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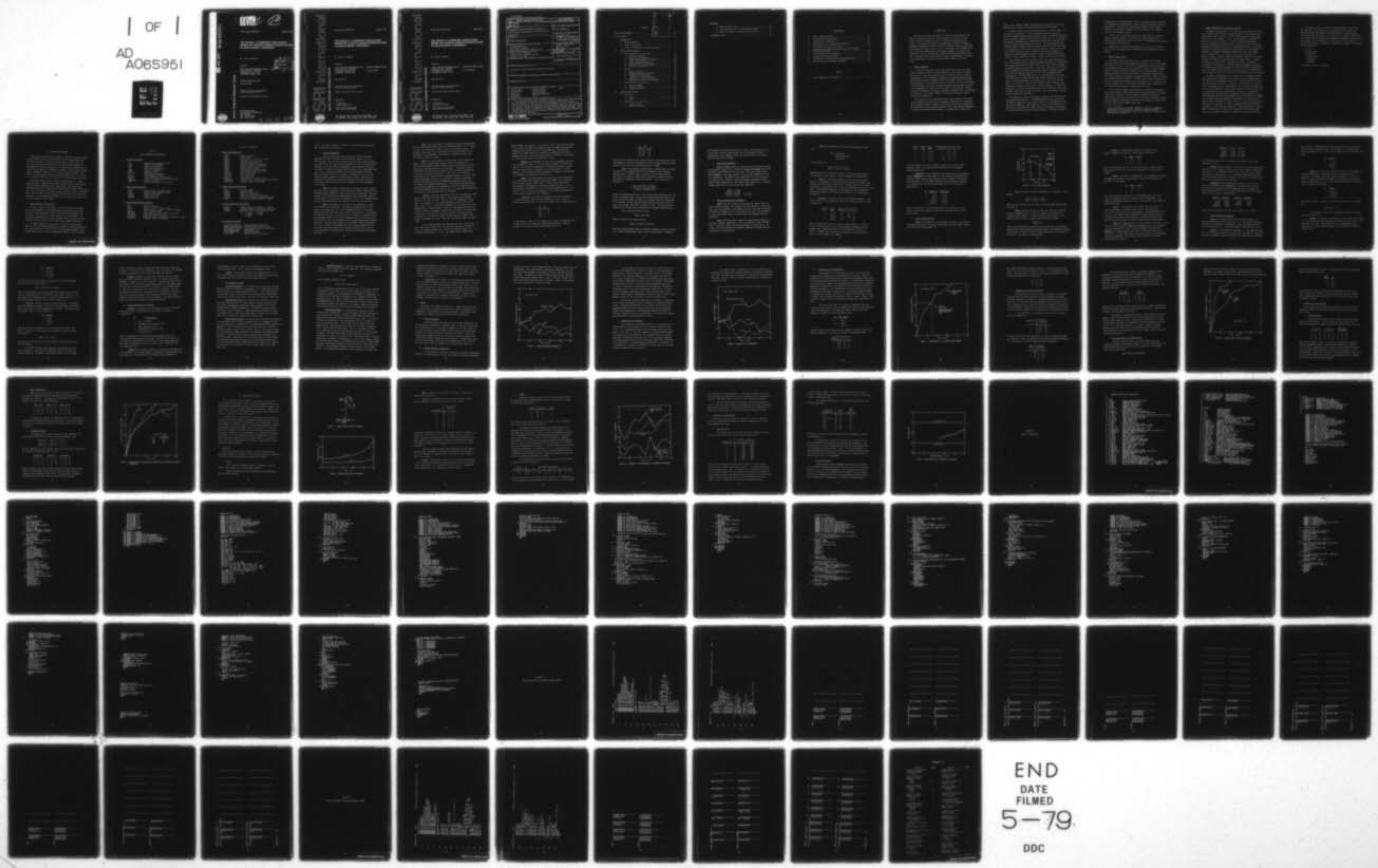

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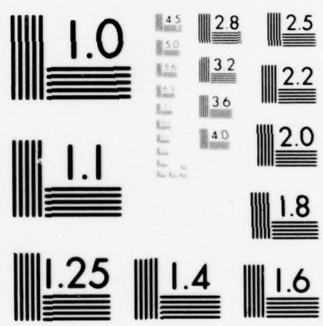

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Technical Report NWRC-TR-21

December 1978

THE MUSAC II COMPUTER SIMULATION MODEL OF PASSIVE SONAR CLASSIFICATION IN MULTITARGET SCENARIOS

By: JEFFREY R. OLMSTEAD

Prepared for:

NAVAL ANALYSIS PROGRAMS (Code 431)
OFFICE OF NAVAL RESEARCH
DEPARTMENT OF THE NAVY
ARLINGTON, VIRGINIA 22217

CONTRACT N00014-78-C-0241

Task NR 274-295

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Approved by:

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20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

This document demonstrates the MUSAC II computer program, which can simulate the classification of multiple target configurations using multiple sensor acoustic information. The model is based on detection of acoustic features so that spectral and spatial information can be simulated; thus, the sonar's bearing and frequency resolution capabilities influence the classification outcome. The classification process is simulated by a Bayesian decision-making approach. This document describes the use of the computer program; a previous report (AD-A028-936) described the methodology.

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I INTRODUCTION

This report describes the MUSAC II computer simulation model; the model can simulate an acoustic classification decision process using passive sonar information available in scenarios involving multiple targets. The study objective was to demonstrate the MUSAC II computer program by analyzing a scenario in which a submarine uses Lofar and Demon information to classify a pair of ships. The purpose of the demonstration was to show the capabilities of the computer program. This study, the fourth of a series, completes the acoustic classification modeling effort that originated in SRI's evaluation of acoustic countermeasures concepts and techniques for the Office of Naval Research (ONR) in the early 1970s.

A. MUSAC Background

In 1971, ONR initiated a long-term research effort with SRI under Contract N00014-71-C-0119 to address modeling of the acoustic classification process. The general objective was to explore alternative analytic methodologies and to recommend a methodology to represent passive sonar classification during a submarine operation against a surface ship group. More specifically, the methodology was to be suitable for use in evaluating tactical deception concepts, including deployment and employment of acoustic countermeasures in the protection of naval surface forces. After an extensive investigation into ways to represent classification, a methodology was created. It was called "MUSAC," an acronym for "Multiple Source Acoustic Classification".

The objectives of a second ONR research task, started in 1973 under Contract N00014-71-C-0419, were to recommend modifications or extensions for incorporating MUSAC routines into existing large-scale antisubmarine and antisurface warfare engagement models, and to apply MUSAC independently for evaluating classification problems. Although several large-scale models, such as APSUB, APSURF, and SIM II, were investigated, the study effort did not succeed in incorporating MUSAC into those models.

The basic product of the second MUSAC task was a computer model that was used on two occasions. The first application was the acoustic deception examples prepared for the project report. The second application was in a Harpoon targeting study and was the first true test of the MUSAC methodology; unfortunately, methodological difficulties arose when the model was used for convergence zone targets. In concluding the second research effort on MUSAC, a draft report was submitted to ONR for review. At the direction of the project scientific officer, the draft report was also reviewed by several Navy laboratories and private companies. In addition to giving valuable criticism, several respondents expressed a need for a model like MUSAC to apply to acoustic classification problems.

A third MUSAC effort was started in 1975 under Contract N0014-76-C-0166. The objective was to enhance the MUSAC methodology by incorporating the suggestions received from its review, and to solve several problems encountered during the application of the model. The project objectives were to generalize and modify the existing computer programs, to analyze and resolve methodologic questions, and to revise and expand MUSAC documentation. The third MUSAC effort was not completed, because the study direction was changed by ONR about halfway through the project. As part of an ONR reorganization, the MUSAC project was transferred from Code 431 to Code 230. After the new scientific officer evaluated the methodology's potential for his Fleet-oriented program, the project was redirected to a tactical development task totally unrelated to the goals of MUSAC. Even with only half the initial funds, good progress was made toward achieving the objectives.

The MUSAC part of the third project produced a completely revised and documented methodology. The MUSAC methodology was restructured extensively enough that it was called "MUSAC II" to distinguish it from the early methodology. Major revisions included a new formulation of a multifeature sonar detection model, different likelihood calculations, and a more generalized decision-making procedure. Although the MUSAC II methodology was well-documented,[1] there were not enough funds to implement the methodology by developing the computer program and demonstrating its capabilities. Revising the original computer model was not feasible because of the many basic changes in the methodology. Thus, MUSAC II required a new computer program.

In 1976, SRI International supported an IR&D project to develop a MUSAC II computer program. The program was coded, keypunched, and corrected for compilation errors; but it was not demonstrated with specific input parameters and functions.

Demonstration of the computer program was the goal of the present MUSAC project; the program and its capabilities are documented in this report.

B. MUSAC II Application

The MUSAC II model may be (1) used as a component of a larger Monte Carlo acoustic warfare engagement simulation, or (2) used by itself as an analytical tool. In the first application, the model can provide classification decisions for the selection of tactics in dynamic engagements in which the simulated kinematics are not predetermined. In the second application, the model can predict classification probabilities and perform sensitivity analyses of acoustic parameters. MUSAC II employs the standard acoustic parameters of classical sonar detection theory. By using a physical-based approach, the model represents the inherent classification capability of a sonar system, particularly the sensitivity of the classification decisions to signal-to-noise ratios.

Large, detailed computer simulations of the future are expected to be an active research medium because of constant improvements in computer capabilities and speed. Since the MUSAC II approach is much more sophisticated than the ad hoc acoustic classification algorithms currently used in engagement simulations, the model will be useful in future sonar systems analyses using computer simulation.

---

1. J. R. Olmstead and T. R. Elfers, "MUSAC II, A Method for Modeling Passive Sonar Classification in a Multiple Target Environment," NWRC-TN-62, SRI International, Menlo Park, California (February 1976), UNCLASSIFIED, AD-A028-936.

C. MUSAC II Methodology and Computer Program

The MUSAC II methodology is a mathematical representation of passive sonar classification, and the principal attribute of the methodology is its multiple-target capability. Almost without exception, other models allow for only one target at a time. The methodology is based on the detection of acoustic features; in this way, spectral and spatial acoustic information is modeled so that the sonar system's bearing and frequency resolution influences the classification outcome. The acoustic features are defined by the analyst; the features can be narrowband, broadband, or modulated broadband classification clues (for example, Lofar or Demon lines). The acoustic features are represented by Bernoulli random variables so that the stochastic structure of the model provides for realistic random variations of acoustic data. A dynamic encounter is represented by a time-step simulation. The MUSAC II methodology is structured for sequential decision-making by the update of classification information and the change in kinematic variables over time. From Monte Carlo replications of the encounter, the probability of making selected tactical and classification decisions can be estimated.

The MUSAC II methodology uses a Bayesian decision-making approach. The analyst first formulates a set of multiple-target hypothesis that will be used in the engagement simulation. The probability of detecting specified acoustic features is calculated at each time step, for each sonar look angle, and for each hypothesis (the true target configuration is one of the hypotheses). These detection probabilities are then used, in conjunction with the observed random features, to calculate the likelihood that the data would be observed if the hypothesis were true. The likelihoods and the prior probabilities are then combined to produce the posterior probability that the Ith hypothesis is true, given the observed data. The analyst defines tactical or classification decisions that are to be simulated, the value of making the decision when each hypothesis is true, and value thresholds. With this decision structure, MUSAC II determines if a decision is to be made at the present time step; if not, another time step is simulated and more data collected.

The computer program is coded in Fortran Extended for SRI's CDC 6400 computer. The source deck is approximately 1,000 cards; and with the currently programmed array dimensions, the program requires about 32,800 words of memory. The running time is directly proportional to the number of runs, number of replications, and number of time steps; the running time is influenced to a lesser extent by the number of target tracks, number of hypotheses, and number of features. For example, with the parameters:

3 runs

20 replications

10 time steps

2 target tracks

9 hypotheses

7 features,

the running time was 121 seconds.

II SINGLE-TARGET EXAMPLE

This chapter describes how the MUSAC II model can simulate a single-target scenario; the next chapter deals with the double target case. The input parameters are first explained, then the model output is discussed, and finally variations on the single-target scenario are investigated to show the sensitivity of classification probabilities to various input parameters. Appendix A contains a listing of the computer model. Appendix B contains (1) a listing of Subroutine INPUT, which shows the input parameter values used in the example; and (2) a listing of the output, which shows the results of the single-target simulation.

The single-target scenario involves classification of a single surface ship by a submarine using Demon information from a hull-mounted array and Lofar information from a towed array. The initial range separation between the target ship and the submarine is about 40 nmi, and the two units approach each other on a near collision course. The engagement lasts for about 1.5 hours and ends when the units are 6 nmi apart. During the 1.5-hour period, the submarine must classify the target as one of three classes of surface ships.

A. Input Parameters and Functions

The model requires 50 parameters and six user-defined functions. Many of the parameters are multivariate, meaning that they are arrays using one or two subscripts. Table 1 lists the input parameters and functions. The input list is subdivided into seven categories. The following sections discuss what the parameters mean, how they are used, and what value they assume in the single-target example computation.

The input parameters for the model are contained in Subroutine INPUT in the form of DATA statements; this method of inputting parameters was chosen because of the versatility of Fortran DATA statements, even though a small price is paid in recompiling INPUT each time the program

Table 1

INPUT PARAMETERS AND FUNCTIONS

1. Scenario Parameters

GV	Random number generative value
NREP	Number of replications
NMAX	Number of time steps
TS	Time step duration (min)
IMAX	Number of hypotheses
MMAX	Number of tracks
KT(I,M)	Hypothesized target type
IR	True hypothesis number
PRIOR(I)	Prior probability of hypothesis
KDMAX	Number of tactical decision alternatives
VAL(I,KD)	Value of decision
FVAL	Decision threshold of test ratio

2. Target Track Parameters

XT(M)	Target initial x-position (nmi)
YT(M)	Target initial y-position (nmi)
CT(N,M)	Target course (deg)
ST(N,M)	Target speed (kt)
DT(N,M)	Target depth (ft)

3. Target Classification Parameters

JMAX	Number of features
NF(J)	Feature off/on (0 = off 1 = on)
KF(J)	Feature type (1 = Lofar 2 = BBand 3 = Demon)
FRQ(J)	Center frequency (Hz)
PLL(J,KT)	Lofar line level (dB // μPa^2 at 1 yd) also
PLL(J,KT)	Demon modulation level (dB)
PBB(NB,KT)	Broadband source spectrum (dB // $\mu Pa^2/Hz$ at 1 yd)
FQB(NB,KT)	Frequency points for PBB (Hz)

Table 1 (Continued)

4. Sonar Array Parameters

LAMAX	Number of arrays
LA(J)	Array number
KA(LA)	Array type (1 = circle, 2 = line)
DH(LA)	Horizontal array size (ft)
DV(LA)	Vertical array size (ft)
HN(LA)	Horizontal number of hydrophones
VN(LA)	Vertical number of hydrophones
SL(LA)	Sidelobe level (ratio)
XO(LA)	Array initial x-position (nmi)
YO(LA)	Array initial y-position (nmi)
CO(N,LA)	Array course (deg)
SO(N,LA)	Array speed (kt)
DO(N,LA)	Array depth (ft)
NA(N,LA)	Array off/on (0 = off, 1 = on)
PNN(NF,LA)	Broadband noise outside array (dB // $\mu Pa^2/Hz$)
FQN(NF,LA)	Frequency points for PNN (Hz)

5. Signal Processing Parameters

LP(J)	Processor number
WTH(LP)	Bandwidth (Hz)
SCR(LP)	Scan rate (number/min)
FCS(LP)	Number of feature cells per scan
TOT(LP)	Total time of feature integration (min)
DET(LP)	Detection threshold (number of sigmas)

6. Acoustic Fluctuation Parameters

MIX(KR)	Mixing constant (0 = gauss, 1 = jump)
SDV(KR)	Standard deviation of random process (dB)
TAU(KR)	Relaxation time of random process (min)

KR: 1 = Lofar 4 = Noise
2 = BBand 5 = PLoss
3 = Demon

7. User-Defined Functions

FLL(J,KT,ST,DT,ASP)	Lofar and Demon source level
FBB(KT,FRQ,ST,DT,ASP)	Broadband source spectrum level
FNN(LA,FRQ,SO,DO,ANG)	Noise spectrum level at array output
FAZ(FRQ,RNG,DO,DT)	Propagation loss
FBM(J,FRQ,BRG,ANG)	Beam pattern ratio
FSL(LA,FRQ)	Reference beam pattern ratio

is run. The input functions are coded as individual Fortran functions, thus allowing for easy changes.

1. Scenario Parameters

GV is the generative value used in the library subroutine RANSET(GV) to start a sequence of random numbers through use of the function RANF. The value of GV can be set to any large positive number, for example GV = 583. The model is programmed so that the random number sequence in one replication is independent of the sequence in another replication. However, the random number sequence is not independent from run to run. By using the parameter GV, the same sequence of random numbers is used from one run to another, providing that each run calls the random number generator the same number of times. The purpose of repeating the sequence is to allow for parameter sensitivity analyses that reflect only the variation of the parameters, not the randomness of the model.

NREP is the number of Monte Carlo replications used to compute statistics of the engagement. The single-target example computation uses 20 replications, although 10 times as many would be preferred. Since the purpose of the study was model demonstration rather than model accuracy, a small number of replications was adequate; a small value of NREP allowed for more model demonstration runs because the cost per run was less.

NMAX is the number of time steps in the engagement, and TS is the duration of each time step. The example computation used 10 time steps of 10 minutes each, for a total engagement time of 100 minutes. Fairly large time steps were used to reduce computer costs. The duration should be set so that (1) the target will not "jump over" phenomena such as convergence zones, (2) the total integration time is not shorter than the time step, and (3) the geometry will not change significantly between time steps. The last point relates to the problem of using the geometry at a point in time as an approximation of an average geometry over the time step. The model assumes that the geometry at the end of the time step is adequate for simulating the integrative processes over the whole time step.

IMAX is the total number of hypothetical target configurations. For the single-target example there are three hypotheses: (1) the target is Type 1, (2) the target is Type 2, and (3) the target is Type 3. For multiple target cases, the track number must also be specified in the definition of the hypothesis. For example, a hypothesis might read: The target on Track 2 is Type 3.

