A TRAINING ANALYSIS EVALUATION OF ASW TRAINER OCEAN MATH MODELS

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I. INTRODUCTION

A fundamental purpose of the Anti-Submarine Warfare (ASW) training effort is to train the crew of an ASW weapon system to efficiently perform its mission -- detect, classify, and when necessary, destroy enemy submarines. Such training is being provided by sophisticated simulators which create and present synthetic target information to trainees. The fidelity of this information is a function of the continual solution of an ocean math model in a simulation computer. Thus, the ocean math model has a major impact on ASW training effectiveness by means of its fundamental contribution to the fidelity of displayed data from which detection and classification decisions can be made; i.e., the cues for submarine detection and classification in the simulated situation are the same as those for the real world.

Within the past several years, increased capability of ASW equipment has necessitated the development of more sophisticated ASW trainers. In order to effectively simulate/stimulate the newer, more sensitive equipment, the trainers have had to correspondingly generate more accurate ocean acoustic phenomena. The demand for greater ocean acoustic fidelity in ASW trainers has raised a familiar debate as to how much simulation fideility is needed to produce effective training. This paper reports on the methods developed by The Singer Company's Simulation Products Division (and the progress to date) to evaluate various ocean math models (in terms of ASW training effectiveness) by means of a unique computer simulation approach.

The most common approach used to measure the effectiveness of competing training systems is to experimentally design a controlled environment where the results using the different training systems, in this case different ocean math models, can be measured. This approach, as depicted on the right side of Figure 1, requires the elements of classical experimental design— experimental and control groups. If that approach were implemented, the training experiment for evaluating candidate ocean math models would be designed to divide the subjects into experimental and control groups, where the former would be trained using a non-standard ocean model, and the latter a standard ASWEPS (Anti-Submarine Warfare Environmental Prediction Service) ocean model. Both groups would exercise human decision making processes while undergoing the same training effort. The ability of the ASW team to efficiently perform the desired mission would be measured by means of a performance evaluation. Based on experimental criteria, the results of the performance evaluation would yield information as to the effectiveness of the different ocean math models.

Although the above approach is the most common used, it is difficult to implement due to logistics problems and the high cost of personnel and equipment needed. These problems precipitated the need for the unique approach diagrammed on the left side of Figure 1. This approach, applying

