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The purpose of this research was to infer information processing strategies from details of an operator's overt responses in a simulated AAW task. A chief petty officer with experience in AAW operations served as an operator in an experiment varying task load and strategy instructions. A mathematical model was developed to test two plausible operator strategies: (1) a range strategy that prescribes "fire at the closest eligible target"; and (2) a threat strategy that prescribes "fire at the eligible target that will

reach ownship the soonest." The threat strategy is optimal in that it minimizes ownship's vulnerability.

It was found that the operator's normal processing mode was to use a range strategy, but he could adopt the more complex threat strategy when so instructed. Vulnerability increased with the threat strategy, despite its optimality; presumably, this was due to its greater processing burden and reduced output rate. While performance declined with increasing workload, there was no evidence for a shift in processing strategy; rather, the effect of workload was to limit the depth to which the operative strategy was pursued. There was a tendency to prosecute targets in clusters based on proximities in bearing. This constituted a processing heuristic for coping with high workloads.

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INFERRING THREAT ASSESSMENT STRATEGIES IN SIMULATED ANTIAIR WARFARE (AAW) OPERATIONS

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NAVY PERSONNEL RESEARCH
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DEVELOPMENT CENTER
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July 1984

INFERRING THREAT ASSESSMENT STRATEGIES IN SIMULATED ANTIAIR WARFARE (AAW) OPERATIONS

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FOREWORD

This research and development was conducted in support of project SF57-525-001-002-03.01 (Human Factors Engineering Technology in Shipboard Combat Systems) under the sponsorship of the Naval Sea Systems Command. The thrust of this project is to enhance the effectiveness of command and control systems through improved design of the human-computer interface. In previous work, a laboratory simulation system was developed to investigate decision making in antiair warfare (AAW) operations and to explore human capacity limits in a multiple-task environment (NPRDC TRs 81-15, 82-21, 84-39; TN 82-26). The present work examined models of human performance in the AAW simulation to identify operative information processing strategies. This effort interacted with and benefited from ongoing Independent Research project ZR000-01-000.022 (Models of Human Performance with Applications to Decision Aiding).

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Technical Director

SUMMARY

Problem

Antiair warfare (AAW) operations require rapid assessment and prosecution of threatening contacts. Since it is unlikely that the human operator/decision maker will be replaced by automation, there is a need to better understand human decision strategies, limitations, and cognitive resources for coping with high workloads. Such knowledge can be used to develop more effective decision aids for joint man-machine problem solving.

Objective

The objective of this effort was to infer human information processing strategies from an operator's overt responses in a simulated AAW task. In particular, an attempt was made to determine:

1. The operator's normal processing mode.

2. Whether an explicit processing instruction yields evidence that the instructed strategy is indeed invoked.

3. Whether increased workload produces an identifiable shift in the operative strategy.

Approach

A chief petty officer with experience in AAW operations served as an operator in an experiment that varied task load and strategy instructions. Data were collected to support detailed analyses and mathematical modeling of operator strategies. A mathematical model was developed based on the targets' ranks on the relevant attributes of range and speed. Two plausible operator strategies were tested: (1) a range strategy that prescribes "fire at the closest eligible target" and (2) a threat strategy that prescribes "fire at the eligible target that will reach ownship the soonest."

Results

1. The operator's normal processing mode was to use a range strategy. However, when so instructed, the operator did adopt the more complex threat strategy.

2. Implementation of the threat strategy, despite its optimality, increased ownship's vulnerability. This was attributed to its increased processing burden and reduced output rate vs. that of the range strategy.

3. No shifts in processing strategy were detected as workload increased, although performance generally declined, as expected.

4. There was a tendency to prosecute targets in clusters based on proximities in bearing. This constituted a processing heuristic for coping with high workloads.

Conclusions

1. A simple mathematical model based on the rankings of the target stimuli can provide suitable tests of the information processing strategies used by an operator.

2. No evidence was obtained for a shift in processing strategy as workload increased; rather, the effect of workload may be to limit the depth to which the operative strategy is pursued.

3. The strategies used by "experts" are not necessarily optimal; they may not be the best guidelines for automated algorithms.

Recommendations

It is recommended that, in continued exploratory research on AAW decision making, particular attention be given to the following:

1. Inclusion of additional dimensions of threat, such as the lethality of the opposing platforms' weapons.

2. Identification of information processing strategies in more complex AAW scenarios.

3. Development and evaluation of decision aids for threat assessment.

CONTENTS

LIST OF FIGURES

INTRODUCTION

Problem

Antiair warfare (AAW) operations require rapid assessment and prosecution of threatening contacts. Since it is unlikely that the human operator/decision maker will be replaced by automation, there is a need to better understand human decision strategies, limitations, and cognitive resources for coping with high workloads. Such knowledge can be used to develop more effective decision aids for joint man-machine problem solving.