MMAX is the total number of target tracks in the simulation; MMAX = 1 for the single-target example. Tracks are thought of as entities unto themselves; when different types of targets are placed on the tracks, different hypotheses are generated. The computer model is simplified by allowing only the tracks of the true target configuration to be used in forming the hypotheses. Thus there is an underlying assumption that the geometry of the engagement situation is known. This simulated knowledge may have an actual basis as objective knowledge (a tracking solution) or subjective knowledge (long-range targets imply low signals and frequency attenuation). The simulation methodology must use reasonable geometries for computations; since the computations were already overburdened with replication, time-step, and feature calculations, the inclusion of pseudo-tracks was not attempted.

KT(I,M) is an array that defines, for the I-th hypothesis, what type of target is on the M-th track. In the single-target example KT(I,1) = 1,2,3 for I = 1,2,3. Thus for the first hypothesis, target Type 1 is on Track 1; for the second hypothesis, target Type 2 is on Track 1; and so on. As currently programmed, up to 10 hypotheses can be defined over two tracks; however, these array dimensions can easily be changed. There is no computer restriction on the number of target types, since "type" is the value of the array, but many types implies many hypotheses, so in effect the number of target types is limited to the number of hypotheses (or less, in the case of multiple target configurations).

IR is the hypothesis that represents the real configuration. In the single-target example IR = 1 for the first run; thus a target of Type 1 is actually present, and it may be classified as Type 1, 2, or 3 by choosing Hypothesis 1, 2, or 3. The single-target example makes three separate runs for *IR = 1,2,3 so that a 3-by-3 classification matrix* can be formed. The MUSAC II methodology does not require that the real configuration be present as one of the hypothetical configurations; however, the computer model was simplified by designating one of the hypotheses as true. Also, the interpretation of "correct" classification is more clear when one of the hypotheses is true.

PRIOR(I) is proportional to the a priori probability that the I-th hypothesis is true. In the single-target example, the priors are equal to 0.1 for all three hypotheses (the priors do not have to add to 1.0, since they are used as weights in the calculations). A priori knowledge, such as order-of-battle estimates or historical track records, can be modeled by appropriately chosen priors.

KDMAX is the total number of tactical decisions alternatives. In the first part of the example calculation, KDMAX = 3 to correspond with the three possible target types. For this case the "tactical alternatives" are decisions to classify the target as Type 1, 2, or 3. Later examples have KDMAX = 2, and the tactical alternatives are (1) to attack, or (2) to break off the approach. As currently programmed, up to 10 decision alternatives can be defined.

VAL(I,KD) is an array that specifies the value of decision alternative KD, given that the I-th hypothesis is true. When the decision alternatives are to classify the target, the VAL(I,KD) matrix is:

$$\begin{array}{c|ccc} & & \mathrm{KD} & \\ \hline & 1 & 0 & 0 \\ \mathrm{I} & 0 & 1 & 0 \\ & 0 & 0 & 1 \end{array} \quad .$$

In other words, a value of 1 is assigned to a correct classification and a value of zero to an incorrect classification decision. When the decision is to attack or not, the VAL(I,KD) matrix is:

	KD	
	300	-500
I	-100	100
	-500	100

where the first column is the "attack" decision. The values imply that a high penalty is paid for attacking Type 2 and 3 targets; however, a high penalty is also paid for not attacking a Type 1 target.

FVAL is the threshold against which a computed ratio is tested. The ratio is the "maximum expected value" divided by the "expected maximum value." "Value" refers to the decision alternative values VAL(I,KD), and "expected" means that the values are averaged by using the posterior probability distribution POST(I). The test ratio is defined as:

$$F = \frac{\text{Max}\ [\Sigma_I\ \text{POST(I)}\ \text{VAL(I,KD)}]}{\Sigma_I\ \text{POST(I)}\ \text{Max}[\text{VAL(I,KD)}]} \quad ,$$

where the maximizing operation is over the decision alternatives KD. The F ratio is between 0 and 1, and for the example calculation FVAL = 0.95. When F is less than FVAL, the decision is deferred and more information is collected by letting the model advance another time step; when F is equal to or greater than FVAL, a decision is made. The chosen decision alternative is the one that corresponds to the maximum expected value:

Select alternative KD* such that:

$$E(KD^*) = \text{Max}\ E(KD) \ .$$

E(KD) is defined as the expected value:

$$E(KD) = \Sigma_I\ \text{POST(I)}\ \text{VAL(I,KD)} \quad .$$

The above decision-making method is slightly different from that described in the MUSAC II methodology report;[1] there, the difference of numerator and demonimator was tested instead of the ratio. One way works as well as the other, and the present method has the advantage of using a dimensionless input parameter, FVAL, that does not have to be changed when the VAL matrix is changed.

2. Target Track Parameters

XT(M) and YT(M) specify the initial position of target Track M. The trajectory through time is defined by CT(N,M) and ST(N,M), the course and speed values during the N-th time step. The model accepts target depth, DT(N,M), as an input parameter, but does not currently use it in any calculations. The primary use of depth would be in the calculation of propagation loss; however, a depth-independent propagation model is used for model demonstration. The single-target example uses a straight-running target and has the following input parameters:

XT(1) =	0 nmi	
YT(1) =	40 nmi	
CT(1,N) =	155 deg	N = 1,10
ST(1,N) =	25 kt	N = 1,10

3. Target Classification Parameters

JMAX is the total number of classification features that are used to classify targets. The example uses seven features: three Lofar lines, and two Demon lines in two bands (a total of four Demon features). As currently programmed, up to 12 features may be used. Any combination of Lofar lines, Demon lines in various bands, and broadband noise may be defined.

NF(J) is an array that singles out classification features to be used or ignored. When NF(J) = 1 the J-th feature is used, and when NF(J) = 0 the J-th feature is treated as though it did not exist. NF used to study the importance of individual features by turning them off and then on in successive runs.

KF(J) tells the model what kind of classification feature J is:

KF = 1 Lofar line
     2 Broadband noise
     3 Demon line .

In the example run:

KF(J) = 1 for J = 1,2,3
KF(J) = 3 for J = 4,5,6,7 .

Broadband noise is included as a feature in case the analyst desires the "loudness" of the target to convey classification information.

FRQ(J) is the center frequency of the J-th classification feature. For example, the three Lofar lines are at 50 Hz, 100 Hz, and 400 Hz, and the two Demon lines are in two bands centered at 2,828 Hz and 5,656 Hz (the geometric mean of the 2 to 4 kHz band and the 4 to 8 kHz band). The frequency parameter is used primarily in the attenuation calculation associated with propagation loss and in the beam pattern calculation.

PLL(J,KT) is the line level of classification feature, J, for target type, KT. For example, the Lofar line levels for Type 1, 2, and 3 targets are:

Feature	Lofar	Target Line Levels (dB)		
J	Line	KT = 1	2	3
1	50 Hz	155	155	0
2	100 Hz	0	150	150
3	400 Hz	150	0	150

where the Lofar line levels are in units of dB relative to 1 μPa^2 at 1 yard. The very small value of 0 dB represents a missing line; for example, Type 1 target has lines at 50 Hz and 400 Hz, but none at 100 Hz. The Demon line levels are also defined in the PLL matrix for Type 1, 2, and 3 targets; for example:

Feature J	Demon Line	Band (kHz)	Target Modulation Levels (dB) KT = 1	2	3
4	A	2 to 4	- 3	-20	-20
5	B	2 to 4	- 3	- 3	-20
6	A	4 to 8	- 3	-20	- 2
7	B	4 to 8	-20	- 3	- 2

where the Demon line levels are decibel values of the square of the modulation index. The large negative modulation levels represent missing Demon lines.

PBB(NB,KT) is the broadband source spectrum level at frequency points, FQB(NB,KT) for target type, KT. The spectrum is described by a piecewise linear function with breakpoints NB; a maximum of six points may be specified. In the example calculation, the spectrum is assumed to be identical for all three target types (for KT = 1,2,3) and is described by:

NB	FQB(NB,KT)	PBB(NB,KT)
1	10 Hz	153 dB
2	100 Hz	155 dB
3	1,000 Hz	145 dB
4	10,000 Hz	125 dB

where the spectrum is in units of dB relative to 1 $\mu Pa^2/Hz$ at 1 yard. Figure 1 shows the broadband spectrum levels and Lofar lines for the Type 1 target.

4. Sonar Array Parameters

LAMAX is the number of sonar arrays in the model. As currently programmed, there can be a maximum of two arrays, and the example calculation uses both of them (LAMAX = 2).

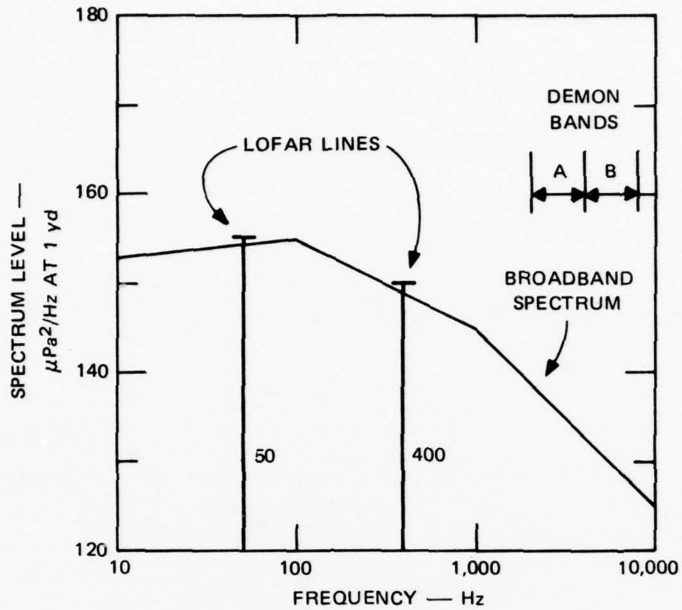

FIGURE 1 TYPE 1 TARGET SPECTRUM

LA(J) specifies from which array Feature J is derived. In the example:

$$LA(J) = 2 \text{ for } J = 1,2,3$$
$$LA(J) = 1 \text{ for } J = 4,5,6,7 .$$

Thus the Lofar features come from Array 2, and the Demon features come from Array 1.

KA(LA) specifies the type of Array LA. There are two types currently programmed: KA = 1 (circle) represents a cylindrical or spherical array, and KA = 2 (line) represents a towed array. In the example the first array is circular and the second is linear:

$$KA(1) = 1$$
$$KA(2) = 2 .$$

Thus the Lofar features are derived from the towed array, and the Demon features from the hull-mounted cylindrical array. The difference between the two types of arrays is in the way the beam pattern is calculated, as described in the section on Function FBM.

DH(LA) is the horizontal dimension, and DV(LA) is the vertical dimension of Array LA. In the example calculations:

LA	DH(LA)	DV(LA)
1	7 ft	5 ft
2	60 ft	0 ft .

Thus the cylindrical array is 7 ft in diameter and 5 ft high, and the towed array is 60 ft long (the vertical dimension for a line array is ignored).

HN(LA) is the number of hydrophones in the horizontal direction, and VN(LA) is the number of hydrophones in the vertical direction for Array LA. In the example:

LA	HN(LA)	VN(LA)
1	15	30
2	11	1

Thus, the cylindrical array has 15 x 11 hydrophones that can receive in any one direction, and the towed array has 30 hydrophones. The number-of-hydrophones parameter is used in function FNN to calculate the directivity index.

SL(LA) is the sidelode level of Array LA; it is input as a ratio rather than as a negative decibel value. The example uses SL = 0.01 for both arrays; this corresponds to a maximum sidelode level of -20 dB. The function that calculates the beam pattern uses SL as a limiting value so that the beam response is at least 20 dB below the main beam response whenever the signal arrives outside the main beam.

XO(LA) and YO(LA) specify the initial position of Array LA. The array's track is defined by CO(N,LA) and SO(N,LA), the course and speed of Array LA during time step N. The model accpets the array depth DO(N,LA) as an input parameter, but does not currently use it in any calculation. As with target depth, array depth could be used in propagation-loss calculations. The tracks of the two arrays in the model demonstration are given by:

Parameter	LA = 1	LA = 2
XO(LA)	0 nmi	-0.5 nmi
YO(LA)	0 nmi	0 nmi
CO(N,LA)	90 deg	90 deg
SO(N,LA)	10 kt	10 kt

The towed array follows 1/2 nmi behind the cylindrical array; both move east at 10 kt.

NA(N,LA) specifies whether or not Array LA is operating during time step N: NA = 0 means that the array is off, and NA = 1 means that the array is on. The NA(N,LA) matrix can be used to turn off a towed array during a course change, or to investigate classification information on one array versus that on another. The example calculation leaves both arrays on during the entire encounter.

PNN(NF,LA) is the broadband noise spectrum level outside Array LA at frequency points FQN(NF,LA). The spectrum is described by a piecewise linear function with breakpoints NF; a maximum of six points may be specified. In the example calculation, the noise spectra outside the two arrays are described by:

FQN(NF,1)	PNN(NF,1)	FQN(NF,2)	PNN(NF,2)
10 Hz	120 dB	10 Hz	75 dB
300 Hz	65 dB	1,000 Hz	65 dB
1,000 Hz	65 dB	10,000 Hz	45 dB
10,000 Hz	45 dB		

where the noise spectra are in units of dB relative to 1 $\mu Pa^2/Hz$.

5. Signal Processing Parameters

LP(J) is the signal processor that produces Feature J; as currently programmed, LP may range from 1 to 5. The example uses three processors to correspond to the different signal processing parameters for Lofar signals (LP = 1), and Demon signals in two bands (LP = 2,3).

WTH(LP) is the bandwidth of processor LP. The bandwidth should be set to the natural width of the signal being processed; the model does not have a mechanism to decrease the Lofar line level when the bandwidth is too narrow. A bandwidth larger than necessary will allow more noise into the system and degrade detection performance. The example Lofar lines are assumed to be 1 Hz wide, and the Demon bands are 2 kHz and 4 kHz wide:

LP	WITH(LP)
1	1 Hz
2	2,000 Hz
3	4,000 Hz .

SCR(LP) is the scan rate of the processor; it is the number of times per minute that a particular frequency or bearing region is processed. For example, the Lofar lines are assumed to lie in a 0 to 600 Hz frequency region that is scanned once per minute, and the Demon lines are assumed to lie in a 0 to 60 Hz modulated frequency region that is also scanned once per minute:

LP	SCR(LP)
1	1 scan/min
2	1 scan/min
3	1 scan/min .

The number of times a feature is scanned in one time step is calculated by:

$$NUM = SCR * TS \quad .$$

In the example, there are 10 independent observations (scans) during each time step.

FSC(LP) is the number of feature cells in one scan for Processor LP. In the Lofar case, one scan covers 600 Hz and the cell size is 1 Hz, therefore, FCS = 600. For the Demon case, it is assumed that the resolution is 1 Hz of modulated frequency, and a 60-Hz scan implies 60 feature cells:

LP	FSC(LP)
1	600 cells
2	60 cells
3	60 cells

By using the scan rate and number of features per scan, the averaging time per scan for a given feature is:

$$TAV = 60/(SCR * FCS) \text{ seconds.}$$

This is the averaging time in the time-bandwidth product used in calculating the standard deviation of the output of the signal processor. In the example, the integration time per scan for a Lofar feature is 0.1 s, and the integration time per scan for Demon feature is 1 s.

TOT(LP) is the total amount of integration time. For example, the Lofar signals are assumed to be traced on a moving paper recorder and about 30 min worth of visual integration is available. The Demon signals are assumed to have 1 min of integration:

LP	TOT(LP)
1	30 min
2	10 min
3	10 min

The model allows for information to be accumulated over several time steps. The number of time steps that are remembered past the current time step is:

$$MEM = (TOT - TS)/TS$$

The memory for Lofar features is two time steps, and the Demon features have zero memory.

The signal processor input parameters are in terms of scan rate, features per scan, and total integration time because these are systems parameters. The MUSAC II methodology, however, uses averaging time per observation, number of independent observations per time step, and number of time steps to be remembered; these are the NUM, TAV, and MEM parameters calculated using the model inputs SCR, FCS, and TOT.

DET(LP) the number of sigmas above the mean reference output where the feature detection threshold is set. The example calculation uses DET = 2 sigmas for all three processors. The processor output of the data channel is the simulated average square pressure. The random output is drawn from a normal distribution and compared to the threshold value; if larger than the threshold, then the feature is detected. The mean and sigma values used to set the threshold value are based on the statistics of the reference channel; these reference statistics are usually different from the statistics of the data channel. The feature detection model is described in the MUSAC II methodology report.[1]

6. Acoustic Fluctuation Parameters

MIX(KR) is a parameter that determines the amount of Gaussian fluctuation versus lambda-sigma jump fluctuations for acoustic phenomenon KR:

KR	Fluctuation in
1	Lofar line level
2	Broadband source spectrum level
3	Demon modulation level
4	Broadband noise spectrum level
5	Propagation loss

These five phenomena are simulated by random variables that are correlated from one time step to another. When MIX = 0 the process is pure Gaussian, and when MIX = 1 the process is pure lambda-sigma jump. The example calculations use MIX = 0.5 which causes a mixture of the two random processes.

SDV(KR) is the standard deviation of fluctuation phenomenon KR. This parameter is the primary method for introducing "modeling noise" into the simulation. The classification performance can be degraded by increasing SDV. A value of SDV = 3 dB is used for four of the five random processes; SDV = 1 dB is used for the modulation levels.

TAU(KR) is the relaxation time of the Gaussian process, and TAU is also the mean time between jumps in the lambda-sigma jump process. The example uses TAU = 3 min for all five random processes.

7. User-Defined Function

FLL(J,KT,ST,DT,ASP) is a function that calculates the Lofar and Demon line levels. As currently programmed, it is a dummy function that sets FLL equal to the input parameter PLL(J,KT). A more sophisticated routine would include an empirically derived equation that functionally relates line level to target speed ST, depth DT, and aspect angle ASP.

FBB(KT,FRQ,ST,DT,ASP) is a function that calculates the broadband source spectrum level for target Type KT at center frequency FRQ. As currently programmed, the function simply interpolates the level/frequency table, PBB(NB,KT)/FQB(NB,KT), to derive the spectrum level at an arbitrary center frequency. A more sophisticated routine would make the spectrum level a function of target speed ST, depth DT, and aspect angle ASP, in addition to frequency and target type.

