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Expert Systems for Sea Mine Warfare

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ABSTRACT

In this paper, the probabilistic inference network (PIN) in a decision support systems environment is used to deal with several uncertain questions. The PIN method is supported by the certainty factors. Calculations involving quantitative probabilities for answering concerned questions enable mine countermeasure (MCM) experts to offer suggestions to a commander for reducing the ship's vulnerability at sea during wartime. For sea mine warfare scenarios, based on an analysis, we have a degree of confidence of 0.6568 to suggest the commander to deploy MCM forces.

1. INTRODUCTION

This paper is aimed to design a probabilistic inference network (PIN) as a part of a decision support system (DSS) inference engine for sea mine warfare. The PIN can be used to offer suggestions to the commander for reducing the vulnerability of ship at sea. This section introduces the problems of sea mine warfare, the objectives and the general background of the paper.

1.1 Statement of the Problem

Historically, sea mines have played an important role in warfare and this a naval officer cannot afford to neglect. During the recent mine campaign in the Middle East involving Iran and Iraq, commanders delayed decisions on whether or not to deploy mine countermeasure (MCM) forces. As a result, damage occurred to ships in a minefield that could have been prevented by the speedy application of MCM. Before an operational mission is commenced, there are several uncertain questions in the mind of a commander: Do minefields exist? Which country laid mines? What type of delivery platform laid the mines? Where are the mines? What kind of mines are they? Do we need to deploy MCM forces? Previously, these uncertain and subjective questions were very difficult to answer by a tactical principle. The specific reasons for any decision are often obscure, and the decision to avoid a minefield or to risk it is influenced by many factors; one of them is the decision maker's perception of the minefield.

In many practical problem-solving situations, available knowledge is either incomplete or inexact.

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Weather prediction and medical diagnosis are two examples. In such cases our knowledge is not adequate enough to use precise logic inference. However, we have ways of drawing inferences from incomplete, inexact, or uncertain knowledge and information. Although our knowledge is not complete, we can make generalisations and provide approximations that help us to summarise our experiences and predict the outcome of events. The generalisations are often subject to error, and yet we still use them because they provide a useful probabilistic tool.

The knowledge that can be stored in a machine is also limited. Intelligent machines often work with incomplete information in the form of quantitative approximations. Probabilistic reasoning methods allow artificial intelligence (AI) systems to use uncertain or probabilistic knowledge so as to take uncertainty into account[1]. In addition, probabilistic methods can help us accumulate evidence for hypotheses in a fair way; they are appropriate tools in making 'just' decisions. Decision theory, related to the theory of probability provides additional techniques that help to minimise risk in making decisions. Therefore, it is appropriate to use the probabilistic reasoning methods in DSS to solve the decision problems involved in sea mine warfare. The decision factors are represented by levels in the PIN. Calculations involving quantitative probabilities for answers to the questions in building a PIN could offer suggestions to the commander for reducing the vulnerability of ship at sea during war time.

1.2 Objectives of the Paper

Sea mine warfare is complex, obscure and controversial. Yet it is an important adjunct of the capacity of countries to wage war. Sea mines have been used in wars for many centuries, and history shows that sea mine warfare is a battle of wits between the mine user and his enemy's countermeasures. In this paper, the emphasis is on MCM, within a specific operational mission to clear up sea mines that were laid by the defending country in the approaching sea area. Without sufficient information about minefields, it is very difficult for the commander of sea mine warfare to decide whether to deploy MCM forces or not. Therefore, we seek to model general decision making in a computationally practical, yet mathematically meaningful way. Here the PIN structures are presented as formal structures for representing decision-making systems. This model can offer an overall picture to the commander of sea mine warfare, comprising several possibilities, including (i) the existence of minefield, (ii) the country that laid the mines, (iii) the mine delivery platform, (iv) the mine location, (v) the kind of mines laid in the minefield and (vi) decisions concerning MCM deployment.

1.3 General Background of the Paper

The problem in sea mine warfare is that in the absence of sufficient information about the minefield, clean up is difficult. In order to find a proper method to help the commander make a decision from the incomplete, inexact, or uncertain knowledge and information, fuzzy logic (FL), which uses uncertain or probabilistic knowledge to account for real uncertainties can be pressed into service. In this paper, FL is incorporated with a DSS application.

The subsequent sub-sections introduce the required backgrounds for designing the PINs. They are: sea mine warfare, AI language LISP, and FL.

1.3.1 Sea Mine Warfare

Sea mine warfare has been divided into three parts: types of mines, the mine delivery, and the minefield planning.

(a) *Types of mines* – Mines are not controlled, but operated automatically by some device activated by the presence of a ship. Mines can be classified as: (i) contact mine (fired by physical contact with the target) and (ii) induced mine (actuated by the effect of a ship on some physical condition in the vicinity of the mine or on radiations emanating from the mine). There are three basic types of the induced mines, namely, magnetic mine, acoustic mine and pressure mine.