Background

The nature of today's threat and the sophistication of modern command and control (C^2) systems impose heavy burdens on decision makers. While innovations in automation (e.g., in the Aegis combat system) address the demands of high-density AAW battles, these do not obviate human decisions. Rather, operators are forced to process more information with less time and error tolerance than ever before. Thus, designers of C^2 systems and associated decision aids must consider the cognitive skills of human operators. Data are required on the kinds of decision strategies they invoke, their limitations in processing information, and the effects of increasing workload demands. Computer support may then be applied more appropriately to enhance the decision-making process.

Only sparse data are available on decision-making processes in C^2 threat assessment tasks. Rigney and Debow (1967) reported a multidimensional scaling analysis of decision strategies in AAW threat evaluation. They found that experts judged threat primarily on target range and, to a much lesser extent, on course. Also, they found that other factors, such as speed, altitude, and composition of the raid, had negligible influence. Since the results were based on static displays, it is of interest to determine if similar results would occur in more dynamic scenarios.

A common finding is that, when information is presented at excessive rates, human performance does not drop catastrophically; rather, it degrades gradually (Norman & Bobrow, 1975) as the decision maker presumably invokes various "coping" strategies (Sheridan & Ferrell, 1974). People apparently adapt by processing less input information and considering fewer decision alternatives as workload increases (Greitzer, Hutchins, & Kelly, 1984; Kelly & Greitzer, 1982; Serfaty, Soulsby, & Kleinman, 1984). Thus, a complex rule may be replaced by a simpler decision heuristic if the operator is overloaded.

Objective

The objective of this effort was to infer human information processing strategies from an operator's overt responses in a simulated AAW task. In particular, attempts were made to determine:

1. The operator's normal processing mode.

2. Whether an explicit processing instruction yields evidence that the instructed strategy is indeed invoked.

3. Whether increased workload produces an identifiable shift in the operative strategy.

APPROACH

AAW Simulation

The present analysis used a simulated AAW task (Hershman & Greitzer, 1982), in which an operator must defend "ownship" by launching missiles against a raid of incoming targets. While the ultimate objective is to intercept all targets at maximum range, limitations in human processing preclude such performance, except for trivially few targets. More realistic, perhaps, is an operational goal that seeks to minimize ownship's vulnerability, or total exposure to threat.

All targets in the simulation have equally lethal weapons. Thus, it is reasonable to adopt a ship vulnerability function that increases nonlinearly as a target approaches, so that the most immediate threats should always be prosecuted first. In particular, let the momentary vulnerability induced by an eligible (i.e., engageable) target equal 1/(time remaining), where the time remaining is measured as display updates until the target would penetrate and score a hit against ownship.[1] The total vulnerability incurred in an engagement is then taken as the sum of the momentary vulnerabilities, accumulated over all updates and over all targets.

To minimize the defined vulnerability, it is clear that the operator should adopt the following threat strategy: "Always fire at the target that will reach ownship the soonest." An alternative prescription is a range strategy that says: "Always fire at the closest eligible target." To the extent that range and vulnerability are correlated, this may be an attractive compromise or "satisficing" (Simon, 1957) option for the operator. Also, it nearly meets the goal of maximizing the size of the "free and clear" zone around ownship.

A third possible goal is the maximization of the average range-at-intercept. This goal is met by a speed strategy that says: "Fire at any eligible fast target; if none exist, then fire at any eligible medium speed target; if none exist, then fire at any eligible slow target." For any limited capacity processor, this would produce an inordinate number of hits on ownship. Past results (Kelly & Greitzer, 1982) render this strategy very unlikely and it is not examined further.

If one adopts the goal of minimizing vulnerability, the threat strategy is optimal. However, this strategy compels the operator to integrate both target range and speed in establishing firing priorities. The range strategy, on the other hand, is not directed at vulnerability per se, but it requires only one target attribute (namely, range) for its implementation. Thus, the operator's processing rate should be higher for the simpler range strategy.

In the face of high task demands, a switch from a threat strategy to a range strategy may incur little or no loss in decision quality, as measured by ownship's vulnerability. Indeed, vulnerability may be reduced if output is sufficiently increased over that of the more complex strategy. Greitzer, Hutchins, and Kelly (1984) could not reliably discriminate in their data a range-based strategy from a threat-based one. The present effort pursues this work by formulating and testing mathematical models of operator strategies.

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[1] In general, it is sufficient to assume any decreasing, concave upward function; that is, the function's first derivative must be < 0 and its second derivative must be > 0.

Procedure

The task (see Hershman & Greitzer, 1982 for details) was run by a Tektronix 4054A microcomputer, which simulates a Navy Tactical Data System (NTDS) display on which hostile air targets approach ownship. In each engagement of approximately 4 minutes, the raiding targets approach at one of three speeds, on constant courses, and from random directions.