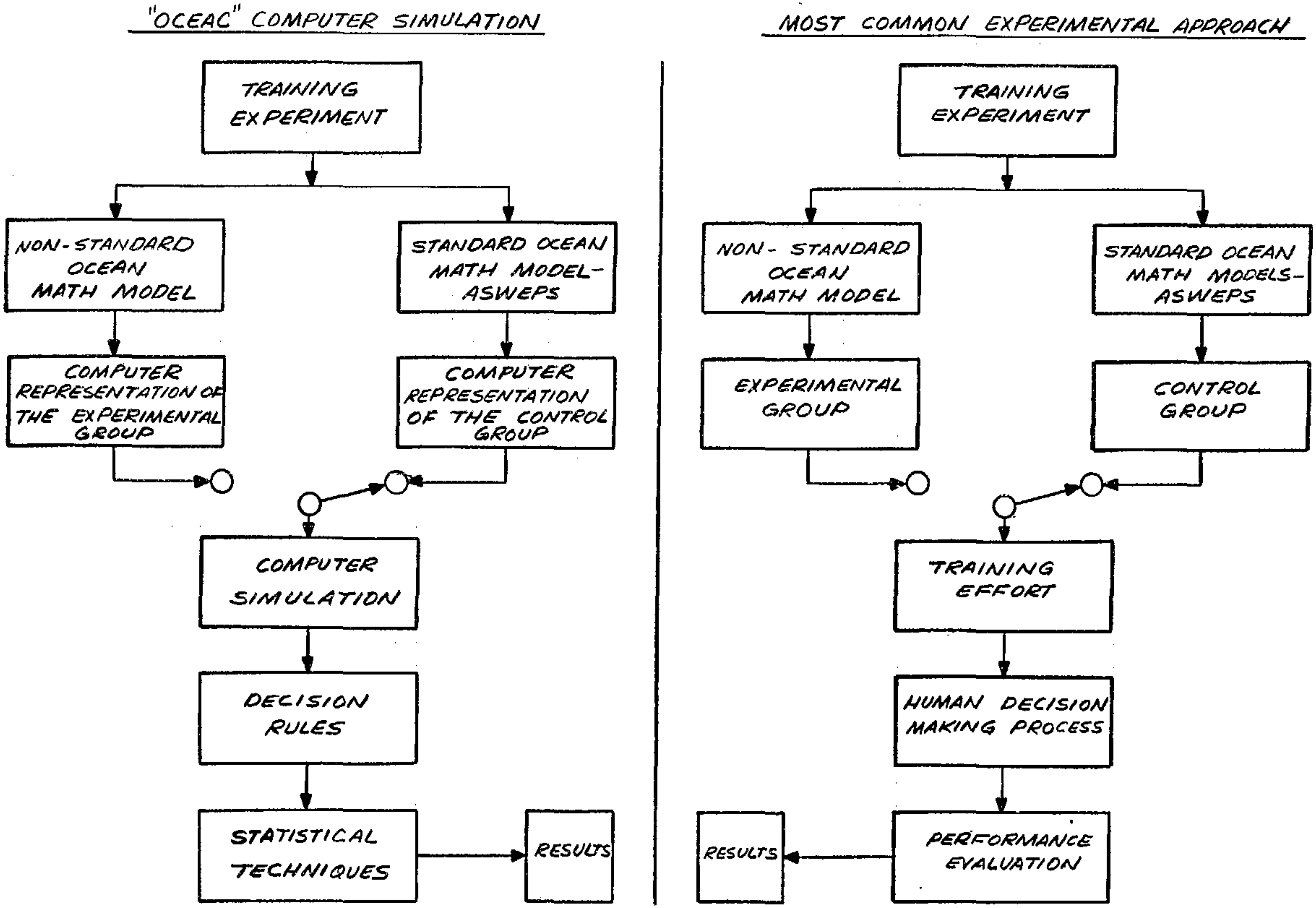

Figure 1. ASW Trainer Ocean Math Model Evaluation Approaches

a computer simulation model named OCEAC*, integrates the techniques of training analysis and operations research.

Using OCEAC, the personnel needed to conduct the common experimental approach mentioned above are replaced by computer representations of both experimental and control groups, and logistics problems (such as aircraft, sonobuoys, etc.) are programmed in the computer simulation. Also, OCEAC uses decision rules to mimic the human decision-making process when detection and classification situations arise, and automatic statistical techniques are used to measure performance evaluation. In the same manner as the classical experimental approach, the results yield training effectiveness information to be used in a selection/evaluation procedure for ASW trainers.

The next section presents the training analysis conducted for the design of OCEAC. Section III discusses the quantification of the training analysis design using operations research techniques.The fourth section discusses the current state of development of OCEAC, and the last section describes results expected in the near future.

II. THE TRAINING ANALYSIS

The design of OCEAC is based on a systematic, three-phase training analysis to:

a) Investigate the role of the ocean math model in ASW training

b) Analyze the ASW training environment by means of interviews with ASW instructors using a questionnaire developed during the investigation of the role of the ocean math model

c) Integrate the data collected from the interviews into the OCEAC design.

A discussion of the phases in the training analysis follows.

Phase I confirmed that, in its most common form, the role of the ASW trainer ocean math model is to perform a continuous solution of complex algorithms of ocean acoustic phenomena as part of a real time simulation program. The ocean math model accounts for ocean acoustic phenomena such as propagation loss. Its output, after adaptations by the computer complex, is presented both visually and aurally to the trainee in the same manner as in the real-world tactical environment. The student, acting as a human decision maker, integrates the ocean math model outputs and other information to make the decision as to whether or not an enemy submarine is present. Thus, the displayed outputs from the ocean math model affect student ASW operator decisions.

*OCEAC is an acronym for the Ocean Accuracy Computer Simulation Model developed by The Singer Company's Simulation Products Division.

During Phase II of the training analysis, a detailed analysis of the ASW training environment was structured to gather design inputs to OCEAC. Based on the previous conclusion that the display outputs from the ocean model affects student ASW operator decisions, the analysis began by investigating how the ASW operator uses the display outputs. This analysis of ASW crew tasks led to the investigation of how ASW training is currently being conducted. In order to structure the ASW training environment for OCEAC development, it was necessary to study that environment in detail. The method to carry out the study took the form of the questionnaire presented in Table 1. These questions were developed from data gathered during Phase I and the subsequent crew task analysis. The questions were structured in a logical order. That is, the first several questions concern the ASW mission itself, followed by questions to determine how the ocean model display data is used in the human decision-making process to accomplish a mission. Then information as to the functions of the instructor were asked, followed by questions concerning instructor actions such as performance evaluation.