Section 4 considers only contact mine and induced mine as the nodes in the PIN for sea mine warfare.

(b) *Mine delivery* – How to implement the minelayer aspect of sea mine warfare is a tactical problem. Indeed the purpose of the mine delivery platform is to carry and lay mines into the minefield. According to the different functions, there are surface delivery, submarine delivery, and aircraft delivery available.

(c) *Minefield planning* – Consider a minefield for which the objective is destruction of enemy shipping. One might hope that several ships would blunder into the field before it is identified by the enemy and the shipping warned away. However, realistically one can only count on the first mine which is detonated. Thereafter, enemy countermeasures will attempt to render the field useless. Hence, a measure of the effectiveness for such a field is the probability that one ship will be sunk.

Generally, the minefield model is based on the following assumptions:

(i) Mines have been laid in secrecy and the enemy is unaware of the field's existence;

(ii) Ships traverse the field on one of two known headings, these being parallel but opposite;

(iii) Ships considered as traffic must pass outside the limits of the field but are equally likely to enter the field at any point within its limits;

(iv) A ship which enters the influence area of the mine will detonate the mine with certainty; and

(v) A mine which is detonated will sink the ship with certainty.

Therefore, the minefield planning will be divided into three parts, viz., shipping traffic lane, coast, and the nearest point land.

1.3.2 LISP

LISP and Prolog are commonly used AI languages. LISP is designed specifically for list processing and symbol manipulating, although it has a capability for numerical data handling as well. LISP also uses lambda calculus as a formal, applicative structure with interesting theoretical properties.

Based upon the sea mine warfare experts analysis, we will design a PIN (detailed account given in Section 4) and use C program to create knowledge base, so as to implement the PIN which is written in LISP

1.3.3 Fuzzy Logic

Fuzzy logic was introduced by Zadeh[2] in 1965 who provided greater detail[3] in 1973 by using fuzzy set theory as the principal tool. FL enables computers to simulate the ambiguities encountered in real-life situations. In Section 3, we will give a detailed explanation of using FL to implement the current probability for each node on the PIN.

1.4 Organisation of the Paper

Section 2 introduces DSS. Section 3 discusses the design process of the PIN. Section 4 presents the results of simulation of sea mine warfare inference network that can be supported by the certainty factors. Section 5 comprises some concluding remarks.

2. DECISION SUPPORT SYSTEMS

Expert system (ES) can be used as DSS. The ES technology is widely perceived as AI technology with maximum potential for the development of applications that require a domain of expert knowledge (EK) data. Expert systems are computer programs that are equipped with EK to help users solve problems. For example, an ES called MYCIN, provides expert advice to medical doctors on the diagnosis and treatment of various types of bacterial infection[4]. In general, an ES contains two basic components: (i) a knowledge base and an inference engine, and (ii) a user interface.

2.1 Knowledge Base and Inference Engine

In a knowledge base, EK data can be expressed as a set of condition-action pairs. In turn, they provide production rules that specify the action to be carried out, if the pre-requisite conditions are satisfied. A typical structure of the condition-action system is shown in Fig. 1.

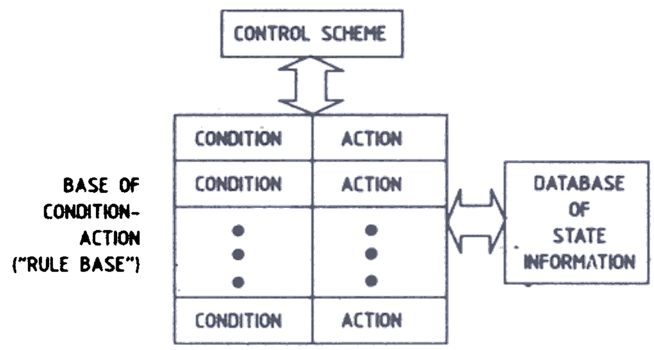

Figure 1. Structure of a condition-action system.

The ES can be described as computer-consultants that emulate human expert reasoning in a problem domain. The process of extracting and encoding a domain knowledge held by human expertise is called knowledge engineering. Today, knowledge engineering remains a time-consuming and labour-intensive process wherein a knowledge engineer, must repeatedly interview one or more human experts over a long time to extract the heuristics to be encoded in the ES knowledge base. The purpose of an inference engine is to control the order of rule activation and to update the belief value of hypotheses based upon acquired evidence.