The operator fires a missile by entering a target's two-digit track number on the computer keyboard. The computer updates the display every 2 seconds. Manipulation of the number of targets and their arrival rates during the middle 2 minutes of an engagement serves to produce various track loads on the operator. Data are stored on floppy diskette for later analysis and reconstruction of operator performance.

A 35-year-old chief petty officer with experience as an air intercept controller and anti-submarine air controller served as an operator. He had been trained earlier on the experimental task.

Design

Two factors were manipulated in a 2x2 experimental design: strategy instructions and workload. In the NORMAL instruction condition, the operator was asked to perform as he normally would in prosecuting the targets. In the THREAT condition, he was explicitly instructed to minimize threat; viz., always try to prosecute the target that will hit ownship the earliest. The THREAT condition was a departure from the operator's normal strategy, but he reported no difficulty in adopting it.

Workload was manipulated by using two target arrival rates: a moderate rate of 0.25 targets per sec (yielding a total of 30 targets) and a high rate of 0.4 targets per sec (with a total of 48 targets). There were 30 engagements in each of the instruction conditions. Nineteen of the NORMAL engagements and 18 of the THREAT engagements had a 0.4 target rate. Two blocks of engagements (NORMAL and THREAT) were run on each of 3 days to complete the data collection.

RESULTS

Data Analysis

Figure 1 shows the means of four performance measures--the skill rating[2] (100 is perfect), range-at-intercept (21 miles is perfect), launch rate, and vulnerability--for the last ten engagements in each of the four experimental conditions. Two-factor analyses of variance showed that the effect of increased workload was significant ($p < .01$) on each measure; that is, the 0.4 target rate reduced the skill rating and range-at-intercept and increased the launch rate and ship's vulnerability. Compared with the NORMAL condition, the THREAT instruction significantly reduced launch rate ($p < .05$) and increased vulnerability ($p < .001$); effects on the other two measures were marginal ($.05 < p < .10$). Since launch rate showed a ceiling effect at low workloads, a separate analysis was made

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[2] The skill rating is defined as R = 100 (average range-at-intercept)- 12 (no. of hits)-2 (no. of inflight launches). An inflight launch is any firing at an engaged target, and is counted as an operator error.

on the high workload data in panel (c); it showed that the THREAT instruction significantly reduced the launch rate in the 0.4 target rate condition ($p < .05$). The THREAT strategy also increased ship's vulnerability under high workload, as the interaction in panel (d) was significant ($p < .001$). These findings suggest that the THREAT condition posed a greater processing burden for the operator than did his NORMAL strategy.

