

COMBAT IDENTIFICATION  
WITH  
BAYESIAN NETWORKS

Submitted to Track Modeling & Simulation

Student Paper

**George Laskey**  
George Mason University  
4400 University Drive  
Fairfax, VA 22202

Program Executive Office For Theater Surface Combatants  
1333 Isaac Hull Avenue Se Stop 4301  
Washington Navy Yard Dc 20376-4301

Naval Research Laboratory  
4555 Overlook Ave SW  
Washington, DC 20375

**Kathryn Laskey**  
George Mason University  
System Engineering & Operations Research Department  
4400 University Drive  
Fairfax, VA 22202

# Report Documentation Page

Form Approved  
OMB No. 0704-0188

Public reporting burden for the collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to a penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.

1. REPORT DATE <b>2002</b>		2. REPORT TYPE		3. DATES COVERED <b>00-00-2002 to 00-00-2002</b>	
4. TITLE AND SUBTITLE <b>Combat Identification with Bayesian Networks</b>				5a. CONTRACT NUMBER	
				5b. GRANT NUMBER	
				5c. PROGRAM ELEMENT NUMBER	
6. AUTHOR(S)				5d. PROJECT NUMBER	
				5e. TASK NUMBER	
				5f. WORK UNIT NUMBER	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) <b>George Mason University, System Architectures Laboratory, C3I Center, Fairfax, VA, 22030</b>				8. PERFORMING ORGANIZATION REPORT NUMBER	
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)				10. SPONSOR/MONITOR'S ACRONYM(S)	
				11. SPONSOR/MONITOR'S REPORT NUMBER(S)	
12. DISTRIBUTION/AVAILABILITY STATEMENT <b>Approved for public release; distribution unlimited</b>					
13. SUPPLEMENTARY NOTES <b>The original document contains color images.</b>					
14. ABSTRACT					
15. SUBJECT TERMS					
16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES <b>13</b>	19a. NAME OF RESPONSIBLE PERSON
a. REPORT <b>unclassified</b>	b. ABSTRACT <b>unclassified</b>	c. THIS PAGE <b>unclassified</b>			

## **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.

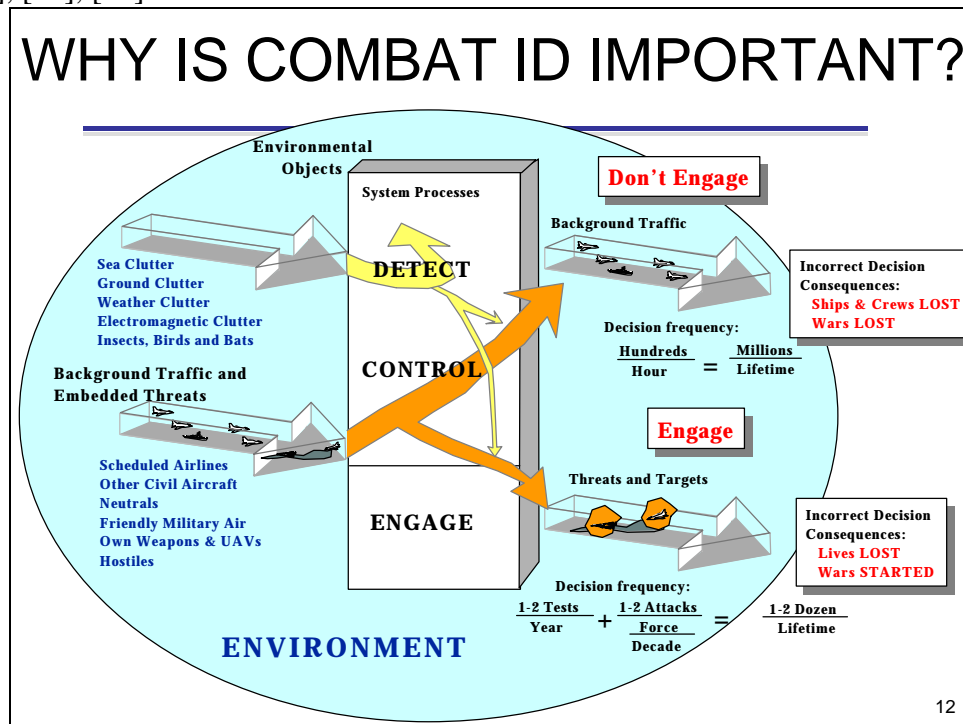
The goal of this project show that the Bayesian Networks can be used to support CID investment decisions. Two investments, a new sensor and good maintenance were compared in a difficult CID scenario in four different environments. The usefulness of the two investments was compared examining the:

- 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.

