_{id}, probability of reacquisition of the MILCO, p_{reacq}, and probability of neutralization, p_{neut}. The calculation of the probability that mines will be detected, p_h, is determined by $p_h = (1 - e^{-x})$ where x denotes the efficiency of the MCM system used. Therefore, calculation of Percent Clearance for mine hunting systems, p_{hunt}, is $p_{hunt} = (1-mu) \times p_h \times p_c \times p_{id} \times p_{reaq} \times p_{neut}$.

There has been much discussion as to the information that should be updated to calculate Percent Clearance in the event of replanning and updating p to incorporate new information obtained throughout the operation. The update of p and the potential inclusion of conditional probabilities within the stages of MCM effort is an area of future research.

Calculating Expected Time Remaining

To the previous question on calculation of the expected time to conduct MCM effort such that every contact in the area is identified as a mine or a non-mine, it is first necessary to determine the probability of the number of total detectable MILCOs in the operational area. This can be determined according to a Bayesian approach similar to that used to determine the number of total mines in the area. The difference here is that the likelihood is determined according to a multinomial distribution.

The multinomial distribution for the likelihood is

$$\Pr(fa, m, r \mid nMIL, q) = \frac{nMIL!}{fa!\,m!\,r!\,(1 - fa - m - r)!}\, p_{fa}{}^{fa}\, p_m{}^{m}\, p_r{}^{r}\, (1 - p_{fa} - p_m - p_r)^{(1 - fa - m - r)}$$

Equation 5

where the information that is required to determine the posterior probability of the number of total detectable MILCOs in the area given *nMIL* number of MILCOs found is as follows:

- *fa* = number of false alarms (or MILCOs confirmed not to be mines)
- *m* = number of mines found and confirmed as mines
- *rMILCOs* = number of detectable non-mine MILCOs remaining
- *r* = number of mines remaining to be found
- *q* = Percent Confirmed

Percent Confirmed is a new term and will be described here. Similar to Percent Clearance describing the fraction of mines removed, Percent Confirmed is the fraction of detectable MILCOs that have been confirmed either as mines or non-mines (false alarms). It is useful in determining the number of detectable non-mine MILCOs that will most likely be found in the area thereby affecting the overall time expected to confirm every detectable MILCO in the area as either a mine or a false alarm. (Note that Percent Confirmed will always be greater than or equal to Percent Clearance.) A representation of Percent Confirmed for those contacts that have been identified, or IDed, is depicted in Figure 6.

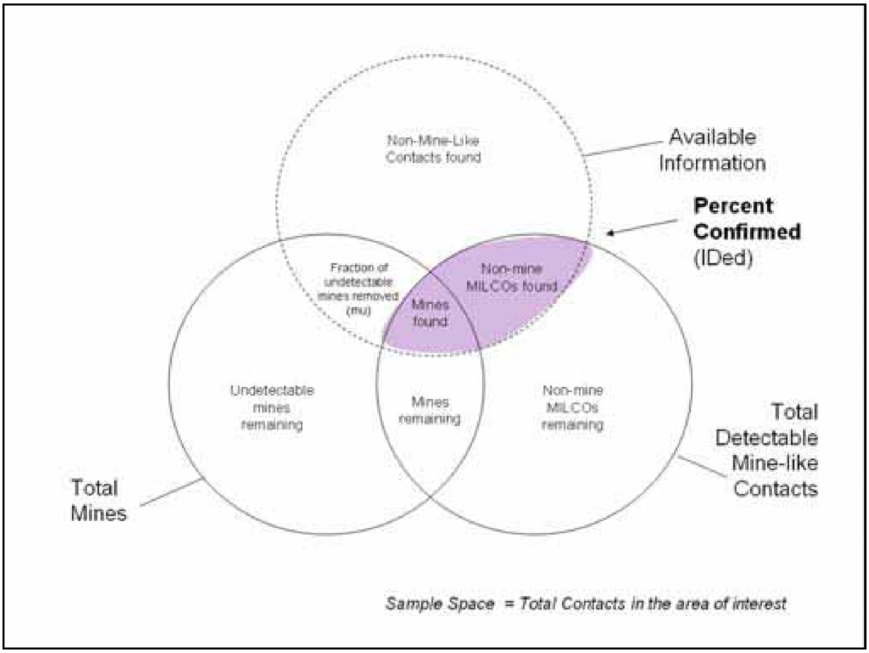

Figure 6. MIW Tactical Contact States.

Pr(*fa*,*m*,*r* | *nMIL*,*q*) is the likelihood function and describes the probability of false alarms given *nMIL* total detectable MILCOs in the area and a probability of encountering a false alarm. The likelihood is more complex this time as there is now a multivariate distribution (analogous to the binomial distribution used before). Probabilities for *fa*, *m*, *rMILCOs*, and *r* can be determined by dividing each by nMIL, or the estimated total detectable MILCOs in the area. The probabilities will be referred to as p_{fa}, p_m, $p_{rMILCOs}$, and p_r. Percent Confirmed is the joint probability of p_{fa} and p_m and therefore, further defined as $q = p_{fa} \times p_m$ since the probabilities are independent.

The prior $\Pr(nMIL)$ describes the probability of the number of detectable total MILCOs in the area. Again, a uniform prior is chosen for simplicity.

The posterior $\Pr(nMIL\,|fa,m,r,q)$ provides the probability of the number of total detectable MILCOs given some information about the probability of false alarms and the number of false alarms already found as well as the probability of encountering a mine and the number of mines remaining in the area.

$$\Pr(nMIL \mid fa,m,r,q) = \frac{\Pr(fa,m,r \mid nMIL,q) \times \Pr(nMIL)}{\sum_{nMIL=1}^{nMIL=NMIL} \sum_{fa=1}^{fa=FA} \sum_{r=1}^{r=R} \sum_{m=1}^{m=M} \Pr(fa,m,r \mid nMIL,q) \times \Pr(nMIL)}$$

Equation 6

The normalization is accomplished by summing over all possible combinations for the number of detectable MILCOs in the area, the number of false alarms found, the number of mines found, and the number of mines remaining. $\Pr(rMILCOs\,|fa,m,r,q)$ can be inferred directly from the posterior given $rMILCOs = nMIL - m - fa - r$ where the number of mines remaining r can be estimated. Additionally, uncertainty bounds can be then calculated around the $\Pr(rMILCOs\,|fa,m,r,q)$ according to the same process described for $\Pr(r\,|n,P)$.