2.2 User Interface

A user interface caters for a smooth communication between the user and the system. It may also provide the user with an insight into the problem-solving process

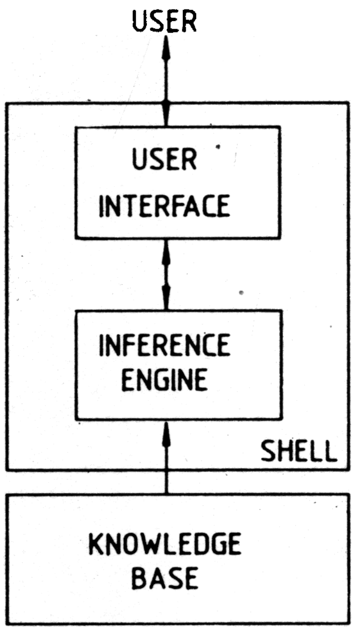

Figure 2. Simplified view of expert system architecture.

carried out by an inference engine. It is convenient to view the inference engine and the interface as one module, usually called an ES shell or shell. Figure 2 illustrates a basic ES architecture.

Most expert systems deal with various classes of inference problems, where the ES must draw conclusions from various evidence or data inputs. In these types of inference problems, the set of rules can be graphically represented in Fig. 3 in the form of a set of inference networks. As illustrated in Fig. 4, an inference network contains top-level hypotheses that are decomposed into various levels of sub-hypotheses. The sub-hypotheses, in turn, are further broken down into specific items of evidence, called nodes, that can support these hypotheses. With each node, there is usually an associated prior probability and a rule for combining a sub-node prior probability into an updated probability for the node. We will give a detailed description in Section 3 of the interrelationship between node (evidence) and sub-node.

3. MATHEMATICAL METHOD

In many practical problem-solving situations not only the available information is incomplete or inexact, but also the knowledge is inadequate to support a desired logical inference. However, we can apply approximations reasoning so as to transfer a specific knowledge into a prediction. This paper applies Tanimoto's PIN[5] that allows the ES to use uncertain or

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IF     : SEA MINE WAS FOUND ON TRAFFIC-LANE
         SEA MINE WAS FOUND ON THE NEAREST-POINT-LAND, OR
         SEA MINE WAS FOUND ON THE COAST.
THEN   : THE CONTACT MINE WAS LAID BY THE ENEMY.

IF     : SEA MINE WAS FOUND ON THE TRAFFIC-LANE,
         SEA MINE WAS FOUND ON THE NEAREST-POINT-LAND, OR
         SEA MINE WAS FOUND ON THE COAST.
THEN   : THE INDUCED MINE WAS LAID BY THE ENEMY.

IF     : THE CONTACT MINE WAS LAID BY THE ENEMY, OR
         THE INDUCED MINE WAS LAID BY THE ENEMY.
THEN   : TO DEPLOY MCM FORCES.
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Figure 3. Sample condition-action rules.

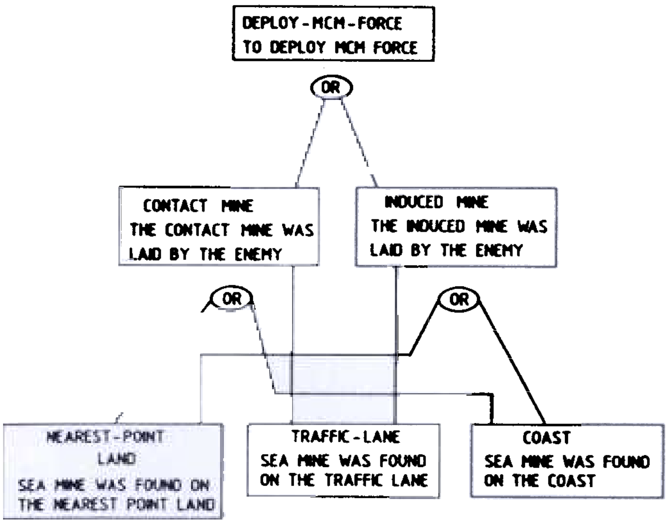

Figure 4. Sample inference network.

probabilistic knowledge. We also apply the concept of FL to solve an inconsistent problem in the PIN.

This Section discusses Bayes's rule, PIN, updating probability in PIN, and neocalculist approach. Use of these techniques to construct a model for sea mine warfare is given in Section 4.

3.1 Bayes' Rule

We assume that a commander wants to know the probabilities that candidate countries have laid mines, given evidence of the existence of a minefield. The general knowledge that may be available include (i) the probability that country-2 has laid mines, regardless of any evidence, (ii) the probability that a minefield exists, given that country-2 has laid mines, and (iii) the probability that a minefield exists, given that country-2 has not laid mines. In addition, the information of an existing minefield is available. Let H be the hypothesis and E be the evidence listed below:

H = 'Country-2 has laid mines,' and
E = 'A minefield has been found.'

Thus we have general information:

(i) $P(\text{H})$: probability that country-2 has laid mines,

(ii) $P(\text{E/H})$: conditional probability that a minefield is discovered, given that country-2 has laid mines, and

(iii) $P(\text{E/-H})$: conditional probability that a minefield is discovered, given that country-2 has not laid mines; assuming a minefield exists.