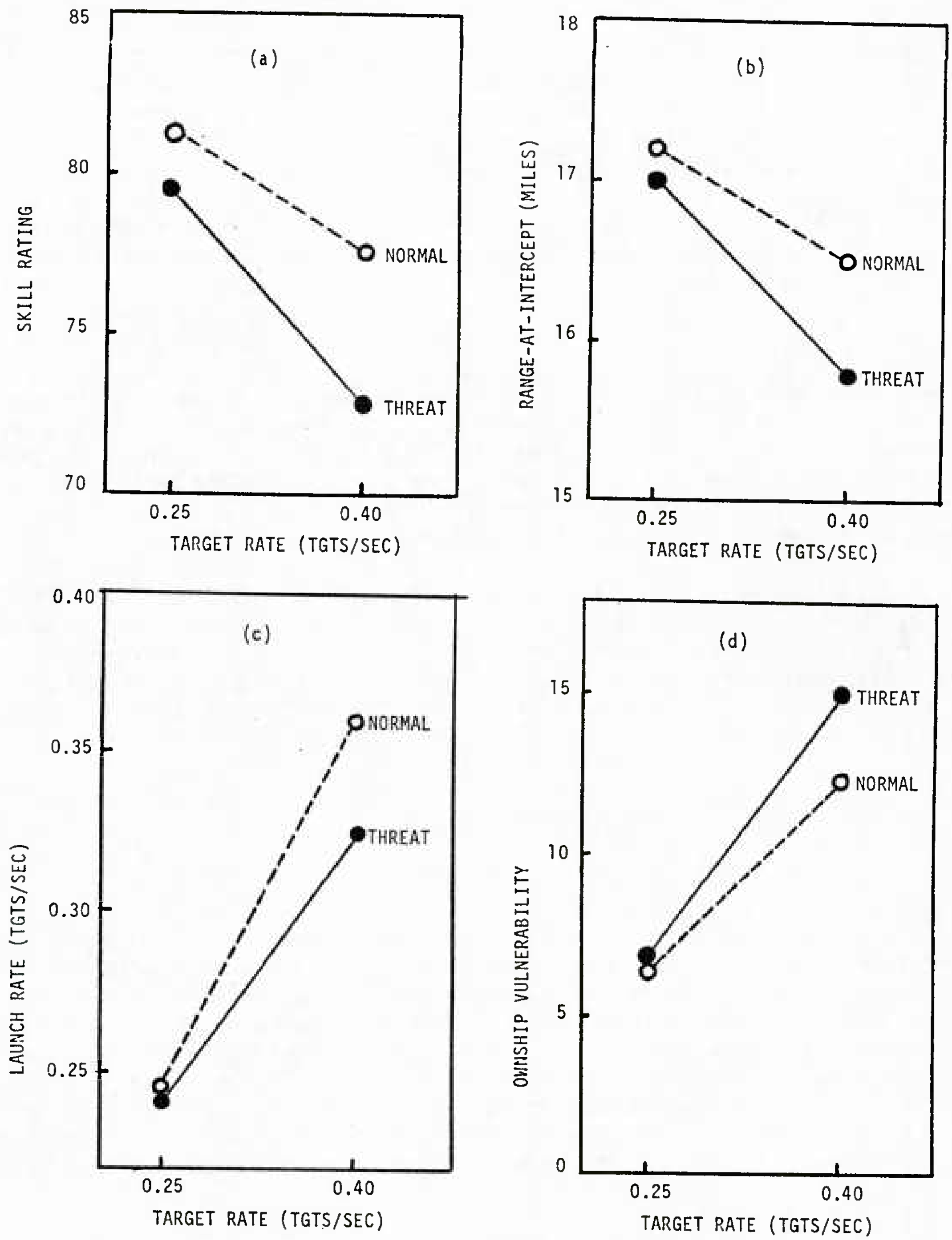

Figure 1. Four performance measures as functions of target rate and instruction condition: (a) skill rating, (b) range-at intercept, (c) launch rate, and (d) ownship vulnerability.

One reason for the increased burden imposed by the THREAT condition is its requirement to search a broader area of the display to find the most threatening target. In contrast, the NORMAL condition might afford an opportunity to prosecute clusters of targets in close proximity to reduce the search times. To test this notion, analyses were conducted on each "burst" of launch activity, operationally defined as a string of launches in consecutive updates. Figure 2 reconstructs the bursts in typical engagements in the two instruction conditions. Launches within a burst are joined by line segments and indicate the extent of the operator's scan of the display. The numerals identify the starting points and chronology of the burst activity.

Table 1 shows various burst statistics for the 0.4 target rate conditions. As hypothesized above, a clustering tactic should produce fewer and larger bursts in the NORMAL condition, but these differences were not significant. Another test for clustering is the angular separation between consecutive intraburst vs. interburst launches. In particular, clustering should produce smaller angular separations for the former and larger separations (near the chance value of 90°) for the latter. If clustering is not operative, the angular separation should approximate 90 degrees for both kinds of launches. These data support differential clustering in the two instruction conditions: For the NORMAL condition, the mean intraburst separation was significantly less ($p < .001$) then the interburst separation, which did not differ reliably from 90 degrees. For the THREAT condition, the mean angles differed reliably ($p < .01$), but neither angle differed statistically from 90 degrees. Thus, there was a reduced tendency to cluster targets in the THREAT condition.

Mathematical Models

To elucidate possible strategies, consider the eligible targets (say, k in number) that might be present on any update. Then rank the k targets based on a presumed strategy. For example, a range strategy would assign rank = 1 to the closest target and rank = k to the most distant one, etc. A threat strategy would give rank 1 to the target that will hit ownship the soonest, etc. As the operator executes a given strategy, his observed launches can be expected to conform generally to the rankings imposed by the operative strategy.

To be more precise, the approach is as follows: Let $p_j(k)$ denote the probability of firing at the jth-ranked (based on any presumed strategy) of k eligible targets. First, a two-parameter model is developed to predict the observed $\{p_1(k)\}$; that is, the probabilities of choosing the best of the eligible targets for observed values of $k = 2,3,...16$. This affords preliminary testing of the range and threat strategies. Then, without estimating additional parameters, predictions are made for each of the $p_j(k)$ distributions (a total of 135 points).

The observed $\{p_1(k)\}$ are graphed as the open circles in Figure 3. Figures 3a and 3b are for the NORMAL instruction condition based on range and threat rankings respectively; and Figures 3c and 3d, for the THREAT instruction. (Data for the two target rates were combined.) If a given strategy is operative, then, as a minimum first test, the observed $\{p_1(k)\}$ based on that strategy generally should decrease as k increases. As seen in Figure 3, both the proposed range and threat strategies meet this test in both instruction conditions.[3]