Similar to the analysis for the MOE of risk, uncertainty bounds can be calculated around the probability of the number of detectable non-mine MILCOs remaining in the area. An input ε is used to calculate the range values for the integral for the posterior probability

$\Pr(rMILCOs \mid fa,m,r,q)$. *rMILCOs* can be interpreted as the set of all possible outcomes for the number of detectable non-mine mine-like contacts remaining in the area.

$$\Pr(a(fa,m,r,q) < rMILCOs < b(fa,m,r,q) \mid fa,m,r,q) = \int_{a(fa,m,r,q)}^{b(fa,m,r,q)} \Pr(rMILCOs \mid fa,m,r,q)\, drMILCOs = 1-\varepsilon$$

Equation 7

The sum of the expected time to address all remaining mines and detectable MILCOs can also be used to determine a value for the time expected to complete the mission to a certain level of risk. The calculation of this expectation is explained below.

The expectation of the time remaining to conduct MCM effort or to identify every MILCO as either a mine or a non-mine is based on both the expected number of mines and the expected number of detectable non-mine MILCOs remaining in the area. The overall expectation is determined by multiplying the expected time to accomplish each task in the MCM sequence by the number of times that each task must be completed for each mine or detectable non-mine MILCO. For every MILCO that is found during minehunting operations (either a remaining mine *r* or a detectable non-mine MILCO, *rMILCO*), the MCM tasks of detection, classification, and identification must be accomplished. Once a MILCO is positively identified as a mine, the MCM tasks of reacquisition and neutralization most be completed. The times for each MCM task are specifically average time for detection, T_{det}, average time for classification, T_{class}, average time for identification, T_{id}, average time for reacquisition, T_{reaq}, and average time for neutralization, T_{neut}.

The expected mines remaining, E(*r*), can be found by $E(r) = \sum_{r=0}^{\infty} r \Pr(r \mid m, p)$. The expected detectable non-mine MILCOs, E*(rMILCOs)*, can be found similarly by the following equation.

$$\mathrm{E}(rMILCOs) = \sum_{r=0}^{\infty} rMILCOs \times \Pr(rMILCOs \mid fa, m, r, q)$$

Equation 8

The calculation to determine the expectation for the time remaining for both the expected mines remaining $\mathrm{E}[T_r]$ and the expected number of detectable non-mine MILCOS remaining $\mathrm{E}[T_{rMILCOs}]$ can be found where $E[T_{rMILCOs}] = \mathrm{E}[rMILCOs] \times [T_{det} + T_{class} + T_{id}]$ and $E[T_r] = \mathrm{E}[r] \times [T_{det} + T_{class} + T_{id} + T_{rea} + T_{neut}]$. Additionally, the time remaining for the expected number of undetectable mines remaining, T_{mur}, must be included. This is computed as $E[T_{mur}] = \mathrm{E}[mur] \times [T_{det} + T_{class} + T_{id} + T_{rea} + T_{neut}]$ where *mur* is the estimated number of undetectable mines remaining in the area.

The calculation to determine the total time remaining to conduct the MCM mission, T_{Total} can therefore be found from the expectation, where Pr(*rMILCOs*), Pr(*r*), Pr*(mur)* can be found from the fraction of total tactical contacts anticipated in the area. The total expected time remaining to complete the MCM mission is therefore given as

$$E[T_{Total}] = \mathrm{E}[T_{rMILCOs}] \times \Pr(rMILCOs) + \mathrm{E}[T_r] \times \Pr(r) + \mathrm{E}[T_{mur}] \times \Pr(mur)$$

The advantage of this determination of the expected time remaining by the average time to complete each MCM task for all remaining MILCOs in the area is that the time lines include the additional time to consider false alarms within an area, in addition to the actual mines both detectable and non-detectable. The role of the environment and particularly a high-clutter environment with many false alarms is shown to directly influence the MCM MOE of time.

Relationship between Expected Risk and Expected Time Remaining

A MIW Commander (MIWC) must consider the relationship between the probability of damage (expected risk) and the expected time remaining to achieve a certain level of risk. The timeframe for an operation may not allow for the identification of every detectable MILCO in the area as either a mine or a false alarm. The MIWC must therefore look to employ the optimum number of assets to achieve a level of risk, often within a given limit of time.

According to the above analysis for each MOE, this trade-off between time and risk may also include the uncertainty surrounding both MOEs. This uncertainty can be determined by the bounds calculated for each MOE. For the purposes of this analysis, uncertainty is shown for risk as that is the primary MOE with which the MIWC is concerned. Risk is calculated as a function of time in order to support operational use of this information. Note that the following analysis could also be used to show the uncertainty surrounding the expected time remaining as a function of risk.

In order to show uncertainty around risk as function of time, a Poisson process is set up in MATLAB to simulate an MCM operation. At some constant rate, detectable MILCOs are found and categorized as either a mine or a false alarm. As each MILCO is discovered and appropriately identified, the probability of damage and the uncertainty bounds around that probability are calculated using the quad() functionality in MATLAB, which provides an approximation for the integral of the function within the identified bounds. Percent Clearance is assumed to be constant at 0.95. The expected time remaining is determined from the expected mines and detectable non-mine MILCOs remaining in the area. In order to show this information most intuitively where time is increasing on the horizontal axis, the time remaining at each point is subtracted from the maximum time remaining that is found. The results of Simulation 1 are provided in Figure 7.

