NAVAL SHIP RESEARCH AND DEVELOPMENT CENTER

Bethesda, Maryland 20034

MAN-MACHINE ROLE IDENTIFICATION IN SEEKING IMPROVED SOLUTIONS TO LARGE-SCALE COMPUTER SIMULATION PROBLEMS

by

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Naval Ship Research and Development Center

and

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HRB - Singer, Inc.

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COMPUTATION AND MATHEMATICS DEPARTMENT

RESEARCH AND DEVELOPMENT REPORT

August 1973

Report 4244

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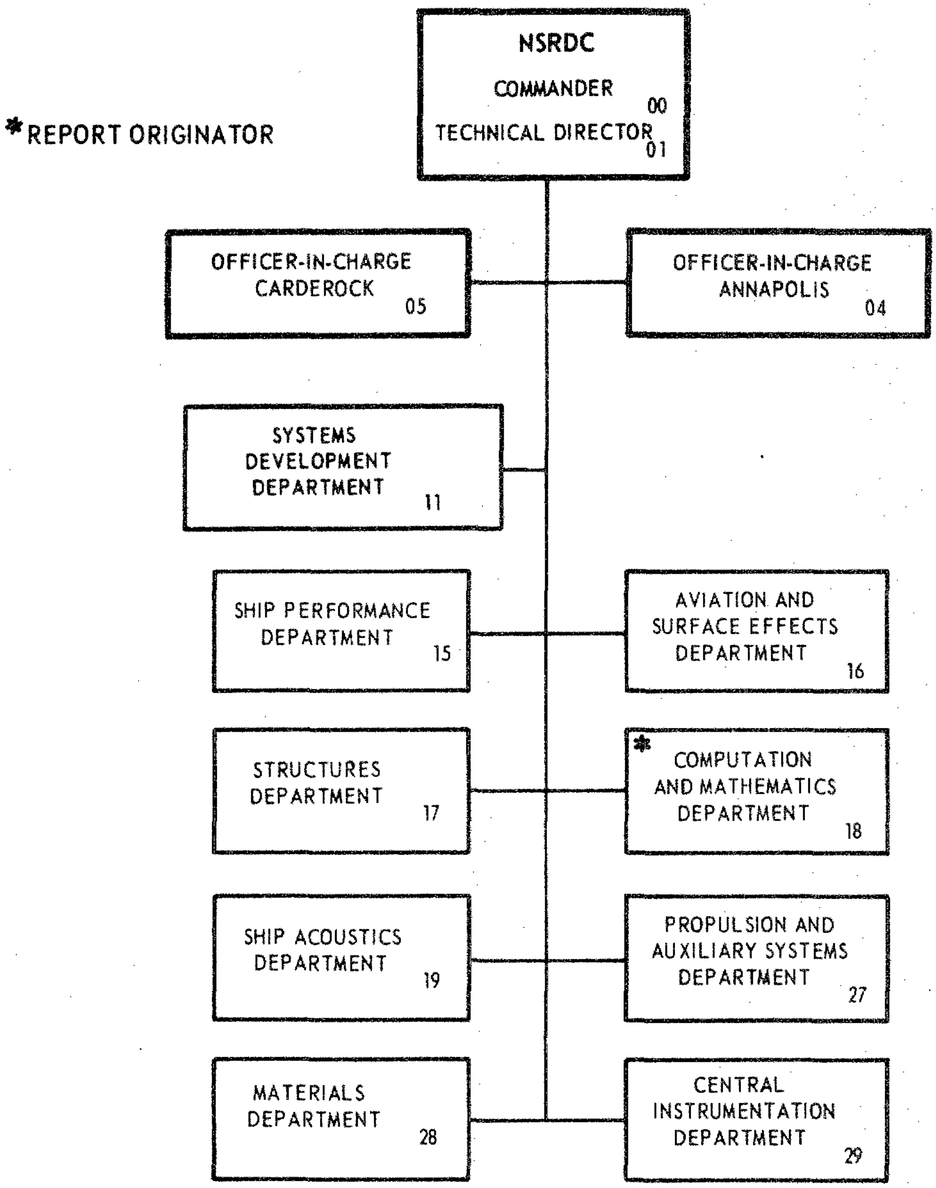

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ABSTRACT

This paper describes insights, procedures, and limitations involved in the semi-automatic solution of large-scale computer simulation problems. It utilizes the experience gained in solving test problems by both a human analyst and an automatic OPTIMIZER program. Particular attention is paid to those tasks performed by the man but not the machine and those tasks best done by the machine. Guidelines are suggested for incorporating some of the human problem-solving processes as a first step toward interactive semi-automatic procedures.

ADMINISTRATIVE INFORMATION

This effort was carried out by the Technology Development Group of the Operations Research Division. It was sponsored by the Naval Analysis Programs of the Office of Naval Research, Code 462, under program elements 65104N, 61102N, and 65152N, and performed under work unit number 1-1863-014.

1. Background

Many of the military operations research problems confronting decision makers today are either too expensive for experimental solution or too complicated for analytical treatment. A solution to these complex problems is frequently sought through computer simulation. However, computer simulation is subject to such practical constraints as reporting deadlines and approved budget expenditures (investment in computer processing and analyst time). These general resource guidelines establish a basic framework which limits the number of alternative problem-solving approaches that may be pursued by the analyst.

The quest for a solution to a complex problem, such as determining the optimal tactics to be exercised in a naval engagement, begins with an analyst making judgments as to possible "good" tactics. Then, using computer simulation, he examines the results of these tactics. On the basis of information gained from the simulation, he may determine other candidate tactics. This process may be repeated a number of times. When the analyst considers that no better results can be obtained or, as is more likely, runs out of time, he selects the "best" tactics in terms of some measure of effectiveness.

In far too many instances, this search for an improved solution degenerates into a trial-and-error process. Recognition of this situation gave rise to the concept of a computer simulation OPTIMIZER.[1] The OPTIMIZER is an executive FORTRAN computer program which can easily be interfaced with a simulation to conduct an adaptive, mathematically-disciplined search for an optimal solution.

The development of the OPTIMIZER was based on a "black box" view of computer simulation. That is, the simulation was regarded as a "black box" in which the values of input parameters (also called input variables) are combined in some manner to produce output parameters.