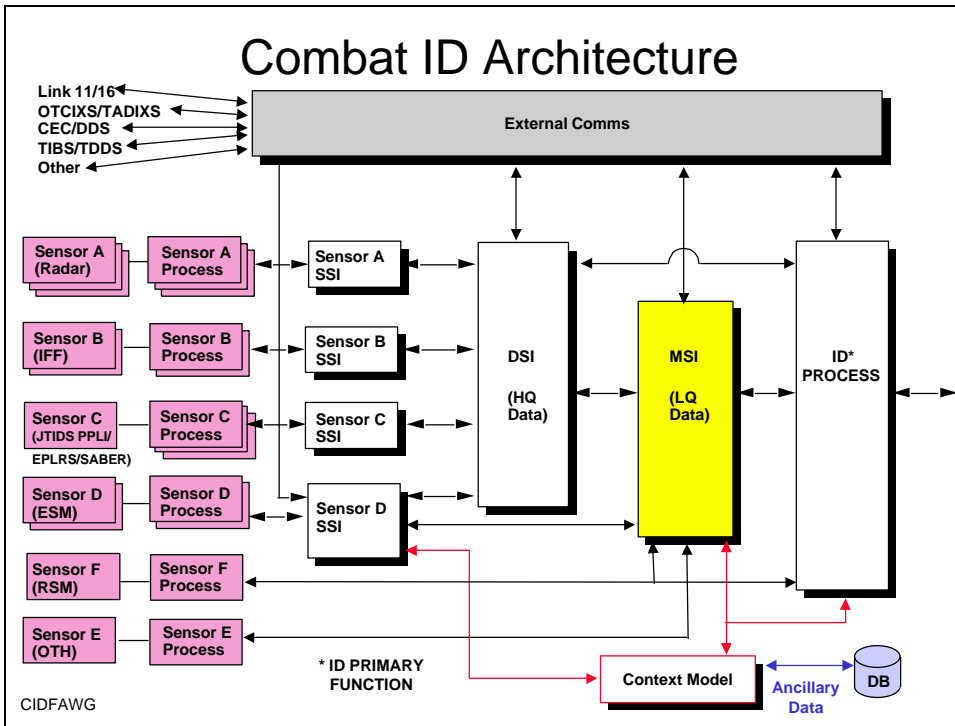


Algorithms to automatically assign an ID date back to when the Navy started putting computers in ships [6]. The first efforts were coded directly into the software and were hard to adapt to different situations. In the 1980's, rule based expert systems were introduced. These systems were more flexible 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]

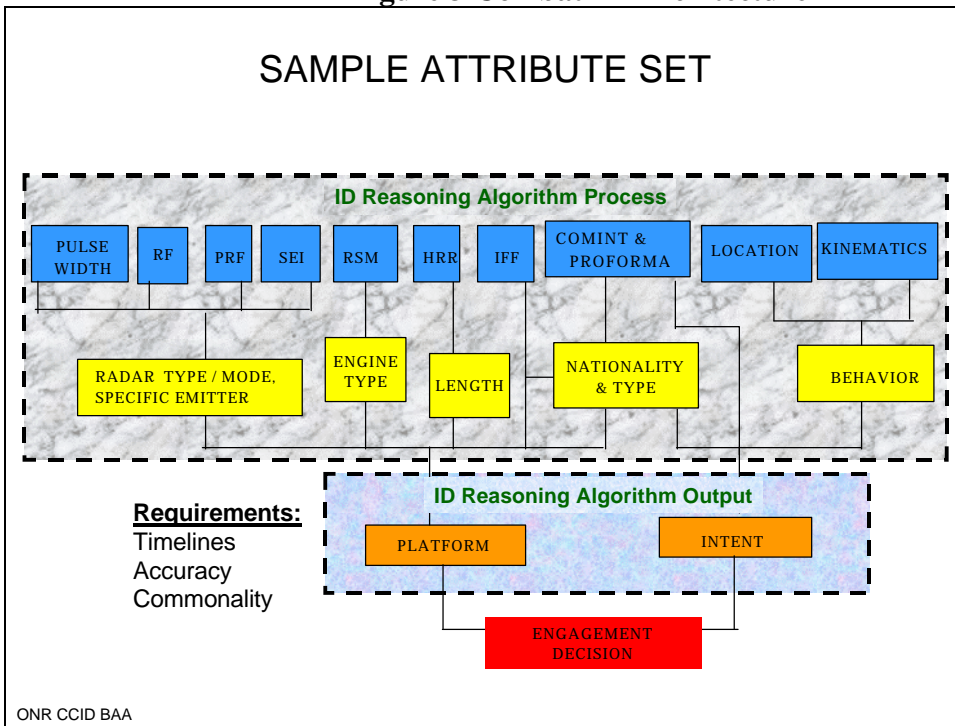


**Figure 2 Importance of Effective CID**

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).