This questionnaire was used in fixed-format interviews with ASW acoustic instructors at the FASOTRAGRULANT and VP-30 detachments, Patuxent River Naval Air Station, Patuxent River, Maryland. By interviewing instructors, detailed data was obtained that only experienced personnel could provide. The instructors were given a briefing on the purpose of developing an ASW ocean model evaluation technique, the necessity for the interview, and the ultimate utilization of the interviews.

Phase III, the integration of data collected from the interviews into the OCEAC design, commenced upon completion of the interviews. The method used was to qualitatively combine answers for each question from the ASW instructor interviews. Next, the answers were grouped into appropriate units such as instructor and student behavior and outcomes from the exhibited behavior. These units were then regrouped into modules.

The problem then arose as to how to link the modules together into a computer simulation model to evaluate ASW training ocean math models. The solution forms the basic design of OCEAC and simulates the ASW environment. The students are taught ASW skills; and, upon completion of training, transfer these skills to the real-world tactical environment. Thus, the modules were grouped into two major areas, training and tactics. OCEAC is designed to evaluate ocean math models by:

a) Measuring the skills learned in training

b) Quantitatively defining the transfer of learned skills to the tactical environment

c) Measuring the performance level in the tactical environment.

The performance results in the tactical environment provide the data necessary to evaluate the level of ocean model fidelity necessary to produce the desired performance in the operational (tactical) environment.

The method of measuring the skills and performance for ocean model evaluation necessitated quantification of the modules in the training and tactics

TABLE 1. QUESTIONNAIRE USED AS BASIS OF INTERVIEWS

1) How does the SENSO interpret the SOSUS data?

2) After the B/T buoy is dropped, how does the SENSO/TACCO modify the ASWEPS curve based on a different B/T velocity profile?

3) How is the sonobuoy spacing range determined from the ASWEPS curves?

4) After the spacing is determined, how is the decision made as to what particular buoy pattern is to be dropped?

5) Can the human decisions that lead to the buoy spacing and buoy drop pattern be readily quantified?

6) How does the equipment (gram/aural) input the receiver intensity level and how does it display that intensity?

7) Which mode of detection, gram or aural, is used more often, is more reliable, and can these feelings be expressed in a probability distribution to be used in a Monte Carlo simulation?

8) Given a change in intensity in either gram or aural, what is the probability distribution that the student should detect this change?

9) Based on the information level of the student (e.g., SOSUS intelligence, knowledge of ocean acoustics, and gram/aural sensory cues) how does the student (or operator) make the decision as to whether or not there is a detection?

10) Does the feedback from the instructor in the form of grading have any effect upon the student's decision process, and if so, can this effect be quantified?

11) Is there a discernable weighting factor in the data that the student uses in order to make a detection? For example, does the student "weigh" the gram more important than aural cues in the detection decision process?

12) Exactly what information does the instructor have in the training environment?

13) How does the instructor use this information to make the decision as to whether or not the student should have made a detection?

14) What thought mechanisms are involved in the instructor's decision as when to give feedback to the student; whether or not to rerun the same training situation; whether to start on a new problem?

15) What factors are involved in the training performance evaluation?

16) How is this performance evaluation used in the training exercise?

area. The operations research techniques used in the quantification are presented next.

III. OPERATIONS RESEARCH QUANTIFICATION TECHNIQUES

The operations research techniques used to quantify the OCEAC design include a computer simulation model, containing both stochastic and deterministic components; a utility function based on utility theory; and human behavior analysis in the form of structured decision rules.

The first quantification problem confronted was the method to:

a) Measure skills learned
b) Transfer skills
c) Measure performance levels.

Figure 2 depicts the block diagram solution. Skills to be taught are inputs to the training area. The skills learned are measured in a utility function*, which serves as the vehicle transferring skills to the real-world