1. Smith, Dennis E.; "An 'OPTIMIZER' for Use in Computer Simulation: Background and Design Concepts," HRB-Singer, Inc., State College, Pa. 16801, July, 1970, Report No. 4352.11-R-1

The input parameters are of two types: (1) controllable factors, and (2) uncontrollable factors. Controllable factors are those input parameters which may be directly controlled by the decision maker in the "real world"; uncontrollable factors are those input parameters over which the decision maker has no direct control. For example, in a destroyer screening problem the controllable factors are those describing escort tactics (such as positions, bearings, speeds, etc.). Uncontrollable factors are those describing enemy tactics and sea environment.

Information gained from studies[2] with a prototype OPTIMIZER verified the potential usefulness of the basic OPTIMIZER concept but pointed out the need for incorporating several additional features into the existing computer program. In addition, a search algorithm based on Response Surface Methodology[3] (RSM), which is a blending of the statistical techniques of experimental design and regression analysis, was identified as tending to offer the greatest payoff in application.

Because of its promise, an RSM search algorithm was selected as the basis of a modified OPTIMIZER containing additional features suggested from experience with the prototype. The OPTIMIZER, as currently designed, is applicable to problems of determining those values of continuous (or approximately continuous) controllable factors which produce an optimum value of one chosen output parameter of interest. This parameter is used as a measure of effectiveness (MOE) for the simulation. Linear constraints on the controllable factors are permitted.

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2. Smith, Dennis E.; "An 'OPTIMIZER' for Use in Computer Simulation: Studies with a Prototype," HRB-Singer, Inc., State College, Pa. 16801, September, 1971, Report No. 4352.11-R-2

3. Box, G.E.P. and Wilson, K.B.; "On the Experimental Attainment of Optimum Conditions," Journal of the Royal Statistical Society (Series B), Vol 13, p. 1, 1951

2. <u>Study Framework</u>

The ASW Programs Surface Ship Engagement Model[4] (APSURF) was chosen as the simulation for test and evaluation of the OPTIMIZER. The general approach was first to solve an anti-submarine-warfare (ASW) problem using an analyst and manual interface with the APSURF model in a conventional manner. The same problem was then solved independently by the OPTIMIZER program. Comparison of the problem-solving methodology and the results obtained in the two problem solutions was used as the basis for OPTIMIZER evaluation.

After this evaluation had been made, the scope of the effort was extended by using this specific encounter as a basis for further investigations into the more general area of automated problem solving. The basic approach was to examine the systematic techniques employed by the human analyst in his solution of the problem, paying particular attention to those aspects, categorized as "sub-analyses," which the analyst performed between certain key runs. Although performed in the analyst's head or on a piece of scratch paper (with possible assistance of prepared graphs), these tasks proved to be complete analyses in themselves. It was hoped that identifying these subtasks would provide a foundation for incorporating them into the OPTIMIZER type of automated process.

Possible ways of combining manual and automated processes have also been investigated. This aspect of the effort involves solving part of the problem manually and then turning the partially solved problem over to the automated process. Such an effort encompasses both establishing the sequence of the solution techniques and also developing methods of using human-processed feedback information to modify the automated process. The sequence of solution techniques was experimented with in

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4. Flum, R.S.; SAO (Systems Analysis Office of PM-4) Report 69-16, "APSURF Mod 1 - ASW Programs Surface Ship Engagement Model," January, 1970 (Unclassified)
    Abstract (AD 881-384L)
    Vol. 1, Part 1 (Sec. 1-5) (AD 881-385L)
    Vol. 1, Part 1 (Sec. 6) (AD 881-386L)
    Vol. 2, Part 1 (Sec. 1-3) (AD 881-387L)
    Vol. 2, Part 1 (Sec. 4 & Appendixes) (AD 881-388L)

the actual OPTIMIZER evaluation. The development of human-processed feedback information will be a future effort and should allow the analyst to override the automated process-selection techniques and direct the machine problem solver to use a different technique when necessary.

This paper will generally describe the evaluation effort[5] already undertaken and the analysis of specific situations which form the basis for recommending future efforts in the man-machine process of semi-automated problem solving with large-scale computer simulation models.

The subsequent sections will cover, in order, the following areas:

- Test Problem Description
- Results of Evaluation Test
- Overview of Analyst's Methodology
- Implications to Semi-Automated Problem Solving

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5. Smith, Dennis E. and Storck, C. Edward; "Application of an 'OPTIMIZER' Computer Program to a Large-Scale Naval Simulation Model," HRB-Singer, Inc., State College, Pa. 16801, June 1973, Report No. 4352.11R-3

3. Test Problem Description[6]

The test problem was designed primarily for the evaluation and hence was not intended to represent an actual ASW study problem. The scenario involved a task force moving north at a constant speed, protected by three escorts. The submarine threat always approached from some northerly direction. The escorts were each assigned a patrol area generally forward of the task force. The first patrol area was northeast of the task force, the second due north, and the third northwest, as illustrated in Figure 1.

The measure of effectiveness (MOE) for the test problem was the product of the probability of detection of the submarine and the average distance from the task force to the submarine when a detection occurred. The evaluation was based on a comparison of the OPTIMIZER's and the analyst's maximization process and on the value of the MOE.

The maximization was accomplished by manipulating the values of 29 controllable variables, subject to constraints. The 29 variables defined (1) the two ranges from the task force to the centers of the first and second patrol areas; (2) the speeds of escorts #1 and #2; (3) the bearing of the center of patrol area #1 from the task force; and (4) six ranges and six bearings from the centers of each of patrol areas #1 and #2. These ranges and bearings defined six points for the respective escorts to patrol. These patrol points were traversed in a specified order defining a patrol pattern for the escort. Each complete cycle was repeated. The patrol pattern for escort #3 was a mirror image of that for escort #1.

6. Mandelbaum, Jay; NSRDC CMD Technical Note, CMD-17-72, "Analyst's Test Problem Used to Evaluate HRB Singer Optimizer for Large-Scale Computer Simulation Models," May 1972