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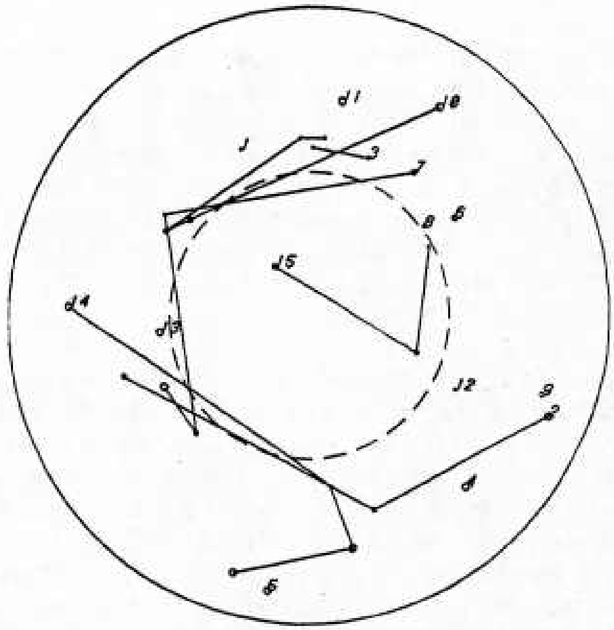
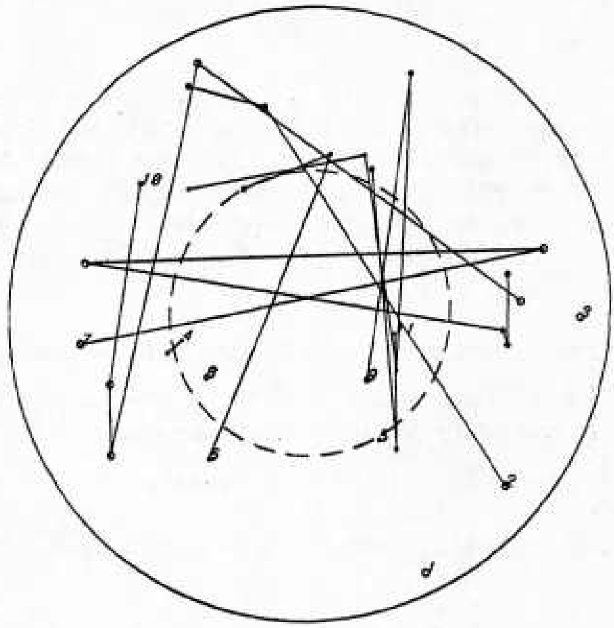
[3] Fewer observations were available for larger k, making these data less reliable.



a. NORMAL instruction condition.



b. THREAT instruction condition.

Figure 2. Launch burst records for two typical engagements. Target rate = 0.25.

Table 1

Target Clustering Statistics

Item	Instruction Condition: NORMAL	Instruction Condition: THREAT
Number of Bursts	14.1	15.4
Size of Bursts	4.1	3.6
Degrees Separation:		
Intraburst	55.2	74.5
Interburst	91.1	88.6

Note. Target rate = 0.4.

As a second test, if the operator is executing the proposed strategy, then the observed $\{p_1(k)\}$ should each exceed 1/k, the values predicted by a random "strategy" (the dashed curves in Figure 3). This holds in Figure 3a but not in Figure 3b, in which the probability of firing at the most threatening of only two targets is less than chance. Thus, data in the NORMAL condition tentatively support a range strategy as opposed to a threat strategy. Similarly, in the THREAT condition of Figures 3c and d, the data suggest the employment of a threat strategy. Note that the observed $\{p_1(k)\}$ do not approach zero, as one might expect. Indeed, the likelihood of choosing the best of 10-16 eligible targets (see footnote 3) is about the same as choosing the best of 5. A possible explanation is that, as the observer searches the display for high priority targets, many of those in the periphery (at long range) can be eliminated. Actually, to execute either strategy, only three targets need be considered: the closest fast, medium, and slow targets. A restricted search, generally near ownship, will likely yield a small set that contains the "promising" targets. Given enough time, the best target in this restricted set can certainly be determined, but the advantage gained must be traded off against search time. In general, as the target density increases, the demand to "keep up" forces the operator to spend less time resolving fine distinctions among several good targets. Thus, for suitably large k, the choice may be random among a restricted set of, say, 3-5 targets. Presumably, target density compels a time pressure that governs the rate at which this choice approaches randomness. Equation (1) captures this interpretation:

$$p_1(k) = b + (1-b)\exp\{-a(k-1)\}, \qquad a,b>0. \tag{1}$$

The parameter b is the chance selection probability in the restricted set of targets, so that 1/b estimates the size of this set. Based on human information processing limitations (e.g., Miller, 1956), one might expect the set size to be about 7, but 3-5 seems more appropriate for this task. This should yield a value for b in the range of 0.20-0.33. The parameter a represents the decision maker's sensitivity to target density[4] by

[4]Alexandridis, Entis, Wohl, and Deckert (1984) used a similar exponential decay function to model the effect of workload on the optimality of an antisubmarine warfare commander's tactical decisions.

