COMBAT IDENTIFICATION
WITH
BAYESIAN NETWORKS

Submitted to Track Modeling & Simulation

Student Paper

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Abstract

Correctly identifying tracks is a difficult but important capability for US Navy ships and aircraft. It is difficult because of the inherent uncertainty, complexity, and short timelines involved. It is important because the price of failure is missed or civilian engagements and fratricide. Today, Navy ships and aircraft primarily use an If-Then rule based system evaluating radar and IFF information to perform Combat Identification (CID). To cope with the uncertainty and complexity of CID, Bayesian networks have been suggested to integrate Radar, IFF, and other lower quality sources to perform the Identification determination. The goal of this project show that Bayesian Networks can be used to support CID investment decisions. Two investments, a new sensor and good maintenance were compared in a difficult CID scenario in four different environments.

1.0 Introduction

Correctly identifying tracks is a difficult but important capability for US Navy ships and aircraft. Combat Identification (CID) is difficult because of the inherent uncertainty, complexity, and short timelines involved. There is uncertainty in associating evidence to an object, uncertainty in association between evidence and identity, classification and intention. CID is complex because of the number of objects, their interactions, the variety of observations of these objects, and the concern that an enemy might try to deliberately to confuse or deceive your sensors. In many cases the time to decide on whether to shoot an object and by implication the time to perform a combat identification is very short.

CID is important because the price of failure is missed or civilian engagements and fratricide. In 1994, the US shot down two of there US Army helicopters and killed 26 people. [1] In 1988, the USS Vincennes shot down a commercial airliner. [2] In 1987, two missiles fired from aircraft hit the USS Stark because they did not shoot the aircraft or incoming missiles. [3].

Today, Navy ships and aircraft primarily use an If-Then rule based system evaluating radar and IFF information to perform Combat Identification (CID). To cope with the uncertainty and complexity of CID, Bayesian networks have been suggested to integrate Radar, IFF, and other lower quality information sources to perform the CID.

The goal of this project show that the Bayesian Networks can be used to support CID investment decisions. Two investments, a new sensor and good maintenance were compared in a difficult CID scenario in four different environments. The usefulness of the two investments was compared examining the:

- Separation in probability that the object is hostile, neutral, or friendly and
- Separation in the utility between the decision to shoot or not to shoot.

Section 2 of this paper provides background information on combat identification, decision analysis, Bayesian networks, and knowledge engineering. Section 3 describes the project while section 4 provides the results. Section 5 is an evaluation of the results. Section 6 summarizes the key results of the paper.

2.0 Background

This project applies the techniques from decision analysis and Bayesian networks to address the challenges of combat identification. The CID network was developed using good knowledge engineering practices. An introduction to these topics is provided in this section.

2.1 Combat Identification

Combat Identification is the process of assigning an identity and classification to each object detected by the host platform. As shown in Figure (1), identity has seven possible states. [4] The three most important for this project are hostile, neutral, and friendly. Classification is more complex. It describes where the object is found - air, surface, etc. It also describes the type of object at different levels of detail from platform type - like fighter - all the way down to each individual aircraft. Nationality tells for which country the aircraft flies. Finally, mission or intent provides information on what the object is doing such as combat air patrol (CAP) or strike. Accurately determining this information is important, as it is a key input to the various decisions including:

- Whether to collect more information about the object,
- Whether to stop the object from performing it's mission, and
- How best to stop the object from performing it's mission.