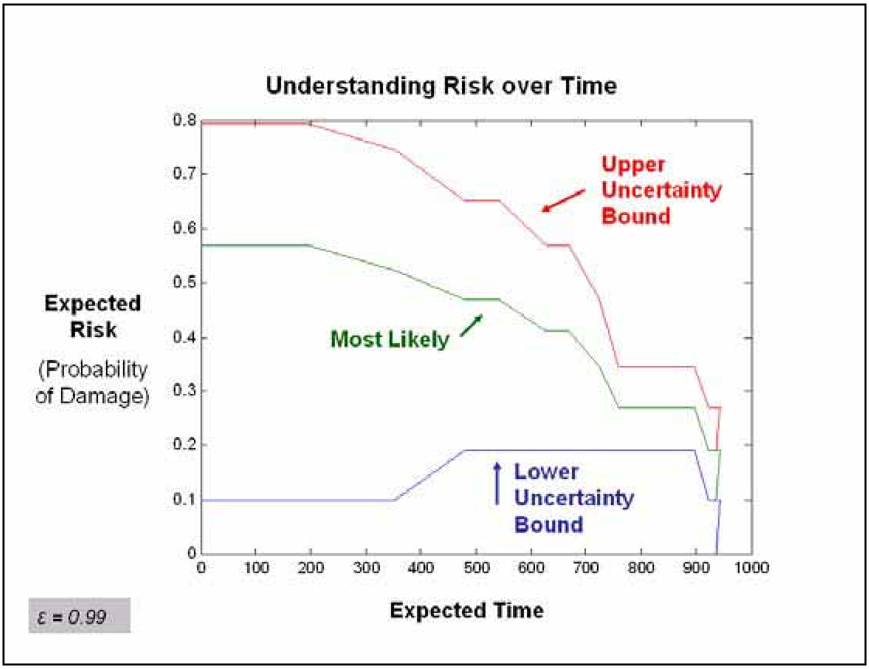

Figure 7. Simulation 1: Uncertainty bounds found around risk MOE as a function of time with probability 1- ε where ε = 0.99.

Assumptions and the data generated as output from Simulation 1 are provided in Appendix A. It is important to note when looking at this process that the assumption of the *a priori* distributions for the number of mines remaining and the number of detectable MILCOs remaining are not updated throughout the simulation. The distributions remain constant in order to show graphically the uncertainty bounds in relationship to the expected time remaining.

Throughout a true operation, however, it would be more realistic to update the assumed prior distributions and consequently updated the expected time remaining in the operation. This is possible to do using the developed Poisson process, but the output does not lend itself to an easy graphical representation due to the changing values for the expected time remaining.[2]

As would be expected, risk or probability of damage decreases over time as a larger proportion of the detectable MILCOs are discovered and identified as either mines or false alarms. The uncertainty bounds move closer towards the probability of damage estimate thereby decreasing the uncertainty around the risk MOE as effort is applied and information is gathered on the MILCOs encountered in the area.

The level used, ε, around the uncertainty bounds is an important input to generate the output in this simulation. The values of ε used to support the simulations discussed here were arbitrarily selected to consider two extremes. Figure 8 shows the output from a second run of the simulation using the same assumptions as inputs except for where ε is .05.

2. This update on the uncertainty bounds and the expected time remaining would be most useful in a replanning (running estimate) situation, where the *a priori* distributions are updated and held constant over the expected time remaining for any given point in time.

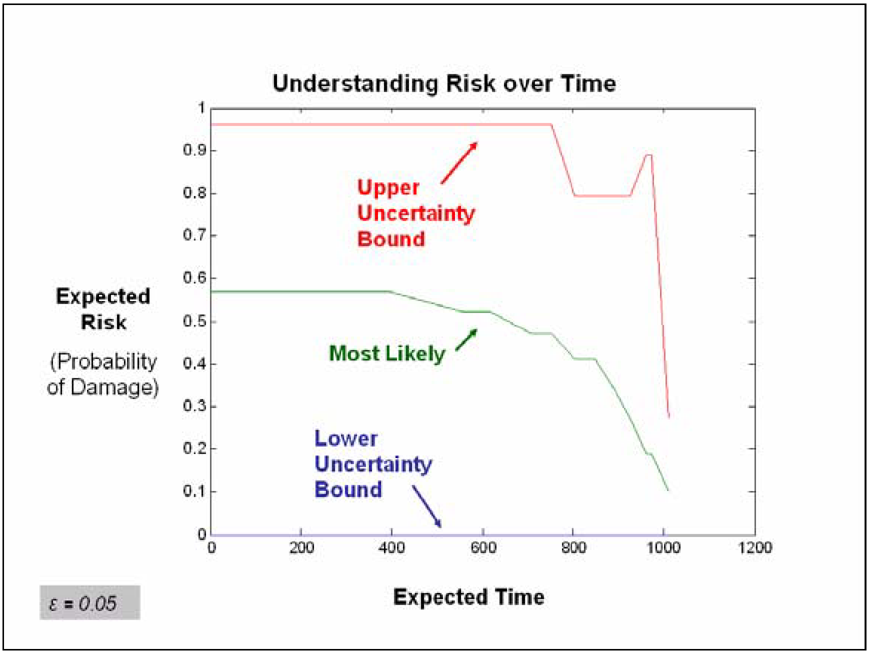

Figure 8. Simulation 2: Uncertainty bounds found around risk MOE as a function of time with probability 1- ε where ε = 0.05.

Due to the random generation of mines or false alarms in the simulation engine, the risk results are not exactly the same in this second simulation. The effect of the changed input is very discernable as the uncertainty bounds are now much farther away from the determined Probability of Damage output. The generated data for Simulation 2 is provided in Appendix B.

Information Scoring

Once the framework has been established for conducting the tradeoff between time and risk MOEs, the question is posed as to how to most efficiently reduce uncertainty around risk as a function of time. The method that is proposed is to determine an overall information score that incorporates both risk and time as a mechanism to determine those data inputs that are most important to effect an improvement in the overall information score. The information score is a mechanism for capturing the uncertainty inherent within the joint probability distribution of these two MOEs and in the uncertainty bounds around that probability. This scoring technique would be a useful tool by which to compare the relative information contribution of multiple variable inputs. The results of a sensitivity analysis of multiple data inputs on this overall information score will not be conducted within this paper but is intended as an area of follow-on research. The intent is to propose a mechanism that can be directly applied to convey both the data requirements to most directly reduce uncertainty and the importance of assumptions on the final answer. By utilizing this methodology discussed at a foundational level within this paper, it is proposed that uncertainty can be most efficiently reduced through the gathering of information throughout the operation.