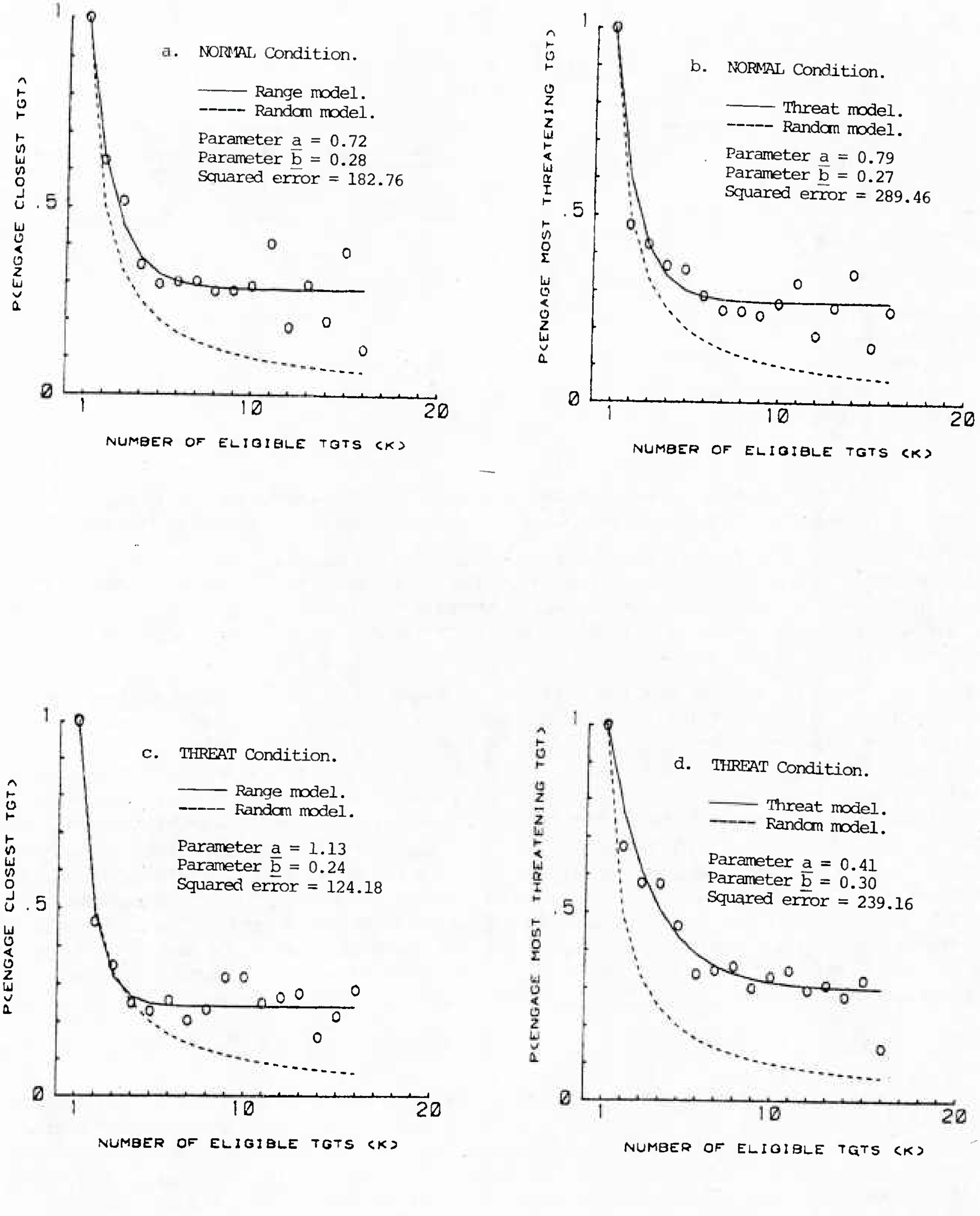


Figure 3. Probability of engaging the first-ranked of k eligible targets as a function of instruction condition and assumed model. Observed data are plotted as open circles.

determining the randomness of the choice of a target in the restricted set; that is, a controls the rate at which $p_1(k)$ approaches its asymptote, b. For example, $a = 0$ implies complete persistence in processing the targets so that the first-ranked target would always be selected, as if there were no time pressure at all. As a increases, there is less dedication to the processing strategy; the operator is willing to compromise his goal, presumably to gain time.

Equation (1) was fit to the observed $p_1(k)$ distributions for the two instruction conditions, assuming each of the two strategies. Returning to Figure 3, these predictions are plotted as solid lines. The values of a and b that minimize the squared error[5] and the obtained square error are also shown.

In the NORMAL condition, the range model provided a better fit to the $p_1(k)$ data, with $a = 0.72$ and $b = 0.28$. The number of targets in the restricted set is estimated at $1/b = 3.6$. In the THREAT condition, the range model again yielded the lower squared error, with best-fitting parameter values $a = 1.13$ and $b = 0.24$. However, as previously noted, the data in Figure 3c do not favor a range strategy; a decision about the operator's strategy must be deferred until the entire probability distributions are analyzed. The threat model yielded the least squares solution $a = 0.41$, $b = 0.30$; in this case, the size of the restricted set is estimated at 3.3.