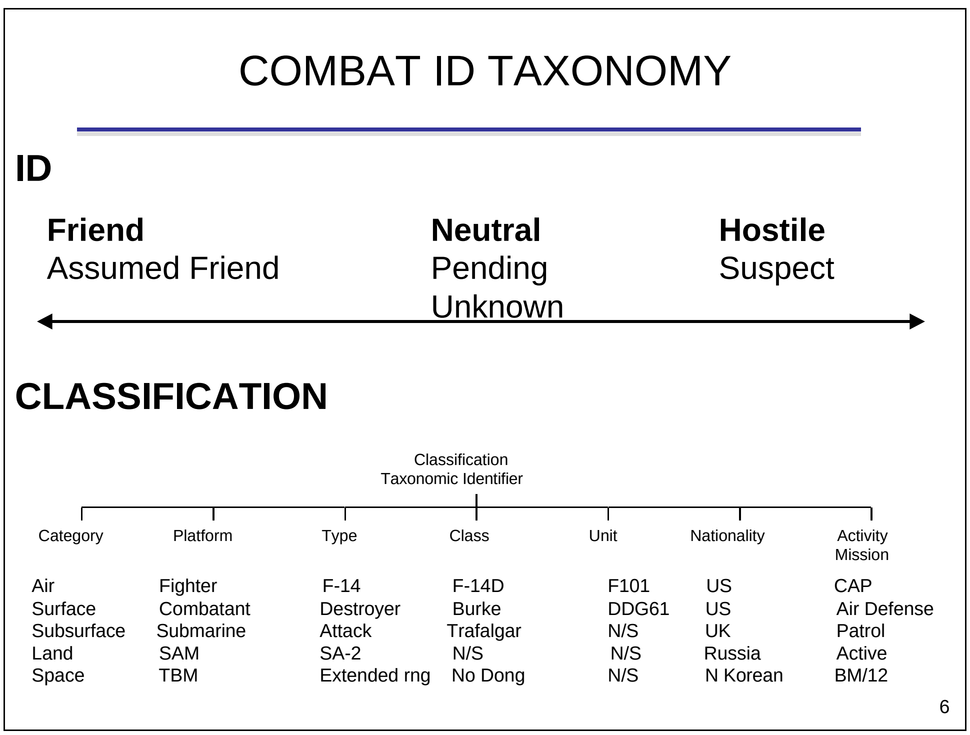

Figure 1 Combat ID Taxonomy

Figure (2) shows why it is important to perform CID correctly [5]. If an object is hostile and you don't destroy it ships & crews are lost and eventually wars are lost. But if the object is friendly or neutral and you destroy it then lives are lost and wars can be started.

Algorithms to automatically assign an ID date back to when the Navy started putting computers in ships [6]. The first efforts were coded directly into the software and were hard to adapt to different situations. In the 1980's, rule based expert systems were introduced. These systems were more flexible because the rules could be adapted to changing situations. These systems tended to use only high quality evidence like position, velocity, and the results of Identification Friend or Foe (IFF) interrogations. Operations and exercise noted problems with these systems and the US Navy has thoroughly explored the causes of these problems and suggested solutions. [4], [5], [7], [8], [9], [10], [11]