Finding the Joint Probability

In order to determine uncertainty at the mission area level, it is necessary to determine a probabilistic statement that encompasses both MOEs and anticipates the remaining MCM effort over which there exists the uncertainty. This can be accomplished by finding the joint probability for all tactical contacts remaining in the operational area. An illustration of this joint probability is shown in Figure 9.

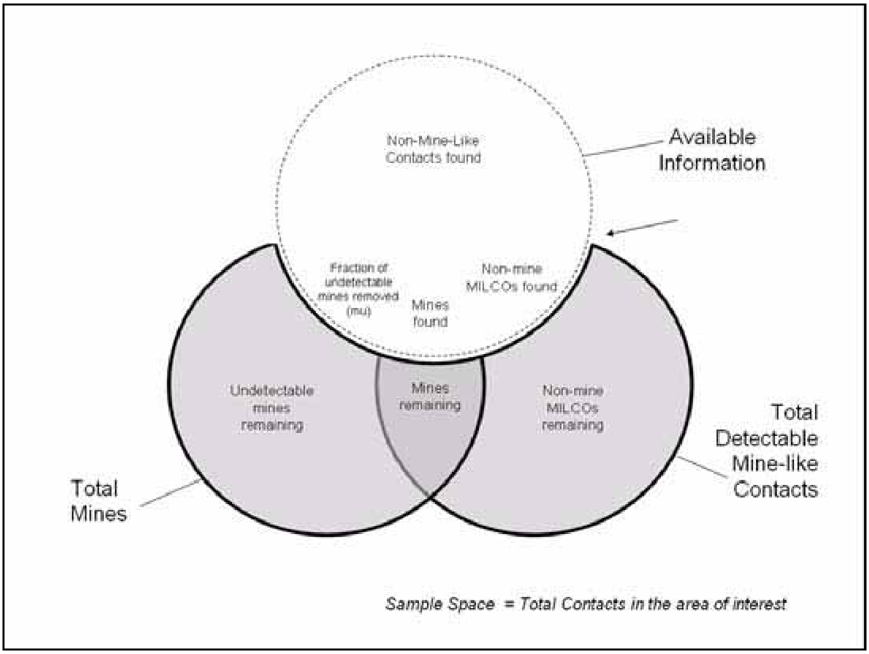

Figure 9. Joint Probability of Remaining MCM Effort.

This uncertainty of the shaded area can be determined by multiplying $\Pr(rMILCOs\,|fa,m,r,q)$ and $\Pr(r\,|m,p)$ to find the joint probability of the number of mines remaining and the number of detectable MILCOs remaining and subtracting the covariance to account for the fact that these two probabilities are not independent. p is again the Percent Clearance and q is the Percent Confirmed.

The joint probability will be referred to as the Probability of Effort to conduct remaining MCM, p_{effort}, and is given below:

$$p_{effort} = [\Pr(rMILCOs \mid fa, m, r, q) \times \Pr(r \mid m, q)] - \mathrm{Cov}(rMILCOs, r)$$

Equation 9

The covariance can be determined by considering the dependency between $\Pr(rMILCOs \mid fa,m,r,q)$ and $\Pr(r \mid m,p)$. $\mathrm{Cov}(rMILCOs, r) = E[(rMILCOs - z)(r - w)]$ where z and w are the expected values for rMILCOs and r, respectively.

Information Scoring Approach

A Relative Information Scoring methodology based on the Classical Expert Judgment Model described previously is employed to determine an information score. This methodology is chosen as this situation is analogous to multiple information sources providing input to the overall mission. As described in the literature review, this information scoring technique is related to the method for calculating entropy, or the amount of uncertainty associated with a random variable.

The scoring approach is to compare the results from multiple data inputs against an empirical background measure. The realizations are found from the previously defined lower-bound, the actual point estimate, and the upper bound for the Probability of Damage, which together specify a 4-bin multinomial distribution. The probabilities for these bins can be determined by applying the previously defined level ε that was used to calculate the range values for the uncertainty bounds around the Probability of Damage. For example, if the previously defined error was 30%, then the 15%, 50%, and 85% percentiles would be specified and the multinomial bins would be distributed as $p_i = (p_1, p_2, p_3, p_4) = (0.15, 0.35, 0.35, 0.15)$. Because there are 4 multinomial bins, then the number of random variables n is 4. The variable outcome v is the result (realization) of the multinomial experiment with probability distribution p_i. Let $q_i(e)$ denote input e's i percentile where v is

v_1 [Interval 1] is $[q_1(e), q_{15}(e)]$ with probability p_1

v_2 [Interval 2] is [$q_{15}(e)$, $q_{50}(e)$] with probability p_2

v_3 [Interval 3] is [$q_{50}(e)$, $q_{85}(e)$] with probability p_3

v_4 [Interval 4] is [$q_{85}(e)$, $q_u(e)$] with probability p_4

The lower bound l for Interval 1 and the upper bound u for Interval 4 are found where l = min{$q_{15}(1)\ldots q_{15}(j), v$} and u = max{$q_{85}(1)\ldots. q_{85}(j)$, v} where j are the number of inputs considered. Therefore, $q_l(e)$ = 1-k(u-l) and $q_u(e)$ = u+k(u-l), where k is a specified overshoot percentage. (k is 10% for this example.) Note that for cases where $q_l(e)$ is found to be less than zero, the value for $q_l(e)$ is constrained at zero.

Relative Information I is therefore

$$I(s,p) = \sum_{i=1}^{n=4} s_i Ln(s_i / p_i)$$

Equation 10

Assuming independence, (p_1, p_2, p_3, p_4) is the probability for each multinomial bin and (s_1, s_2, s_3, s_4) is the empirical distribution, and (v_1,v_2,v_3,v_4) is the realization of the average joint probability of the two MOEs in the corresponding intervals. s_i is the number of variables in interval i divided by the empirical estimate for p_i.

It is useful to note that in using this methodology to calculate the informativeness for every variable input into the joint probability of the MOEs, all information scores are determined against the same uniform empirical estimate and are therefore calculated relative to the other scores determined with respect to a common background measure.