Now, the value of $P(\text{H/E})$, which represents the probability that country-2 has laid mines given that a minefield is discovered, can be computed by Bayes' rule:

$$P(\text{H/E}) = \frac{P(\text{E/H})\,P(\text{H})}{P(\text{E})}$$

where

$$P(\text{E}) = P(\text{E/H})P(\text{H}) + P(\text{E/–H})P(\text{–H})$$

To illustrate the case, we assume the following values:

$P(\text{H}) = 0.01 \quad P(\text{E/H}) = 0.85 \quad P(\text{E/–H}) = 0.001.$

From the formula described above, we can compute

$P(\text{E}) = (0.85)(0.01) + (0.001)(1 - 0.01)$

which is approximately 0.0095 and

$P(\text{H/E}) = (0.85)(0.01)/0.0095 = 0.8957$

Thus, the probability that country-2 has laid mines, given that the minefield is discovered, is about 0.9. On the other hand, if the minefield is not discovered, the probability that country-2 has laid mines would be

$$P(\text{H/–E}) = \frac{P(\text{–E/H})P(\text{H})}{P(\text{–E})} = \frac{(1\text{–}0.85)\,(0.01)}{(1\text{–}0.0095)}$$

$$= 0.1581$$

3.2 Probabilistic Inference Networks

3.2.1 Appropriate Domains

Making a decision means choosing among alternative courses of action with or without all the relevant information and often with some uncertain information as well. The need for a right decision making is omnipresent in our society. For instance, as far as ordinary people are concerned the need arises at a simple level of choosing whether or not to step around a puddle on a rainy day, or at a complicated level of choosing a treatment plan for a medical patient. For a mathematician, he may choose a set of possible directions in which to search for a manifestation.

3.2.2 Heuristical Elements of Inference Networks

Because of the incomplete knowledge of a conditional probability distribution for various possible states of evidence, the PIN cannot usually be developed directly from Bayes' rule. A reasonable alternative is to develop an hierarchy of 'fuzzy' assertions or hypotheses by using substantiated hypotheses at level 1 to infer hypotheses at level 1+1 as indicated in Figs. 5 and 6. In fact, Bayes' rule can be used directly to substantiate (establish probability values for) hypothesis at level 1 from the observed evidence while 'fuzzy inference rules' are used to obtain probabilities for other hypotheses at level 1+1, given the evidence.

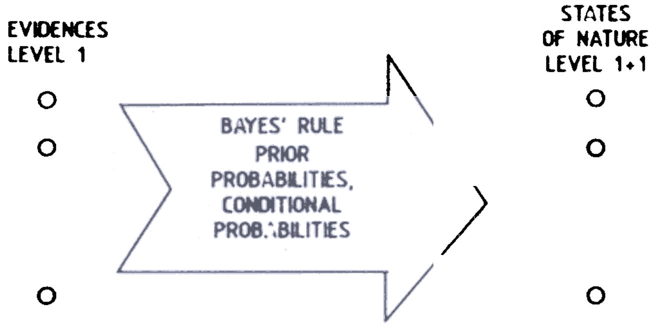

Figure 5. Bayes' rule application.

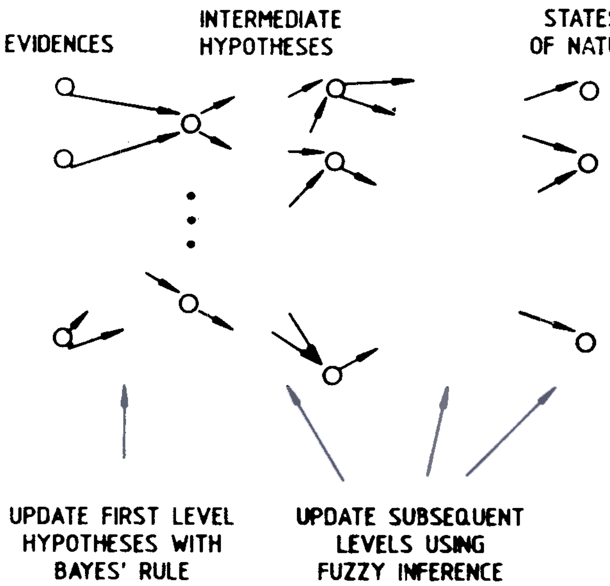

Figure 6. Heuristic inference system.

3.2.3 Fuzzy Inference Rules

Fuzzy inference rules are functions for propagating probability values[5]. The general form of such a function is:

$$f : (0,1)^n \rightarrow (0,1)$$

Thus, a fuzzy inference rule maps an n-tuple of probabilities as arguments and into a single probability. The truth table and two sets of inference rules for propositional calculus are shown in Table 1.