$$Action \ Taken = \underset{a_i}{\operatorname{argmax}} \sum_{j=1}^N U(C_{ij})p_j$$

**Equation 1**

## 2.3 Bayesian Networks

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

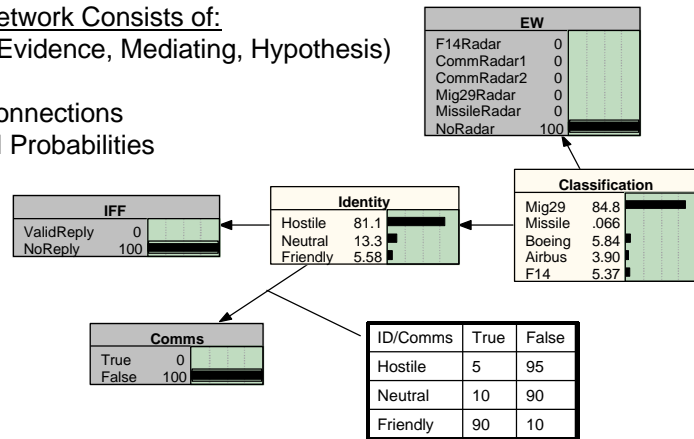
- A set of variables and a set of directed edges between variables
- Each variable has a finite set of mutually exclusive states.
- The variables together with the directed edges form a directed acyclic graph (DAG)
- To each variable A with parents,  $B_1, \dots, B_n$ , there is attached the potential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

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. They 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.

# WHAT IS A BAYESIAN NETWORK?

Bayesian Network Consists of:

- Variables (Evidence, Mediating, Hypothesis)
- States
- Directed Connections
- Conditional Probabilities



**Standard Problem:  
Probability of Hypothesis given Evidence P(H|E)**

18

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

20

**Figure 6 Developing and Evaluated Bayesian Networks**

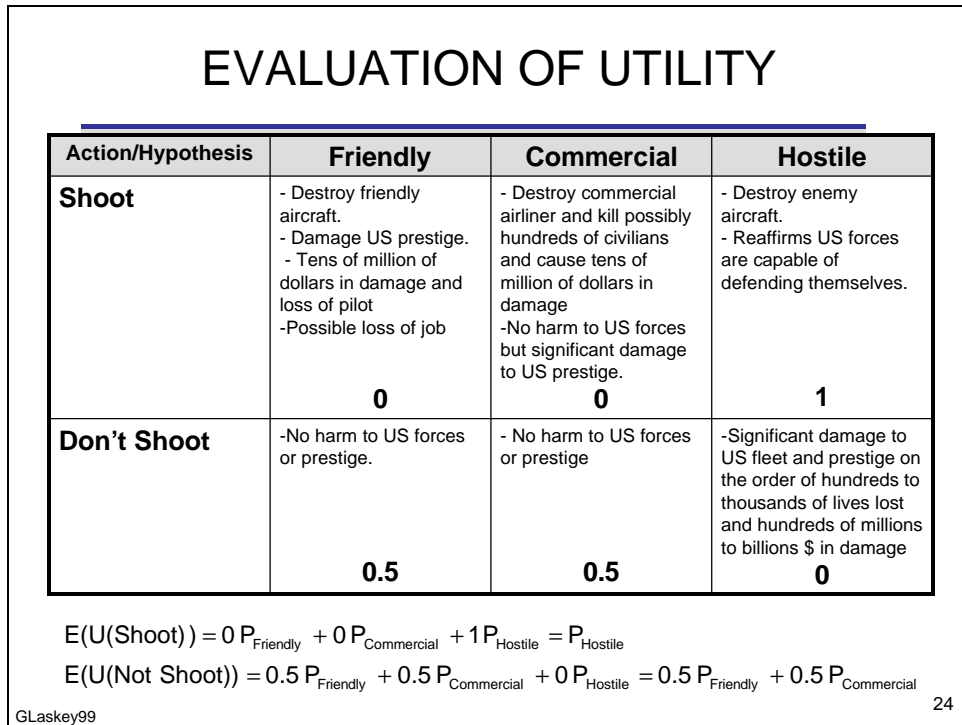
### 3.0 Project Description

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.