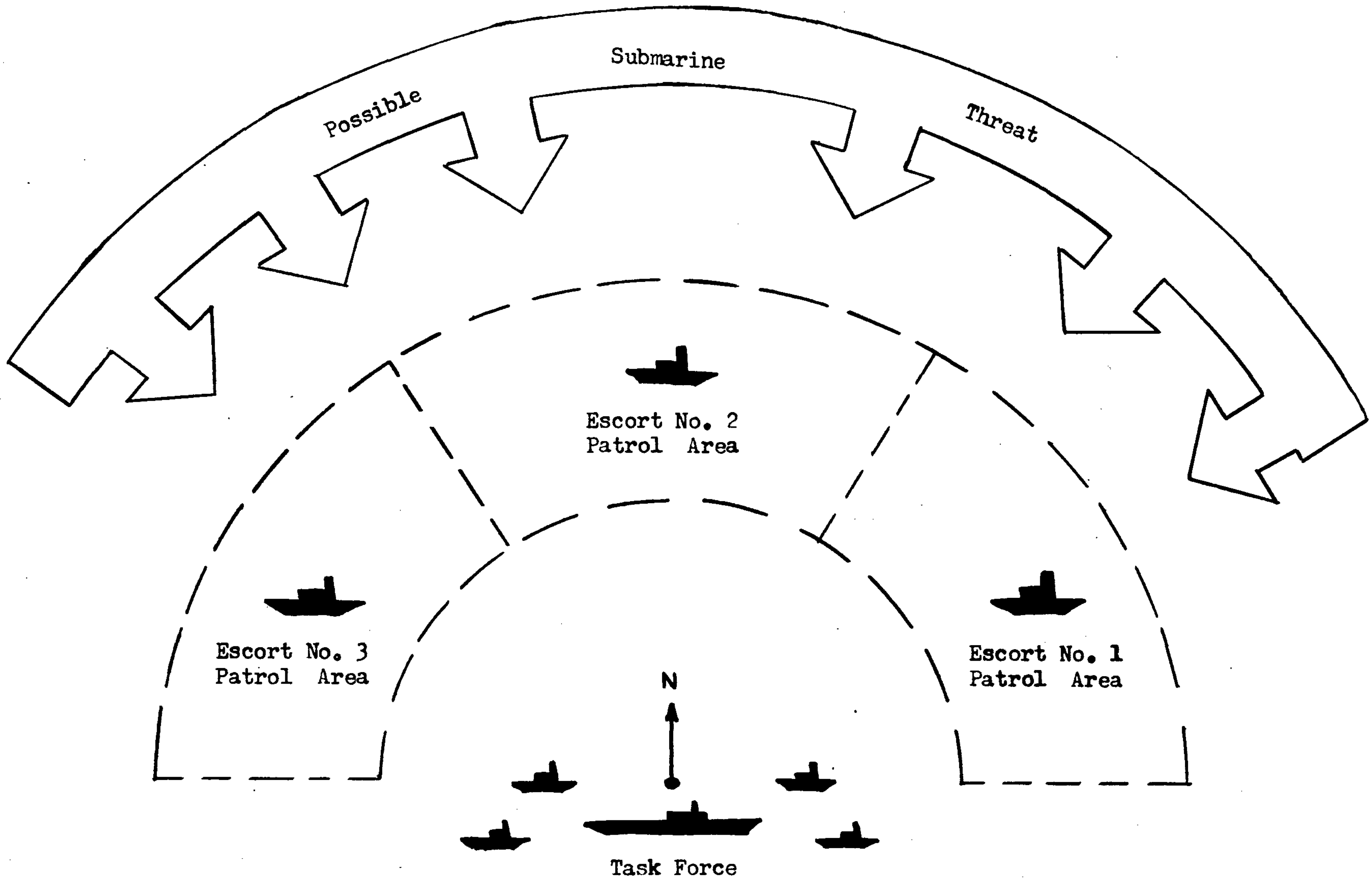

Figure 1 - Test Problem Scenario

4. Results of Evaluation[7]

The first objective of the study described in this paper was to provide an evaluation of the OPTIMIZER, based on direct comparison of the solution obtained by the analyst and that found by the OPTIMIZER-controlled simulation runs. Evaluation of the overall study involved three primary OPTIMIZER search attempts.

Examination of these three search cases revealed that the completely automated OPTIMIZER search did not fare well compared to the analyst's search. However, a good solution involving only a small number of runs was obtained by the OPTIMIZER when it was allowed to start its search after a preliminary analyst search. In fact, the value of the MOE produced by the OPTIMIZER using this preliminary analyst search was the highest value obtained among all the simulation runs made by either the analyst or the OPTIMIZER.

Starting from a "base case" or starting point chosen by the analyst and using the 29 controllable factors described previously, the OPTIMIZER search located an MOE value which was decidedly inferior to the MOE values found by the analyst. (See Figure 2.) Although the OPTIMIZER used all 29 factors in conducting its search, the analyst essentially reparameterized the problem so that he had to manipulate only a small number of these factors in his optimization attempt. An OPTIMIZER search was then conducted using the six reparameterized factors. The OPTIMIZER's performance using these six factors was significantly better than its performance using the original 29 factors. However, by run No. 30, it became apparent that the analyst was still outperforming the OPTIMIZER. (See Figure 3.)

Because of the OPTIMIZER's relative lack of success, it was hypothesized that (1) the relationship of the MOE to the controllable factors might be quite complex in the starting region for the search, and (2) through his intuitive understanding of the problem the analyst

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7. Mandelbaum, Jay; NSRDC CMD Technical Note, CMD-2-73, "HRB Singer Optimizer Performance on an Evaluation Test Problem," January 1973