FNN(LA,FRQ,SO,DO,ANG) is a function that calculates the broadband noise spectrum level at a center frequency, FRQ, at the output of Array LA. The function first interpolates the level/frequency table, PNN(NF,LA)/FQN(NF,LA), to derive the spectrum level outside the array. Then the directivity index is calculated for either circle or line arrays by using the array dimensions DH(LA) and DV(LA), and numbers of hydrophones HN(LA) and VN(LA). (See the source listing of Function FNN in Appendix A for the exact method.) The noise level at the array output is then computed by subtracting the directivity index from the interpolated noise level. A more sophisticated routine would make the output noise level a function of array speed SO, array depth DO, and the point angle of the sonar beam ANG.

FAZ(FRQ,RNG,DO,DT) is a function that calculates the propagation loss at a center frequency, FRQ, and range, RNG. The currently programmed function has a spreading term:

$$66 + 17 \log(RNG)$$

and a frequency attenuation term:

$$0.08 * RNG * (FRQ/1{,}000)^{1.4} \quad .$$

A more sophisticated routine would contain a table look-up that included the effects of array depth, DO, and target depth, DT, in addition to frequency and range. In the description of the MUSAC II methodology, two propagation loss functions are possible: one a simulation of the real propagation loss, the other a simulation of the sonarman's expectation of the propagation loss. The real function would be used to calculate the hypothesized signal level statistics. The computer model was simplified by using FAZ for both the real and expected propagation loss functions.

FBM(J,FRQ,BRG,ANG) is a function that calculates the beam pattern ratio for Array LA(J) at center frequency FRQ when the target is on bearing BRG and the beam is pointed at angle ANG (both angles are measured from the course vector associated with the array). As a way of limiting the computations, the pointing angle, ANG, is restricted to equal the target bearings. Thus if there are two target tracks, Subroutine FBM is used four times each time step: the beam is pointed at Track 1 and the response from Tracks 1 and 2 is calculated; the beam is then pointed at Track 2 and the response from Tracks 1 and 2 is again calculated. The FBM routine contains four algorithms, one for each combination of two types of arrays (circle, line) and two types of signals (narrowband, broadband). The beamwidth of a circle array remains constant over pointing angle, where as the beamwidth of a line array increases when the beam pointing angle approaches the direction angle of the line array (endfire). The narrowband algorithm calculates the nulls in the beam pattern. The broadband algorithm uses a flat response; it simulates the process of averaging over frequency, a process that blends the single-frequency beam pattern structure into a smooth response function over angle. The basic beam pattern in all four cases is a simple $(\sin(x)/x)^2$ response function. Details of the function are found in the source listing of Appendix A.

FSL(LA,FRQ) is a function that calculates the beam pattern ratio for the reference channel of Array LA at center frequency FRQ. The value of the function is usually the sidelobe ratio, SL(LA); however, if the mainlobe of an array is very large, then the reference ratio may be larger than the sidelobe input parameter. The reference beam pattern is used in calculating the statistics of the reference channel. Because target signals are included in the reference calculations, the model properly simulates sidelobe masking of signals in the mainbeam.

B. Output

The results of the MUSAC II model are (1) range and bearing lists, (2) average values of posterior probabilities, and (3) probabilities of preference, classification, and tactical decision. Probabilities are estimated by computing percentage of Monte Carlo replications.

1. Range and Bearing

The first page of the output lists the range, RNG(LA,M,N), and relative bearing, BRG(LA,M,N), from each array, LA, to each target track, M, for each time step, N. As shown in Appendix B, the first column is the range from Array 1 (hull-mounted array) to Track 1; and the second column is the range from Array 2 (towed away) to Track 1. Since the single-target example uses only one track, the next two columns do not contain values; these columns are used if there is a second target track. The rows of the range and bearing list represent time steps; the first row is at time 10 min, the second row is at time 20 min, and so on.

2. Average Posterior Probability

At each time step, the model calculates the posterior probability, POST(I,N), that Hypothesis I is true, given that the data have accumulated through time step N. These probabilities are saved and averaged over the replications; the average posterior probability, EPOST(I,N), is listed in columns that represent the hypotheses, and rows that represent the time steps. In Appendix B, there are three columns for the hypotheses of the single-target example (Type 1, Type 2, and Type 3 target) and 10 rows for the time steps from 10 min to 100 min. Figure 2 is a graph of the average posterior as a function of time.

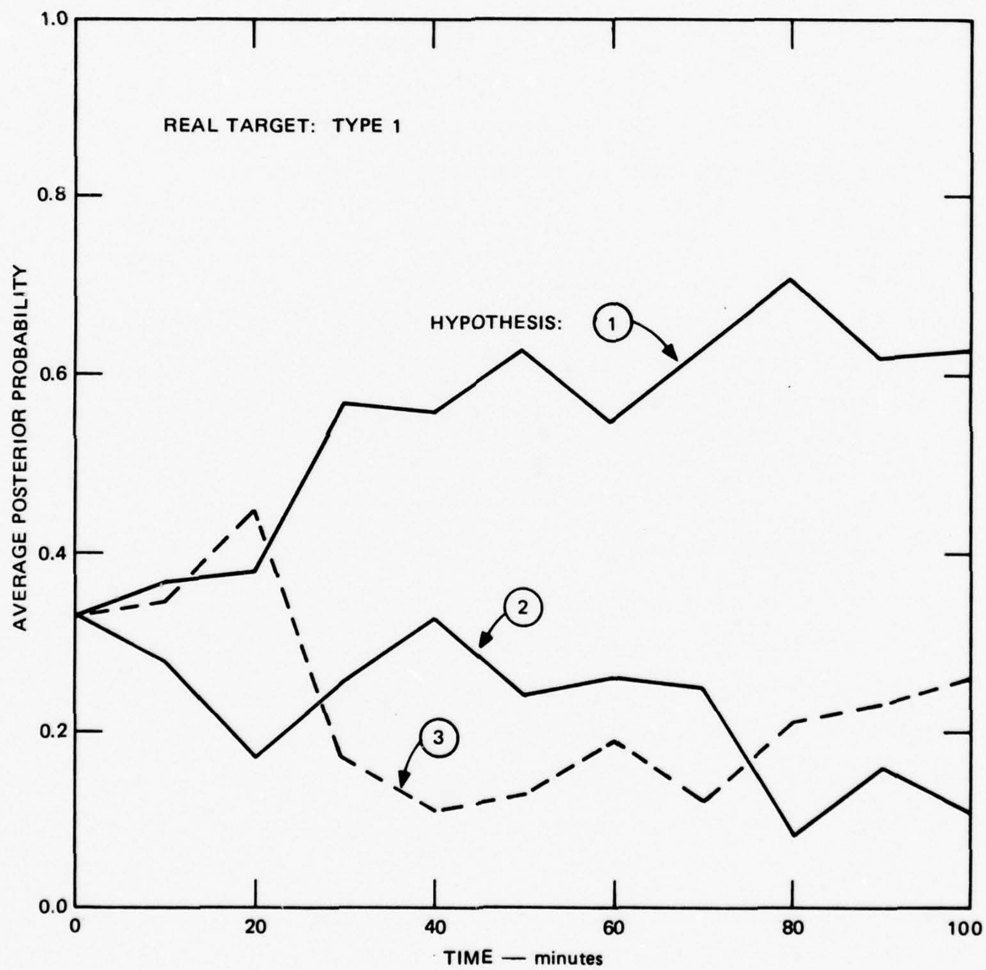

FIGURE 2 AVERAGE POSTERIOR PROBABILITY

The calculation of posterior probability includes effects of (1) the true probabilities of feature detection, (2) the hypothesized probabilities of feature detection, (3) multiple tracks, (4) multiple features on the same and different arrays, (5) memory over time, and (6) a priori probabilities. The MUSAC II methodology description must be consulted to understand how these effects are combined. The computer implementation is similar to the referenced methodology except that (1) sums of logarithms of likelihoods were used instead of products of likelihoods, and (2) the total likelihood was scaled from 1 to 1,000--thus no hypothesis could be more than 1,000 times more likely than another. These computer implementation steps were taken to avoid certain numeric problems in the calculation of posterior probabilities.

The average posterior probability is included as a simulation result because the values can give an indication of feature detection status. Average posteriors that are nearly equal arise because distinguishing features are not detected; dissimilar average posteriors indicate that combinations of distinguishing features were detected. Posterior probabilities are not probabilities of classification, and are only indicative of the classification results.

3. Probability of Preference

The probability of preference, POP(I,N), is the percent of replications for which Hypothesis I was the preferred answer at Time Step N. If a classification decision must be made at Time Step N (not before N, not after N), then the probability of preference would equal the probability of classification. But the model allows for only one classification decision, which can occur at any time step; therefore, a different name was coined for the concept of step-to-step classification probabilities. In determining the probability of preference, the I-th hypothesis is preferred if POST(I,N) is larger than all the other posterior probabilities at time step N.

The example output in Appendix B lists the probabilities of preference in columns that represent hypotheses, and rows that represent time steps (the values are in increments of 0.05 because 20 replications were used). Figure 3 shows the example probabilities of preference as a function of time.

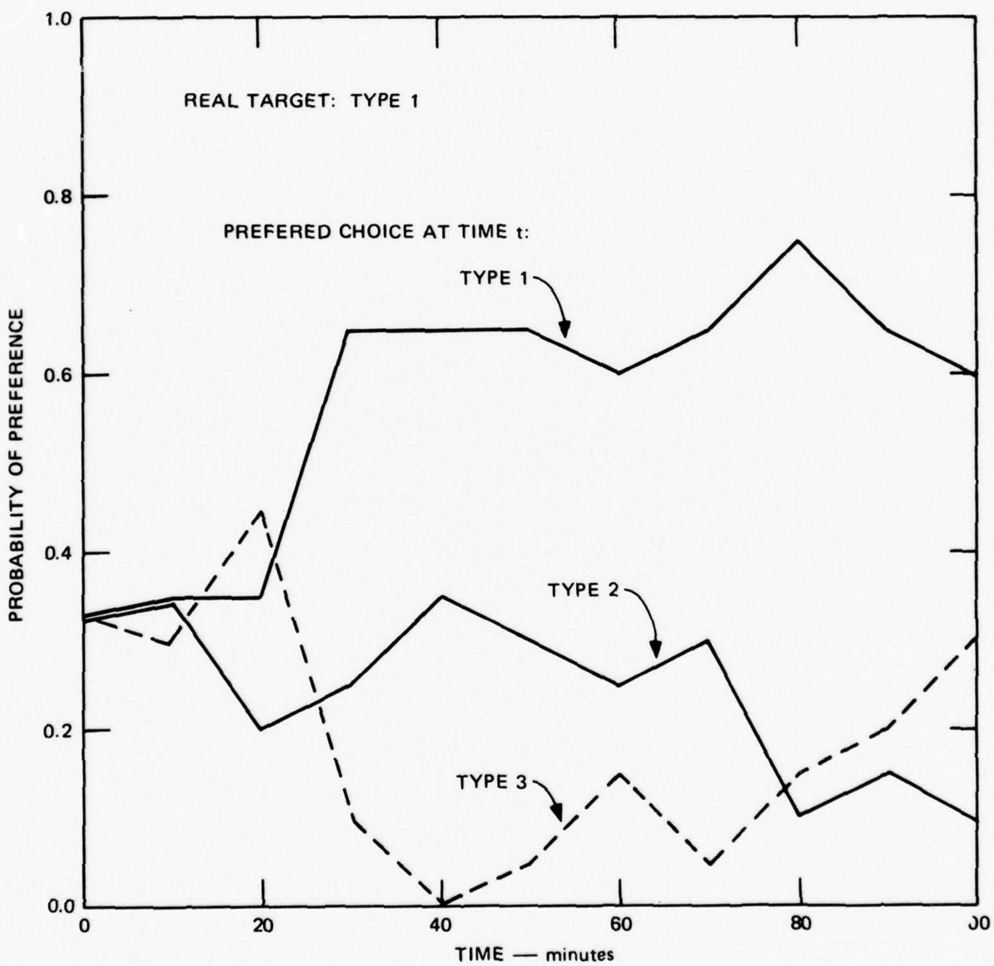

FIGURE 3 PROBABILITY OF PREFERENCE

4. Probability of Classification

The probability of classification, PLC(I), is the percent of replications for which the I-th hypothesis was was chosen. Since the probability of classification does not contain any information about when the decision was made, the time distribution for each decision, DISTR(I,N), is also calculated. Under the condition that the decision was ultimately Hypothesis I, DISTR(I,N) is the probability that the decision was made at or before Time Step N. The probabilities of classification and the time distribution are on page 3 of the output. In the single target example, 55 percent were correctly classified, 15 percent were classified as Type 2 target, and 30 percent were classified as Type 3 target. Figure 4 shows how the 55 percent correct classification decisions were distributed in time.

The first three pages of the output in Appendix B show the results of Run 1, and the next six pages are the results of two additional runs of the simulation. The three runs differ in the value of the parameter IR which is the true hypothesis index:

Run	Real Target
1	Type 1
2	Type 2
3	Type 3

When the results of the three runs are combined, a matrix of the classification probabilities (in units of percent) can be constructed:

Real Target	Classified as 1	2	3
1	55	15	30
2	10	65	25
3	5	10	85

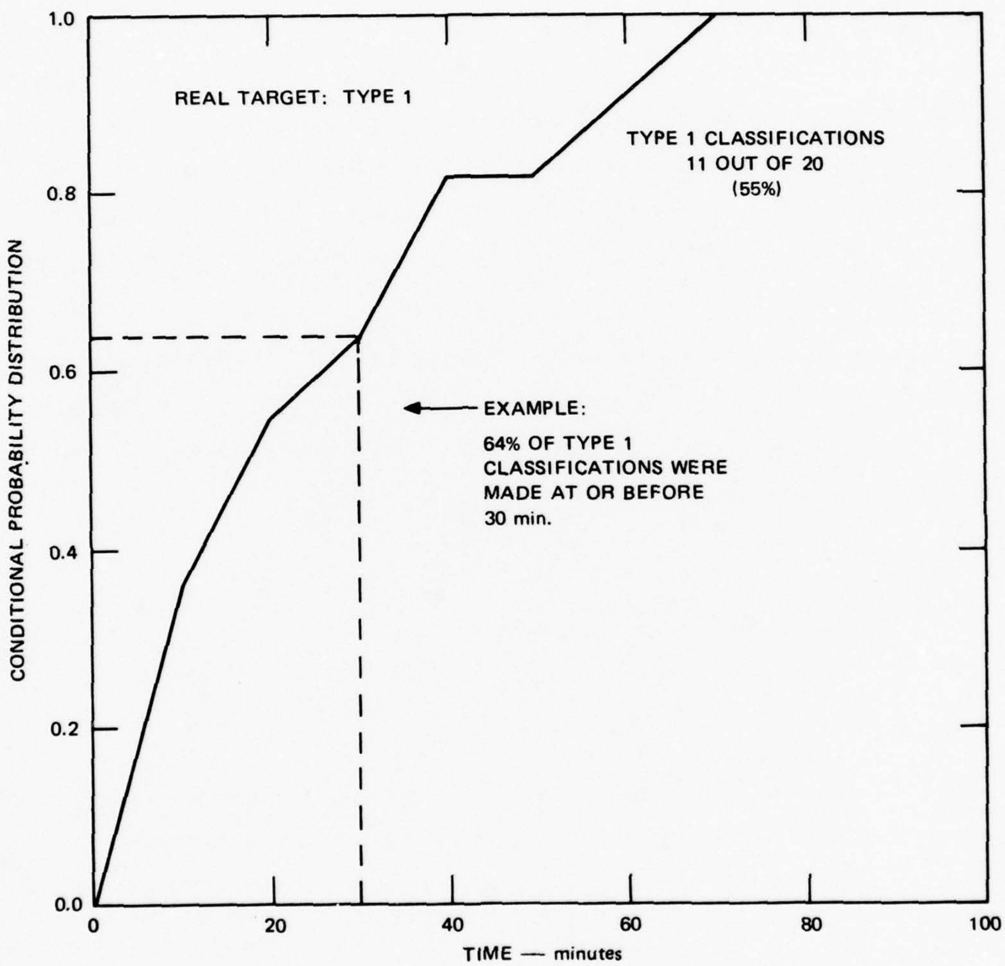

FIGURE 4 DISTRIBUTION OF A CLASSIFICATION DECISION

For example, when the real target was Type 3, 5 percent of the replications (1 out of 20) were classified as Type 1. In the remainder of this report, the above matrix is called the "classification matrix," and only the essential information is displayed:

55	15	30
10	65	25
5	10	85 .

5. <u>Probability of Tactical Decision</u>

The probability of tactical decision, PKD(KD), is the percent of replications for which the KD-th tactical alternative was chosen. Tactical alternatives are related to hypotheses through the value matrix, VAL(I,KD). For the output shown in Appendix B, the value matrix was a 3-by-3 identity matrix, and thus the tactical alternatives were the same as the hypotheses. This is the reason that the probability of tactical decision output is identical to the probability of classification output.

To see the effect of a different value structure, the value matrix was changed to:

Hypothesis	Tactical Alternative 1	Tactical Alternative 2
1	300	-500
2	-100	100
3	-500	100 .

By making three runs of the simulation, a "tactical alternative matrix" was computed; it shows the percent of replications for which Alternative 1 or 2 was chosen for each of three real-target conditions:

Real Target	Tactical Alternative 1	Tactical Alternative 2
1	55	45
2	0	100
3	0	100 .

The tactical decision is based on maximizing engagement value, determined from the value matrix and the posterior probabilities. A classification decision on the best hypothesis is also made by choosing the highest posterior probability at the time of the tactical decision. Therefore, a classification matrix was produced using the new value structure, and this matrix is compared to the classification matrix of the original simulation:

New Value Structure			Base Case		
50	15	35	55	15	30
0	70	30	10	65	25
0	0	100	5	10	85 .

Changing the value matrix from an identity matrix to a matrix representing tactical tradeoffs changes the classification probabilities, sometimes for the better and sometimes for the worse.

The timing of the tactical decision is also a simulation output. Figure 5 shows the time distribution of tactical decisions for the case where the real target was Type 1. Both decision alternatives are shown on the figure; Alternative 1 is defined as an "attack" decision and Alternative 2 is a "no-attack" decision. For a Type 1 target, the attack decisions were more likely than the no attack decisions (55 percent versus 45 percent) and they occurred at shorter ranges (longer times) than the no-attack decisions.