Using this approach, both Percent Clearance and Percent Confirmed are influential in effecting the overall Information Score through employing MCM effort. If this same information scoring technique was conducted using only risk as a driver with Percent Clearance as the sole motivation for MCM effort, the expected number of detectable non-mine MILCOs in the area would have no impact on the overall information score. This result would therefore be counterintuitive as one would expect the information score to improve as information, even contextual information, is discovered.

The usefulness of this Information Scoring methodology is to provide a way of quantitatively evaluating operational courses of action based on their respective ability to collect additional information and of then presenting these options as recommendation(s) to the decision-maker. A quantitative approach allows an automated tactical decision aid to interpret the informational value of potential courses of action and provide recommendations as to how to improve situational awareness even if this is not in direct support to the primary MOEs. An interesting consideration is where the collection of information itself can be a course of action and should be considered as a viable option. A simple example is that an MIWC will often survey an area to gather information before proceeding to further tactical operations. An experienced commander knows intuitively that gathering information is an important first step in the operation. This Information Scoring approach provides a quantitative methodology to arrive at a comparable conclusion and to present this possible course of action to a commander within an automated tactical decision aid. Potential options of operational "next steps" within an automated system would be based on the anticipated value of gathering new information in addition to options to directly impact the operational MOEs.

Building a Probabilistic Data Model

Once the MOEs, their respective uncertainty bounds, and the overall information score have been determined, this metadata can be incorporated into the data model for the area. As with the MIW Contact Data Model previously discussed, an abstract data model for the overall MIW area can now be developed. Utilizing the state information captured into the lower level of the data structure (tactical contact level), probabilistic information can now be derived and aggregated at the higher level (area level). Figure 10 shows a representative MIW Area Data Model where *State* is included as a type of metadata in addition to more traditional metadata types. State is now defined as a random variable for the number of contacts in the area for the previously identified states at the tactical contact level. The states at this aggregated level are now:

- *Number of contacts that are mines that are detectable/not detectable*
- *Number of contacts that have been found/have not been found*
- *Number of contacts that are mine-like/not mine-like*
- *Number of contacts that are mines/not mines*

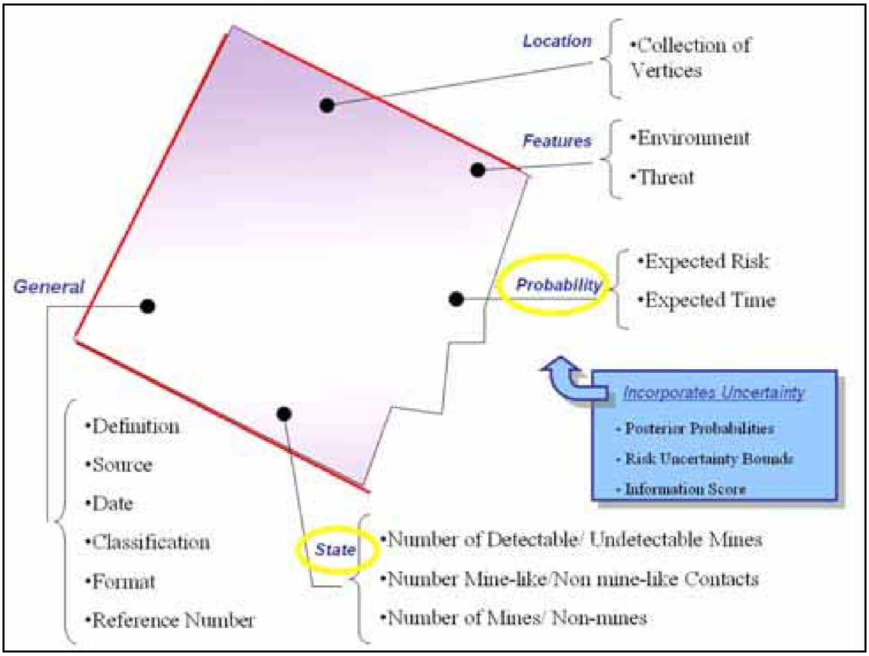

Figure 10. MIW Area Data Model.

Probability has now been added as a metadata type for this area level data model. Uncertainty information is provided in several ways through the addition of this probabilistic metadata. The first way in which uncertainty information is conveyed is through the probability itself, which inherently conveys a level of uncertainty. The sensitivity of this metric to the underlying assumption of the number of contacts in the area is also communicated through the uncertainty bounds for both MOEs of estimated risk and the expected time to complete the MCM effort. Finally, an information score is provided to show the level of informativeness known with respect to the primary metric of the estimated risk to a transiting ship.

The utility of this probabilistic data model is illustrated in Figure 11. As the mission is conducted and additional information is collected, the data model can enable the recalculation of probabilities to show progress towards the mission objectives and the corresponding reduction in uncertainty over time.

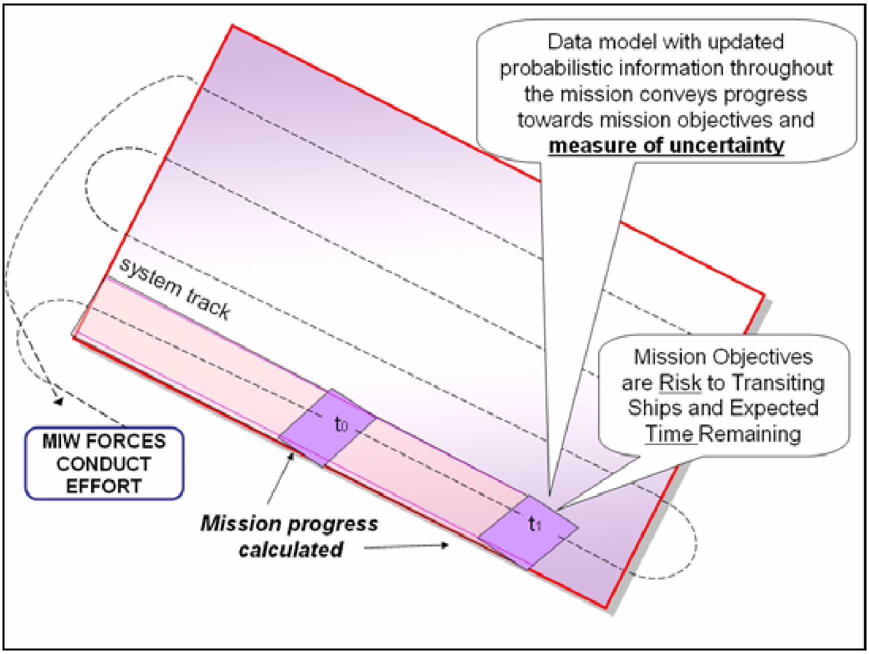

Figure 11. Utilizing a Probabilistic Data Model.