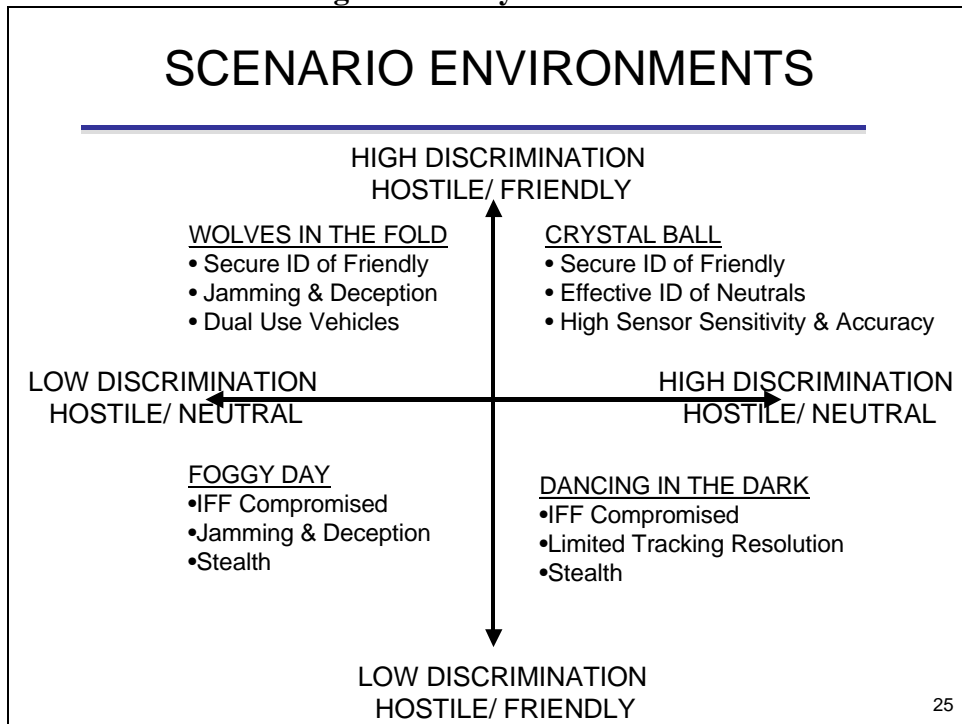
This project builds on an earlier effort [16], [17] comparing different probabilistic approaches to performing combat identification. We reused the deliberately ambiguous scenario from the previous project. In this operational scenario a ship is assigned as battle group screen and has confirmed that 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.