6. Engagement Measure-of-Effectiveness

The final output statistic is a single number called the engagement measure-of-effectiveness (MOE). It is the average value of the final tactical decision based on the true hypothesis; it is averaged over all the replications:

$$MOE = [\Sigma \ VAL(IR,KDF)]/NREP \ ,$$

where IR is the true hypothesis, KDF is the final tactical decision, and NREP is the number of replications. When the value matrix is the identity matrix, the MOE is just the probability of correct classification.

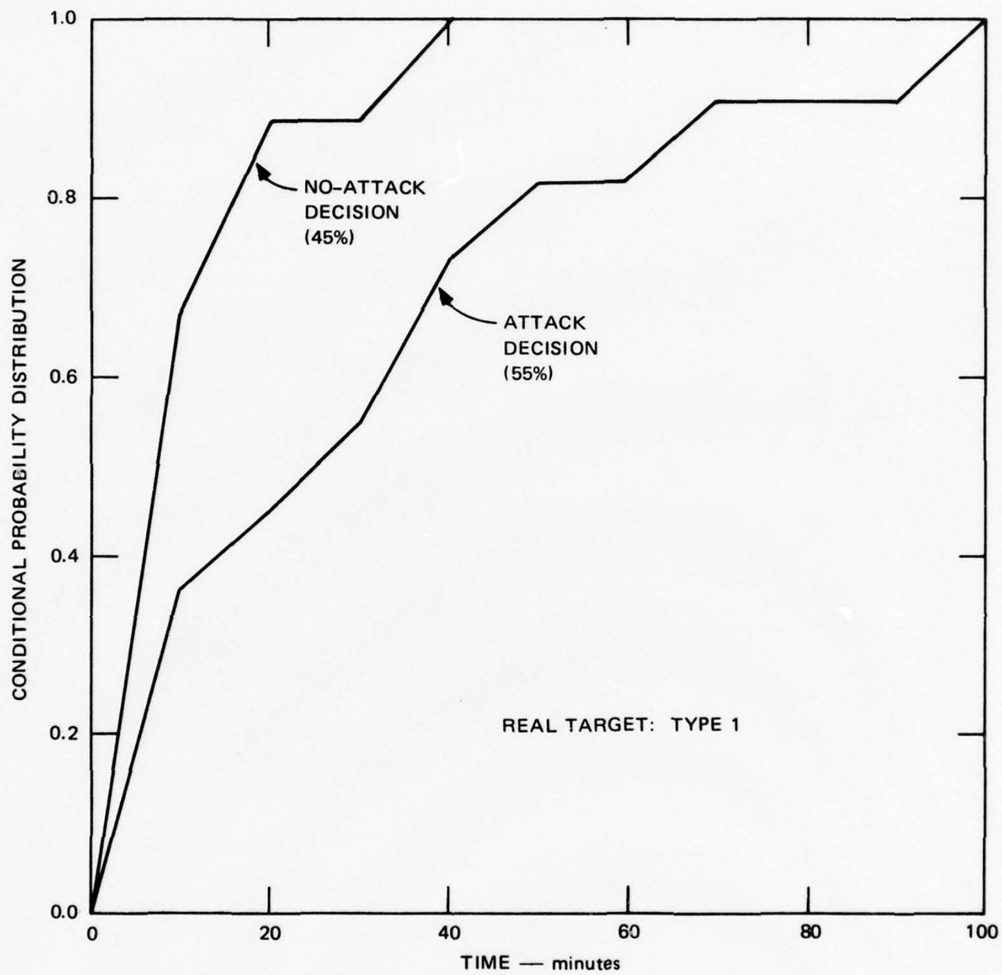

FIGURE 5 DISTRIBUTION OF TACTICAL DECISIONS

With the altered value structure of the previous section, the engagement MOEs for the three runs were:

Real Target	MOE
1	-60
2	100
3	100

Even though the correct classification probabilities for Type 2 and Type 3 targets were different (70 percent versus 100 percent) the MOEs were the same, and thus engagements with either of these targets types is equally "valuable".

C. Variations on the Base Case

The following sections describe the sensitivity of single-target simulation results when selected parameters are varied from their base-case values.

1. Lofar and Demon

The model was run with only Lofar features and then run again with only Demon features. These two cases were then compared to the base case classification matrix in which both Lofar and Demon were used:

Lofar Only			Demon Only			Both Lofar and Demon		
70	10	20	65	20	15	55	15	30
15	85	0	25	55	20	10	65	25
10	25	65	15	15	70	5	10	85

When the real target was Type 1 or 2, the use of both Lofar and Demon features degraded the correct classification probabilities relative to the Lofar-only or Demon-only cases. However, when the target was Type 3, the use of both sets of features increased the probability of correct classification. Adding more features to aid in classifying a target does not necessarily improve the classification performance; in fact, adding more features may degrade the performance.

2. Decision Threshold

When the decision threshold, FVAL, was varied, the classification matrices changed and the time distribution of classification decisions also changed. For example, the classification matrices were computed for three values of the threshold:

FVAL = 0.8			FVAL = 0.95			FVAL = 0.99		
35	25	40	55	15	30	50	15	35
10	60	30	10	65	25	0	80	20
5	20	75	5	10	80	10	10	80

In general, by reducing the threshold, there are fewer correct classification decisions but they are made sooner. The time distribution of the correct classification decisions for the three FVAL runs is shown in Figure 6.

3. Standard Deviation

The random process standard deviation vector, SDV(KR), was varied from the base case value by subtracting and adding 1 dB:

Variation 1: SDV = 2, 2, 0, 2, 2
Base case: SDV = 3, 3, 1, 3, 3
Variation 2: SDV = 4, 4, 2, 4, 4

The SDV components are Lofar, BBand, Demon, PLoss, and Noise, respectively. The resulting classification matrices were:

Variation 1			Base Case			Variation 2		
60	15	25	55	15	30	50	20	30
5	70	25	10	65	25	15	65	20
10	5	85	5	10	85	15	20	65

When SDV became larger, more classification mistakes were made. Within limits, the SDV parameter may be used to adjust the model results to correspond with experimental data points. Then the model can predict classification results for cases not covered in the experiment.

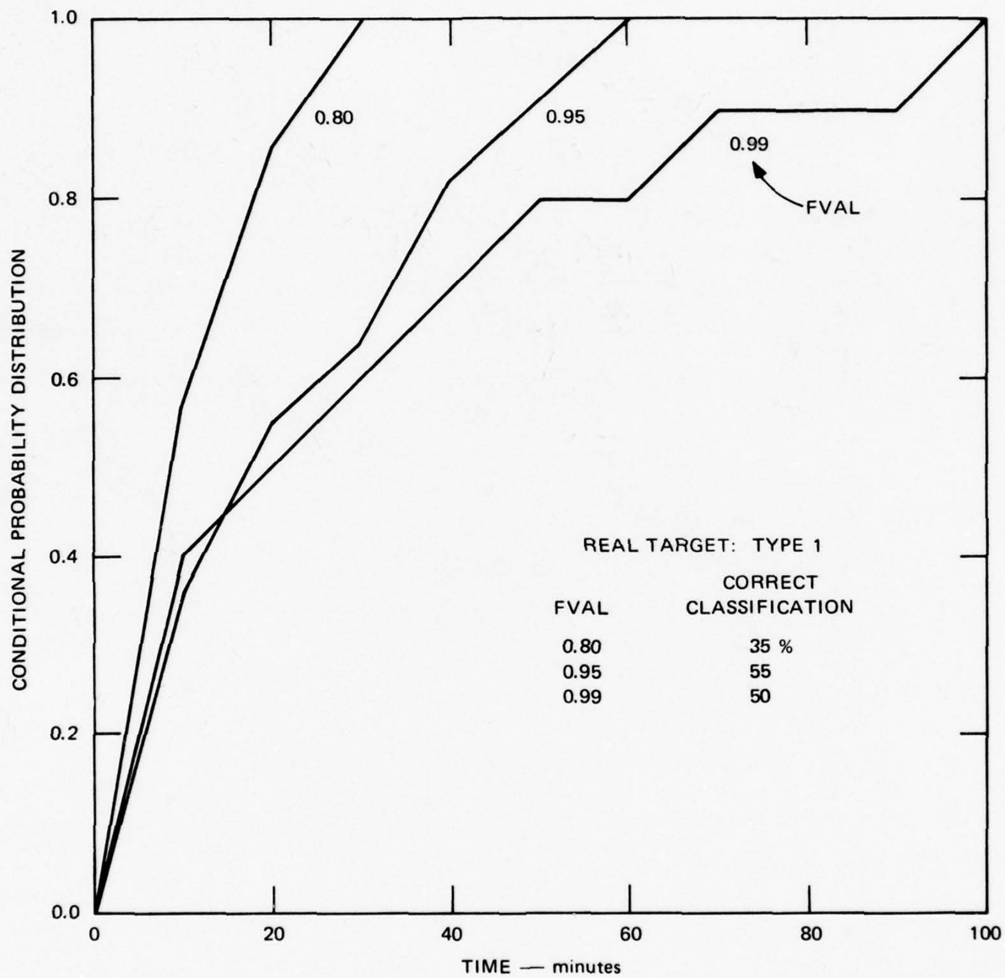

FIGURE 6 DISTRIBUTION OF CLASSIFICATION DECISIONS FOR DIFFERENT DECISION THRESHOLDS

III DOUBLE-TARGET EXAMPLE

This chapter describes how MUSAC II can simulate a scenario in which there are two targets. Many of the input parameters used in the single-target example are used again in the double-target example; only the changes to the single-target example are discussed. Appendix C contains: (1) a listing of the double-target base-case input parameters and (2) a listing of the base-case output.

The double-target scenario involves the passive acoustic classification of two surface ships by a submarine using Demon information from a hull-mounted array and Lofar information from a towed array. The scenario geometry is shown in Figure 7. Initial range separation between the submarine and the two target ships is about 40 nmi. The surface ships are 5 nmi apart and travel on a near-collision course with the submarine. During the 1.5-hour engagement the submarine must classify the targets as one of nine possible target configurations. Figure 8 shows the relative bearing to the two target tracks as a function of time. The initial target separation is about 6 degrees and the final separation about 36 degrees.

A. Base Case

The double-target base case example is used to demonstrate the multitarget capability of MUSAC II and to provide results for comparison with cases in which selected input parameters are varied.

1. Input

Only five input parameters need to be changed to turn the single-target example into a double-target example.

IMAX is increased from three hypotheses to nine hypotheses, which are detailed below.

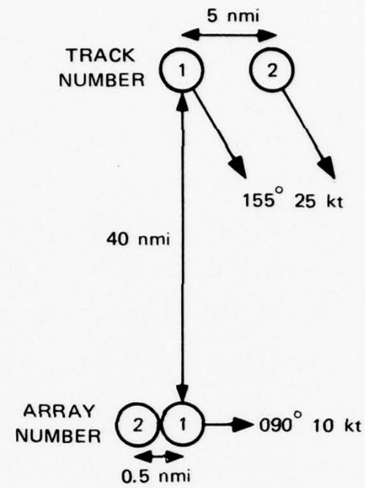

FIGURE 7 DOUBLE-TARGET SCENARIO GEOMETRY

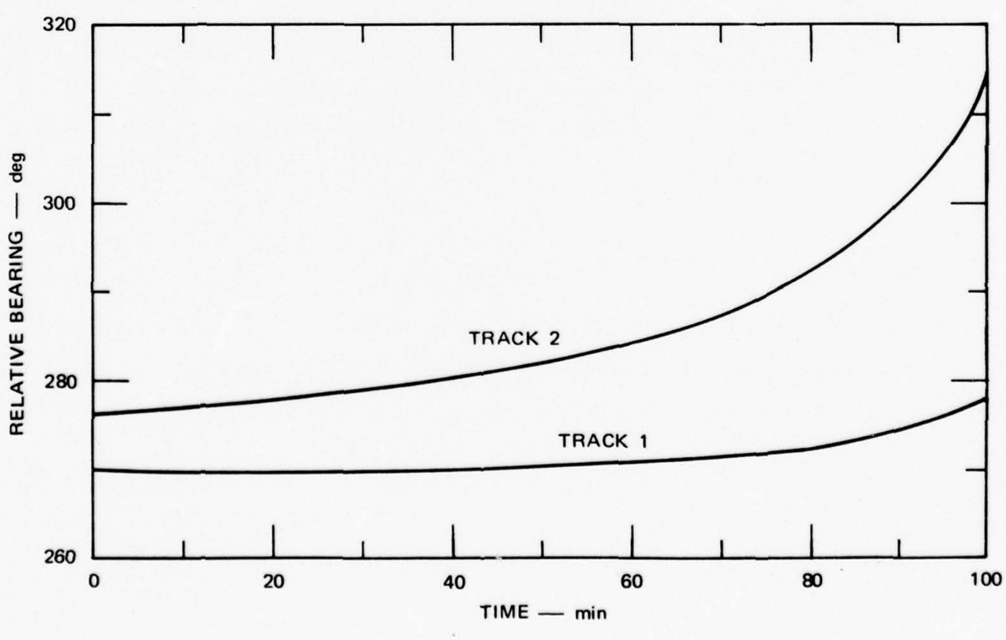

FIGURE 8 BEARING SEPARATION OF TARGETS

NMAX is increased from 1 track to 2 tracks; in this way, two targets can be simulated.

KT(I,M) is increased from a 3-by-1 array to a 9-by-2 array. The nine hypotheses are defined by the KT array as follows:

Hypothesis	Target Type on Track 1	Target Type on Track 2
1	1	1
2	1	2
3	1	3
4	2	1
5	2	2
6	2	3
7	3	1
8	3	2
9	3	3

For example, Hypothesis 8 states that: "Target Type 3 is on Track 1 and Target Type 2 is on Track 2." For small numbers of target types and tracks, the above combinational method of constructing hypotheses can be used. However, when the scenario is complex, the analyst must reduce the number of hypotheses by excluding the ones with very low a priori probability.

IR is the hypothesis number that represents the real target configuration. Hypothesis 3 was chosen as reality for the base case (IR = 3). Therefore, a target of Type 1 is on Track 1 and a target of Type 3 is on Track 2.

KDMAX is changed from a total of 3 to 9 tactical alternatives so that the tactical alternatives remain the same as the nine classification alternatives. As a variation on the base case, an engagement value structure that is not an identity matrix is used.

2. Output

Appendix C shows the results of the double-target base case. The range and relative bearing versus time are listed for four columns of array/track combinations.

Column	Array	Track
1	1	1
2	2	1
3	1	2
4	2	2

The relative target bearing from Array 1 to Tracks 1 and 2 (Columns 1 and 3) were previously shown in Figure 8.

The average posterior probability and the probability of a preference are listed in 9 columns and 10 rows, which relate to the 9 hypotheses and 10 time steps. Figure 9 shows the probability of preference for Hypothesis 3 (the correct hypothesis) plotted as a function of time on the lowest curve. Two other curves are shown for comparison. The middle curve is the sum of the preference probabilities for Hypotheses 1, 2, and 3; it is the probability that target Type 1 is on Track 1 and that any target type was on Track 2. The top curve is the sum of the preference probabilities for Hypotheses 1, 2, 3, 4, and 7; it is the probability that target Type 1 was present. Figure 9 demonstrates that probabilities may be added together to construct higher-order hypotheses using the elemental hypotheses of the model.

The probability of classification (in percent) for the double-target base case was computed as:

Real	Classified Configuration								
Configuration	1,1	1,2	1,3	2,1	2,2	2,3	3,1	3,2	3,3
1,3	35	5	20	5	0	5	10	0	20

Correct classification occurred for only 20 percent of the replications, and classifying the correct target type on Track 1 (1,1 1,2 1,3) occurred

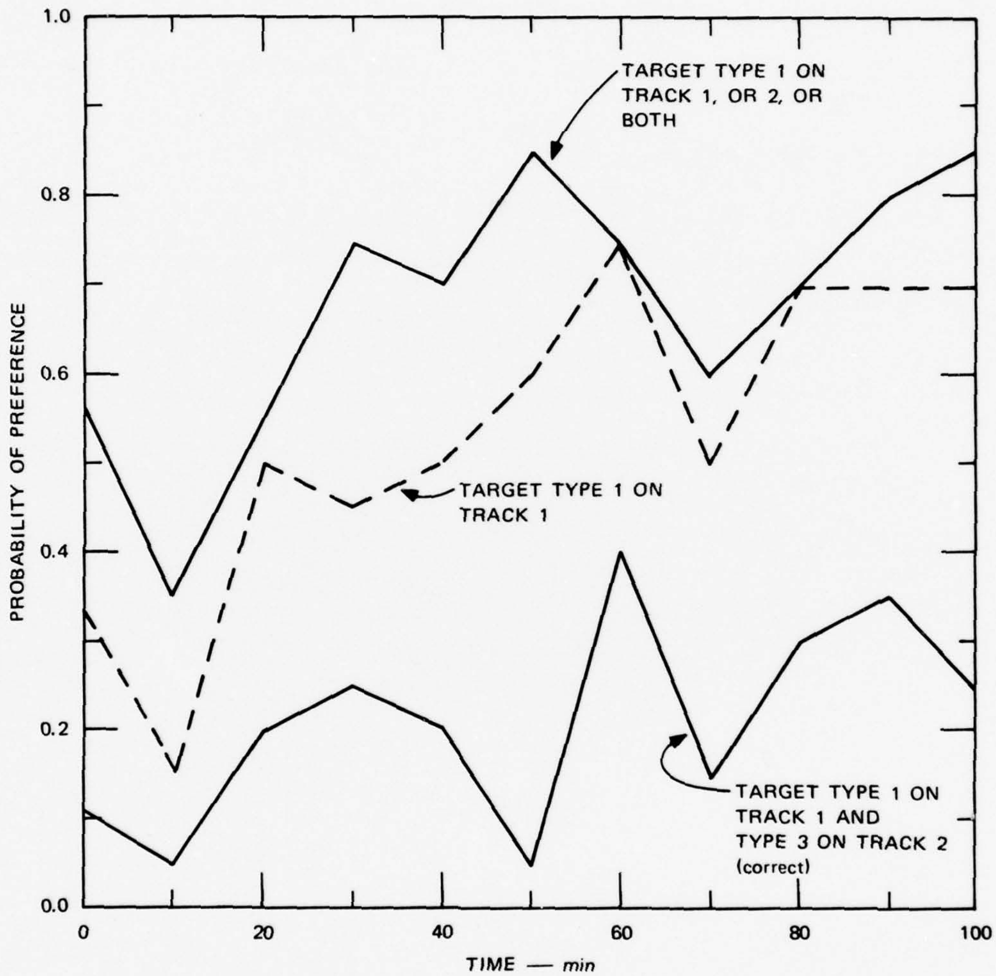

FIGURE 9 PROBABILITY OF PREFERENCE FOR COMBINED HYPOTHESES

for 60 percent of the replications. A classification matrix could have been computed by performing nine runs and changing the true configuration each run. The above result is one row of the classification matrix.