This probabilistic information can also be incorporated using methods other than inclusion within a data model construct. With the move towards net-centric architectures, however, the incorporation of probabilistic information into semantic data models offers a flexible, robust, and scalable option for managing uncertainty within a net-centric and service-oriented operational environment.

Conclusion

This research uses the MIW example to examine the importance of uncertainty in assessing MOEs within the C2 process. A method is shown for determining uncertainty bounds for risk, a primary metric for this mission area. To show the trade-off between time and risk, a method is developed for determining the expected time remaining to conduct MCM effort. An information scoring technique is developed to assess the overall uncertainty associated with the mission area. This overall information score is useful in generating COAs to increase understanding of risk in a given timeframe to conduct MCM operations. Of note, Percent Confirmed is a driver of contributing information to the MIW mission in addition to the traditional MCM metric of Percent Clearance.

To support the determination of uncertainty within a net-centric C2 architecture, a framework is presented to manage this additional information by expanding a semantic data model construct to include probabilistic information. This data-focused construct offers a simple and scalable approach to providing the context of uncertainty within a semantic data model wherein multiple applications and services might be drawing upon commonly defined information. This construct can be described as a "Network Centric Semantic Web."

This concept is a natural extension of the DoD's net-centric data strategy and supports NCW. By incorporating uncertainty information at the data level, the potential for interoperability and sharing of this information by multiple applications and systems is maximized. The approach also provides an opportunity to incorporate uncertainty within existing C2 models for NCW. Specifically, uncertainty information can be incorporated in an existing C2 model with the inclusion of probabilistic information, derivation of aggregated probabilistic information as described, and calculation of an information score using the proposed approach. Preliminary discussions with architects of semantic-based models for C2 indicate that the approach is feasible and supportable within some current M&S constructs. As with other related efforts supporting NCW, the challenge may be in defining common definitions to support interoperability of this shared information.

References

Abbas, Ali E. 2003. Entropy Methods in Decision Analysis. Ph.D.diss., Stanford University.

Alberts, David S. and Richard E. Hayes. 2006. *Understanding Command and Control.* Washington, D.C.: CCRP.

Bain, Lee and Max Engelhardt. 1991. *Statistical Analysis of Reliability and Life-Testing Models: Theory and Methods.* New York NY: Marcel Dekker, Inc.

Baker, Joni and W. Reynolds Monach, 2006. Estimating Risk to Transiting Ships Due to Multiple Threat Mine Types. *Military Operations Research* 2, no. 3:35-47.

Beasty, Michael, Art Degroat, Randy Horne, Glynndon Jones, Diane Kosky, Tim Logan, Curtis McVey, Kevin Oakes, Christina Smith, and Fred Sutter. 2007. *Mine Countermeasures (MCM) Theory Primer* (Unclassified). Technical Report NSWC PC/MP/HA12-07-003, Naval Surface Warfare Center- Panama City Division.

Bedford, Tim, and Robert Cooke. 2001. *Probabilistic Risk Analysis: Foundations and Methods.* United Kingdom: Cambridge, University Press.

Bryan, Karna. 2006. *Algorithms for Decision Aid for Risk Evaluation (DARE) version 2.1.* Technical Report NURC-FR-2006-002, NATO Undersea Research Centre (NURC).

Clemen, Robert T. 1996. *Making Hard Decision: An Introduction to Decision Analysis*. Pacific Grove: Duxbury Press.

Costa, Paulo Cesar G., 2005. Bayesian Semantics for the Semantic Web. Ph. D.diss., George Mason University.

Costa, Paulo, Kathryn B. Laskey, Kenneth J. Laskey, and Edward J. Wright. "Probabilistic Ontologies: The Next Step for Net-Centric Operations." Proceedings of the 12th International Command and Control Research and Technology Symposium.

Darilek, Richard E., Walter L. Perry, Jerome Bracken, John Gordon IV, and Brian Nichiporuk. 2001. *Measures of Effectiveness for the Information-Age Army.* RAND Corporation: 61-65.

Discenza, Joseph H. and Peter P. Haglich. 1996. *Structured Essential Model for Mine Warfare*. Technical Report, Naval Surface Warfare Center – Dahlgren Division.

Ding, Zhongli, Yun Peng, and Rong Pan. 2005. "BayesOWL: Uncertainty Modeling in Semantic Web Ontologies." *Soft Computing in Ontologies and Semantic Web.* Baltimore MD: University of Baltimore County, p. 3-29.

Ferris, John. "NCW, C4ISR, IO and RMA: Toward a Revolution in Military Intelligence?" Available from http://ccw.politics.ox.ac.uk/events/archives/tt05_ferris_paper.pdf. Internet; accessed 13 September 2008.

Girardin, Valerie. "Entropy Maximization for Markov and Semi-Markov Processes." *Methodology and Computing in Applied Probability* 6 (Mar 2004) 1: 109-127.

Halpern, Joseph. 2005. *Reasoning about Uncertainty*. Cambridge MA: The MIT Press.

Hanselman, Duane and Bruce Littlefield. 2005. *Mastering MATLAB® 7*. Upper Saddle River, NJ: Pearson Prentice Hall.

Jaynes, E.T. 1957. "Information Theory and Statistical Mechanics." *The Physical Review* 106, no 4 (May 1957): 620-630.

Kant, Sashi and Evangelos Mamas. Statistical Reasoning – A Foundation for Semantic Web Reasoning. In Proceedings of the ISWC-URSW held in Galway, Ireland, 2005,108-109.

Koks, Don and Subhash Challa. 2003. "An Introduction to Bayesian and Dempster-Shafer Data Fusion." *DSTO-TR-1436.*

Laskey, Kathryn B. 1989. "Belief in Belief Functions: An Examination of Shafer's Canonical Examples." *In Uncertainty in Artificial Intelligence* 3, L.N. Kanal, T.S. Levitt, and J.F. Lemmer, eds., North-Holland.