Table 1. Inference rules and two fuzzy logics

A	B	$-A$	$A \wedge B$	$A \vee B$	$A \rightarrow B$	$A \oplus B$
F	F	T	F	F	T	F
F	T	T	F	T	T	T
T	F	F	F	T	F	T
	T	F	T	T	T	F
	b	1–a	min(a,b)	max(a,b)	max(1–a,b)	xor(a,b)

3.2.4 Design of Inference Networks

To design a PIN, the following basic steps are required[5]:

(i) Determination of relevant inputs (i.e., set of possible evidence),

(ii) Determination of states of nature or decision alternatives,

(iii) Determination of intermediate assertions that may be useful in the PIN,

(iv) Formulation of inference links, and

(v) Tuning the probabilities and/or the fuzzy inference functions.

For sea mine warfare, the relevant input is the likelihood of the existence of a minefield. For the case studied in Section 4, if country-1 is known to use submarines to lay mines, then the other mine delivery platforms, the ships or aircraft, may be declared relevant through correlation with the country-1. Relevance determination is non-trivial and requires experts' knowledge. The states of nature are learned from experience or through training. In our case, it is a decision of whether or not to deploy the MCM force. The intermediate assertions include the country involved in laying mines, the delivery platform used to lay the mines, and their location and types.

Formulation of inference links may be done on the basis of correlations among attributes. In order to increase complexity of relationships we have[5]:

(i) Conjunction–C occurs whenever both A and B occur,

(ii) Disjunction–C occurs whenever either A or B occurs, and

(iii) Exclusive disjunction–either A or B occurs but not both.

Whenever the node(s) for the state of nature has been connected (possibly via intermediate nodes) to the inputs, the PIN topology has been constructed. Probability updating functions still need to be chosen to propagate the effects of inputs throughout the network.

If Bayes' rule is to be used to compute the first-level inference in the network, then there is no need for fuzzy inference rules at that level. But FL updating functions (which are defined later) may be used at subsequent levels to represent how information is to propagate through these levels. Probability values associated with various parts of the network need to be tuned to give reasonable performance. Prior probabilities for states of nature and intermediate assertions must be specified. The conditional probabilities are also essential for Bayesian updating, and they must be well-chosen to give reasonable results. Statistical methods might be employed to improve probability estimates.

3.3 Updating in Inference Networks

In a PIN, the general format of an inference rule is : the statement P(H/E) is interpreted 'if E, then H,' where E is the evidence and H is the hypothesis. In some cases, we may have multiple evidences E_1, E_2, ..., E_n where E_i is the i^{th} piece of evidence bearing on the hypothesis instead of the simple evidence E. Each inference rule has a certain strength associated with it, which is the power of the evidence to confirm the hypothesis in that rule. We now discuss the meaning for updating probabilities associated with hypothesis on the basis of certainty in the sense that the evidence is given. The 'subjective-Bayesian' updating rules have proved to be useful in ES such as PROSPECTOR[6] which will be used here.

In doing so, we adopt the mathematical model in conjunction with 'odds likelihood formula [5,7]. From the odds likelihood formula, we considered uncertain evidence and the dilemma for PIN to update the probabilities. Finally, we obtain a practical mathematical method for updating the probability for an inference.

3.4 Neocalculist Approach[1]

A certainty factor (CF) is a number between –1 and +1 that reflects the degree of belief in a hypothesis[4] Positive CFs indicate there is evidence that the hypothesis is valid. When CF=1 the hypothesis is known to be correct. On the other hand, negative CFs indicate that the evidence suggests that hypothesis is false. The value of every clinical parameter is stored by MYCIN along with an associated CF to indicate the situation 'belief'. In MYCIN, CF can be computed by the two measures: 'Belief' (MB) and 'Disbelief' (MD) are defined as follows:

(i) MB(H,E) = X means 'The measure of increased belief in the hypothesis H based on the evidence E, is X'.

(ii) MD(H,E) = Y means 'The measure of increased disbelief in the hypothesis H based on the evidence E, is Y'.

Recalling the subjective probability theory discussed in Section 3.1, we may argue that the expert's probability P(H) reflects his belief in H. Thus, 1–P(H) can be viewed as an estimate of the expert's disbelief regarding the truth of H. If P(H/E) is greater than P(H), the observation of E increases the expert's belief in H while decreasing his disbelief regarding the truth of H. In fact, MB[H,E] is given by the following:

$$MB(\mathrm{H,E}) = \frac{P(\mathrm{H/E}) - P(\mathrm{H})}{1 - P(\mathrm{H})}$$

On the other hand, if P(H/E) were less than P(H), the observation of E would decrease the expert's belief in H while increasing his disbelief regarding the truth of H. MD(H,E) is given by:

$$MD(\mathrm{H,E}) = \frac{P(\mathrm{H}) - P(\mathrm{H/E})}{P(\mathrm{H})}$$

Note that one piece of evidence cannot both favour and disfavour a single hypothesis. If MB[H,E]>0 then MD(H,E) = 0. If MD(H,E)>0 then MB(H,E) = 0.