Only two double-target classification decisions were made before the last time step, whereas all 20 single-target decisions were made before the last time step. Classifying multiple target configurations is harder than single targets when the same decision threshold is used.

B. Variations on the Base Case

The tactical value structure was varied and compared to the base case; then the decision threshold was varied to demonstrate the use of the engagement MOE output.

1. Tactical Value

The tactical value matrix, VAL (I,KD), was altered to see the effect of a new value structure; the new value matrix was:

Hypothesis	Tactical Alternative 1 = Attack	 2 = No
1	600	-1,000
2	200	-400
3	-200	-400
4	200	-400
5	-200	200
6	-600	200
7	-200	-400
8	-600	200
9	-1,000	200

The values were obtained from the previous example by adding single-target values to produce double-target values. For example, Hypothesis 3 involved target Types 1 and 3. Attacking a Type 1 target was worth 300 points and not attacking was worth -500 points; whereas not attacking a Type 3 target was worth -500 points and not attacking was worth 100 points. Therefore the attack alternative for the third hypothesis was worth (300) + (-500) = (-200) and the no-attack alternative was worth

(-500) + (100) = (-400). Of course, other methods can be devised to produce a value matrix that reflects the value of a tactical action taken against a multitarget group.

The computed probabilities of classification (in percent) for the two cases were:

Classified Configuration	Base Case	New Value Structure
1,1	35	40
1,2	5	5
1,3 (true)	20	35
2,1	5	0
2,2	0	0
2,3	5	0
3,1	10	10
3,2	0	0
3,3	20	10

The result of using the new value structure was an increase in correct classifications.

The probability of tactical decisions was 65 percent for the attack alternative and 35 percent for the no-attack alternative. The median time for an attack decision was about 40 min and the median time for a no-attack decision was about 15 min. The time distribution of decision-making under the new value structure was sharply different from the distribution for the base case, where almost all decisions were delayed until the end of the engagement.

2. Decision Threshold

Figure 10 shows how the engagement MOE changed as a function of the decision threshold when the tactical value matrix of the last section was used. The maximum engagement value is attained when the decision is to attack, and the minimum when the decision is not to attack. This graph of engagement MOE versus a system parameter demonstrates how system analyses may be performed with the MUSAC II simulation model.