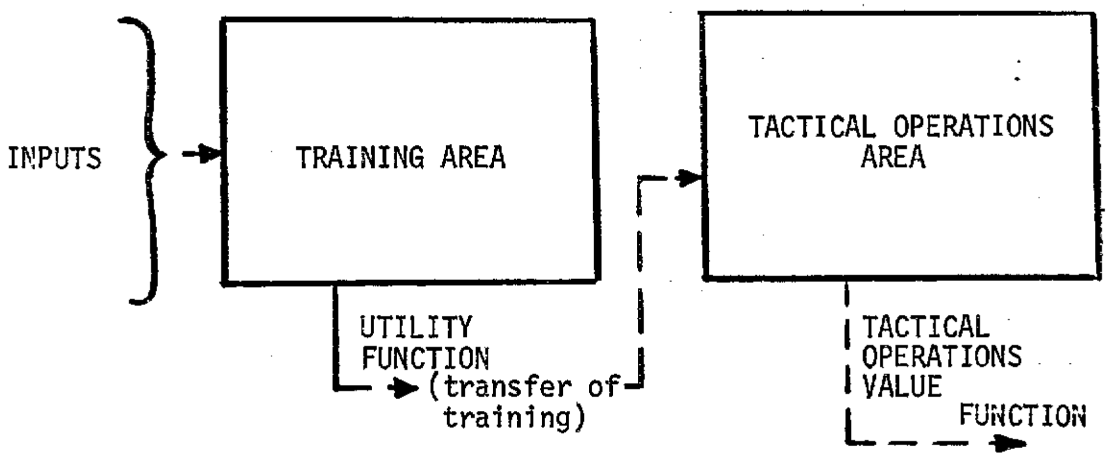

Figure 2. Quantification Solution.

* The utility function developed in this study is Based on utility theory--a theory of decision making under risk. In this writer's opinion, one of the major applications of utility theory is its ability to quantify human decisions under the conditions of uncertainty. For purposes of this study, the utility function developed represents the transfer of training from the training area to the tactical operations area in Figure 2. In this context, utility means the level of performance confidence that the student transfers from training to tactics. The trainee's performance confidence level is based upon such factors as the number of correct and incorrect decisions, instructor feedback, etc.

tactical area. The performance levels are measured in a tactical operations value function.

Further quantification was accomplished as shown in Figures 3 and 4 which detail the modules in the training and tactics areas. The modules in Figure 3 are the Student, Outcomes, Grading, and Utility; in Figure 4 the ASW Team and the Outcomes. The algorithms in both figures form the computations in the OCEAC model.

The first algorithm (A1) in the training area (see Figure 3) represents the behavior of the SENSO/TACCO in computing the sonobuoy spacing distance for a mission to detect an enemy submarine. This algorithm is a decision rule developed from analysis of human behavior extracted from the interviews questionnaire results presented in Section II, and is

$$FOM = SL - AMBNOS - RD \tag{1}$$

where

FOM = Figure of merit

SL = Source level

AMBNOS = Ambient noise

RD = Recognition differential

and

$$SPACE = 1.5\ R \tag{2}$$

where

SPACE = Computed sonobuoy spacing distance to be used in the drop pattern

R = FOM range value from the appropriate ASWEPS curve.

After executing the sonobuoy drop pattern with the computed spacing distance, the student makes detection decisions. Algorithms A2, A3, and A4 represent these decisions. A2, a deterministic component which simulates the display to the student from ocean model computation outputs, is comprised of the experimental ocean acoustic model defined as:

a) A propagation loss table (PL) for R, where R is the range between the source and receiver

b) The target represented by a source level (SL)

c) Environmental factors represented by ambient noise (AMBNOS).

The A2 formulas are:

$$RECINT = SL - PL \tag{3}$$

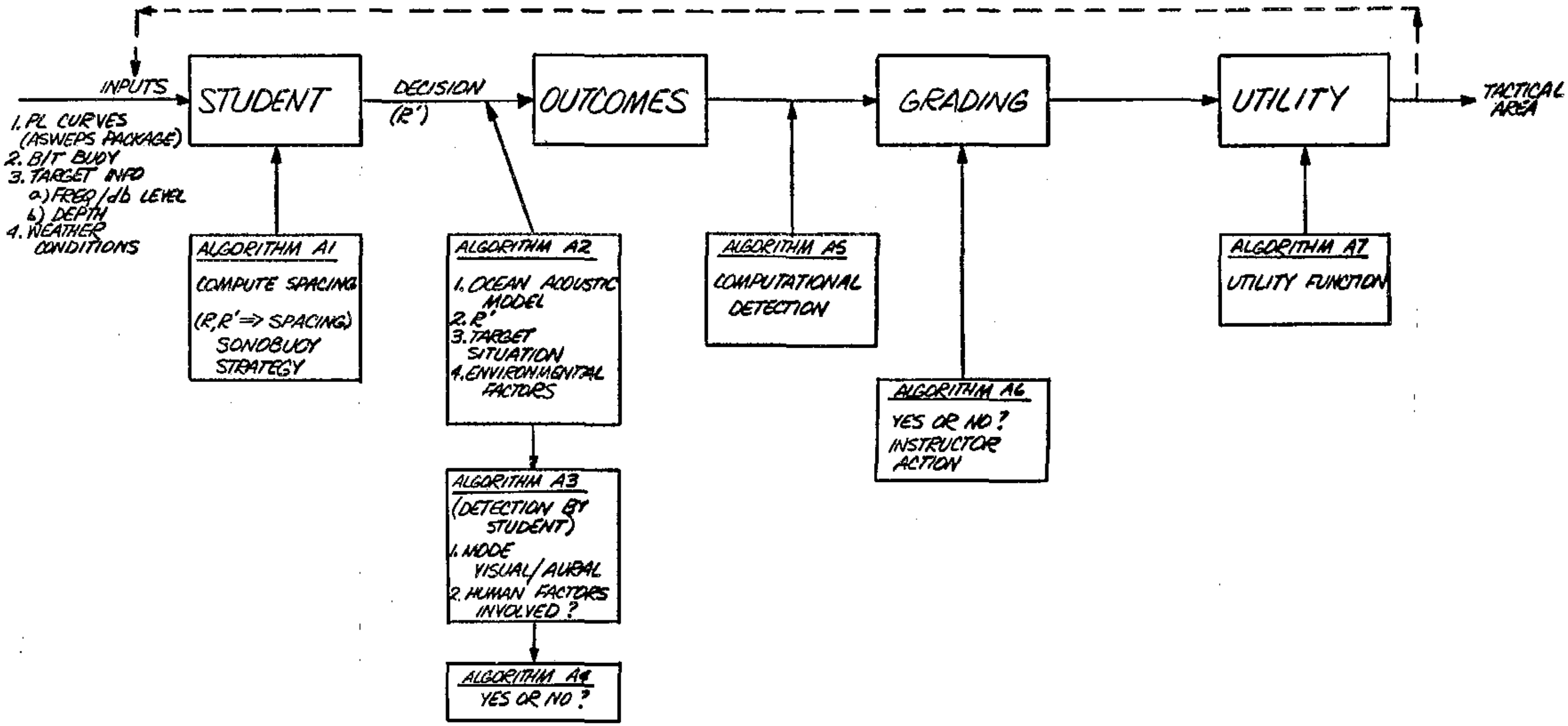

Figure 3. Training Area

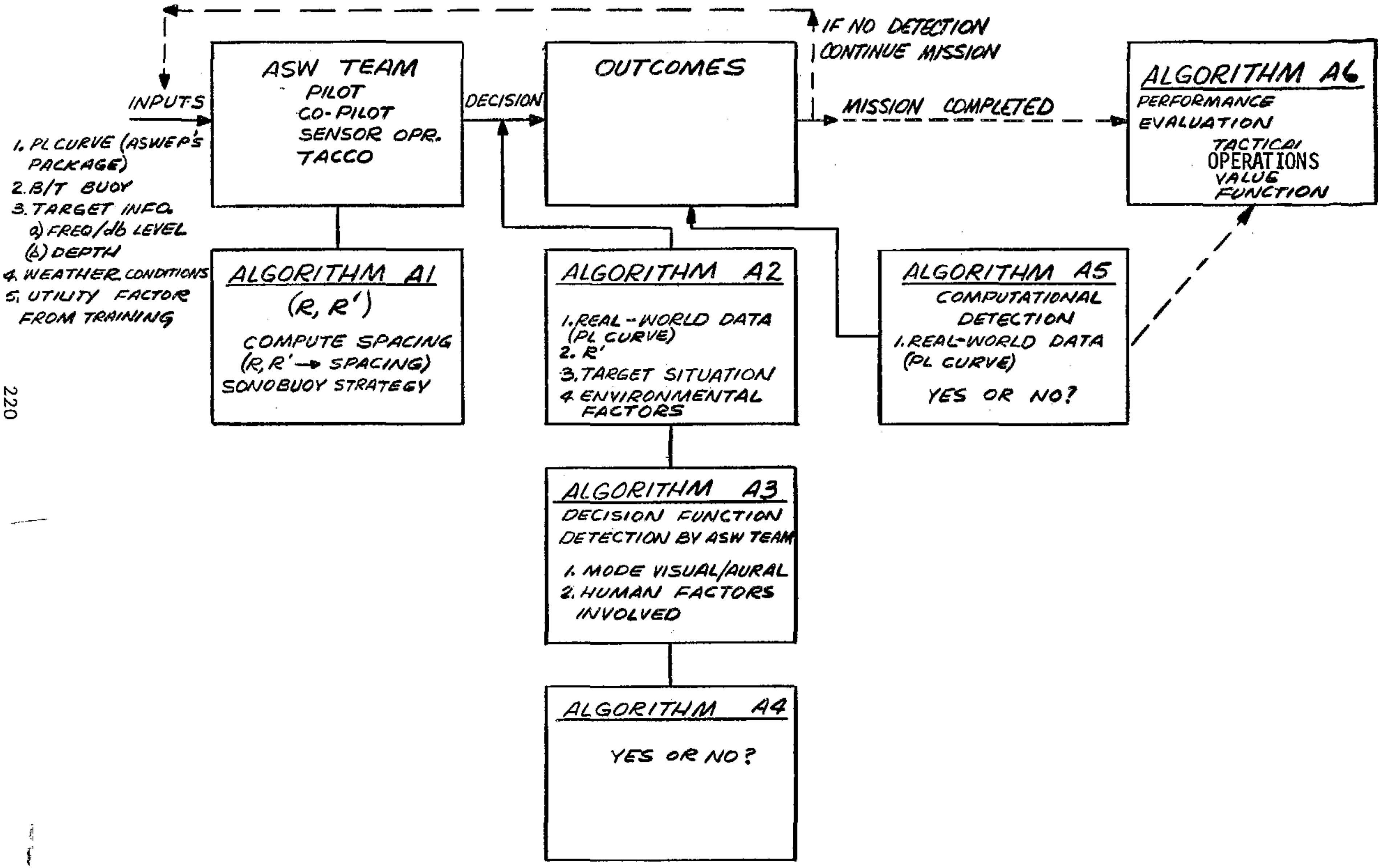

Figure 4. Tactical Area

where

RECINT = Acoustic intensity at the receiver

and

SE = RECINT - AMBNOS (4)

where

SE = Signal excess for a particular display mode.

Following A2, A3 computes the information/cues used by the student's detection decision by quantifying the human factor present in the detection mode chosen. (As of this writing, the visual mode only has been quantified.) A4, the actual decision, represents stochastic processes such as the probability of a human eye detecting a certain intensity of lightness or darkness on a display unit.

The A3 computation is:

IPX = A coded number that quantifies the SE shading intensity on the visual display. (5)

The A4 equations are

A PERCEPTION = RANF $\leq$ CUMDIS + ψfactor (6)

where the student's perception of a shading is computed by generating a random number and comparing it to a cumulative perception probability distribution for the shading plus a psychological factor such as experience

YES/NO = f (TIME, perception ratio) (7)

where the detection function is a decision rule representing the student's behavior. To make a detection, the student must have experienced a required ratio of perception over a specified period of time.