These definitions may be specified in terms of conditional and a priori probabilities:

$$MB(\mathrm{H,E}) = \begin{cases} 1 & \text{if } P(\mathrm{H})=1, \\ \dfrac{\max(P(\mathrm{H/E}),P(\mathrm{H})) - P(\mathrm{H})}{\max(1,0) - P(\mathrm{H})} & \text{otherwise} \end{cases}$$

$$MD(\mathrm{H,E}) \quad \begin{cases} 1 & \text{if } P(\mathrm{H})=0 \\ \dfrac{\min(P(\mathrm{H/E}),P(\mathrm{H}) - P(\mathrm{H})}{\min(1,0) - P(\mathrm{H})} & \text{otherwise.} \end{cases}$$

Note that here P(H) is used to denote a priori probabilities. The CF is defined in terms of MB and MD as:

$$CF(\mathrm{H,E}) = MB(\mathrm{H,E}) - MD(\mathrm{H,E}).$$

In the next Section, we will explain how the CF value may reinforce our confidence in the fuzzy inference model. Section 4 also simulates the PIN.The network includes nodes, prior-probability, current-probability, and arc expression. On the other hand, we compute the CFs from the input probabilities which can be used to confirm the current probability for each node in the network. The CF approach may give the commander an alternative view of the problem.

4. INFERENCE NETWORK

To illustrate this technique for subjective-Bayesian inference in sea mine warfare, we consider the problems occasionally faced by the commander in war time.

From Section 1, the questions that concern the commander in sea mine warfare are the following:

(i) Do minefields exist?

(ii) Which country will lay the mines?

(iii) What delivery platform will lay the mines?

(iv) Where are the mines?

(v) What kind of mines are they? and

(vi) Do we need to deploy MCM forces?

The answers to this kind of questions are uncertain, and accordingly there must be some arbitrariness in any method for them. The method presented here is one of many possibilities; it embodies one of many possible sets of heuristics for predicting whether or not to deploy the MCM force on the basis of pre-mission observations.

This section explores some heuristics for sea mine warfare evaluation, discusses simulation results, and comments on the neocalculist approach.

4.1 Heuristics for Mine Warfare Evaluation

Figure 7 shows all the nodes and arcs of the PIN for our problem. The prior probabilities on nodes which can be found in Appendices B and C (Ref. 7) are omitted. The nodes and interrelative arcs data are inputted by the user into the C program.

Before actually using a sea area to carry out an operational mission, the importance of taking into consideration the threat by other enemy's weapons, e.g., mines cannot afford to be neglected. 'Do minefields exist?' is the commander's major concern. Normally, belligerents will know whether or not minefields exist from the announcement of a minelayer or the report of a mine investigator.

In Fig. 7, the main variable to be predicted is the 'deploy-MCM-force of mine warfare'. This comprises such features as contact mine and induced mine. Since it cannot be known for certain whether the sea area has been mined, the inferences we have made about whether or not to deploy the MCM force can be probabilistic at best. Since it is difficult to know the statistical relationships among these variables with any degree of accuracy, the results are quite uncertain. All we can say is that our system will incorporate the judgment of an 'imaginary' expert.

Since the input variable, the minefield, can conceivably affect our estimate of the MCM force deployment, we shall design a network in which the various tactical concerns are inputs and the final node corresponds to deploy-MCM-force. To simplify the relationships between input and output to the point where we can rationally model them, we introduce a number of intermediate variables as shown in Fig. 7. The relationship between input and intermediates, between intermediates and themselves, and between