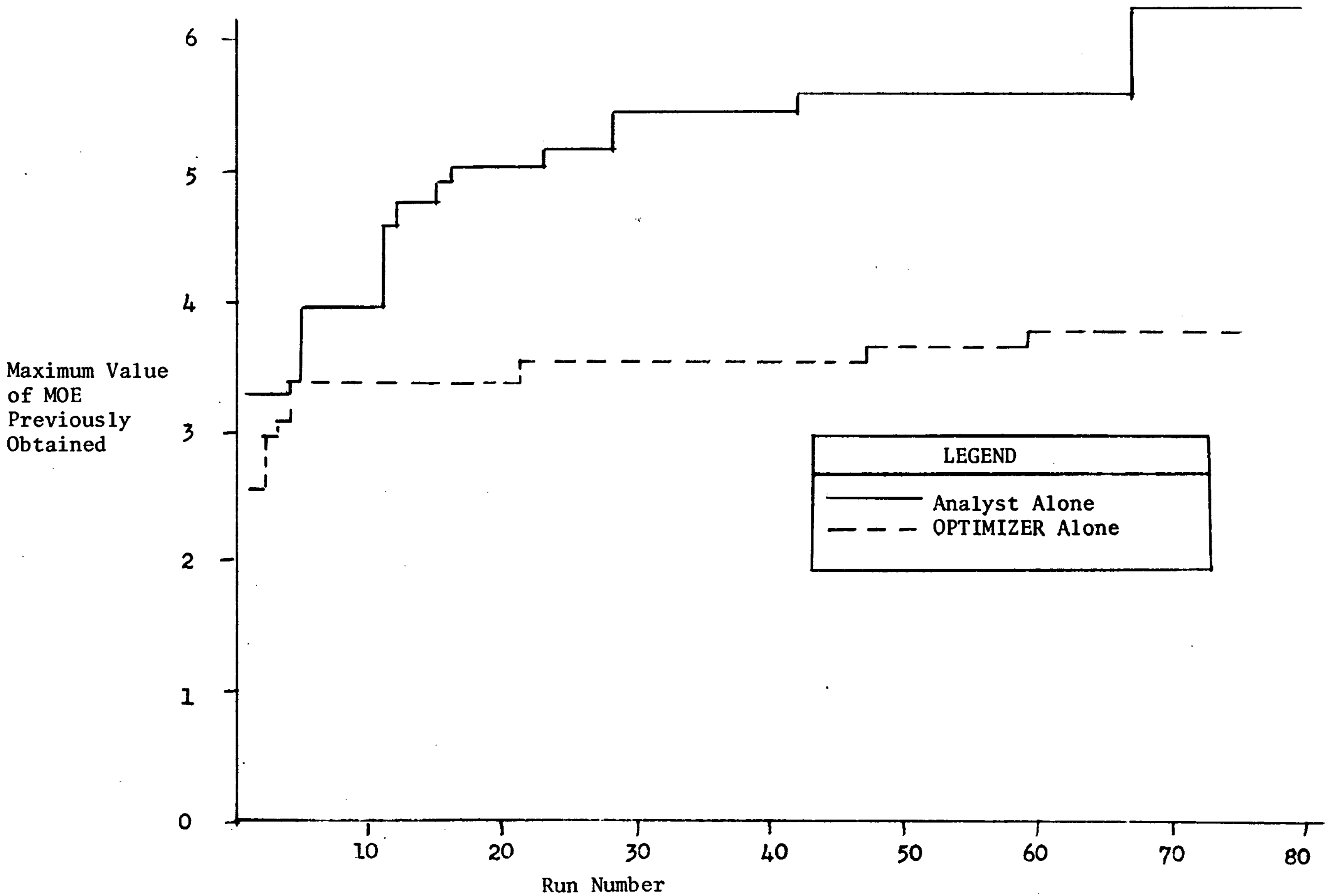

Figure 2 - OPTIMIZER and Analyst Run Histories (OPTIMIZER Search No. 1)

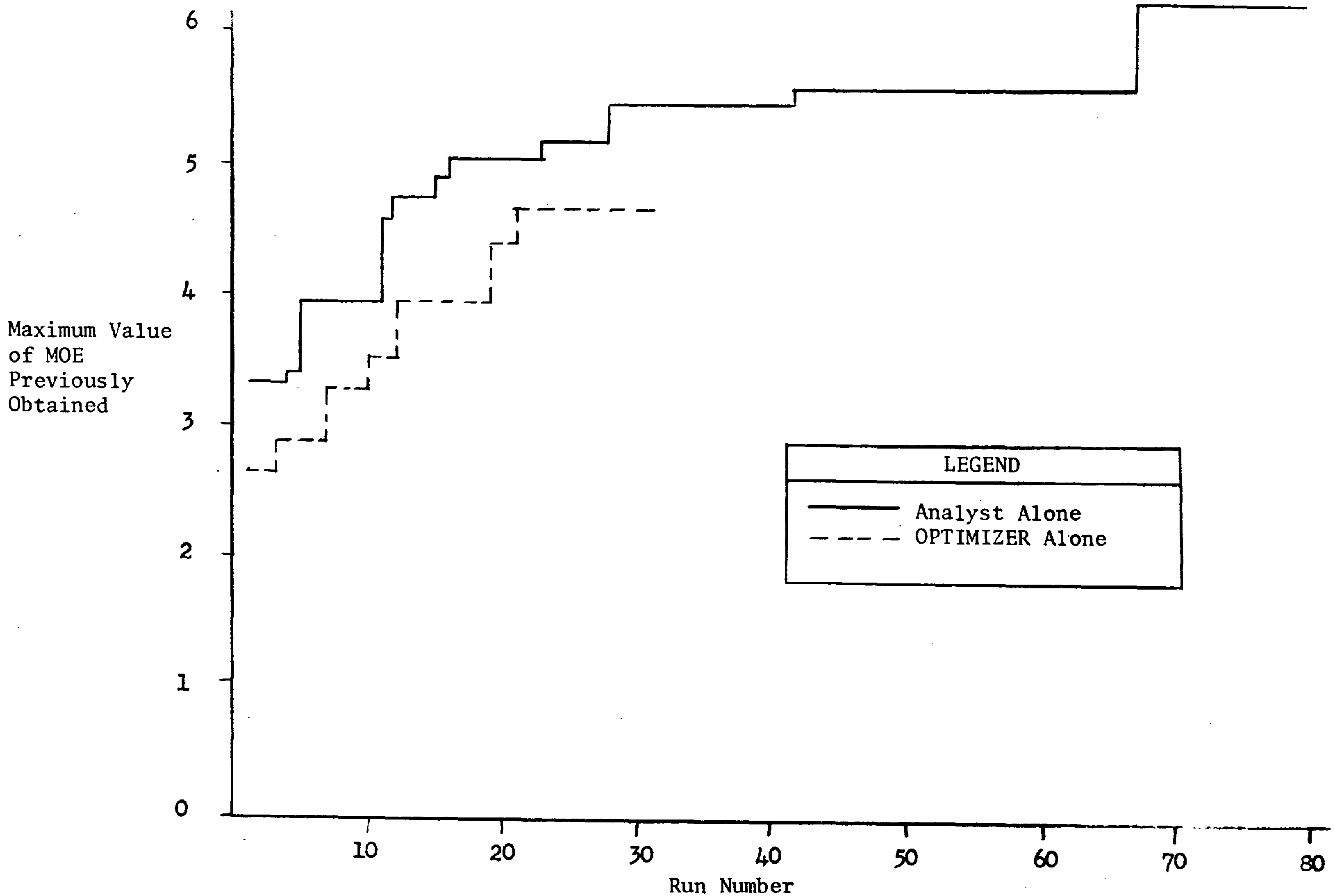

Figure 3 - OPTIMIZER and Analyst Run Histories (OPTIMIZER Search No. 2)

managed to guide his search around these complexities, while the OPTIMIZER could not. Therefore, a better procedure might be for the analyst, using his knowledge and intuition, to first make some exploratory simulation runs to get the search into the "right ball park," so to speak, and then use the OPTIMIZER to provide a mathematically-disciplined search. Since the MOE values produced by the analyst's computer run showed that the most progress was made during the first 11 simulation runs and that further progress was more gradual, the OPTIMIZER search was started from the point corresponding to the analyst's run No. 11. This time the OPTIMIZER located a maximum MOE value on run No. 36 (i.e., on the OPTIMIZER's 26th run) and indicated at run No. 50 that this was the best it could do. It should be noted that the analyst's MOE values never surpassed this value and, in fact, did not come close until run No. 67. (See Figure 4.)