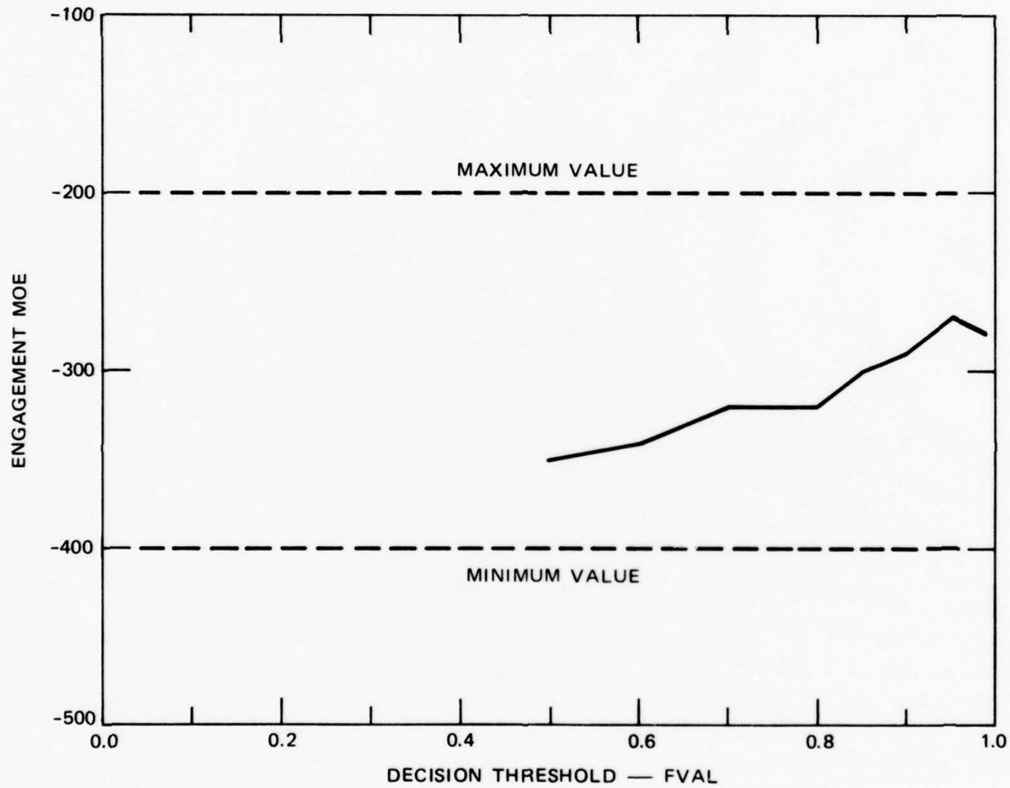

FIGURE 10 MOE SENSITIVITY TO DECISION THRESHOLDS

Appendix A

MUSAC II SOURCE CODE

```
      PROGRAM MUSAC2(OUTPUT,TAPE6=OUTPUT)
C
C
C
C   INPUT
C   ** GV             RANDOM NUMBER GENERATIVE VALUE
C   ** NREP           NUMBER OF REPLICATIONS
C   ** NMAX           NUMBER OF TIME STEPS
C   ** TS             TIME STEP DURATION (MIN)
C   ** IMAX           NUMBER OF HYPOTHESES
C   ** MMAX           NUMBER OF TRACKS
C   ** KT(I,M)        HYPOTHESIZED TARGET TYPE
C   ** IR             TRUE HYPOTHESIS NUMBER
C   ** PRIOR(I)       PRIOR PROBABILITY OF HYPOTHESIS
C   ** KDMAX          NUMBER OF TACTICAL DECISION ALTERNATIVES
C   ** VAL(I,KD)      VALUE OF DECISION
C   ** FVAL           DECISION THRESHOLD OF RATIO (MAX.EXP.VALUE)/(EXP.MAX.VALUE)
C   ** XT(M)          TARGET INITIAL POSITION (NMI)
C   ** YT(M)          TARGET INITIAL POSITION (NMI)
C   ** CT(N,M)        TARGET COURSE (DEG)
C   ** ST(N,M)        TARGET SPEED (KT)
C   ** DT(N,M)        TARGET DEPTH (FT)
C   ** JMAX           NUMBER OF FEATURES
C   ** NF(J)          FEATURE OFF/ON (0=OFF 1=ON)
C   ** KF(J)          FEATURE TYPE (1=LOFAR 2=BBAND 3=DEMON)
C   ** FRQ(J)         CENTER FREQUENCY (HZ)
C   ** PLL(J,KT)      LOFAR LINE LEVEL (DB UPA2 1YD) ALSO
C   ** PLL(J,KT)      DEMON MODULATION LEVEL (DB)
C   ** PBB(NB,KT)     BROADBAND SOURCE SPECTRUM OF TARGET (DB UPA2/HZ 1YD)
C   ** FQB(NB,KT)     FREQUENCY POINTS FOR PBB (HZ)
C   ** LAMAX          NUMBER OF ARRAYS
C   ** LA(J)          ARRAY NUMBER
C   ** KA(LA)         ARRAY TYPE (1=CIRCLE 2=LINE)
C   ** DH(LA)         HORIZONTAL ARRAY SIZE (FT)
C   ** DV(LA)         VERTICAL ARRAY SIZE (FT)
C   ** HN(LA)         HORIZONTAL NUMBER OF HYDROPHONES
C   ** VN(LA)         VERTICAL NUMBER OF HYDROPHONES
C   ** SL(LA)         SIDELOBE RATIO
C   ** XO(LA)         ARRAY INITIAL POSITION (NMI)
C   ** YO(LA)         ARRAY INITIAL POSITION (NMI)
C   ** CO(N,LA)       ARRAY COURSE (DEG)
C   ** SO(N,LA)       ARRAY SPEED (KT)
C   ** DO(N,LA)       ARRAY DEPTH (FT)
C   ** NA(N,LA)       ARRAY OFF/ON  (0=OFF  1=ON)
C   ** PNN(NF,LA)     BROADBAND NOISE OUTSIDE ARRAY (DB UPA2/HZ)
C   ** FQN(NF,LA)     FREQUENCY POINTS FOR PNN (HZ)
C   ** LP(J)          PROCESSOR NUMBER
C   ** WTH(LP)        BANDWIDTH (HZ)
C   ** SCR(LP)        SCAN RATE (NUMBER/MIN)
C   ** FCS(LP)        NUMBER OF FEATURE CELLS PER SCAN
C   ** TOT(LP)        TOTAL TIME OF FEATURE INTEGRATION (MIN)
C   ** DET(LP)        DETECTION THRESHOLD (NUMBER OF SIGMAS)
C   ** MIX(KR)        MIXING CONSTANT (0.=GAUSS 1.=JUMP)     KR 1=LOFAR 4=NOISE
C   ** SDV(KR)        STD DEV OF RANDOM PROCESS (DB)            2=BBAND 5=PLOSS
C   ** TAU(KR)        RELAXATION TIME OF RANDOM PROCESS (MIN)   3=DEMON
```

```
C  ** FLL(J,KT,ST,DT,ASP)       LOFAR AND DEMON SOURCE LEVEL
C  ** FBB(KT,FRQ,ST,DT,ASP)     BROADBAND SOURCE SPECTRUM LEVEL
C  ** FNN(LA,FRQ,SO,DO,ANG)     NOISE SPECTRUM LEVEL AT ARRAY OUTPUT
C  ** FAZ(FRQ,RNG,DO,DT)        REAL PROPAGATION LOSS (DB)
C  ** FBM(J,FRQ,BRG,ANG)        BEAMPATTERN RATIO
C  ** FSL(LA,FRQ)               REFERENCE BEAMPATTERN RATIO
C
C
C
C
C
C  INTERNAL
C  ** I               HYPOTHESIS NUMBER
C  ** J               FEATURE NUMBER
C  ** K               LOOK ANGLE NUMBER
C  ** M               TRACK NUMBER
C  ** N               TIME STEP NUMBER
C  ** NN              REPLICATION NUMBER
C  ** KR              KIND OF RAMDOM PROCESS  1=LINE 2=BROADBAND
C  **                           3=MODULATION 4=NOISE 5=PROP LOSS
C  ** KD              TACTICAL DECISION NUMBER
C  ** TAV(LP)         AVERAGING TIME PER FEATURE CELL (SEC)
C  ** NUM(LP)         NUMBER OF SCANS PER TIME STEP
C  ** MEM(LP)         NUMBER OF TIME STEPS IN LIKELIHOOD CALCULATION
C  ** RNG(LA,M,N)     RANGE (NMI)
C  ** BRG(LA,M,N)     RELATIVE BEARING (DEG)
C  ** ASP(LA,M,N)     TARGET ASPECT (DEG)
C  ** ANG(LA,K,N)     SONAR LOOK ANGLE (DEG)
C  ** TLL(J,M,N)      LINE LEVEL TABLE (DB)
C  ** TBB(J,M,N)      BROADBAND SPECTRUM TABLE (DB)
C  ** TNN(J,K,N)      NOISE TABLE (DB)
C  ** TAZ(J,M,N)      REAL PROP LOSS TABLE (DB)
C  ** TBM(JKMN)       BEAM PATTERN TABLE (RATIO)
C  ** TSL(J)          SIDE LOBE TABLE (RATIO)
C  ** XS(IJKN)        HYPOTHETICAL LOFAR SIGNAL
C  ** XV(IJKN)        HYPOTHETICAL LOFAR SIGNAL SQUARED
C  ** XSP(IJKN)       HYPOTHETICAL BROADBAND SIGNAL
C  ** XDSP(IJKN)      HYPOTHETICAL DEMON SIGNAL
C  ** JUMP(KR,J,M)    LAST VALUE OF JUMP PROCESS RANDOM VARIABLE
C  ** GAUSS(KR,J,M)   LAST VALUE OF GAUSSIAN PROCESS RANDOM VARIABLE
C  ** BIAS(KR)        BIAS ADDED TO COMPENSATE FOR RANDOM PROCESS (DB)
C  ** PDETZ(J,K)      PROBABILITY OF DETECTION OF TRUE DATA
C  ** PDET(I,J,K)     PROBABILITY OF DETECTION OF HYPOTHETICAL DATA
C  ** LIKE(I,N)       LIKELIHOOD OF DATA
C  ** POST(I,N)       POSTERIOR PROBABILITY OF HYPOTHESIS
C  ** IB(N)           MAXIMUM POSTERIOR HYPOTHESIS
C  ** VMAX(I)         MAXIMUM OF VAL(I,KD) OVER KD
C  ** KDF             FINAL TACTICAL DECISION
C  ** NSTOP           TIME STEP OF FINAL DECISION
C  INTERNAL FUNCTIONS
C  ** FLBC(N,K)                 LOG OF BINOMIAL COEFFICIENT
C  ** PROB(MU,SIG,THRESH)       PROB NORMAL RAN.VAR.  GE  THRESHOLD
C  ** RNORM(O.)                 RANDOM NORMAL DEVIATE (MU=0 SIG=1)
C  ** RANDOM(MIX,SDV,TAU,TS,    CALCULATES ZERO-MEAN RANDOM
C  **       JUMP,GAUSS,DELTA)          DEVIATE FROM MIXED PROCESS
```

```
C
C
C   OUTPUT
C   ** RNG(LA,M,N)    RANGE (NMI)
C   ** BRG(LA,M,N)    RELATIVE BEARING (DEG)
C   ** EPOST(I,N)     AVERAGE POSTERIOR PROBABILITY
C   ** POP(I,N)       PROBABILITY OF PREFERENCE
C   ** PCL(I)         PROBABILITY OF CLASSIFICATION
C   ** DISTR(I,N)     DISTRIBUTION OF CLASSIFICATION DECISION
C   ** PKD(KD)        PROBABILITY OF TACTICAL DECISION
C   ** HISTO(KD,N)    DISTRIBUTION OF TACTICAL DECISION
C   ** VMOE           ENGAGMENT MEASURE OF EFFECTIVENESS
C
C
C
C
      COMMON /A/ GV,NREP,NMAX
      COMMON /B/ IMAX,MMAX,JMAX
      COMMON /C/ LAMAX,KDMAX,IR
      COMMON /D/ LP(12),LA(12),NA(20,2),KA(2)
      COMMON /E/ KF(12),NF(12),KT(10,2),TS
      COMMON /F/ XO(2),YO(2),CO(20,2),SO(20,2),DO(20,2)
      COMMON /G/ XT(2),YT(2),CT(20,2),ST(20,2),DT(20,2)
      COMMON /H/ WTH(5),TAV(5),NUM(5),DET(5),MEM(5)
      COMMON /I/ DH(2),DV(2),HN(2),VN(2),SL(2)
      COMMON /J/ FRQ(12),PLL(12,3)
      COMMON /K/ PBB(6,3),FQB(6,3)
      COMMON /L/ PNN(6,2),FQN(6,2)
      COMMON /M/ MIX(5),SDV(5),TAU(5),BIAS(5)
      COMMON /N/ PRIOR(10),VAL(10,10),FVAL,VMAX(10)
      COMMON /O/ RNG(2,2,20),BRG(2,2,20),ASP(2,2,20)
      COMMON /P/ TLL(12,2,20),TBB(12,2,20),TNN(12,2,20)
      COMMON /Q/ TAZ(12,2,20),TBM(960),TSL(12)
      COMMON /R/ JUMP(5,12,2),GAUSS(5,12,2)
      COMMON /S/ PDETZ(12,2),PDET(10,12,2)
      COMMON /T/ POST(10,20),IB(20)
      COMMON /U/ NSTOP,KDF
      COMMON /V/ XS(4800),XV(4800),XSP(4800),XDSP(4800)
C
      DIMENSION EPOST(10,20),DISTR(10,20),TOTAL(10),PCL(10),
     +          HISTO(10,20),SUM(10),PKD(10),POP(10,20)
      REAL MIX
C
      CALL INPUT
      DO 90 IR=1,3
      CALL TABLE
      CALL SAVE
      DO 12 I=1,IMAX
      TOTAL(I)=0.
      DO 12 N=1,NMAX
      EPOST(I,N)=0.
      POP(I,N)=0.
   12 DISTR(I,N)=0.
      DO 14 KD=1,KDMAX
      SUM(KD)=0.
```

```
      DO 14 N=1,NMAX
   14 HISTO(KD,N)=0.
      VMOE=0.
C
C  ** REPLICATION NN-LOOP
      CALL RANSET(GV)
      DO 50  NN=1,NREP
C  ** INITIALIZE RANDOM PROCESSES
      DO 10 KR=1,5
      DO 10 J=1,JMAX
      DO 10 M=1,MMAX
      JUMP(KR,J,M)=RNORM(0.)*SDV(KR)
   10 GAUSS(KR,J,M)=RNORM(0.)*SDV(KR)
C
C  ** TIME STEP N-LOOP
      DO 30 N=1,NMAX
      CALL DETECT(N)
      CALL BAYES(N)
      DO 25 I=1,IMAX
   25 EPOST(I,N)=EPOST(I,N)+POST(I,N)
      IBN=IB(N)
      POP(IBN,N)=POP(IBN,N)+1.
   30 CONTINUE
C
      CALL DECIDE
      II=IB(NSTOP)
      TOTAL(II)=TOTAL(II)+1.
      DO 40 N=NSTOP,NMAX
   40 DISTR(II,N)=DISTR(II,N)+1.
      SUM(KDF)=SUM(KDF)+1.
      DO 45 N=NSTOP,NMAX
   45 HISTO(KDF,N)=HISTO(KDF,N)+1.
      VMOE=VMOE+VAL(IR,KDF)
   50 CONTINUE
C
      DO 60 I=1,IMAX
      PCL(I)=TOTAL(I)/NREP
      DO 60 N=1,NMAX
      EPOST(I,N)=EPOST(I,N)/NREP
      POP(I,N)=POP(I,N)/NREP
      IF(TOTAL(I).EQ.0.) GO TO 60
      DISTR(I,N)=DISTR(I,N)/TOTAL(I)
   60 CONTINUE
      DO 70 KD=1,KDMAX
      PKD(KD)=SUM(KD)/NREP
      IF(SUM(KD) .EQ.0.) GO TO 70
      DO 65 N=1,NMAX
   65 HISTO(KD,N)=HISTO(KD,N)/SUM(KD)
   70 CONTINUE
      VMOE=VMOE/NREP
      WRITE(6,100)
      WRITE(6,150) RNG
      WRITE(6,120)
      WRITE(6,150) BRG
      WRITE(6,200)
```

```
      WRITE(6,250) EPOST
      WRITE(6,270)
      WRITE(6,250) POP
      WRITE(6,300)
      WRITE(6,250) PCL
      WRITE(6,400)
      WRITE(6,250) DISTR
      WRITE(6,500)
      WRITE(6,250) PKD
      WRITE(6,600)
      WRITE(6,250) HISTO
      WRITE(6,700) VMOE
   90 CONTINUE
C
  100 FORMAT(1H1,*RANGE*)
  120 FORMAT(//* BEARING*)
  200 FORMAT(1H1,*AVERAGE POSTERIOR PROBABILITY*)
  270 FORMAT(//* PROBABILITY OF PREFERENCE*)
  300 FORMAT(1H1, *PROBABILITY OF CLASSIFICATION*)
  400 FORMAT(/* DISTRIBUTION OF CLASSIFICATION DECISION*)
  500 FORMAT(//* PROBABILITY OF TACTICAL DECISION*)
  600 FORMAT(/* DISTRIBUTION OF TACTICAL DECISION*)
  700 FORMAT(//* ENGAGMENT MOE  =*,F7.3)
  150 FORMAT(5X,4F10.2)
  250 FORMAT(5X,10F10.2)
      END
```

```
      SUBROUTINE INPUT
C
      COMMON /A/ GV,NREP,NMAX
      COMMON /B/ IMAX,MMAX,JMAX
      COMMON /C/ LAMAX,KDMAX,IR
      COMMON /D/ LP(12),LA(12),NA(20,2),KA(2)
      COMMON /E/ KF(12),NF(12),KT(10,2),TS
      COMMON /F/ XO(2),YO(2),CO(20,2),SO(20,2),DO(20,2)
      COMMON /G/ XT(2),YT(2),CT(20,2),ST(20,2),DT(20,2)
      COMMON /H/ WTH(5),TAV(5),NUM(5),DET(5),MEM(5)
      COMMON /I/ DH(2),DV(2),HN(2),VN(2),SL(2)
      COMMON /J/ FRQ(12),PLL(12,3)
      COMMON /K/ PBB(6,3),FQB(6,3)
      COMMON /L/ PNN(6,2),FQN(6,2)
      COMMON /M/ MIX(5),SDV(5),TAU(5),BIAS(5)
      COMMON /N/ PRIOR(10),VAL(10,10),FVAL,VMAX(10)
C
      DIMENSION SCR(5),FCS(5),TOT(5)
      REAL MIX
C
      DATA GV   /808./
      DATA NREP /20/
      DATA NMAX /10/
      DATA TS   /10./
      DATA IMAX /3/
      DATA MMAX /1/
      DATA KT /1,2,3, 17*0/
      DATA IR   /1/
      DATA PRIOR/10*.1/
      DATA KDMAX /3/
      DATA VAL  /9*(1.,0.,0.,0.,0.,0.,0.,0.,0.,0.,0.),1./
      DATA FVAL /.95/
      DATA XT /0.,5./
      DATA YT /40.,40./
      DATA CT /40*155./
      DATA ST /40*25./
      DATA DT /40*30./
      DATA JMAX /7/
      DATA NF /1,1,1,1,1,1,1, 5*0/
      DATA KF /1,1,1,3,3,3,3, 5*0/
      DATA FRQ /50.,100.,400.,2*2828.,2*5656., 5*0./
      DATA PLL /155., 0., 150.,  -3.,-3.,-3.,-20.,    5*0.,
     +          155.,150., 0.,  -20.,-3.,-20.,-3.,    5*0.,
     +            0., 150.,150.,  -20.,-20.,-2.,-2.,  5*0./
      DATA PBB /3*( 153.,155.,145.,125.,0.,0.)/
      DATA FQB /3*( 10.,100.,1000.,10000.,0.,0.)/
      DATA LAMAX /2/
      DATA LA /2,2,2,1,1,1,1, 5*0/
      DATA KA /1,2/
      DATA DH /7.,60./
      DATA DV /5.,0./
      DATA HN /15.,30./
      DATA VN /11.,1./
      DATA SL /.01,.01/
      DATA XO /0.,-.5/
```

```
      DATA YØ /0.,0./
      DATA CØ /40*90./
      DATA SØ /40*10./
      DATA DØ /40*100./
      DATA NA /40*1/
      DATA PNN /120.,65.,65.,45., 2*0.,
     +          75.,65.,45.,3*0./
      DATA FQN /10.,300.,1000.,10000.,2*0.,
     +          10.,1000.,10000.,3*0./
      DATA LP /1,1,1,2,2,3,3, 5*0/
      DATA WTH /1.,2000.,4000., 2*0./
      DATA SCR /1.,1.,1., 2*0./
      DATA FCS /600.,60.,60., 2*0./
      DATA TØT /30.,10.,10., 2*0./
      DATA DET /2.,2.,2., 2*0./
      DATA MIX /5*0.5/
      DATA SDV /3.,3.,1.,3.,3./
      DATA TAU /5*3./
C
C  ** CALCULATE TAV, NUM, MEM
      DØ 30 LL=1,5
      TAV(LL)=60./(SCR(LL)*FCS(LL))
      NUM(LL)=SCR(LL)*TS+.5
      MEM(LL)=TØT(LL)/TS-.5
   30 CØNTINUE
C
C  ** CALCULATE BIAS
      DØ 40 KR=1,5
   40 BIAS(KR)=(SDV(KR)**2)/8.68
C
C  ** FIND MAXIMUM VALUE
      DØ 50 I=1,IMAX
      VMAX(I)=-1.E99
      DØ 50 KD=1,KDMAX
      IF(VAL(I,KD).GT.VMAX(I)) VMAX(I)=VAL(I,KD)
   50 CØNTINUE
      RETURN
      END
```

```
      SUBROUTINE TABLE
C
      COMMON /A/ GV,NREP,NMAX
      COMMON /B/ IMAX,MMAX,JMAX
      COMMON /C/ LAMAX,KDMAX,IR
      COMMON /D/ LP(12),LA(12),NA(20,2),KA(2)
      COMMON /E/ KF(12),NF(12),KT(10,2),TS
      COMMON /F/ XO(2),YO(2),CO(20,2),SO(20,2),DO(20,2)
      COMMON /G/ XT(2),YT(2),CT(20,2),ST(20,2),DT(20,2)
      COMMON /J/ FRQ(12),PLL(12,3)
      COMMON /K/ PBB(6,3),FQB(6,3)
      COMMON /L/ PNN(6,2),FQN(6,2)
      COMMON /O/ RNG(2,2,20),BRG(2,2,20),ASP(2,2,20)
      COMMON /P/ TLL(12,2,20),TBB(12,2,20),TNN(12,2,20)
      COMMON /Q/ TAZ(12,2,20),TBM(960),TSL(12)
C
C  ** CALCULATE RANGE, RELATIVE BEARING, AND ASPECT ANGLE
      U=3.1416/180.
      DO 50 L=1,LAMAX
      DO 50 M=1,MMAX
      XOL=XO(L)   $YOL=YO(L)
      XTM=XT(M)   $YTM=YT(M)
      DO 50 N=1,NMAX
      X=XTM-XOL
      Y=YTM-YOL
      R=SQRT(X*X+Y*Y)
      SINB=X/R
      COSB=Y/R
      CCO=CO(N,L)*U
      CCT=(CT(N,M)-180.)*U
      SINO=SIN(CCO)
      COSO=COS(CCO)
      SINT=SIN(CCT)
      COST=COS(CCT)
      SBRG=SINB*COSO-COSB*SINO
      CBRG=COSB*COSO+SINB*SINO
      SASP=SINB*COST-COSB*SINT
      CASP=COSB*COST+SINB*SINT
      RNG(L,M,N)=R
      BRG(L,M,N)=ATAN2(SBRG,CBRG)/U
      ASP(L,M,N)=ATAN2(SASP,CASP)/U
      IF(BRG(L,M,N).LT.0.) BRG(L,M,N)=360.+BRG(L,M,N)
      XOL=XOL+SO(N,L)*TS*SINO/60.
      YOL=YOL+SO(N,L)*TS*COSO/60.
      XTM=XTM-ST(N,M)*TS*SINT/60.
      YTM=YTM-ST(N,M)*TS*COST/60.
   50 CONTINUE
C
C  ** GENERATE TABLES
      DO 100 J=1,JMAX
      IF(NF(J).EQ.0) GO TO 100
      KR=KF(J)
      L=LA(J)
      TSL(J)=FSL(L,FRQ(J))
      DO 90 N=1,NMAX
```

```
      IF(NA(N,L).EQ.0) GØ TØ 90
      DØ 70 M=1,MMAX
      TAZ(J,M,N)=FAZ(FRQ(J),RNG(L,M,N),DØ(N,L),DT(N,M))
      IF(KT(IR,M).EQ.0) GØ TØ 70
      TLL(J,M,N)=FLL(J,KT(IR,M),ST(N,M),DT(N,M),ASP(L,M,N))
      TBB(J,M,N)=FBB(KT(IR,M),FRQ(J),ST(N,M),DT(N,M),ASP(L,M,N))
   70 CØNTINUE
      DØ 80 K=1,MMAX
      ANG=BRG(L,K,N)
      TNN(J,K,N)=FNN(L,FRQ(J),SØ(N,L),DØ(N,L),ANG)
      DØ 80 M=1,MMAX
      JKMN=1+(J-1+JMAX*(K-1+MMAX*(M-1+MMAX*(N-1))))
      TBM(JKMN)=FBM(J,FRQ(J),BRG(L,M,N),ANG)
   80 CØNTINUE
   90 CØNTINUE
  100 CØNTINUE
      RETURN
      END
```

```
      SUBROUTINE SAVE
C
      COMMON /A/ GV,NREP,NMAX
      COMMON /B/ IMAX,MMAX,JMAX
      COMMON /C/ LAMAX,KDMAX,IR
      COMMON /D/ LP(12),LA(12),NA(20,2),KA(2)
      COMMON /E/ KF(12),NF(12),KT(10,2),TS
      COMMON /G/ XT(2),YT(2),CT(20,2),ST(20,2),DT(20,2)
      COMMON /J/ FRQ(12),PLL(12,3)
      COMMON /M/ MIX(5),SDV(5),TAU(5),BIAS(5)
      COMMON /O/ RNG(2,2,20),BRG(2,2,20),ASP(2,2,20)
      COMMON /P/ TLL(12,2,20),TBB(12,2,20),TNN(12,2,20)
      COMMON /Q/ TAZ(12,2,20),TBM(960),TSL(12)
      COMMON /V/ XS(4800),XV(4800),XSP(4800),XDSP(4800)
C
      DIMENSION AH(2),P(10,2),PP(10,2),S(10),V(10),SP(10),DSP(10)
C
C  ** FEATURE J-LOOP
      DO 160 J=1,JMAX
      IF(NF(J).EQ.0) GO TO 160
      KR=KF(J)
      L=LA(J)
C  ** TIME STEP N-LOOP
      DO 150 N=1,NMAX
      IF(NA(N,L).EQ.0) GO TO 150
C  ** TRACK M-LOOP
      DO 50 M=1,MMAX
C  ** CALCULATE PROPAGATION LOSS
      AH(M)=10.**((TAZ(J,M,N)+BIAS(5))/10.)
C  ** HYPOTHESIS I-LOOP
      DO 50 I=1,IMAX
      IF(KT(I,M).EQ.0) GO TO 50
C  ** CALCULATE HYPOTHETICAL SOURCE LEVELS
      PIM =     FBB(KT(I,M),FRQ(J),ST(N,M),DT(N,M),ASP(L,M,N))
      IF(KR-2)41,42,41
   41 PP(I,M)=10.**((PIM+BIAS(2))/10.)
      P(I,M)=    FLL(J,KT(I,M),ST(N,M),DT(N,M),ASP(L,M,N))  $GO TO 43
   42 P(I,M)=    PIM
   43 P(I,M)=10.**((P(I,M)+BIAS(KR))/10.)
   50 CONTINUE
C  ** LOOK ANGLE K-LOOP
      DO 120 K=1,MMAX
      DO 60 I=1,IMAX
      S(I)=0. $V(I)=0. $SP(I)=0. $DSP(I)=0.
   60 CONTINUE
C  ** SUM OF SOURCES
C  ** TRACK M-LOOP
      DO 80 M=1,MMAX
      JKMN=1+(J-1+JMAX*(K-1+MMAX*(M-1+MMAX*(N-1))))
      B=TBM(JKMN)
C  ** CALCULATE HYPOTHETICAL SIGNALS AND SOURCE NOISE
C  ** HYPOTHESIS I-LOOP
      DO 80 I=1,IMAX
      IF(KT(I,M).EQ.0) GO TO 80
      IF(KR-2)74,75,76
```

```
C   ** LOFAR
   74 Q=P(I,M)*B/AH(M)
      S(I)=S(I)+Q
      V(I)=V(I)+Q*Q
      SP(I)=SP(I)+PP(I,M)*B/AH(M)
      GO TO 80
C   ** BROADBAND
   75 SP(I)=SP(I)+P(I,M)*B/AH(M)
      GO TO 80
C   ** DEMON
   76 IF(P(I,M).GT.1.)P(I,M)=1.
      Q=PP(I,M)*B/AH(M)
      DSP(I)=DSP(I)+0.5*Q*P(I,M)
      SP(I)=SP(I)+Q
   80 CONTINUE
C   ** SAVE VALUES
      DO 90 I=1,IMAX
      IJKN=1+(I-1+IMAX*(J-1+JMAX*(K-1+MMAX*(N-1))))
      XS(IJKN)=S(I)
      XV(IJKN)=V(I)
      XSP(IJKN)=SP(I)
      XDSP(IJKN)=DSP(I)
   90 CONTINUE
C
  120 CONTINUE
  150 CONTINUE
  160 CONTINUE
      RETURN
      END
```

```
      SUBROUTINE DETECT(N)
C
      COMMON /A/ GV,NREP,NMAX
      COMMON /B/ IMAX,MMAX,JMAX
      COMMON /C/ LAMAX,KDMAX,IR
      COMMON /D/ LP(12),LA(12),NA(20,2),KA(2)
      COMMON /E/ KF(12),NF(12),KT(10,2),TS
      COMMON /H/ WTH(5),TAV(5),NUM(5),DET(5),MEM(5)
      COMMON /M/ MIX(5),SDV(5),TAU(5),BIAS(5)
      COMMON /P/ TLL(12,2,20),TBB(12,2,20),TNN(12,2,20)
      COMMON /Q/ TAZ(12,2,20),TBM(960),TSL(12)
      COMMON /R/ JUMP(5,12,2),GAUSS(5,12,2)
      COMMON /S/ PDETZ(12,2),PDET(10,12,2)
      COMMON /V/ XS(4800),XV(4800),XSP(4800),XDSP(4800)
C
      DIMENSION PZ(2),PPZ(2),AZ(2),
     +          S(10),V(10),SP(10),DSP(10),MU(10),SG(10)
      REAL JUMP,NPZ,MUZ,MUZS,MU,MIX
C
C  ** FEATURE J-LOOP
      DO 150 J=1,JMAX
      IF(NF(J).EQ.0) GO TO 150
      L=LA(J)
      IF(NA(N,L).EQ.0) GO TO 150
      LPJ=LP(J)
      W=WTH(LPJ)
      T=TAV(LPJ)
      WT=W*T
      SWT=SQRT(WT)
      KR=KF(J)
      BS=TSL(J)
C
C  ** TRACK M-LOOP
      DO 50 M=1,MMAX
      IF(KT(IR,M).EQ.0) GO TO 50
C
C  ** CALCULATE REAL SOURCE LEVELS
      IF(KR-2)31,32,31
   31 CALL RANDOM(MIX(2),SDV(2),TAU(2),TS,
     +             JUMP(2,J,M),GAUSS(2,J,M),DELTA)
      PPZ(M)=10.**((TBB(J,M,N)+DELTA)/10.)
      PZ(M)=TLL(J,M,N)  $GO TO 33
   32 PZ(M)=TBB(J,M,N)
   33 CALL RANDOM(MIX(KR),SDV(KR),TAU(KR),TS,
     +             JUMP(KR,J,M),GAUSS(KR,J,M),DELTA)
      PZ(M)=10.**((PZ(M)+DELTA)/10.)
C
C  ** CALCULATE PROPAGATION LOSS
      CALL RANDOM(MIX(5),SDV(5),TAU(5),TS,
     +             JUMP(5,J,M),GAUSS(5,J,M),DELTA)
      AZ(M)=10.**((TAZ(J,M,N)+DELTA)/10.)
   50 CONTINUE
C
C  ** LOOK ANGLE K-LOOP
      DO 120 K=1,MMAX
```

```
C
C   ** INITIALIZE SUMS
       SZ=0. $VZ=0. $ SPZ=0. $SPZS=0. $DSPZ=0.
C   ** SUM OF SOURCES
C   ** TRACK M-LOOP
       DO 80 M=1,MMAX
       IF(KT(IR,M).EQ.0) GO TO 80
       JKMN=1+(J-1+JMAX*(K-1+MMAX*(M-1+MMAX*(N-1))))
       B=TBM(JKMN)
C   ** CALCULATE REAL SIGNALS AND SOURCE NOISE
       IF(KR-2)64,65,66
C   ** LOFAR
    64 Q=PZ(M)*B/AZ(M)
       SZ=SZ+Q
       VZ=VZ+Q*Q
       SPZ=SPZ+PPZ(M)*B/AZ(M)
       GO TO 80
C   ** BROADBAND
    65 Q=PZ(M)/AZ(M)
       SPZ=SPZ+Q*B
       SPZS=SPZS+Q*BS
       GO TO 80
C   ** DEMON
    66 IF(PZ(M).GT.1.)PZ(M)=1.
       Q=PPZ(M)*B/AZ(M)
       DSPZ=DSPZ+0.5*Q*PZ(M)
       SPZ=SPZ+Q
    80 CONTINUE
C
C   ** CALCULATE NOISE
       CALL RANDOM(MIX(4),SDV(4),TAU(4),TS,
      +             JUMP(4,J,1), GAUSS(4,J,1), DELTA)
       NPZ=10.**((TNN(J,K,N)+DELTA)/10.)
C
C   ** CALCULATE MEAN AND STD DEV FOR REAL DATA AND REFERENCE CHANNELS
       IF(KR-2)94,95,96
C   ** LOFAR
    94 RZ=(SPZ+NPZ)*W
       MUZ=SZ+RZ
       SGZ=SQRT(SZ*SZ-VZ+2.*SZ*RZ/WT+RZ*RZ/WT)
       MUZS=RZ
       SGZS=MUZS/SWT
       GO TO 100
C   ** BROADBAND
    95 RPZ=SPZ+NPZ
       MUZ=RPZ*W
       SGZ=MUZ/SWT
       RPZS=SPZS+NPZ
       MUZS=RPZS*W
       SGZS=MUZS/SWT
       GO TO 100
C   ** DEMON
    96 RPZ=SPZ+NPZ
       MUZ=(DSPZ+RPZ)*W
       SGZ=MUZ/SWT
```

```
      MUZS=RPZ*W
      SGZS=MUZS/SWT
  100 CONTINUE
C
C  ** CALCULATE MEAN AND STD DEV OF HYPOTHETICAL DATA CHANNEL
C  ** HYPOTHESIS I-LOOP
      DO 110 I=1,IMAX
      IJKN=1+(I-1+IMAX*(J-1+JMAX*(K-1+MMAX*(N-1))))
      S(I)=XS(IJKN)
      V(I)=XV(IJKN)
      SP(I)=XSP(IJKN)
      DSP(I)=XDSP(IJKN)
      IF(KR-2)104,105,106
C  ** LOFAR
  104 RI=(SP(I)+NPZ)*W
      MU(I)=S(I)+RI
      SG(I)=SQRT(S(I)**2-V(I)+2.*S(I)*RI/WT+RI*RI/WT)
      GO TO 110
C  ** BROADBAND
  105 RPI=SP(I)+NPZ
      MU(I)=RPI*W
      SG(I)=MU(I)/SWT
      GO TO 110
C  ** DEMON
  106 RPI=SP(I)+NPZ
      MU(I)=(DSP(I)+RPI)*W
      SG(I)=MU(I)/SWT
  110 CONTINUE
C
C  ** CALCULATE PROBABILITY OF DETECTION
      A=MUZS+DET(LPJ)*SGZS
      PDETZ(J,K)=PROB(MUZ,SGZ,A)
      DO 115 I=1,IMAX
      PDET(I,J,K)=PROB(MU(I),SG(I),A)
  115 CONTINUE
C
  120 CONTINUE
  150 CONTINUE
      RETURN
      END
```

```
      SUBROUTINE BAYES(N)
      COMMON /A/ GV,NREP,NMAX
      COMMON /B/ IMAX,MMAX,JMAX
      COMMON /C/ LAMAX,KDMAX,IR
      COMMON /D/ LP(12),LA(12),NA(20,2),KA(2)
      COMMON /E/ KF(12),NF(12),KT(10,2),TS
      COMMON /H/ WTH(5),TAV(5),NUM(5),DET(5),MEM(5)
      COMMON /N/ PRIOR(10),VAL(10,10),FVAL,VMAX(10)
      COMMON /S/ PDETZ(12,2),PDET(10,12,2)
      COMMON /T/ POST(10,20),IB(20)
C
      DIMENSION PLIKE(10),LIKE(10,12,20)
      REAL LIKE
C
C  ** CALCULATE LOG LIKELIHOODS
      DO 5 I=1,IMAX
      DO 5 J=1,JMAX
      LIKE(I,J,N)=0.
    5 CONTINUE
C  ** FEATURE J-LOOP
      DO 20  J=1,JMAX
      IF(NF(J).EQ.0) GO TO 20
      LAJ=LA(J)
      IF(NA(N,LAJ).EQ.0) GO TO 20
      LPJ=LP(J)
      LMAX=NUM(LPJ)
C  ** LOOK ANGLE K-LOOP
      DO 15  K=1,MMAX
C  ** CALCULATE NUMBER OF DETECTIONS DURING N-TH TIME STEP
      IF(LMAX.GE.50) GO TO 11
      LX=0
      DO 10 L=1,LMAX
      X=RANF(0.)
      IF(X.LE.PDETZ(J,K))LX=LX+1
   10 CONTINUE
      GO TO 12
   11 LX=LMAX*PDETZ(J,K)+.5
   12 C=FLBC(LMAX,LX)
C  ** HYPOTHESIS I-LOOP
      DO 15 I=1,IMAX
      PD=ALOG(PDET(I,J,K))
      PE=ALOG(1.-PDET(I,J,K))
      Z=C+ LX*PD+ (LMAX-LX)*PE
      LIKE(I,J,N)=Z+LIKE(I,J,N)
   15 CONTINUE
   20 CONTINUE
C
C  ** SUM OVER FEATURES AND MEMORABLE TIME STEPS
      DO 30 I=1,IMAX
      PLIKE(I)=0.
      DO 30 J=1,JMAX
      LPJ=LP(J)
      MO=N-MEM(LPJ)
      IF(MO.LT.1)MO=1
      DO 30 M=MO,N
```

```
      PLIKE(I) =PLIKE(I)+ LIKE(I,J,M)
   30 CONTINUE
C
C  ** SCALE PRODUCT FROM 1. TO 1000.(MAXIMUM)
      PMAX=-1.E99
      PMIN=0.
      DO 32 I=1,IMAX
      IF(PLIKE(I).GT.PMAX) PMAX=PLIKE(I)
      IF(PLIKE(I).LT.PMIN) PMIN=PLIKE(I)
   32 CONTINUE
      PP=PMAX-PMIN
      IF(PP.LT.6.908) PP=6.908
      DO 34 I=1,IMAX
   34 PLIKE(I)=EXP(6.908*(PLIKE(I)-PMIN)/PP)
C
C  ** CALCULATE POSTERIOR PROBABILIES
      SUM=0.
      DO 40 I=1,IMAX
      SUM=SUM+PLIKE(I) *PRIOR(I)
   40 CONTINUE
      DO 50 I=1,IMAX
      POST(I,N)=PLIKE(I) *PRIOR(I)/SUM
   50 CONTINUE
C
C  ** FIND  I  OF MAXIMUM POSTERIOR
      PMAX=0.
      DO 60 I=1,IMAX
      IF(PMAX.GE.POST(I,N)) GO TO 60
      PMAX=POST(I,N)
      IB(N)=I
   60 CONTINUE
      RETURN
      END
```

```
      SUBROUTINE DECIDE
      COMMON /A/ GV,NREP,NMAX
      COMMON /B/ IMAX,MMAX,JMAX
      COMMON /C/ LAMAX,KDMAX,IR
      COMMON /N/ PRIOR(10),VAL(10,10),FVAL,VMAX(10)
      COMMON /T/ POST(10,20),IB(20)
      COMMON /U/ NSTOP,KDF
C
      DIMENSION EVAL(10)
C
      DO 50 N=1,NMAX
C  ** CALCULATE EXP VALUE OF DECISION
C  ** DECISION ALTERNATIVE K-LOOP
      DO 10 K=1,KDMAX
      EVAL(K)=0.
C  ** HYPOTHESIS I-LOOP
      DO 10 I=1,IMAX
      EVAL(K)=EVAL(K)+VAL(I,K)*POST(I,N)
   10 CONTINUE
C
C  ** CALCULATE MAX EXP VALUE AND BAYES DECISION
C  ** DECISION ALTERNATIVE K-LOOP
      EMAX=-1.E99
      DO 30 K=1,KDMAX
      IF(EVAL(K).LE.EMAX)GO TO 30
      EMAX=EVAL(K)
      KDF=K
   30 CONTINUE
C
C  ** CALCULATE EXP VALUE OF PERFECT  NFORMATION
C  ** HYPOTHESIS I-LOOP
      EVPI=0.
      DO 40 I=1,IMAX
      EVPI=EVPI+VMAX(I)*POST(I,N)
   40 CONTINUE
C
C  ** TEST IF DECISION IS MADE
      IF(EMAX/EVPI.GE.FVAL) GO TO 60
   50 CONTINUE
      NSTOP=NMAX
      RETURN
   60 NSTOP=N
      RETURN
      END
```

```
      FUNCTION FNN(L,FRQ,SO,DO,ANG)
      COMMON /D/ LP(12),LA(12),NA(20,2),KA(2)
      COMMON /I/ DH(2),DV(2),HN(2),VN(2),SL(2)
      COMMON /L/ PNN(6,2),FQN(6,2)
C
      DO 10 NF=1,6
      IF(FQN(NF,L)-FRQ) 10,15,20
   10 CONTINUE
   15 FNN=PNN(NF,L)  $GO TO 25
   20 F=FQN(NF-1,L)
      R=ALOG10(FRQ/F)/ALOG10(FQN(NF,L)/F)
      P=PNN(NF-1,L)
      FNN=P+R*(PNN(NF,L)-P)
   25 CONTINUE
C
C  ** DIRECTIVITY CALCULATION
      W=5000./FRQ
      IF(KA(L).EQ.2) GO TO 30
      A=SQRT(4.*3.1416)
      H=A*DH(L)/W
      IF(H.LT.1.)H=1.
      IF(H.GT.HN(L)) H=HN(L)
      V=A*DV(L)/W
      IF(V.LT.1.)V=1.
      IF(V.GT.VN(L)) V=VN(L)
      DI=H*V  $GO TO 40
   30 DI=2.*DH(L)/W
      IF(DI.LT.1.)DI=1.
      IF(DI.GT.HN(L)) DI=HN(L)
C
   40 FNN=FNN-10.*ALOG10(DI)
      RETURN
      END
```

```
      FUNCTION FLL(J,KT,ST,DT,ASP)
      COMMON /J/ FRQ(12),PLL(12,3)
      FLL=PLL(J,KT)
      RETURN
      END
```

```
      FUNCTION FBB(KT,FRQ,ST,DT,ASP)
      COMMON /K/ PBB(6,3),FQB(6,3)
      DO 10 NB=1,6
      IF(FQB(NB,KT)-FRQ)10,15,20
   10 CONTINUE
   15 FBB=PBB(NB,KT)  $RETURN
   20 F=FQB(NB-1,KT)
      R=ALOG10(FRQ/F)/ALOG10(FQB(NB,KT)/F)
      P=PBB(NB-1,KT)
      FBB=P+R*(PBB(NB,KT)-P)
      RETURN
      END
```

```
      FUNCTION FSL(LA,FRQ)
      COMMON /I/ DH(2),DV(2),HN(2),VN(2),SL(2)
      PI=3.1416
      X=PI*DH(LA)*FRQ/5000.
      FSL=SL(LA)
      IF(X.GT.PI) RETURN
      B=1.
      IF(X.GT..001) B=(SIN(X)/X)**2
      IF(B.GT.SL(LA)) FSL=B
      RETURN
      END
```

```
      FUNCTION FAZ(FRQ,RNG,DO,DT)
      FAZ=66.+17.*ALOG10(RNG)
      FAZ=FAZ+.08*((FRQ/1000.)**1.4)*RNG
      RETURN
      END
```

```
      FUNCTION   FBM(J,FRQ,BRG,ANG)
      COMMON /D/ LP(12),LA(12),NA(20,2),KA(2)
      COMMON /E/ KF(12),NF(12),KT(10,2),TS
      COMMON /I/ DH(2),DV(2),HN(2),VN(2),SL(2)
C
      PI=3.1416  $U=PI/180.
      L=LA(J)
      C=PI*DH(L)*FRQ/5000.
      IF(KA(L).EQ.2) GO TO 30
C
C  ** CIRCLE ARRAY
      Y=BRG-ANG
      IF(Y.LT.0.) Y=360.+Y
      FBM=0.
      IF(Y.GT.90. .AND. Y.LT.270.) RETURN
      X=ABS(C*SIN(Y*U))
      IF(KF(J).NE.1) GO TO 20
C  ** NARROWBAND
   10 FBM=1.
      IF(X.GT..001) FBM=(SIN(X)/X)**2
      IF(X.GT.PI .AND. FBM.GT.SL(L)) FBM=SL(L)
      RETURN
C  ** BROADBAND
   20 FBM=SL(L)
      IF(X.GT.PI) RETURN
      B=1.
      IF(X.GT..001) B=(SIN(X)/X)**2
      IF(B.GT.SL(L)) FBM=B
      RETURN
C
C  ** LINE ARRAY
   30 X=ABS(C*(COS(BRG*U)-COS(ANG*U)))
      IF(KF(J).EQ.1) GO TO 10
      GO TO 20
      END
```

```
      FUNCTION FLBC(N,K)
**    LOG OF BINOMIAL COEFFICENT
      DATA MM /50/
      L=N-K
      IF(K.EQ.0.OR.L.EQ.0) GO TO 30
      IF(K.EQ.1.OR.L.EQ.1) GO TO 40
      IF(K.GE.MM.AND.L.GE.MM) GO TO 50
      IF(K.GE.MM) GO TO 70
      IF(L.GE.MM) GO TO 90
      A=1.
      LPO=L+1
      DO 10 I=LPO,N
   10 A=A*I
      B=1.
      DO 20 I=1,K
   20 B=B*I
      FLBC=ALOG(A/B)
      RETURN
   30 FLBC=0.
      RETURN
   40 FLBC=ALOG(FLOAT(N))
      RETURN
*STIRLING N.=SQRT(2PI)*(N**(N+.5))*EXP(-N)
   50 EN=N $EK=K $EL=L
      A=.9189385332
      B=(N+.5)*ALOG(EN)
      C=(K+.5)*ALOG(EK)
      D=(L+.5)*ALOG(EL)
      FLBC=-A+B-C-D
      RETURN
   70 EN=N $EK=K
      A=(N+.5)*ALOG(EN)
      B=(K+.5)*ALOG(EK)
      C=1.
      DO 80 I=2, L
   80 C=C*I
      FLBC=A-N-B+K-ALOG(C)
      IF(L.GE.MM) K=L
      RETURN
   90 KK=K $K=L $L=KK
      GO TO 70
      END
```

```
      FUNCTION PROB(MU,SIG,THRESH)
C  ** PROB THAT  NORMAL RANDOM VARIABLE IS GREATER THAN THRESHOLD
      REAL MU
      DATA D1 / 0.0498673470 /
      DATA D2 / 0.0211410061 /
      DATA D3 / 0.0032776263 /
      DATA D4 / 0.0000380036 /
      DATA D5 / 0.0000488906 /
      DATA D6 / 0.0000053830 /
C
      A=ABS(THRESH-MU)
      IF(A.EQ.0.) GO TO 50
      IF(SIG.LE.A/3.08) GO TO 40
      X=A/SIG  $X2=X*X  $X3=X2*X
      G=1.+D1*X+D2*X2+D3*X2*X+D4*X2*X2+D5*X3*X2+D6*X3*X3
      PROB=.5/G**16
   30 IF(THRESH.LT.MU) PROB=1.-PROB
      RETURN
   40 PROB=.001  $GO TO 30
   50 PROB=.5
      RETURN
      END
```

```
      SUBROUTINE RANDOM(MIX,SDV,TAU,TS,JUMP,GAUSS,DELTA)
      REAL MIX,JUMP
C
      X=RANF(0.)
      RHO=EXP(-TS/TAU)
      IF(X.GT.RHO)JUMP=SDV*RNORM(0.)
      GAUSS=RHO*GAUSS+SDV*SQRT(1.-RHO*RHO)*RNORM(0.)
      DELTA=MIX*JUMP+SQRT(1.-MIX*MIX)*GAUSS
      RETURN
      END
```

```
      FUNCTION RNORM(V)
      SUM=0.
      DO 10 I=1,12
   10 SUM=SUM+RANF(0.)
      RNORM=SUM-6.
      RETURN
      END
```