Laskey, Kathryn B. "MEBN: A Logic for Open-World Probabilistic Reasoning." *GMU C4I Center Technical Report C4I-06-01*.

Laskey, George and Kathryn B. Laskey. Combat Identification with Bayesian Networks. In Proceedings of the CCRTS, 2002.

Mansell, T.M., D.R. Skinner, and K.K. Benke. *Application of Artificial Intelligence in Decision Making in Mine Countermeasures*. Technical Report DSTO- TR-0279. Maritime Operations Division: Aeronautical and Maritime Research Laboratory.

Mazzieri, Mauro and Aldo Franco Dragoni. "A Fuzzy Semantics for Semantic Web Languages." Available from http://ftp.informatik.rwth-aachen.de/Publications/CEUR-WS/Vol-173/paper2.pdf. Internet; accessed 23 October 2007.

Mazzuchi, Thomas A., "Class Notes on Techniques of Risk Analysis" Washington D.C.: George Washington University. Spring 2007.

Merrick, Jason R., J. Rene van Dorp, and Varun Dinesh. "Assessing Uncertainty in Simulation-Based Maritime Risk Assessment." *Risk Analysis: An International Journal* 25, no. 3 (June 2005) 731-743.

Moffat, James. 2003. *Complexity Theory and Network Centric Warfare.* Washington, D.C: CCRP.

Park, Sungwoo, Frank Pfenning, and Sebastian Thrun. "A Probabilistic Language based upon Sampling Functions." *Proceedings of the 32nd ACM SIGPLAN-SIGACT symposium on Principles of programming languages* 40, no. 1 (January 2005): 171-182.

Pool, Mike, Francis Fung, Stephen Cannon, and Jeffrey Aikin. "Is it worth a hoot? Qualms about OWL for Uncertainty Reasoning" *Proceedings from International Semantic Web Conference* (2005) 1-11.

Rausand, Marvin and Arnljot Hoyland. 2004. *System Reliability Theory: Models, Statistical Methods, and Applications.* New Jersey: John Wiley & Sons.

Ross, Sheldon. 2006. *A First Course in Probability*. New Jersey: Pearson Prentice Hall.

Spiegel, Michael, Ross Gore, and Paul F. Reynolds, Jr. Quantifying and Analyzing Uncertainty in Simulations to Enable User Understanding. Charlottesville: University of Virginia. January 2008.

Stenbit, John P., Linton Wells, II., & David S. Alberts. 2002. *NATO Code of Best Practice for C2 Assessment*. Washington, DC: CCRP Publication Series.

Stoiles, Giorgos, Nikos Simou, Giorgos Stamou, and Stefanos Kollias, "Uncertainty and the Semantic Web," *IEEE Intelligent Systems*, vol. 21, no. 5, 84-87, Sep/Oct, 2006.

Stoutenburg, Suzette, Leo Obrst, Deborah Nichols, Jason Peterson, and Adrian Johnson. "*Toward a Standard Rule Language for Semantic Integration of the DoD Enterprise*." MITRE Technical Paper (June 2005).

Studer, Urban M. "Probability theory and inference: How to draw consistent conclusions from incomplete information." *Qualitative Research in Psychology* 3 (2006): 329-345.

Sudano, J.J. The system probability information content (PIC) relationship to contributing components, combining independent multi-source beliefs, hybrid and pedigree pignistic probabilities. In Proceedings of the Fifth International Conference on Information Fusion 2, 2002, 1277-1283.

Washburn, Alan. "Notes on Mine Warfare." Monterey: Naval Post Graduate School. Available from http://diana.cs.nps.navy.mil/%7Earwashbu/. Internet; accessed October 2007.

U.S. Department of Defense. Program Executive Office Littoral and Mine Warfare. 2007. *Mine and Undersea Warfare Measures of Effectiveness.* Instruction 3370.1 (draft).

"W3C Semantic Web FAQ" Available from www.w3.org/RDF/FAQ. Internet; accessed 2 November 2008.

Appendix A: Simulation 1 Assumptions and Data

I. Simulation 1 Assumptions

Assumption Description	Assumption Value	Comment
Average Detection Time	*30*	Average Time for all MCM systems
Average Classification Time	*5*	Average Time for all MCM systems
Average Time to conduct Identification	*1*	Average Time for all MCM systems
Average Time to conduct Reacquisition	*1*	Average Time for all MCM systems
Average Time to conduct Neutralization	*2*	Average Time for all MCM systems
Uncertainty Bound Level	$\varepsilon = .99$	
Percent Clearance	$p=.95$	Percent Clearance is assumed fully achieved
Estimated number of Mines in the area	$n=9$	Estimated number of number of mines is not updated throughout the simulation
Estimated Number of Detectable MILCOs in the area (including mines)	$nMILCOs=40$	Number of total detectable MILCOs is not updated throughout the simulation
Number of Mines Initially Found	$m=1$	Process begins after the first mine is found
Ship Damage Distance	$SD = 60$	Ship Damage Distance remains constant throughout the simulation
Channel Width Distance	$CW = 600$	Channel Width Distance remains constant throughout the simulation
Poisson Process for finding mine and non-mine tactical contacts	*constant rate* ($\lambda=1/25$)	rate used for simulation has no bearing on the results
Number of Undetectable Mines in the area	$mu=0$	Number of undetectable mines in the area is assumed to be zero.