In summary, the OPTIMIZER functioned best as part of a complementary two-stage optimization process which coupled the knowledge and intuition of the analyst with the mathematically-disciplined search of the OPTIMIZER.

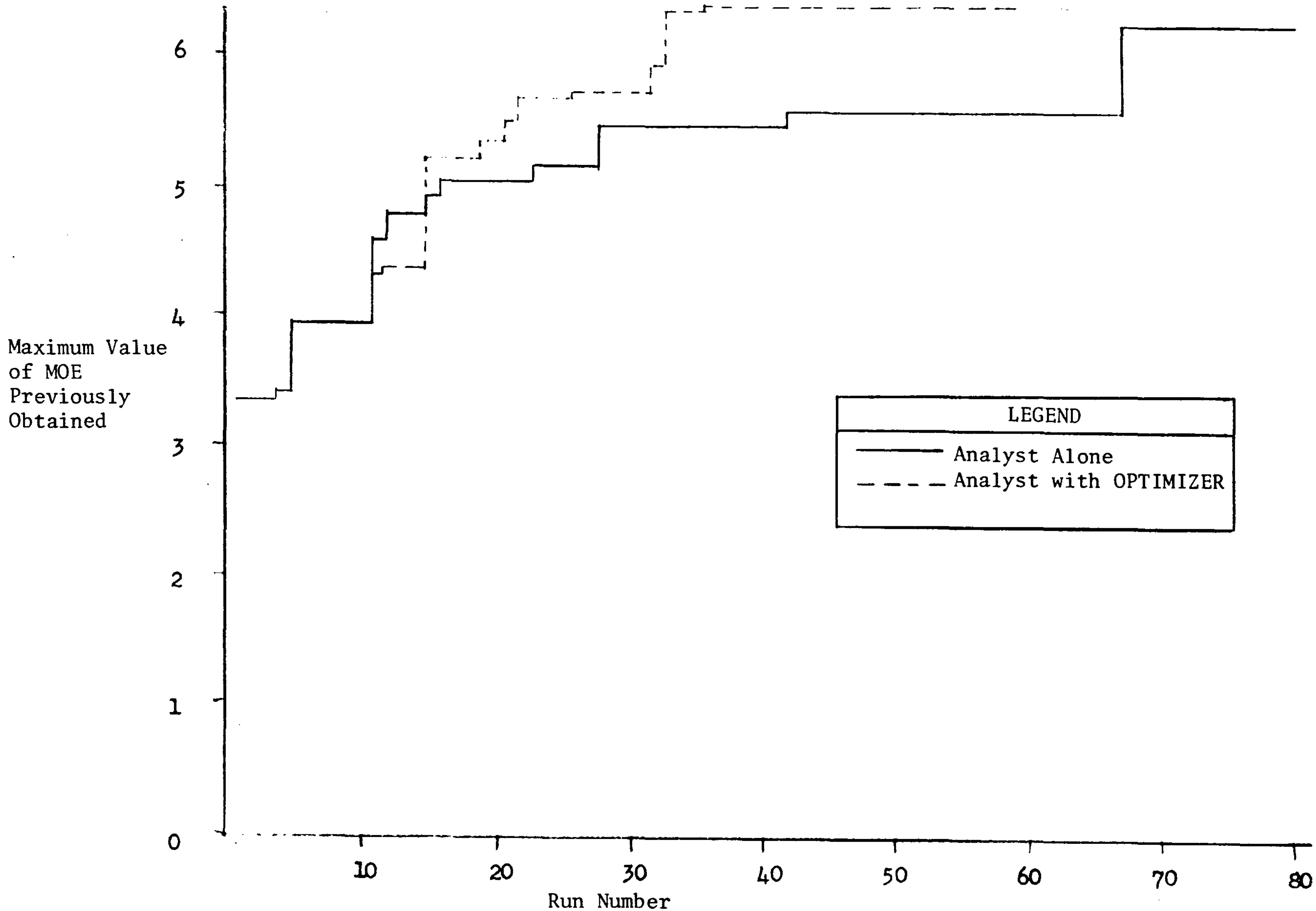

Figure 4 - OPTIMIZER and Analyst Run Histories (OPTIMIZER Search No.3)

5. Overview of Analyst's Methodology[8]

The apparent superiority of the analyst over the OPTIMIZER led us to look briefly into the procedures used by the analyst in solving this particular problem. Such an investigation, it was hoped, would provide insight into human problem-solving methods that could be automated. This section discusses some of the specific techniques the analyst used in attempting to solve this particular problem.

The human analyst solves optimization problems by developing a strategy to explore the cause-and-effect relationships between the variables and the MOE. The major characteristic of an optimization problem that prevents the analyst from adopting an efficient search strategy is usually the limit on the number of variables he can manipulate. Even if the number of variables is small, the causal relationships may be in an unmanageable or unrecognizable form. In either case the first task of an analyst is to reduce the problem to a more workable form. Many methods can be used to accomplish this. Three such reductions, which lowered the number of variables from 29 to four, were actually applied while solving this test problem.

The first reduction involved the speeds of the first and second escorts. The MOE to be maximized was the product of the probability of detection and the average range of detection. The probability of detection could be increased if more area per unit time were covered by an escort's sonar. An increase in the speed of an escort would allow this greater coverage if the performance of the sonar were not downgraded by this increase in speed. A calculation was made which determined that there would be almost no downgrading of sonar performance between the minimum and maximum allowed speeds for an escort. Hence the two speeds were set to their maximum values and were no longer manipulated. Actual simulation runs were made to verify the expected improvement in the value of the MOE resulting from this simplification.

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8. Mandelbaum, Jay; NSRDC CMD Technical Note, CMD-42-72, "Methodology Used in Solving a Test Problem Designed for Evaluating the HRB Singer Optimizer for Large-Scale Computer Simulation Models," September 1972

The second reduction involved equalizing the distances from the task force to the centers of the first and second patrol areas. There was no clear advantage in having a difference between these distances and consequently, three simulation runs were made to specifically test whether any advantage existed. Since the results showed a lower value of the MOE when such a difference existed, one of the distances was eliminated as an independent variable.