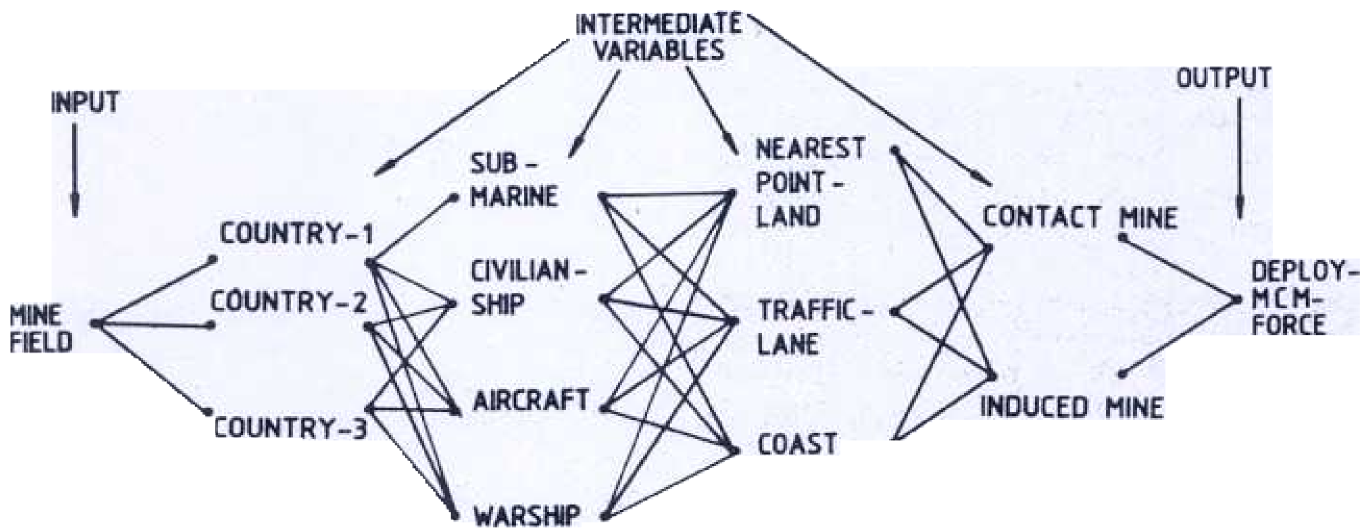

Figure 7. Probabilistic inference network for mine warfare problem.

intermediates and output are easier to understand and describe than the relationship from input directly to output. In our case the input is a minefield, and we introduce a set of three 'first intermediate variables' as intermediates: country-1, country-2, and country-3. These are predicted directly from the input variable. A set of four 'second intermediate variables' are: warship, civilian-ship, aircraft, and submarine. These are predicted directly from the first intermediate variables. A set of three 'third intermediate variables' are: nearest-land-point, traffic-lane, and coast. These are predicted directly from the second intermediate variables. A set of two 'fourth intermediate variables' are: contact mine and induced mine. These are predicted directly from the third intermediate variables. The output is 'deploy-MCM-force', which is predicted directly from the fourth intermediate variable.

4.2 Simulation Results

From an ES, we now explain simulation steps shown in Fig. 8. A C program[7] *mcm.c* takes expert's inputs for constructing PIN: nodes name, prior-probability and current-probability for each node, arc expression including the atoms name and the necessary conditions P(E/H) and P(E/-H) for computing sufficiency and necessity. A sample usage session of *mcm.c* and its corresponding output can be found in Appendices B and C, respectively of Ref. 7. This output from *mcm.c* would be the data segment, *mcmdata.c*, for the LISP PIN.

For simulation, we load the inference network *mcm.l* into the LISP interpreter. A detailed simulation run

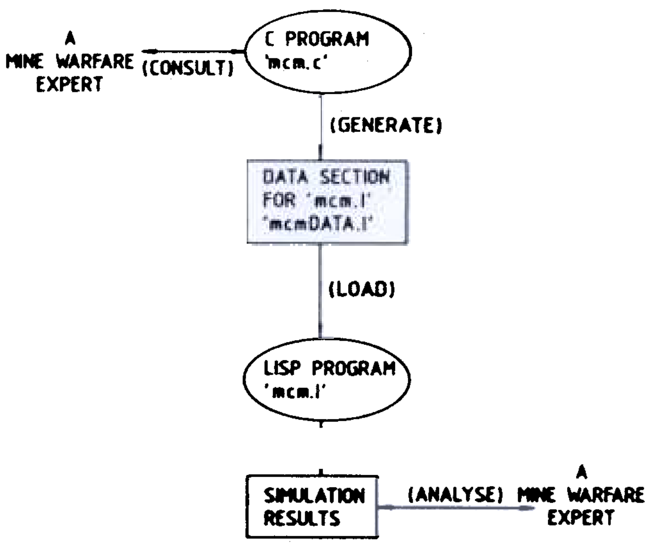

Figure 8. Procedure to simulate the programs.

can be found in Appendix D of Ref. 7. We will concentrate on the current probability of each node at the last line of each block. For example, in the simulation result, current probability of node country-2 is as follows:

> Inhibitive probability updating for node country-2 along arc:
> (minefield 850.0 0.1502) with prior odds 0.0101010101010101. Prior and current probs of evident are 0.9 and 0.5.
> Current probability of node country-2 is 0.006228832619601373.

The results for the remaining nodes can also be found in Appendix D of Ref. 7.

Table 2 summarises simulation results given in Appendix D of Ref. 7. Analysing the results and investigating the degree of confidence provides the possible value for deploying the MCM forces.

In Table 2, the current probabilities of each node taken from Appendix D of Ref. 7 are sorted in reverse order of the inference network levels. From Fig. 7, a comparison of the current probabilities of the nodes at the same level results in the following conclusion.