The detection decision by the student is the outcome module in Figure 3. Next, algorithms A5 and A6 measure the skills learned in the form of grading by the instructor. These algorithms are quantified as input tables to OCEAC, and simulate the instructor's design of the training problem presented to the student. A5 and A6 grade the student's detection decision based on the detection sonobuoy, signal excess, and the time of detection.

Finally, when the training problem is completed, the skills learned by the student and transferred to the tactical area are computed in algorithm A7 as follows:

UF = Ratio of correct perceptions to total perceptions (if correct detection made), or 0 (if correction detection not made) (8)

where

$$UF = \text{Utility factor}$$

The tactical area (see Figure 4) receives the same inputs as the training area with the addition of the utility factor (UF) from training. The performance confidence levels (i.e., UF) operators receive from training affect tactical decisions made. Algorithm A1, a decision rule, computes the sonobuoy spacing distance in the same manner as A1 in the training area, thus

$$FOM = SL - AN - RD \quad \text{(see EQ.1)} \tag{9}$$

and

$$SPACE = \begin{Bmatrix} CONFC1 \\ CONFC2 \\ CONFC3 \end{Bmatrix} R \tag{10}$$

where

SPACE = Computed sonobuoy spacing distance to be used in the drop pattern

CONFC1, CONFC2, CONFC3 = Input constants reflecting the following UF's:

If $0 \leq UF \leq 0.33$, use CONFC1

If $0.34 \leq UF \leq 0.67$, use CONFC2

If $0.68 \leq UF \leq 1.0$, use CONFC3

$$CONFC1 < CONFC2 < CONFC3$$

R = FOM range value from the appropriate ASWEPS curve.