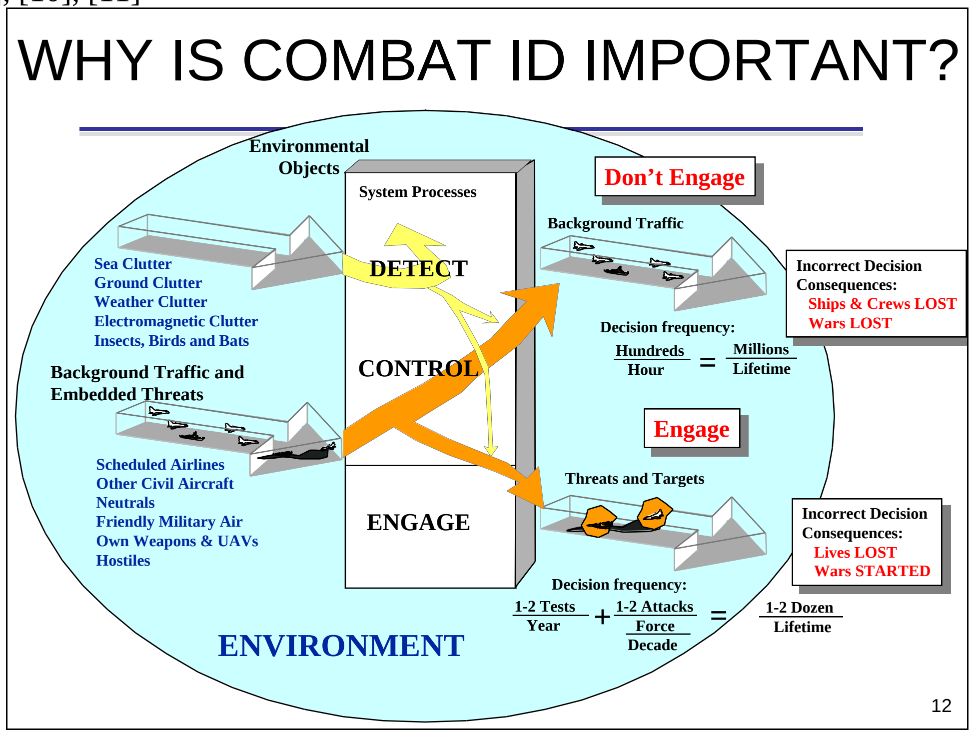

Figure 2 Importance of Effective CID

The Combat ID Functional Allocation Working Group suggested an architecture, shown in figure (3) to integrate all information including high quality data, like radar and IFF, and lower quality data like Electronic Support (think radar detectors) and intelligence information. [8] In July of 2001, the Office of Naval Research released a broad agency announcement (BAA) for composite combat identification to prototype systems that could perform this data fusion shown in Figure (4). [4] One of the methods suggested in the BAA was the use of Bayesian Networks.