Appendix B

INPUT AND OUTPUT OF THE SINGLE-TARGET EXAMPLE

```
      SUBROUTINE INPUT
C
      COMMON /A/ GV,NREP,NMAX
      COMMON /B/ IMAX,MMAX,JMAX
      COMMON /C/ LAMAX,KDMAX,IR
      COMMON /D/ LP(12),LA(12),NA(20,2),KA(2)
      COMMON /E/ KF(12),NF(12),KT(10,2),TS
      COMMON /F/ XO(2),YO(2),CO(20,2),SO(20,2),DO(20,2)
      COMMON /G/ XT(2),YT(2),CT(20,2),ST(20,2),DT(20,2)
      COMMON /H/ WTH(5),TAV(5),NUM(5),DET(5),MEM(5)
      COMMON /I/ DH(2),DV(2),HN(2),VN(2),SL(2)
      COMMON /J/ FRQ(12),PLL(12,3)
      COMMON /K/ PBB(6,3),FQB(6,3)
      COMMON /L/ PNN(6,2),FQN(6,2)
      COMMON /M/ MIX(5),SDV(5),TAU(5),BIAS(5)
      COMMON /N/ PRIOR(10),VAL(10,10),FVAL,VMAX(10)
C
      DIMENSION SCR(5),FCS(5),TOT(5)
      REAL MIX
C
      DATA GV   /808./
      DATA NREP /20/
      DATA NMAX /10/
      DATA TS   /10./
      DATA IMAX /3/
      DATA MMAX /1/
      DATA KT /1,2,3, 17*0/
      DATA IR   /1/
      DATA PRIOR/10*.1/
      DATA KDMAX /3/
      DATA VAL  /9*(1.,0.,0.,0.,0.,0.,0.,0.,0.,0.,0.),1./
      DATA FVAL /.95/
      DATA XT /0.,5./
      DATA YT /40.,40./
      DATA CT /40*155./
      DATA ST /40*25./
      DATA DT /40*30./
      DATA JMAX /7/
      DATA NF /1,1,1,1,1,1,1, 5*0/
      DATA KF /1,1,1,3,3,3,3, 5*0/
      DATA FRQ /50.,100.,400.,2*2828.,2*5656., 5*0./
      DATA PLL /155., 0., 150.,  -3.,-3.,-3.,-20.,   5*0.,
     +          155.,150., 0.,  -20.,-3.,-20.,-3.,   5*0.,
     +           0., 150.,150.,  -20.,-20.,-2.,-2.,  5*0./
      DATA PBB /3*( 153.,155.,145.,125.,0.,0.)/
      DATA FQB /3*( 10.,100.,1000.,10000.,0.,0.)/
      DATA LAMAX /2/
      DATA LA /2,2,2,1,1,1,1, 5*0/
      DATA KA /1,2/
      DATA DH /7.,60./
      DATA DV /5.,0./
      DATA HN /15.,30./
      DATA VN /11.,1./
      DATA SL /.01,.01/
      DATA XO /0.,-.5/
```

```
      DATA YO /0.,0./
      DATA CO /40*90./
      DATA SO /40*10./
      DATA DO /40*100./
      DATA NA /40*1/
      DATA PNN /120.,65.,65.,45., 2*0.,
     +          75.,65.,45.,3*0./
      DATA FQN /10.,300.,1000.,10000.,2*0.,
     +          10.,1000.,10000.,3*0./
      DATA LP /1,1,1,2,2,3,3, 5*0/
      DATA WTH /1.,2000.,4000., 2*0./
      DATA SCR /1.,1.,1., 2*0./
      DATA FCS /600.,60.,60., 2*0./
      DATA TOT /30.,10.,10., 2*0./
      DATA DET /2.,2.,2., 2*0./
      DATA MIX /5*0.5/
      DATA SDV /3.,3.,1.,3.,3./
      DATA TAU /5*3./
C
C  ** CALCULATE TAV, NUM, MEM
      DO 30 LL=1,5
      TAV(LL)=60./(SCR(LL)*FCS(LL))
      NUM(LL)=SCR(LL)*TS+.5
      MEM(LL)=TOT(LL)/TS-.5
   30 CONTINUE
C
C  ** CALCULATE BIAS
      DO 40 KR=1,5
   40 BIAS(KR)=(SDV(KR)**2)/8.68
C
C  ** FIND MAXIMUM VALUE
      DO 50 I=1,IMAX
      VMAX(I)=-1.E99
      DO 50 KD=1,KDMAX
      IF(VAL(I,KD).GT.VMAX(I)) VMAX(I)=VAL(I,KD)
   50 CONTINUE
      RETURN
      END
```