II. Simulation 1 Data

Mines Remaining (r)	Detectable non-mine minelike Contacts (rMILCOs)	Number of mines +/- Risk to determine Probability Bounds (int)	Lower Bound	Risk (Probability of Damage)	Upper Bound	Estimated Time Remaining
8	30	7	0.1	0.5695	0.7941	1051.1
8	29	7	0.1	0.5695	0.7941	982.1
8	28	7	0.1	0.5695	0.7941	916.6
8	27	7	0.1	0.5695	0.7941	855.7
7	27	6	0.1	0.5217	0.7458	696.3
6	27	4	0.19	0.4686	0.6513	570.6
6	26	4	0.19	0.4686	0.6513	508
5	26	3	0.19	0.4095	0.5695	423.8
5	25	3	0.19	0.4095	0.5695	380.8
4	25	2	0.19	0.3439	0.4686	326
3	25	1	0.19	0.271	0.3439	292.8
3	24	1	0.19	0.271	0.3439	261.3
3	23	1	0.19	0.271	0.3439	236.9
3	22	1	0.19	0.271	0.3439	217.4
3	21	1	0.19	0.271	0.3439	201.5
3	20	1	0.19	0.271	0.3439	188.4
3	19	1	0.19	0.271	0.3439	177.4
3	18	1	0.19	0.271	0.3439	168.1
3	17	1	0.19	0.271	0.3439	160.2
3	16	1	0.19	0.271	0.3439	153.4
2	16	1	0.1	0.19	0.271	127.3
2	15	1	0.1	0.19	0.271	119.7
2	14	1	0.1	0.19	0.271	113
2	13	1	0.1	0.19	0.271	107.2
1	13	1	0	0.1	0.19	114.8

Appendix B: Simulation 2 Assumptions and Data

I. Simulation 2 Assumptions

Assumptions remain the same as in Simulation 1, except for input used to determine the uncertainty bounds, which is $\varepsilon = 0.05$.

II. Simulation 2 Data

Mines Remaining (r)	Detectable non-mine minelike Contacts (rMILCOs)	Number of mines +/- Risk to determine Probability Bounds (int)	Lower Bound	Risk (Probability of Damage)	Upper Bound	Estimated Time Remaining
8	30	23	0	0.5695	0.9618	1051.1
8	29	23	0	0.5695	0.9618	982.1
8	28	23	0	0.5695	0.9618	916.6
8	27	23	0	0.5695	0.9618	855.7
8	26	23	0	0.5695	0.9618	799.5
8	25	23	0	0.5695	0.9618	747.8
8	24	23	0	0.5695	0.9618	700.2
8	23	23	0	0.5695	0.9618	656.4
7	23	24	0	0.5217	0.9618	493.4
7	22	24	0	0.5217	0.9618	460.9
7	21	24	0	0.5217	0.9618	432.9
6	21	25	0	0.4686	0.9618	345
6	20	25	0	0.4686	0.9618	327.4
6	19	25	0	0.4686	0.9618	312.5
6	18	25	0	0.4686	0.9618	299.8
5	18	10	0	0.4095	0.7941	247.7
5	17	10	0	0.4095	0.7941	239.1
5	16	10	0	0.4095	0.7941	231.6
5	15	10	0	0.4095	0.7941	225.2
5	14	10	0	0.4095	0.7941	219.7
5	13	10	0	0.4095	0.7941	214.8
5	12	10	0	0.4095	0.7941	210.7
5	11	10	0	0.4095	0.7941	207.1
5	10	10	0	0.4095	0.7941	203.9
4	10	11	0	0.3439	0.7941	165.2
4	9	11	0	0.3439	0.7941	162.8
3	9	12	0	0.271	0.7941	125.2
2	9	19	0	0.19	0.8906	90.4
2	8	19	0	0.19	0.8906	87.4
2	7	19	0	0.19	0.8906	84.9
2	6	19	0	0.19	0.8906	82.8
2	5	19	0	0.19	0.8906	81
2	4	19	0	0.19	0.8906	79.6
2	3	19	0	0.19	0.8906	78.6
2	2	19	0	0.19	0.8906	77.9
1	2	2	0	0.1	0.271	40.2

Appendix C: List of Acronyms

C2	Command and Control
COA	Course of Action
DARE	Decision Aid for Risk Evaluation
MOE	Measure of Effectiveness
MCM	Mine Countermeasures
MIW	Naval Mine Warfare
MIWC	Mine Warfare Commander
MILCOs	Mine-Like Contacts
M&S	Models & Simulation
MEBN	Multi-Entity Bayesian Network Logic
NCW	Network Centric Warfare
OWL	Ontology Web Language
PIC	Probabilistic Information Content
WWW	World Wide Web

Appendix D: List of Variables

Bn = probability of identification and removal techniques succeeding once the mine has been identified as a mine-like contact

CW = channel width distance

D = damage

fa = number of false alarms (or MILCOs confirmed not to be mines)

I = Relative information

j = number of inputs considered in information scoring approach

k = specified overshoot percentage in information scoring approach

l = lower bound for lowest interval in information scoring approach

m = number of mines found and confirmed as mines

mu = fraction of undetectable mines

n = estimated total mines in the area

$nMIL$ = estimated total detectable number of MILCOs in the area

p = Percent Clearance (average cumulative probability that a mine located at any given point within the area has been removed)

p_c = probability of correctly classifying a mine as a mine-like object

p_{cum} = cumulative Percent Clearance

p_{effort} = Probability of Effort

p_h = probability of detecting mines with an MCM system

p_{hunt} = Percent Clearance using MCM hunting technique

p_i = probability of each multinomial bin information scoring approach

p_{id} = probability of identification

p_{neut} = probability of neutralization

p_{reacq} = probability of reacquisition of the MILCO

x = *efficiency of MCM system*

p_{sweep} = Percent Clearance using a MCM sweeping technique

q = percent confirmed

r = mines remaining

r = number of mines remaining to be found

rMILCOs = number of detectable non-mine MILCOs remaining

SD = ship damage distance

s_i = empirical distribution in information scoring approach

T_{class} = average time for classification

T_{det} = average time for detection

T_{id} = average time for identification

T_{mur} = time remaining for the expected number of undetectable mines remaining

T_{neut} = average time for neutralization

T_r = time remaining to conduct MCM on the expected mines remaining

T_{reaq} = average time for reacquisition

$T_{rMILCOs}$ = time remaining to conduct MCM on the expected number of detectable non-mine MILCOS remaining

T_{Total} = total time remaining to complete the MCM mission

u = upper bound for highest interval in information scoring approach

v = the result (realization) of a multinomial experiment to determine an information score using uncertainty bounds

w = expected number of mines remaining

z = expected number of detectable non-mine MILCOs remaining

ε = the level used to calculate the uncertainty bounds