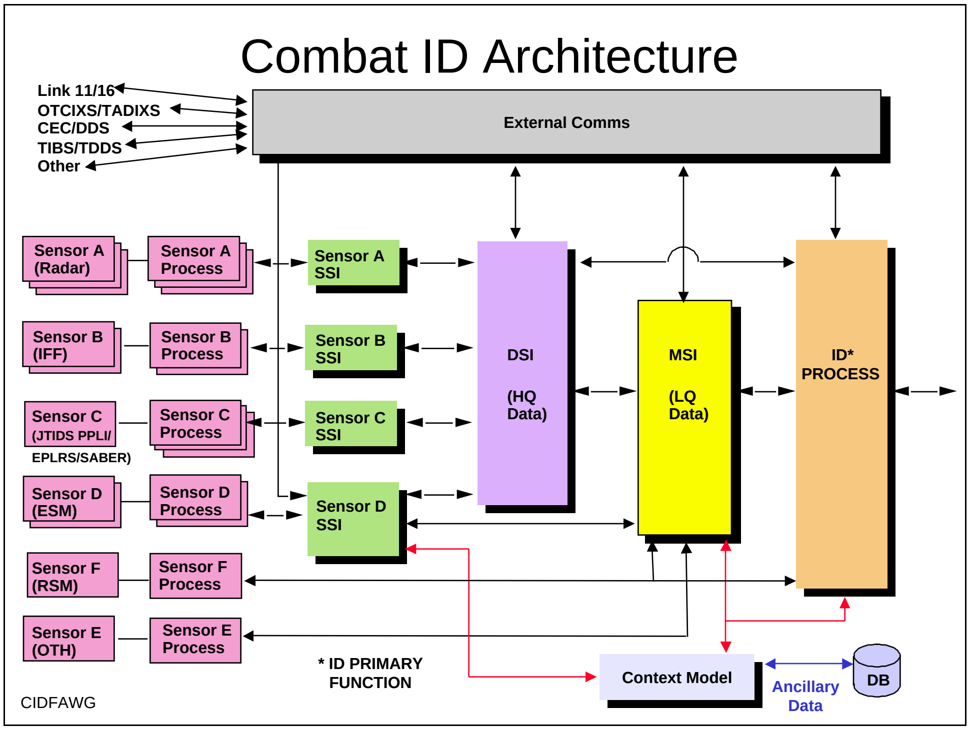

Figure 3 Combat ID Architecture

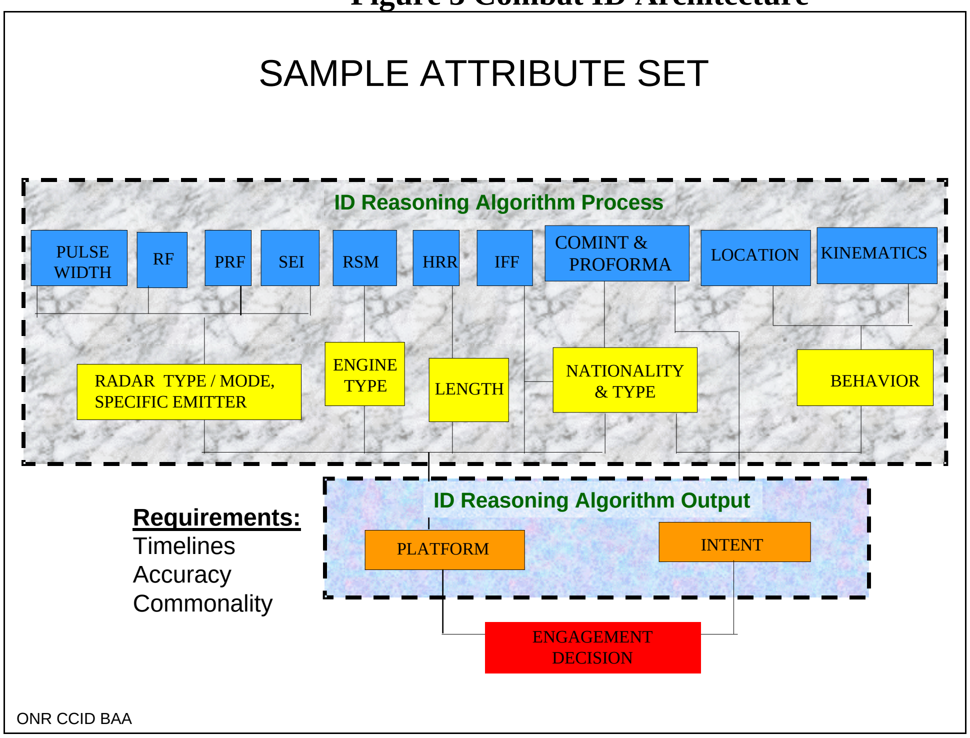

Figure 4 Contributors to Combat ID

2.2 Decision Analysis

Clemen's book "Making Hard Decisions" [13] is an excellent introduction to decision analysis. Some of the key ideas from this text and the course notes on decision theory relevant to this project [12] are that the interaction of decision options and states of the world are consequences. For simple decision situations this interaction can be recorded in a table with options on one axis and possible states of the world as the other. Each cell in the table can be assigned a utility score with 0 for the least desirable consequence and 1 for the most desirable consequence. With these two cells as anchors all the other cells can be assigned a based on preference for the consequence compared to these best and worst consequence. From this table an expected utility can be calculated for each option. The best option is the one that has the maximum expected utility. This is represented mathematically in Equation (1).

$$\textit{Action}\quad\textit{Taken} = \underset{a_i}{\arg\max} \sum_{j=1}^{N} U(C_{ij})\,p_j$$

Equation 1

2.3 Bayesian Networks

Jensen [14], defines a Bayesian Network as consisting of the following:

- A set of variables and a set of directed edges between variables
- Each variable has a finite set of mutually exclusive states.
- The variables together with the directed edges form a directed acyclic graph (DAG)
- To each variable A with parents, B_1, … B_n, there is attached the potential table $P(A|\ B_1, \ldots, B_n)$

These graphical models are effective and efficient method of dealing with uncertainty. An example Bayesian network is shown in figure (6). The standard problem involving a Bayesian network is given evidence calculate the probability of various states of hypothesis acting through various mediating variables. Bayesian networks are easy to create/ modify. These networks can mix historical, modeling and simulation, and expert judgment. The structure and parameters can learned from data. They offer several advantages over standard statistical techniques because they make use of the conditional independence to reduce the number of parameters to estimate. They are easy to compute. Efficient algorithms were developed in the late 1980's for computing probabilities. The can accommodate missing data. There are fewer parameters to estimate than standard statistical model. These graphical models are more understandable than neural nets. Algorithms also exist to calculate the most probable explanation and consistency of evidence.