Equation (1) predicts only the likelihood that the best of k targets be engaged; however, the observer's operative strategy should also be manifest in the relative frequency with which the lower-ranked targets are prosecuted. In particular, consider an engagement of the second-ranked of k targets. It is proposed that this event occurs only if the first-ranked is not selected (perhaps overlooked, processed with error, etc.), and then the best of the remaining (k-1) targets is engaged. Thus, the prediction is that

$$p_2(k) = \{1-p_1(k)\}\, p_1(k-1).$$

Extending this simple notation to the probability $p_j(k)$ that the jth-ranked target is the one fired at, the result is:

$$p_j(k) = p_1(k-j+1) \prod_{i=1}^{j-1} \{1-p_1(k-i+1)\}, \qquad j>1 \tag{2}$$

The model thus makes predictions for j=2,...k based only on the $\{p_1(k)\}$, for which Equation (1) used 15 data points to estimate the two parameters, a and b.

Tests of Models

Figures 4 and 5 show, for each instruction condition and presumed strategy (range or threat), the observed data (open circles), the ensemble of 135 predictions for k=2 to 16, j=1 to k (solid curves), and predictions for a strategy that fires at random (dashed lines).

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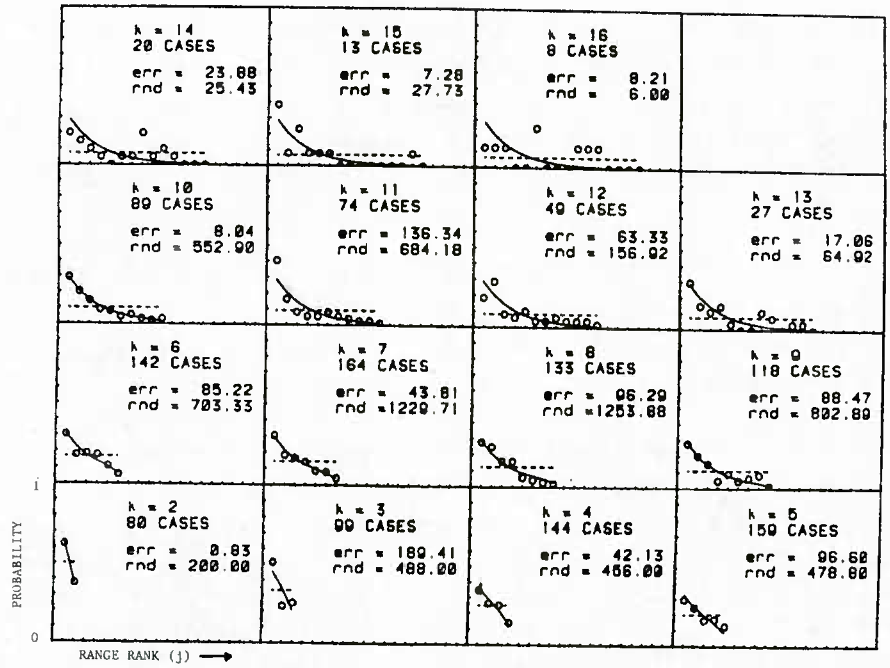
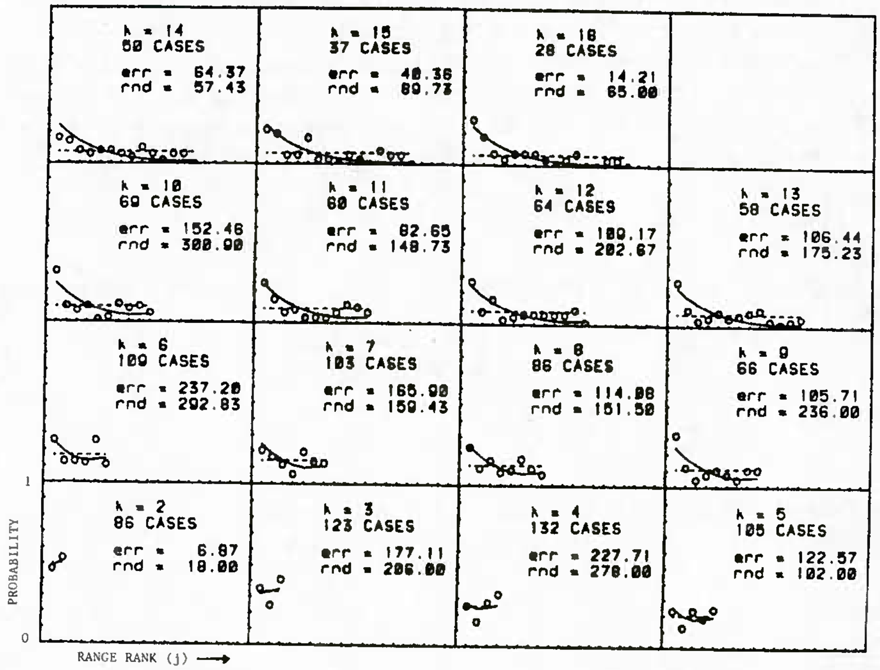
[5] Observed and predicted frequencies (rather than probabilities) were used in all of the least-squares analyses; that is, the prediction errors were weighted by the number of cases available for each k.