The third reduction, by far the most substantial, involved the six ranges and six bearings from the centers of the first and second patrol areas which defined points to be traversed in a fixed order. These points formed the escort patrol patterns. The analyst had no intuitive grasp of the effect on a patrol pattern of varying ranges and bearings of these points. He did, however, have an intuitive grasp of the general type of patrol pattern that should be used, that some type of zig-zag pattern would give the best results. Hence the variation of ranges and bearings was reduced to the variation of zig-zag type patterns. For such patterns, the variation took the form of changing the width of the area traversed. Thus the 24 ranges and bearings were reduced to only two variables, a width for the first patrol area and a width for the second patrol area. With the specification of a zig-zag pattern and a designated pattern width, the 12 ranges and bearings for each patrol area were completely defined and therefore removed as independent variables.

The final four controllable variables remaining after the preliminary simulation runs were the range to the center of the patrol areas, the bearing of the first patrol area from the task force, and the widths of the first and second patrol areas. These variables were manipulated to find an optimal value of the MOE. One critical fact must, however, be stated: an optimal solution to the four-variable problem is not guaranteed to be an optimal solution to the 29-variable problem. Simulation itself is an heuristic process. The simplifications which reduce the number of variables to a workable form, when simulating for an optimal solution, are also done heuristically. The object is thus not to find a true optimal solution but rather to obtain in the most efficient manner a value of the MOE judged satisfactorily close to the optimal value.

After the reduction of variables, the next step in the development of an efficient search strategy is partitioning the problem into subproblems. This partitioning is, in general, also an heuristic process since usually one cannot be sure that each subproblem is independent of all others. For the specific test problem, some extreme cases were run to permit establishment of an approximate initial value for the distance to the center of the patrol areas. Runs were then made, which sometimes varied the widths of the patrol areas and sometimes varied the bearing of the first patrol area, in order to improve the value of the MOE.

Once the subproblems have been defined, one final component of the search strategy remains to be specified: the decision criteria used to change the variables from run to run. The governing criterion is that the change must increase the value of the MOE. However, it may not be possible to determine before making a run that such an improvement will result. In such a case it may be useful to define a related MOE in such a way that it will exhibit the same behavior as the actual MOE for given conditions but will more readily provide an indication of whether the change will improve the value of the real MOE. However, whether or not the related MOE exhibits the proper behavior usually can only be assumed. Even when the proper behavior is exhibited, the question as to whether the value of the real MOE will be improved may be answered incorrectly. The difficulty lies in the fact that the selection of a related MOE must be done heuristically. One cannot be sure that a change in the controllable variables will produce the desired effect on the true MOE even if the expected change does occur to the related MOE.

The analyst's solution of the test problem contained two examples of use of related MOE's. Two graphs (Figure 5) were made for each run (each "run" involved 100 iterations of the problem), one graph for

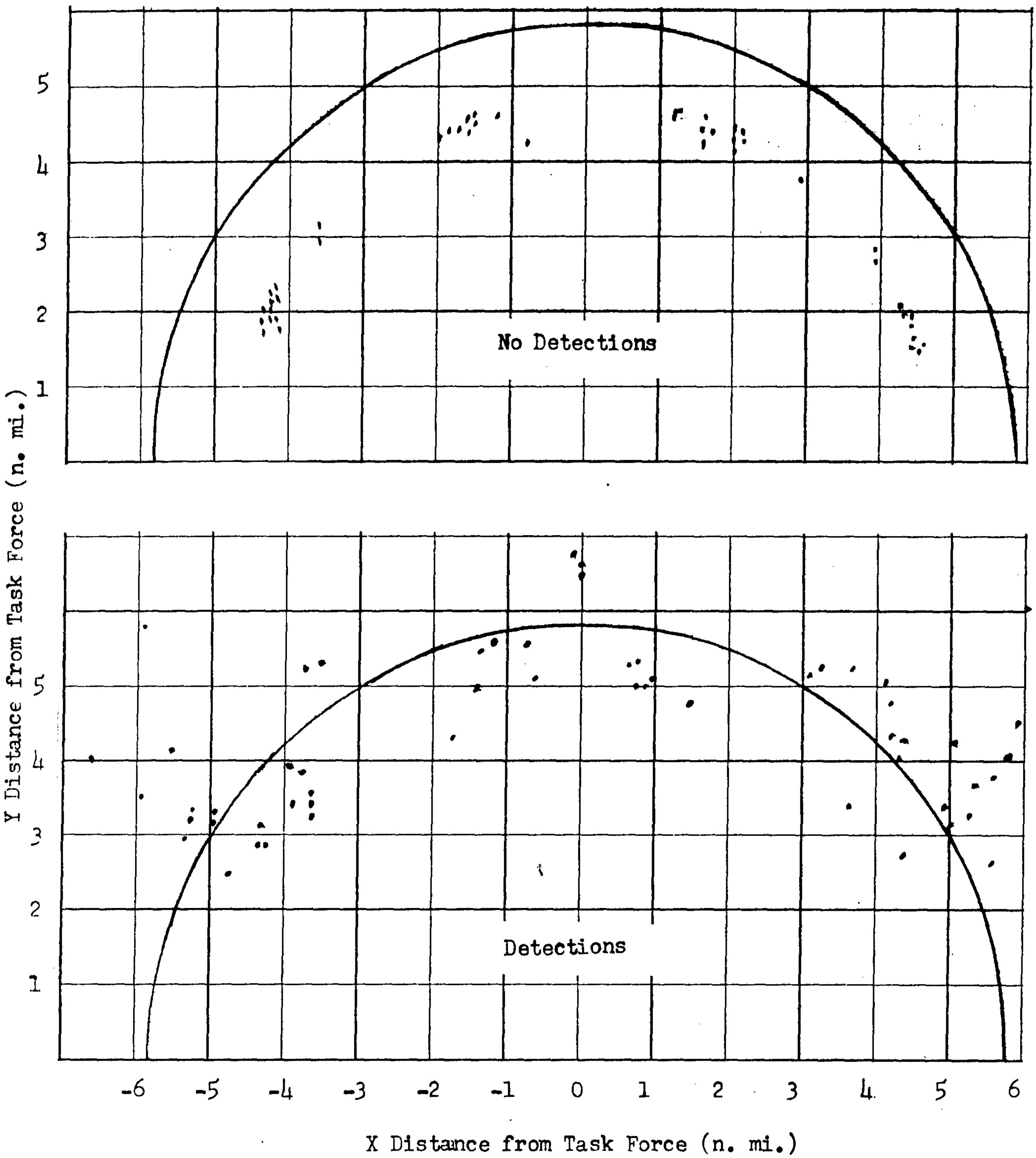

Figure 5 - Relative Detection and No-Detection Graphs

those iterations in which detections occurred, and the other for those iterations in which detections did not occur. The relative position of the submarine with respect to the task force at the end of each iteration was plotted as a point. Clusters of points on the no-detection graph indicated where sonar coverage was weakest. The related MOE was the density of the clusters of points. High-density clusters implied holes in the screen and hence the patrol-area widths needed to be increased.