Table 2. Summary of the simulation results

Node name	Current probability of node
Deploy-MCM-force	0.6568
Induced mine	0.7229
Contact mine	0.8970
Coast	0.7371
Traffic lane	0.7694
Nearest-point-land	0.4616
Warship	0.6094
Aircraft	0.2896
Civilian ship	0.3039
Submarine	0.4667
Country-3	0.3966
Country-2	0.0062
Country-1	0.7979

For this sea mine warfare scenario, the analysis reveals a confidence degree of 0.6568 to suggest the commander to deploy MCM forces. The MCM forces may confront the threat of contact mine, or even the threat of induced mine. Owing to the assumption of this task, the enemy may possibly, first lay mines in the traffic lane of our fleet; secondly, in the coast; and finally at a nearest land point that is an aid to navigation. The enemy will probably use in descending order warships, civilian ships and finally airplanes to lay mines. Country-1 may consider using submarines to lay mines, because it is safer. The countries that might lay mines are country-1, country-3, and country-2, in that order. However, to defend herself, country-2's probability of laying mines increases. If there are mines in the traffic lane and neither country-1 nor country-3 laid the mines, then either country-2 laid them or they are residual mines from the past. Therefore, to avoid being hit by mines, our fleets are strictly prohibited from entering the waters until they are cleaned up by our MCM forces.

4.3 Comments on the Neocalculist Approach

As mentioned in Section 3, *CF* can be computed by the definition of Bayes' rule, *MB*, *MD*, and *CF* after we input the necessary probabilities. The results of the *CF* for the relationship between H and E in Fig. 7 are given in Table 3.

The notation *CF*(H,E) = X is used to represent the *CF* for the hypothesis H based upon evidence E. For example, the last hypothesis and evidences in Table 3 are expressed as:

H = To deploy the MCM force,
E1 = Contact mine
E2 = Induced mine

Thus, *CF*(H,E1VE2)=1.0, this sample hypothesis above may be qualified as follows:

CF(H,E1VE2)=1.0 : There is definite (1.0) *CF* to deploy the MCM forces.

The rest of the *CF*(H,E) value is listed in Appendix E of Ref. 7.

From the above discussion, we conclude that Tanimoto's method[5] is consistent with MYCIN's method[4]: both methods resolve the inconsistency by the piecewise linear equations for updating the probabilities instead of using a linear equation. We also show that MYCIN and Tanimoto's method are different: Tanimoto computes the current probability at each node while MYCIN computes the value of *CF* for each node. For example, Table 2 has a degree of confidence of 0.6568 to suggest the commander to deploy MCM forces by the current probability of the deploy-MCM-force node. From Table 3, CF(H,E1VE2) = 1.0 means that it is definite (1.0) to deploy the MCM forces based upon the disjunctive evidence: sea mines are contact mines (E1) or the mines are induced mines (E2). This *CF* value (1.0) enhances the determination obtained by Tanimoto's method (original value of 0.6568) of the commander to deploy the MCM forces. In other words, *CF* and Tanimoto's methods could be treated as complementary.

Table 3. Summary of the certainty factor

Hypotheses	Evidences	Logic Condition	Certainty Factors
Country-1	Minefield	Independent	–0.9693
Country-2	Minefield	Independent	0.8946
Country-3	Minefield	Independent	–0.2958
Submarine	Country-1	Independent	0.7297
Civilian-ship	Country-1	Independent	–0.9650
	Country-2	Independent	0.9980
	Country-3	Independent	0.7059
Aircraft	Country-1	Independent	–0.9764
	Country-2	Independent	–0.4444
	Country-3	Independent	–0.9979
Warship	Country-1	Independent	0.9301
	Country-2	Independent	0.9980
	Country-3	Independent	–0.9540
Nearest-point-land	Submarine	Independent	–0.9964
	Aircraft	Independent	–0.6667
Nearest-point-land	Civilianship or Warship	Disjunctive	0.8077
Traffic-lane	Submarine or Civilianship or Warship or Aircraft	Disjunctive	0.9982
Coast	Submarine	Independent	0.6774
	Aircraft	Independent	–0.2857
Coast	Civilian ship or Warship	Disjunctive	0.9833
Contact mine	Traffic lane	Independent	0.9862
Contact mine	Nearest-point-land or Coast	Disjunctive	0.8644
Induced mine	Traffic lane	Independent	0.8077
Induced mine	Nearest-point-land or Coast	Disjunctive	0.7825
Deploy-MCM-force	Contact mine or Induced mine	Disjunctive	1.0

5. CONCLUSION

In this paper, we have proposed a probabilistic inference network in DSS to reach decisions regarding mine countermeasures. Implemented in LISP and C computer languages, this intelligent sea mine warfare

DSS is capable of assisting the commander in making efficient and accurate decisions in sea mine warfare even under uncertain information. For sea mine warfare scenarios, based on the Tanimoto's method of analysis, a degree of confidence of 0.6568 suggested the commander to deploy MCM forces. On the other hand, $CF = 1.0$ indicated the certainty of deploying the MCM forces. In other words, CF and Tanimoto's method could be treated as complementary.

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