A high UF results in a larger multiplier in Equation 10, yielding SPACE. Increasing SPACE decreases the probability of detection. Thus, more confidence from training (i.e., a higher UF) reduces the necessary probability of detection, resulting in a larger sonobuoy spacing distance. Conversely, a low UF results in a smaller multiplier, effecting a decrease in SPACE which, in turn, increases the probability of detection.

The ASW team executing the sonobuoy drop pattern with the computed spacing distance makes detection decisions. Algorithms A2, A3, and A4 represent these decisions in a manner similar to the corresponding algorithms in the training area. Algorithm A2's formula, Equations 11 and 12, are the same as Equations 3 and 4 with one exception: experimental ocean math model propagation loss table value PL is replaced with PLX, the real-world propagation loss value.

$$RECINT = SL - PLX \tag{11}$$

$$SE = RECINT - AMBNOS \tag{12}$$

The A3 formula is the same as is training (see Equation 5). The perception and detection formulas (A4) are modified by the UF in a manner similar to Equation 10. The operator's perception formula, Equation 13, reflects the UF as follows:

$$\text{A PERCEPTION} = \text{RANF} \geq \text{CUMDIS} + \text{Modified } \psi \text{ factor} \tag{13}$$

where a perception, RANF, and CUMDIS are the same as in Equation 6, and the modified ψ factor reflects performance confidence by increasing the ability to make perceptions with a high confidence and decreasing the ability with a lower confidence.

The detection decision rule, YES/NO, also reflects the UF as follows:

$$\text{YES/NO} = f\ (\text{time, perception ratio}) \tag{14}$$

where the YES/NO function is same as Equation 7 with one exception: the required ratio of perception over a specified period of time is altered by the UF as follows:

if $0 \leq UF \leq 0.33$, the required ratio is raised since the confidence is low

if $0.34 \leq UF \leq 0.67$, the required ratio is the same since the confidence is medium

if $0.68 \leq UF \leq 1.0$, the required ratio is lowered since the confidence is high.

The detection decision by the team is the outcome module in Figure 4. Next, Algorithm A5 represents realistically whether a valid detection has occurred in the real world tactical situation. A5 is similar to Algorithm A6 in training with respect to its input table structure.

Upon completion of the mission, the tactical operation value function, Algorithm A6, is computed as follows:

$$\text{Tactical operations value} = \begin{cases} 0 & \text{(if no correct detection made)} \\ 100 - \text{PENFAC} & (\text{if } 0 \leq \text{TIME} \leq \text{T1}) \\ 90 - \text{PENFAC} & (\text{if T1} < \text{TIME} \leq \text{T2}) \\ 80 - \text{PENFAC} & (\text{if T2} < \text{TIME} \leq \text{T3}) \\ 70 - \text{PENFAC} & (\text{if T3} < \text{TIME} \leq \text{T4}) \\ 60 - \text{PENFAC} & (\text{if T4} < \text{TIME} \leq \text{T5}) \\ 0 & (\text{if TIME} \geq \text{T5}) \end{cases} \quad \begin{matrix}\text{(If correct detection made)}\end{matrix} \tag{15}$$

where

TIME = Time that the correct detection was acquired

T1 thru T5 = Input parameters representing realistic judgements

PENFAC = Ratio of incorrect perceptions to total perceptions.

This Tactical Operations Value is the performance measurement for the experimental ocean math model for a particular mission. The interpretation of this value and the development of OCEAC to date are discussed in the next section.

IV. THE OCEAC MODEL

The Singer Ocean Accuracy Model (OCEAC) is a computer simulation model featuring convenient parameter inputs and an easily interpretable printout of results for decision making by both management and scientists. The capabilities to date are as follows:

a) Up to five training ocean math models can be evaluated against five different missions in one computer run.

b) The training ocean math models can be evaluated in an overall fashion, i.e., the best ocean model for several missions. Alternatively, the ocean models can be evaluated as to which training model is the best for a particular mission.

c) The simulation model has the potential to include many types of ASW tactical missions, where a mission can be specified in the following five parts:

1) Combat Condition (peace, war, or cold war)

2) Operations Area (ocean location)

3) Target Information:

- Expected acoustic frequency spectrum
- Type of target
- Mode of operation
- Expected tactics:
  - --Depth
  - --Heading
  - --Speed Rate

4) Mission Objectives:

- Track target only
- Search and destroy target

5) Mission Tactics:

- Directed procedure
- Optional procedure
- Sonobuoy decisions (type, life, depth setting)

d) Individual differences for both students and instructors can be represented in the model. Such factors as experience, confidence, and anxiety have an effect on the decisions made.

e) The ocean math model data is input in a convenient format. The specific mission, submarine(s) target information (and location), and environmental conditions are input to the ocean math model which then (through its acoustic mathematical equations) produce the propagation loss curve for the particular given conditions. Then the curves are input to the simulation model. The output of the ocean models (propagation loss curves) are input in tables.