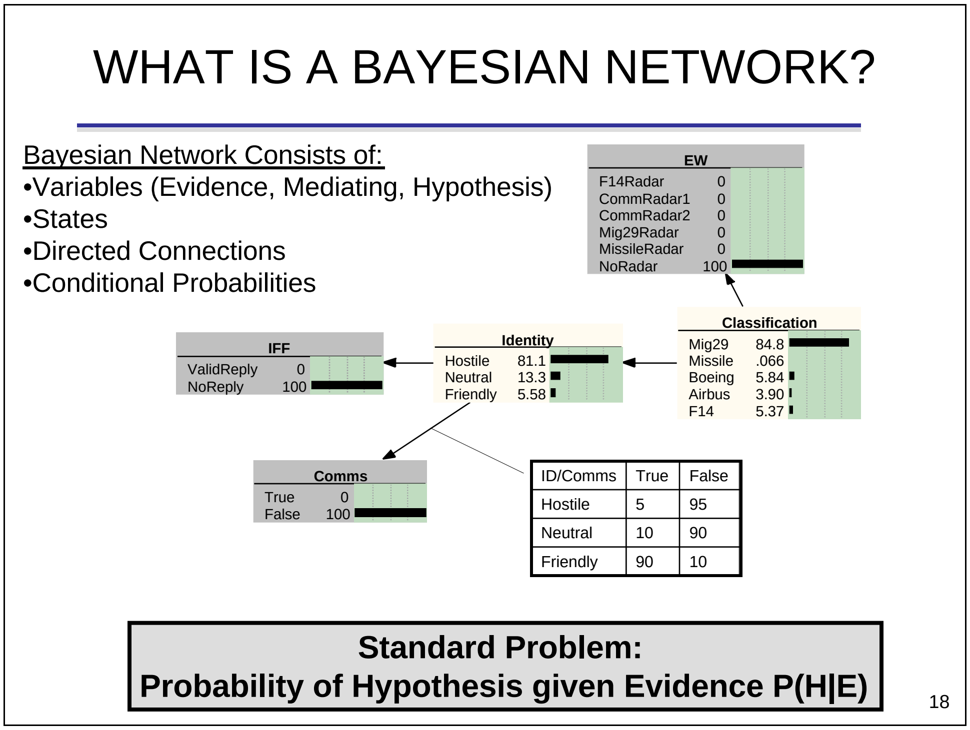

Figure 5 Bayesian Network

2.4 Knowledge Engineering

To create effective Bayesian networks good knowledge engineering is required. [15] Knowledge engineering is the process of eliciting, modeling and evaluating knowledge from an expert so that it can be used to support decision-makers.

The first step in the knowledge elicitation process is to define the goal of the modeling process. The next step is to select possible nodes in the network. These nodes will be evidence, hypothesis or mitigating variables. The third step is to list the possible states for each node. The fourth step is to establish the connection between nodes. These connections can be created by experts or learned from the data. Finally probability and conditional probabilities need to be elicited or learned.

Once an initial model is developed it needs to be evaluated before it can be used. First the nodes need to be examined. Are all the evidence and hypothesis nodes present? Have you minimized the number of mediating variable to support calculation and explanation? Next examine the states of each remaining node. Are the states mutually exclusive and collectively exhaustive? Have you minimized the number of states for each node looking for opportunity to merge states? Is it clear how you would select a state for each node? Finally, examine the connections between nodes. Do the connections correctly model conditional independence? Have you minimized the number of multiply connect nodes since these significantly increase computation time? These steps are summarized in Figure 6.

HOW ARE BNs DEVELOPED AND EVALUATED?

Knowledge Engineer Works With the Domain Expert to Elicit and Validate BN Components Using Existing Tools

COMPONENT	ELICITATION	EVALUATION
Nodes	Evidence, Hypothesis, Mediating, Historical Data	Minimize Mediating Variables to Reduce Parameters to Estimate
States	Possible Values for Each Node	Clear Assignment Rules, Mutually Exclusive, Collectively Exhaustive, Minimum Necessary
Connections	Causal, Conditional Independence	Ensure No Cycles, Minimize Multiple Connections and Number of Parents
Probabilities	Informed Expert Opinion, Historical Data	Modeling & Simulation, Experiments, Data Collection to Validate

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Figure 6 Developing and Evaluated Bayesian Networks

3.0 Project Description

For this project, we implemented a combat ID Bayesian network to evaluate two investments. One investment was to perform good sensor and database maintenance policies and the other investment was to integrate a new sensor but not perform good maintenance on the sensors.

This project builds on an earlier effort [16], [17] comparing different probabilistic approaches to performing combat identification. We reused the deliberately ambiguous scenario from the previous project. In this operational scenario a ship is assigned as battle group screen and has confirmed that it's radar, communication, IFF, ES equipment is working. Friendly aircraft are returning from a strike mission with some aircraft reporting damage. A new aircraft detected headed towards battle group but the ship has no IFF, no communication, and no ES from the aircraft. The aircraft is in a return to force corridor flying at 675 knots. The ships Commanding Officer has to decide whether to shoot the aircraft. To help make this decision a decision table is created as figure 7 showing the consequence of each combination of action and possible identity. A utility for each consequence is assigned with a utility of 0 for shooting a friendly or commercial aircraft and a utility of 1 for shooting a hostile aircraft.