RANGE

40.00	40.00	I	I
36.22	36.23	I	I
32.45	32.45	I	I
28.67	28.68	I	I
24.90	24.91	I	I
21.12	21.14	I	I
17.35	17.38	I	I
13.58	13.62	I	I
9.82	9.87	I	I
6.07	6.16	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I

BEARING

270.00	270.72	I	I
270.15	270.94	I	I
270.33	271.22	I	I
270.57	271.56	I	I
270.87	272.02	I	I
271.28	272.63	I	I
271.87	273.52	I	I
272.78	274.89	I	I
274.40	277.30	I	I
278.03	282.64	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I

AVERAGE POSTERIOR PROBABILITY

.37	.28	.35
.38	.17	.45
.57	.26	.17
.56	.33	.11
.63	.24	.13
.55	.26	.19
.63	.25	.12
.71	.08	.21
.62	.16	.23
.63	.11	.26

PROBABILITY OF PREFERENCE

.35	.35	.30
.35	.20	.45
.65	.25	.10
.65	.35	0.00
.65	.30	.05
.60	.25	.15
.65	.30	.05
.75	.10	.15
.65	.15	.20
.60	.10	.30

```
PROBABILITY OF CLASSIFICATION
          .55       .15       .30       I         I         I         I         I         I         I

DISTRIBUTION OF CLASSIFICATION DECISION
          .36       .33       .50       I         I         I         I         I         I         I
          .55       .33      1.00       I         I         I         I         I         I         I
          .64       .67      1.00       I         I         I         I         I         I         I
          .82       .67      1.00       I         I         I         I         I         I         I
          .82      1.00      1.00       I         I         I         I         I         I         I
          .91      1.00      1.00       I         I         I         I         I         I         I
         1.00      1.00      1.00       I         I         I         I         I         I         I
         1.00      1.00      1.00       I         I         I         I         I         I         I
         1.00      1.00      1.00       I         I         I         I         I         I         I
         1.00      1.00      1.00       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I

PROBABILITY OF TACTICAL DECISION
          .55       .15       .30       I         I         I         I         I         I         I

DISTRIBUTION OF TACTICAL DECISION
          .36       .33       .50       I         I         I         I         I         I         I
          .55       .33      1.00       I         I         I         I         I         I         I
          .64       .67      1.00       I         I         I         I         I         I         I
          .82       .67      1.00       I         I         I         I         I         I         I
          .82      1.00      1.00       I         I         I         I         I         I         I
          .91      1.00      1.00       I         I         I         I         I         I         I
         1.00      1.00      1.00       I         I         I         I         I         I         I
         1.00      1.00      1.00       I         I         I         I         I         I         I
         1.00      1.00      1.00       I         I         I         I         I         I         I
         1.00      1.00      1.00       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I
            I         I         I       I         I         I         I         I         I         I

ENGAGMENT MOE  =   .550
```

RANGE

40.00	40.00	I	I
36.22	36.23	I	I
32.45	32.45	I	I
28.67	28.68	I	I
24.90	24.91	I	I
21.12	21.14	I	I
17.35	17.38	I	I
13.58	13.62	I	I
9.82	9.87	I	I
6.07	6.16	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I

BEARING

270.00	270.72	I	I
270.15	270.94	I	I
270.33	271.22	I	I
270.57	271.56	I	I
270.87	272.02	I	I
271.28	272.63	I	I
271.87	273.52	I	I
272.78	274.89	I	I
274.40	277.30	I	I
278.03	282.64	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I

AVERAGE POSTERIOR PROBABILITY

.16	.50	.34
.08	.53	.39
.13	.69	.18
.25	.66	.09
.24	.63	.13
.05	.79	.16
.16	.68	.16
.02	.72	.26
.13	.76	.11
.13	.72	.15

PROBABILITY OF PREFERENCE

.05	.75	.20
0.00	.70	.30
0.00	.90	.10
.25	.70	.05
.20	.75	.05
0.00	.95	.05
.10	.85	.05
0.00	.80	.20
.15	.80	.05
.10	.80	.10

```
PROBABILITY OF CLASSIFICATION
            .10        .65        .25        I          I          I          I          I          I          I

DISTRIBUTION OF CLASSIFICATION DECISION
           0.00        .08        .40        I          I          I          I          I          I          I
           0.00        .15       1.00        I          I          I          I          I          I          I
           0.00        .23       1.00        I          I          I          I          I          I          I
           0.00        .46       1.00        I          I          I          I          I          I          I
           1.00        .69       1.00        I          I          I          I          I          I          I
           1.00        .77       1.00        I          I          I          I          I          I          I
           1.00        .77       1.00        I          I          I          I          I          I          I
           1.00        .85       1.00        I          I          I          I          I          I          I
           1.00        .85       1.00        I          I          I          I          I          I          I
           1.00       1.00       1.00        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I

PROBABILITY OF TACTICAL DECISION
            .10        .65        .25        I          I          I          I          I          I          I

DISTRIBUTION OF TACTICAL DECISION
           0.00        .08        .40        I          I          I          I          I          I          I
           0.00        .15       1.00        I          I          I          I          I          I          I
           0.00        .23       1.00        I          I          I          I          I          I          I
           0.00        .46       1.00        I          I          I          I          I          I          I
           1.00        .69       1.00        I          I          I          I          I          I          I
           1.00        .77       1.00        I          I          I          I          I          I          I
           1.00        .77       1.00        I          I          I          I          I          I          I
           1.00        .85       1.00        I          I          I          I          I          I          I
           1.00        .85       1.00        I          I          I          I          I          I          I
           1.00       1.00       1.00        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I
              I          I          I        I          I          I          I          I          I          I

ENGAGMENT MOE  =   .650
```

RANGE

40.00	40.00	I	I
36.22	36.23	I	I
32.45	32.45	I	I
28.67	28.68	I	I
24.90	24.91	I	I
21.12	21.14	I	I
17.35	17.38	I	I
13.58	13.62	I	I
9.82	9.87	I	I
6.07	6.16	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I

BEARING

270.00	270.72	I	I
270.15	270.94	I	I
270.33	271.22	I	I
270.57	271.56	I	I
270.87	272.02	I	I
271.28	272.63	I	I
271.87	273.52	I	I
272.78	274.89	I	I
274.40	277.30	I	I
278.03	282.64	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I

AVERAGE POSTERIOR PROBABILITY

.17	.30	.53
.10	.19	.71
.26	.20	.54
.38	.33	.29
.41	.28	.31
.20	.34	.46
.20	.22	.58
.15	.16	.69
.12	.20	.68
.20	.11	.69

PROBABILITY OF PREFERENCE

.05	.35	.60
.05	.20	.75
.20	.25	.55
.35	.35	.30
.45	.30	.25
.15	.30	.55
.20	.20	.60
.10	.15	.75
.05	.20	.75
.15	.05	.80

```
PROBABILITY OF CLASSIFICATION
           .05       .10       .85       I         I         I         I         I         I         I

DISTRIBUTION OF CLASSIFICATION DECISION
          0.00      0.00       .18       I         I         I         I         I         I         I
          0.00      0.00       .47       I         I         I         I         I         I         I
          0.00      0.00       .71       I         I         I         I         I         I         I
          1.00       .50       .76       I         I         I         I         I         I         I
          1.00       .50       .76       I         I         I         I         I         I         I
          1.00       .50       .76       I         I         I         I         I         I         I
          1.00       .50       .82       I         I         I         I         I         I         I
          1.00       .50       .88       I         I         I         I         I         I         I
          1.00       .50      1.00       I         I         I         I         I         I         I
          1.00      1.00      1.00       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I

PROBABILITY OF TACTICAL DECISION
           .05       .10       .85       I         I         I         I         I         I         I

DISTRIBUTION OF TACTICAL DECISION
          0.00      0.00       .18       I         I         I         I         I         I         I
          0.00      0.00       .47       I         I         I         I         I         I         I
          0.00      0.00       .71       I         I         I         I         I         I         I
          1.00       .50       .76       I         I         I         I         I         I         I
          1.00       .50       .76       I         I         I         I         I         I         I
          1.00       .50       .76       I         I         I         I         I         I         I
          1.00       .50       .82       I         I         I         I         I         I         I
          1.00       .50       .88       I         I         I         I         I         I         I
          1.00       .50      1.00       I         I         I         I         I         I         I
          1.00      1.00      1.00       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I
             I         I         I       I         I         I         I         I         I         I

ENGAGMENT MOE  =   .850
```

Appendix C

INPUT AND OUTPUT OF THE DOUBLE-TARGET EXAMPLE

```
      SUBROUTINE INPUT
C
      COMMON /A/ GV,NREP,NMAX
      COMMON /B/ IMAX,MMAX,JMAX
      COMMON /C/ LAMAX,KDMAX,IR
      COMMON /D/ LP(12),LA(12),NA(20,2),KA(2)
      COMMON /E/ KF(12),NF(12),KT(10,2),TS
      COMMON /F/ XO(2),YO(2),CO(20,2),SO(20,2),DO(20,2)
      COMMON /G/ XT(2),YT(2),CT(20,2),ST(20,2),DT(20,2)
      COMMON /H/ WTH(5),TAV(5),NUM(5),DET(5),MEM(5)
      COMMON /I/ DH(2),DV(2),HN(2),VN(2),SL(2)
      COMMON /J/ FRQ(12),PLL(12,3)
      COMMON /K/ PBB(6,3),FQB(6,3)
      COMMON /L/ PNN(6,2),FQN(6,2)
      COMMON /M/ MIX(5),SDV(5),TAU(5),BIAS(5)
      COMMON /N/ PRIOR(10),VAL(10,10),FVAL,VMAX(10)
C
      DIMENSION SCR(5),FCS(5),TOT(5)
      REAL MIX
C
      DATA GV   /808./
      DATA NREP /20/
      DATA NMAX /10/
      DATA TS   /10./
      DATA IMAX /9/
      DATA MMAX /2/
      DATA KT   /1,1,1,2,2,2,3,3,3,0,
     +           1,2,3,1,2,3,1,2,3,0/
      DATA IR   /3/
      DATA PRIOR/10*.1/
      DATA KDMAX /9/
      DATA VAL  /9*(1.,0.,0.,0.,0.,0.,0.,0.,0.,0.),1./
      DATA FVAL /.95/
      DATA XT /0.,5./
      DATA YT /40.,40./
      DATA CT /40*155./
      DATA ST /40*25./
      DATA DT /40*30./
      DATA JMAX /7/
      DATA NF /1,1,1,1,1,1,1, 5*0/
      DATA KF /1,1,1,3,3,3,3, 5*0/
      DATA FRQ /50.,100.,400.,2*2828.,2*5656., 5*0./
      DATA PLL /155., 0., 150.,  -3.,-3.,-3.,-20.,   5*0.,
     +          155.,150., 0.,  -20.,-3.,-20.,-3.,   5*0.,
     +           0., 150.,150.,  -20.,-20.,-2.,-2.,  5*0./
      DATA PBB /3*( 153.,155.,145.,125.,0.,0.)/
      DATA FQB /3*( 10.,100.,1000.,10000.,0.,0.)/
      DATA LAMAX /2/
      DATA LA /2,2,2,1,1,1,1, 5*0/
      DATA KA /1,2/
      DATA DH /7.,60./
      DATA DV /5.,0./
      DATA HN /15.,30./
      DATA VN /11.,1./
      DATA SL /.01,.01/
```


PRECEDING PAGE BLANK-NOT FILMED

```
      DATA XØ /0.,-.5/
      DATA YØ /0.,0./
      DATA CØ /40*90./
      DATA SØ /40*10./
      DATA DØ /40*100./
      DATA NA /40*1/
      DATA PNN /120.,65.,65.,45., 2*0.,
     +          75.,65.,45.,3*0./
      DATA FQN /10.,300.,1000.,10000.,2*0.,
     +          10.,1000.,10000.,3*0./
      DATA LP /1,1,1,2,2,3,3, 5*0/
      DATA WTH /1.,2000.,4000., 2*0./
      DATA SCR /1.,1.,1., 2*0./
      DATA FCS /600.,60.,60., 2*0./
      DATA TØT /30.,10.,10., 2*0./
      DATA DET /2.,2.,2., 2*0./
      DATA MIX /5*0.5/
      DATA SDV /3.,3.,1.,3.,3./
      DATA TAU /5*3./
C
C  ** CALCULATE TAV, NUM, MEM
      DØ 30 LL=1,5
      TAV(LL)=60./(SCR(LL)*FCS(LL))
      NUM(LL)=SCR(LL)*TS+.5
      MEM(LL)=TØT(LL)/TS-.5
   30 CØNTINUE
C
C  ** CALCULATE BIAS
      DØ 40 KR=1,5
   40 BIAS(KR)=(SDV(KR)**2)/8.68
C
C  ** FIND MAXIMUM VALUE
      DØ 50 I=1,IMAX
      VMAX(I)=-1.E99
      DØ 50 KD=1,KDMAX
      IF(VAL(I,KD).GT.VMAX(I)) VMAX(I)=VAL(I,KD)
   50 CØNTINUE
      RETURN
      END
```

RANGE

40.00	40.00	40.31	40.38
36.22	36.23	36.58	36.65
32.45	32.45	32.86	32.94
28.67	28.68	29.15	29.25
24.90	24.91	25.47	25.58
21.12	21.14	21.82	21.95
17.35	17.38	18.21	18.37
13.58	13.62	14.70	14.90
9.82	9.87	11.36	11.62
6.07	6.16	8.39	8.74
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I

BEARING

270.00	270.72	277.12	277.83
270.15	270.94	278.01	278.78
270.33	271.22	279.08	279.94
270.57	271.56	280.44	281.40
270.87	272.02	282.19	283.28
271.28	272.63	284.52	285.79
271.87	273.52	287.79	289.28
272.78	274.89	292.65	294.42
274.40	277.30	300.44	302.57
278.03	282.64	314.20	316.55
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I
I	I	I	I

AVERAGE POSTERIOR PROBABILITY

.02	.04	.07	.03	.10	.10	.13	.12	.38	I
.13	.08	.17	.09	.04	.08	.07	.09	.25	I
.18	.12	.20	.12	.03	.04	.12	.07	.12	I
.18	.07	.18	.11	.07	.15	.08	.04	.11	I
.25	.22	.14	.15	.07	.06	.04	.04	.04	I
.19	.09	.33	.04	.07	.12	.05	.03	.09	I
.10	.15	.21	.05	.07	.09	.07	.09	.17	I
.15	.14	.28	.06	.03	.13	.04	.07	.10	I
.16	.12	.33	.07	.03	.10	.07	.01	.12	I
.23	.11	.25	.07	.02	.08	.09	.03	.12	I
I	I	I	I	I	I	I	I	I	I
I	I	I	I	I	I	I	I	I	I
I	I	I	I	I	I	I	I	I	I
I	I	I	I	I	I	I	I	I	I
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PROBABILITY OF PREFERENCE

.05	.05	.05	0.00	.15	0.00	.10	.15	.45	I
.25	.05	.20	.05	0.00	.05	0.00	.10	.30	I
.10	.10	.25	.10	0.00	.05	.20	.05	.15	I
.25	.05	.20	.10	0.00	.10	.10	.05	.15	I
.30	.25	.05	.25	.05	0.00	0.00	0.00	.10	I
.30	.05	.40	0.00	.10	.10	0.00	0.00	.05	I
.10	.25	.15	.05	.05	.10	.05	.15	.10	I
.25	.15	.30	0.00	0.00	.10	0.00	.10	.10	I
.20	.15	.35	0.00	0.00	.10	.10	0.00	.10	I
.40	.05	.25	.05	0.00	.05	.10	0.00	.10	I
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PROBABILITY OF CLASSIFICATION

.35	.05	.20	.05	0.00	.05	.10	0.00	.20	I

DISTRIBUTION OF CLASSIFICATION DECISION

0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	.50	I
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	.50	I
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	.50	I
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	.50	I
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	.50	I
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	.50	I
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	.50	I
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	.50	I
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	.50	I
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PROBABILITY OF TACTICAL DECISION

.35	.05	.20	.05	0.00	.05	.10	0.00	.20	I

DISTRIBUTION OF TACTICAL DECISION

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0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	.50	I
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	.50	I
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	.50	I
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	.50	I
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	.50	I
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	.50	I
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	.50	I
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