At one point in the analyst's solution of the test problem, there were two different candidate zig-zag type patrol patterns. One run was made with each pattern keeping the four variables at the same values. The detection graphs indicated that there were more detections at larger ranges in one of the two cases. Here the related MOE was the percentage of detections beyond the distance to the center of the patrol areas, and the analyst thus chose the zig-zag pattern yielding detections at the larger range.

With the development of the related MOE's, the analyst's strategy was complete. He was able to optimize the reduced problem intelligently. One additional factor was involved in the selection of related MOE's: since information about their behavior was constantly being accumulated as runs were being made, uncertainty associated with them was reduced. The only observed limitation in the analyst's method was the inability to deal effectively with several subproblems simultaneously.

6. Implications for Semi-Automated Problem Solving

Within the context of solving simulation-optimization problems, four levels of approaches to a solution can be defined. These levels range from a completely deterministic solution procedure to the traditional human analyst approach.

The lowest level (Level 1) approach consists of a series of deterministic manipulations of the variables, each followed by a simulation run, until the MOE is considered maximized. (See Figure 6.) This approach is impractical for most applications, since deterministic solutions do not exist for most simulation problems.

The Level 2 approach involves an automatic manipulation of the variables much as the OPTIMIZER operates. (See Figure 7.) By monitoring a measure of effectiveness, an heuristic method of manipulating the variables and running the simulation is automatically selected (the selection process itself is also heuristic) and applied. This process continues until an answer is determined. This approach has the advantage of looking at all the variables at once, of not requiring subproblem definition, and of obtaining a solution under severe time constraints. The disadvantage is that the automatic method selection process may not respond properly or efficiently to the sequence of simulation results.

The Level 4 approach is the entirely manual one used in the analyst's solution of the test problem (see Figure 8) and discussed in Section 5.

The Level 3 approach lies between the automatic OPTIMIZER approach and the traditional analyst one. (See Figure 9.) This Level 3 approach appears to be the most fruitful, and it is thus recommended that such approaches be the subject of further research. The automatic method selection and variable manipulation features of Level 2 should be retained to eliminate the need for subproblems. However, provisions should exist for dynamically overriding the selected method with one chosen by the analyst from a library of such methods.