**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.

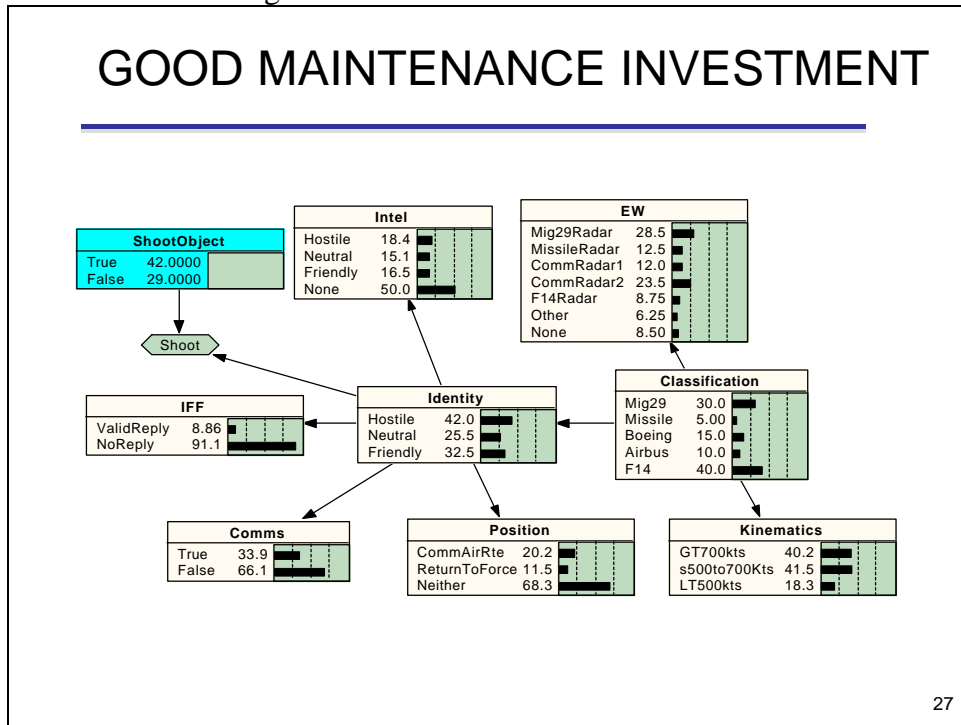


Figure 9 Good Maintenance Bayesian Network

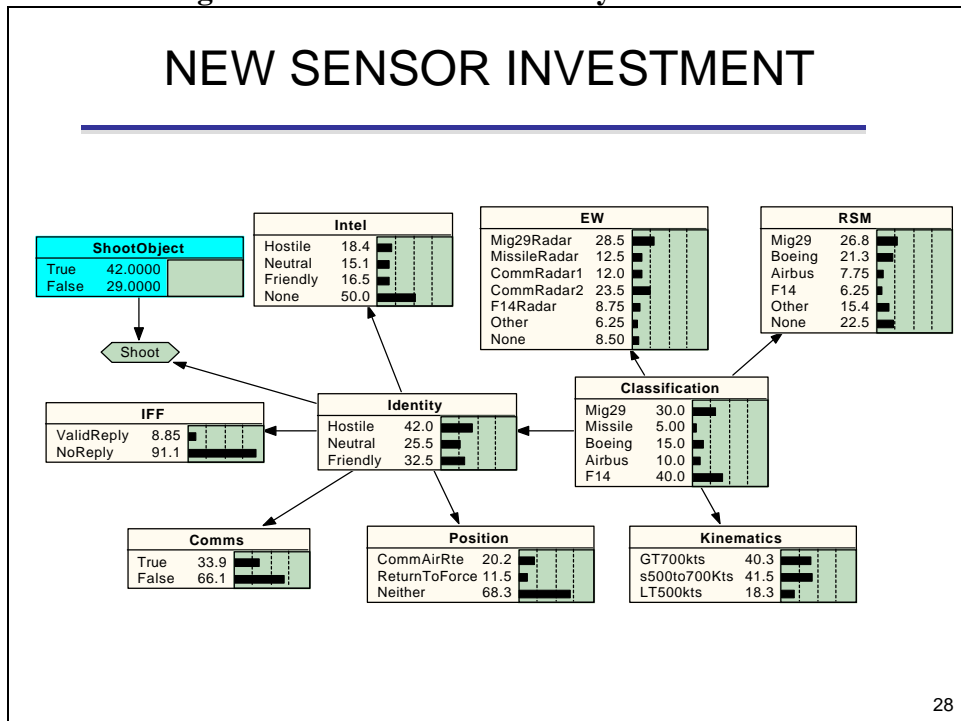


Figure 10 New Sensor Bayesian Network

#### ***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 provided. 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.

## Bibliography

- 1 John F. Harris and John Lancaster, "U.S. jets over Iraq mistakenly down two American helicopters, killing 26: officials set investigation of incident", Washington Post, April 15, 1994; Page A01.
- 2 Molly Moore, "the USS Vincennes and a deadly mistake: highly sophisticated

- combat ship at center of defense department investigation”, Washington Post, July 4, 1988 ; Page A23.
- 3 George C. Wilson and Lou Cannon, “Iraqi missile hits U.S. frigate: at least 3 dead pentagon says 30 missing in attack that may have been 'inadvertent'”, May 18, 1987 Washington Post; Page A01.
  - 4 ONR Composite Combat ID BAA, Jul 2001, [Http://www.ONR.Navy.Mil](http://www.ONR.Navy.Mil)
  - 5 Common Command & Decision KPP Analysis, May 2001
  - 6 David Boslaugh, When Computers Went to Sea: The Digitization of the United States Navy, IEEE Computer Society, Los Alamitos, CA, June 1999.
  - 7 OPNAV Surface Navy Combat ID Working Group, Jun 93
  - 8 Combat ID Functional Allocation WG, May 96
  - 9 Multi Sensor Integration SET, Oct 97
  - 10 Combat ID SET, Aug 2000
  - 11 Combat ID Capstone Requirements Document, May 2001
  - 12 David Schum, Decision Theory and Analysis Class Notes - SYST 573, Fall 99
  - 13 Robert Clemen, Making Hard Decisions, Brooks/Cole publishing CA, 1996.
  - 14 Finn Jensen Bayesian networks and decision graphs, Springer, New York, 2001.
  - 15 Computational Models for Probabilistic Inference, IT 819, K. Laskey 01
  - 16 Alternative Systems of Probabilistic Reasoning, INFT 842, Schum 99
  - 17 Combat ID: An Application of Probabilistic Reasoning, G. Laskey Dec 99