In its computer form, OCEAC is a FORTRAN program designed in a modular fashion and consisting of the following 11 modules or routines:

	ROUTINE NAME	FUNCTIONAL DESCRIPTION
1.	OCEAC	Main routine, controls the OCEAC model
2.	SIMTRN	Controls the training area
3.	SIMTAC	Controls the tactical area
4.	FOMCMP	Computes FOM
5.	RSPACE	Computes sonobuoy spacing distance
6.	MISSON	Defines the mission
7.	DETECT	Decision rules for detection
8.	GRADE	Grades detection decision
9.	TIMCHK	Checks instructor tables for GRADE
10.	STATXX	Computes statistics
11.	PRNOUT	Prints out results.

OCEAC evaluates ASW training ocean math models using the following methodology. The main routine, controlling OCEAC, first simulates the training area by releasing control to SIMTRN which reads in the user input parameters and sets up the training problem. Next, FOMCMP computes the basic FOM, recognizing multiple modes of sensor operation, adjusting for different equipment recognition differential levels, and allowing for ambient noise. Then the TACCO's decision making process in determining the buoy spacing is computed by a decision rule in RSPACE. SIMTRN gives control to MISSON which updates the simulation clock, maneuvers target submarines, and "flys" the aircraft (dropping sonobuoys to specified depths, with specified life time, and in a given barrier pattern). MISSON then executes DETECT, GRADE, and TIMCHK until either a correct detection is made, or the simulation time limit is violated. Upon completion of the mission, STATXX calculates the utility factor, UF, described in the previous section.

OCEAC then simulates the training area for the remaining ASW training math models. An array is set up to hold the UF values for training ocean math models for each mission.

Then OCEAC simulates the tactical area by relinquishing control to SIMTAC which executes FOMCMP and RSPACE. The FOM value and spacing distance are computed using the performance confidence training utility factor value (the UF value for the ocean math model and mission under SIMTAC control) as described in Section II. Then MISSON drives DETECT, GRADE, and TIMCHK (also using the UF) in the same manner as it did for the training area. Upon completion of the mission, STATXX calculates an intermediate training mission value, TRNMSN, holding it in an array in the same manner as the UF array was formed.

The TRNMSN array then forms the tactical operations value by computing the average training value for each ocean math model. The results of OCEAC--i.e., the average training values (from 0 to 100) for the candidate ocean math models--are then subject to evaluation. As a general rule, the higher the training value the better the ocean math model is for ASW training purposes.

V. EXPECTED RESULTS

As of the writing of this paper, the Singer simulation model to evaluate ASW training ocean math models is being validated. The ocean math models to be evaluated are high, low, and constant propagation loss ocean models which are most suitable for validating OCEAC. In the near future, it is expected that sophisticated ocean models such as ray tracing, normal mode, and the fast field program (FFP) will be evaluated under several different mission conditions. At this time, the only mission incorporated in OCEAC is the detection of an enemy submarine. In conjunction with evaluating more realistic and complex ASW training ocean math models, more missions will be developed to reflect a meaningful airborne ASW weapon system environment. Upon completion of the above plans, preparation will commence to validate the Singer approach by conducting an experimental training mission with both live subjects and the method proposed in this paper. A high correlation between results obtained with the OCEAC model in comparison with using live subjects to evaluate ASW trainer ocean math models would support the usage of the training analysis and operations research techniques presented in this paper.

In conclusion, upon completion of validation, this simulation model will provide management with a cost-effective and convenient method to evaluate the best ASW training ocean math model for their needs.

ABOUT THE AUTHOR

MR. M. ARONSON received his B.S. (Psychology) from the University of Maryland in 1967, and his M.B.A. (Management Science) from the University of Maryland in 1972. A Senior Systems Analyst in the Simulation Products Division of the Singer Company, Mr. Aronson is currently specializing in applying operations research techniques to methods of evaluating training systems.