In order to increase the robustness of this scenario the scenario is evaluated in different environments described in figure 9. Traditionally, different scenarios would be strung together to form a design reference mission for evaluation. The drawback is that these scenarios are all from the same future and the utility may be different futures. The echoes the criticism that we are always fighting the last war and are surprised. Scenario Analysis has been used for many years in business to select make decisions that are robust in different futures. Four or five scenarios are drawn from different futures and policies are evaluated in each of these futures. In the CID domain the different futures are distinguished by the ability to discriminate between hostile and friendly tracks on one axis and hostile and neutral tracks along a perpendicular axis.

EVALUATION OF UTILITY

Action/Hypothesis	Friendly	Commercial	Hostile
Shoot	- Destroy friendly aircraft. - Damage US prestige. -Tens of million of dollars in damage and loss of pilot -Possible loss of job **0**	- Destroy commercial airliner and kill possibly hundreds of civilians and cause tens of million of dollars in damage -No harm to US forces but significant damage to US prestige. **0**	- Destroy enemy aircraft. - Reaffirms US forces are capable of defending themselves. **1**
Don't Shoot	-No harm to US forces or prestige. **0.5**	- No harm to US forces or prestige **0.5**	-Significant damage to US fleet and prestige on the order of hundreds to thousands of lives lost and hundreds of millions to billions $ in damage **0**

$$E(U(Shoot)) = 0\,P_{Friendly} + 0\,P_{Commercial} + 1P_{Hostile} = P_{Hostile}$$

$$E(U(Not\ Shoot)) = 0.5\,P_{Friendly} + 0.5\,P_{Commercial} + 0\,P_{Hostile} = 0.5\,P_{Friendly} + 0.5\,P_{Commercial}$$

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Figure 7 Utility Evaluation

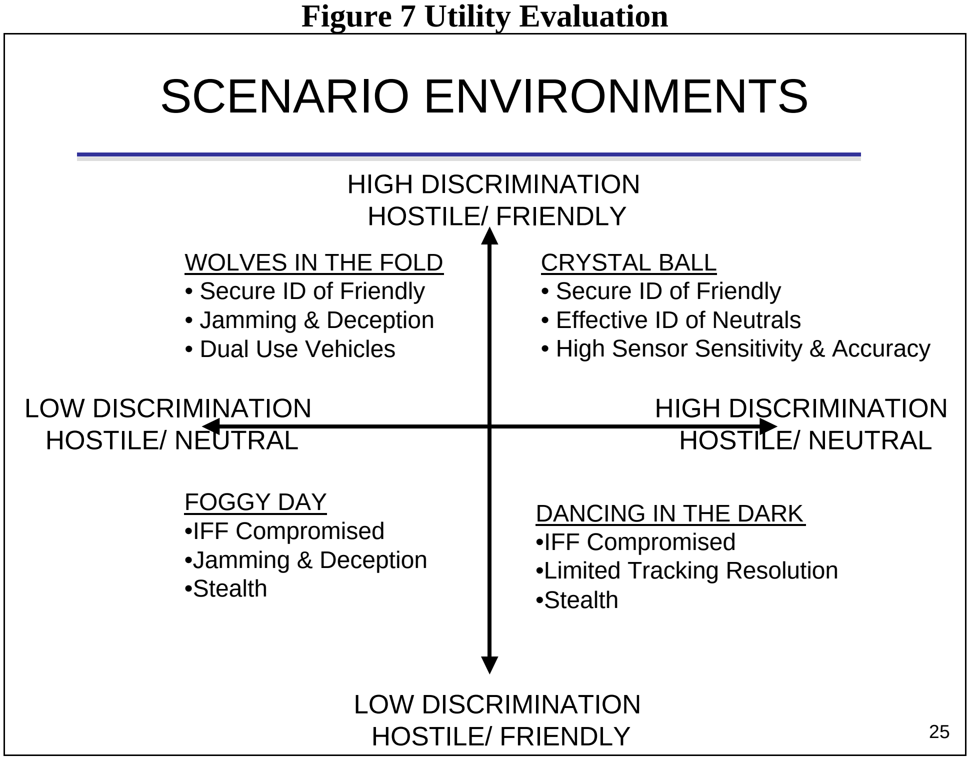

Figure 8 Environments

4.0 Results

For this project we created and evaluated a Bayesian Network using the computer program Netica shown in figures 10 and 11.