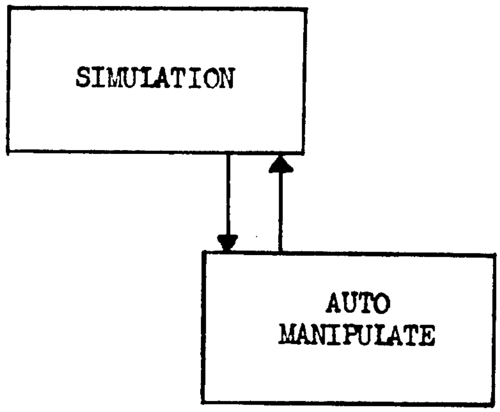

Figure 6 - Level 1 Solution - Deterministic

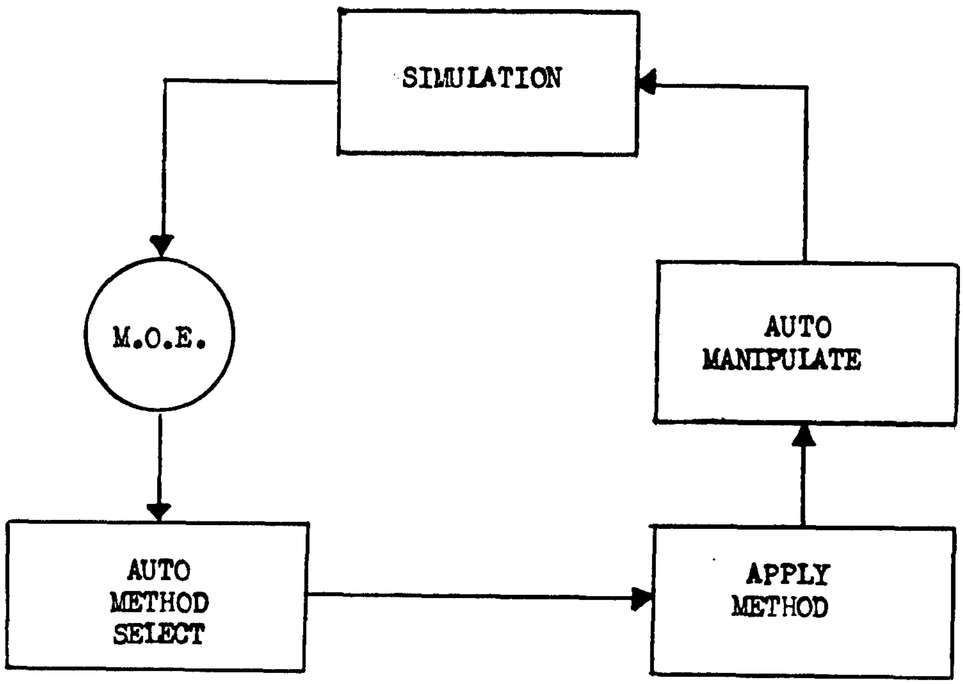

Figure 7 - Level 2 Solution - Automated Heuristic

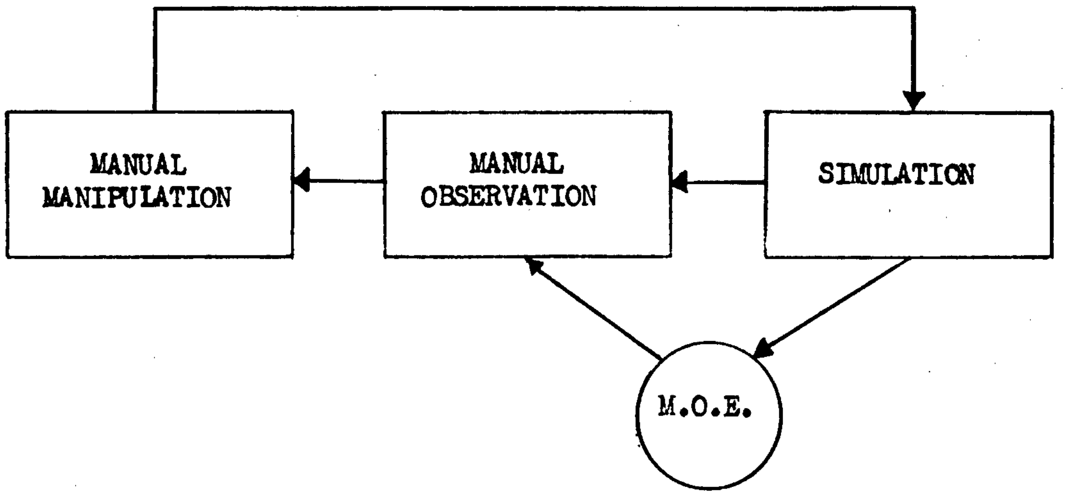

Figure 8 - Level 4 Solution - Human Analyst

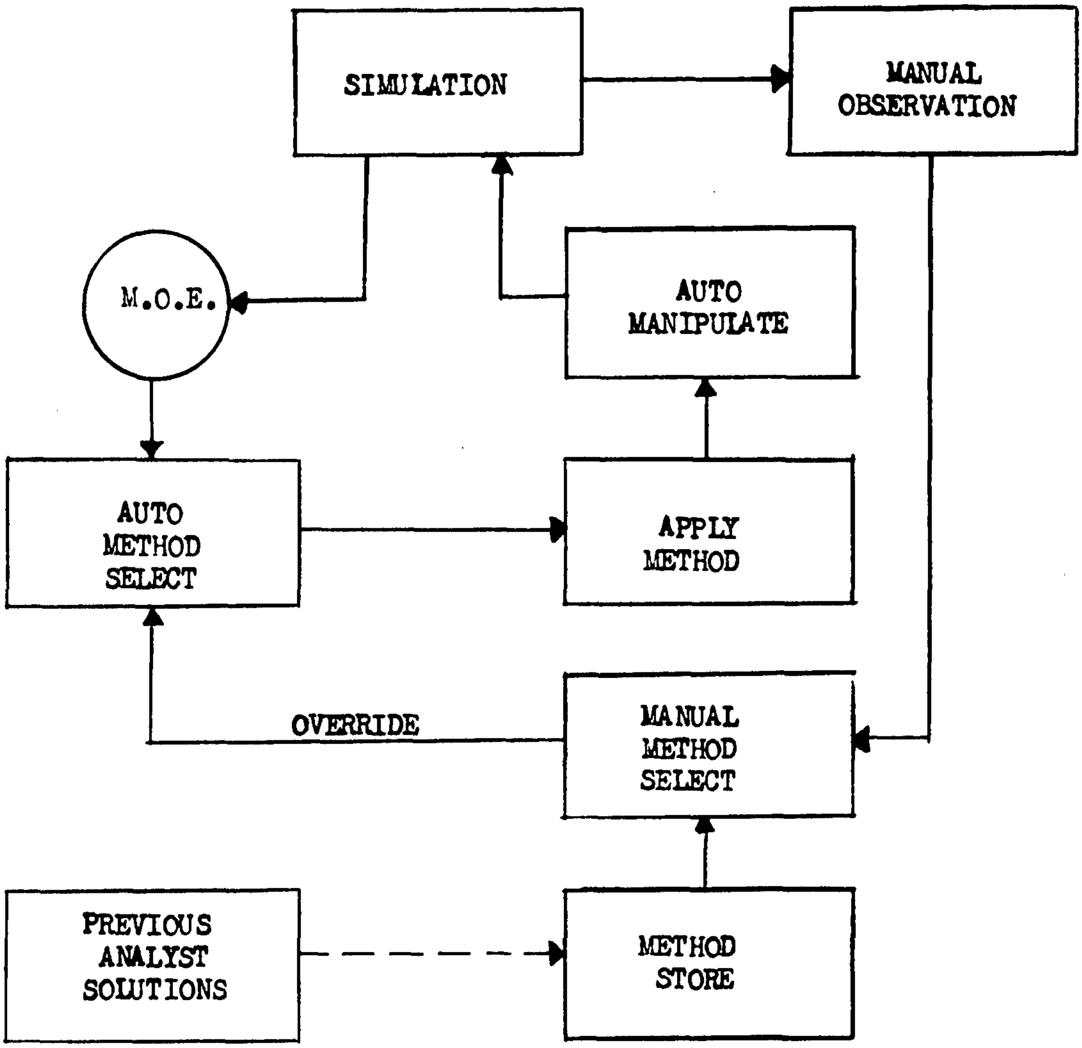

Figure 9 - Level 3 Solution - Man/Machine

This method library should be expanded by cataloging actual methods employed by the analyst when solving problems with the Level 4 approach. Examples of such methods can be drawn from the test problem solution presented in this paper. Extremum points should be run to eliminate variable combinations that might otherwise be tested in a purely automatic approach. Geometric considerations should be applied to reduce the number of variables and hence substantially reduce the number of possible combinations of the variables.

The case discussed in this paper, in which the OPTIMIZER was given the analyst's eleventh run as a start point, indicates the possible advantages of such an approach. A large number of runs would have been required for the OPTIMIZER to find such a start point, and it is quite possible that the OPTIMIZER could never have done it. Once the start point was determined, however, the OPTIMIZER rapidly moved toward its solution. Hence the suggested Level 3 approach takes advantage of the strong points of both man and machine. In the actual experiment, the man was used to converge rapidly to a fairly good solution and then the computer was used for a rapid advance to a solution which is closer to optimal.

In general, the power of the automated process, especially as it applies to problem solving, lies in its ability to extend the capabilities of a man, not to replace him. It is the conclusion of the authors that applications exist in which an automated problem solver will work effectively when properly teamed with a man. It is also considered that great benefit can ensue from this man-machine interface, both in extending the capabilities of an analyst and especially in drastically cutting down the time to solution.

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13. ABSTRACT

This paper describes insights, procedures, and limitations involved in the semi-automatic solution of large-scale computer simulation problems. It utilizes the experience gained in solving test problems by both a human analyst and an automatic OPTIMIZER program. Particular attention is paid to those tasks performed by the man but not the machine and those tasks best done by the machine. Guidelines are suggested for incorporating some of the human problem-solving processes as a first step toward interactive semi-automatic procedures.

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Simulation						
Optimum-Seeking Techniques						
Search Techniques						
APSURF Model						
Problem Solving						
ASW Tactics						