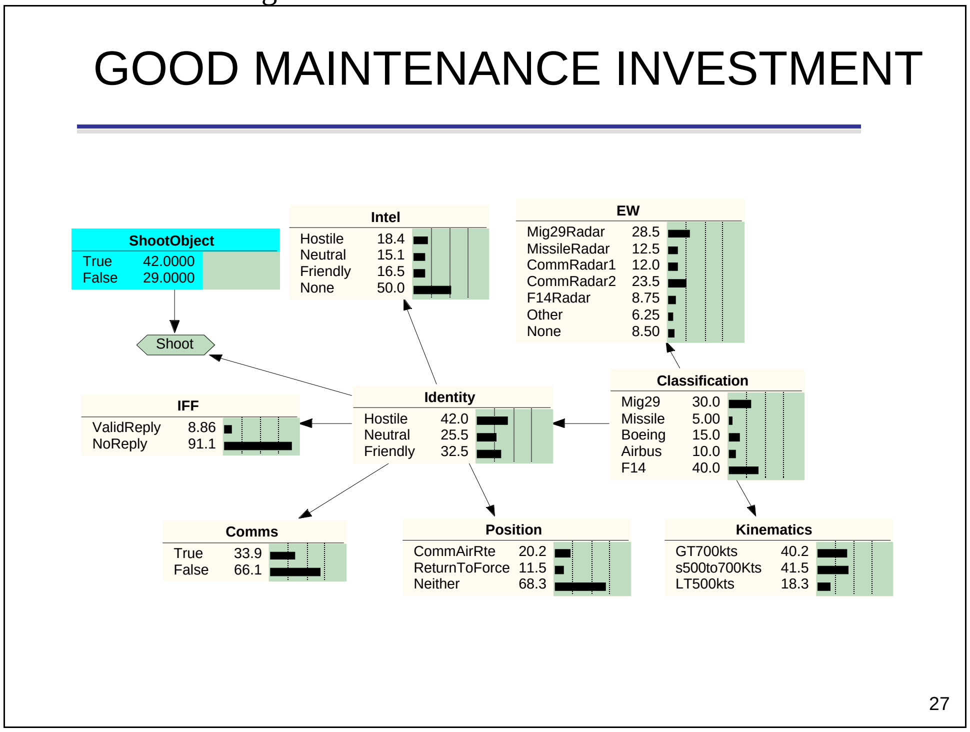

Figure 9 Good Maintenance Bayesian Network

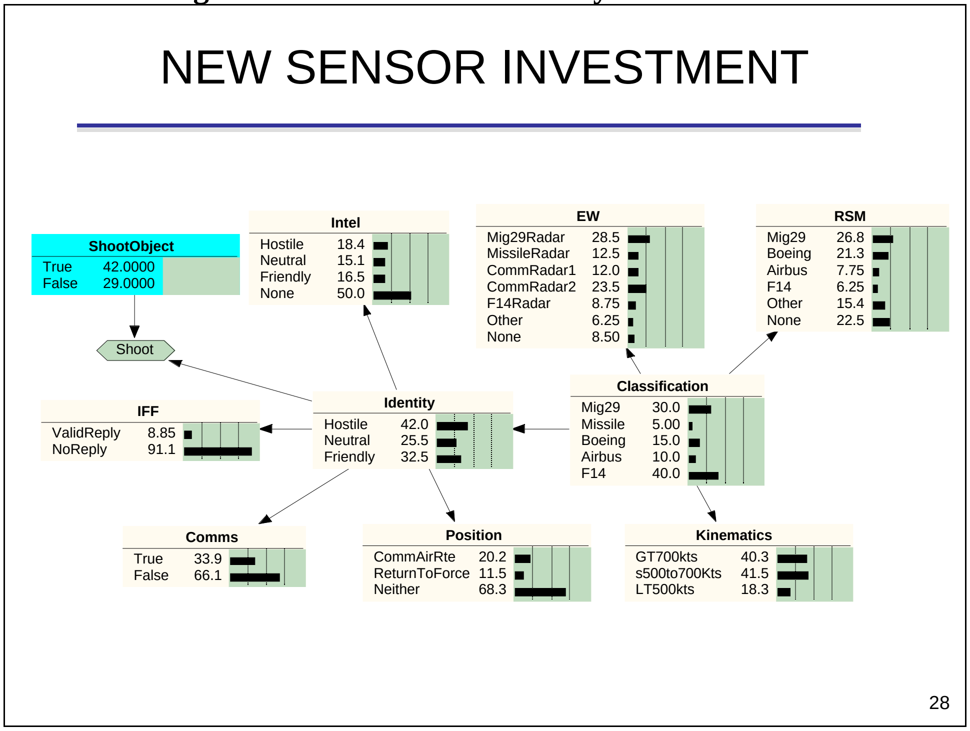

Figure 10 New Sensor Bayesian Network

4.1 Model Evaluation

Model evaluation consists of four steps – Node Evaluation, State Evaluation, Network Evaluation, and Probability Evaluation.

The first step was node evaluation. The nodes either are either evidence nodes or hypothesis nodes. The only mediating node is classification. It is needed since it represents the actual track

State Evaluation is next. Once node appropriateness was evaluated the states of each node was examined. The states of each node were deemed to be mutually exclusive and collectively exhaustive. Some of the nodes had their states combined like the IFF node had the garbled and no reply merged and the RSM and EW node would have many more states in a deployed that are collected in the 'other' state. Each state also passes the clarity test in that it is possible to unambiguously assign a state to each node.

The third step in the model evaluation was the network evaluation – do the links between the nodes make sense. The graph depicts two nodes that D-separate the graph. If you know the identity then you it doesn't matter to evaluating classification whether you also know the state of the intel, IFF or comms nodes. Similarly if you know the state of classification it doesn't matter in evaluating identity whether you also know the states of the EW, RSM, and Kinematics node. This network is also singularly connected easing network evaluation. This network properly reflects causal relationships since the classification causes particular identities and the identity causes the IFF reply as examples

Finally an assessment was made on how the probabilities would be assigned to each parent node – in this case classification. Order of battle information for each region is suggested as a way to assign the probabilities for this network. This would augmented by informed expert judgment for the new sensor added.

4.2 Performance Evaluation

Table 1 provides the contribution of the new sensor and table 2 provides the contribution good sensor maintenance. For the new sensor investment the performance of the IFF, Comms, Intel, and EW nodes were degraded. The crystal ball environment was the reference environment. For "Wolves in the Fold" and "Foggy Day" environment the ES the degraded making it more likely that commercial and hostile forces would be confused. For "Dancing in the Dark" and "Foggy Day" environment the IFF and Comms nodes were degraded. Table 3 compares the two investments. In this scenario, the preferred investment is to integrate the new sensor.

Table 1 New Sensor Results

Environment	P(H|E)	P(N|E)	P(F|E)	U(S)	U(DS)
Wolves in the Fold	72	25	2	72	14
Crystal Ball	79	18	2	79	10
Dancing in the Dark	53	28	19	53	24
Foggy Day	53	28	19	53	24
AVERAGE	64	25	11	64	18

Table Legend:

P(H|E) Probability Object Is Hostile Given Evidence
P(N|E) Probability Object Is Neutral Given Evidence
P(F|E) Probability Object Is Friendly Given Evidence
U(S) Utility of Shoot Decision
U(DS) Utility of Don’t Shoot Decision

Table 2 Good Maintenance Results

Environment	P(H|E)	P(N|E)	P(F|E)	U(S)	U(DS)
Wolves in the Fold	55	42	3	55	20
Crystal Ball	55	42	3	5	20
Dancing in the Dark	42	46	11	42	29
Foggy Day	42	46	11	42	29
AVERAGE	49	44	7	36	25

Table 3 Comparison Of Investments

INVESTMENT	U(S)	U(DS)	DIFF
Good Maintenance	36	25	12
New Sensor	64	18	46

5.0 Summary

In this paper the background necessary to develop a Bayesian Network to perform CID was provide. Two CID investments were compared using a Bayesian network. For the deliberately ambiguous scenario the contribution measured as the difference in the utility between shooting and not shooting was compared and integrating a new sensor was preferred.

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