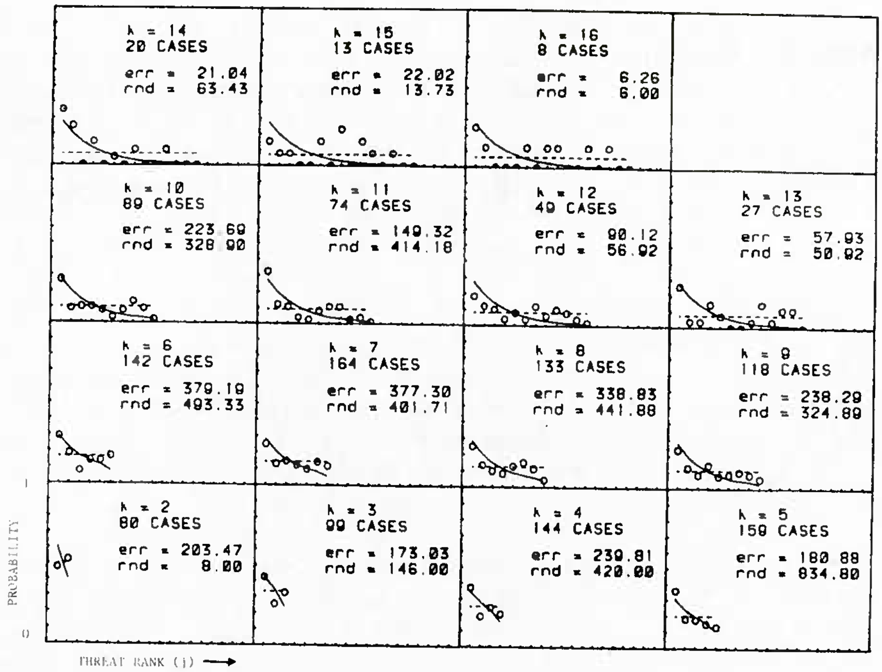


a. NORMAL instruction condition.

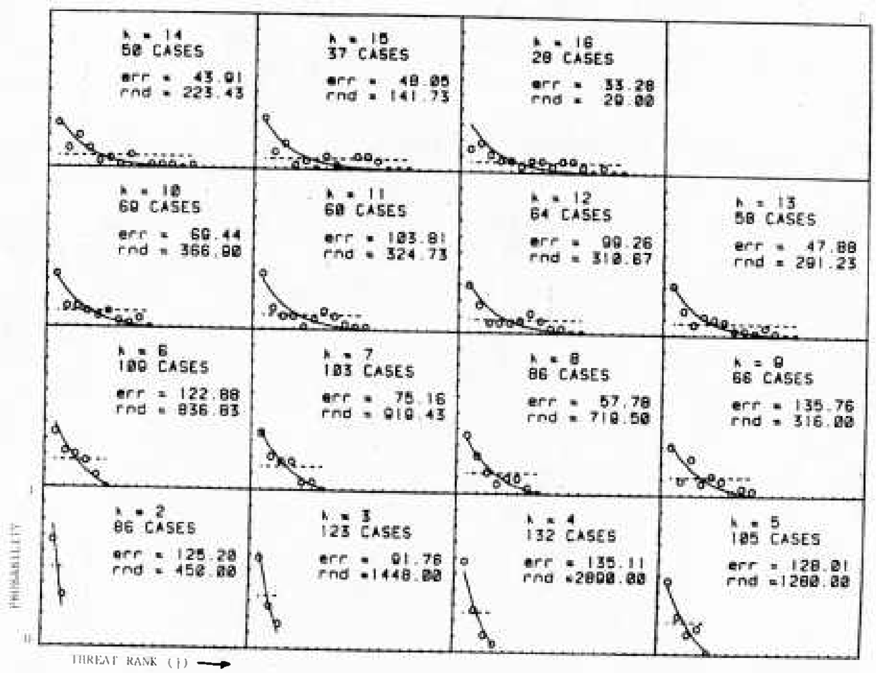


b. THREAT instruction condition.

Figure 4. RANGE model predictions (——), RANDOM model predictions (----), and observed probabilities of firing (o) at the jth closest target. Number of targets (k) = 2 to 16. (Note: Values shown for err and rnd = squared errors for range and random models respectively.)



a. NORMAL instruction condition.



b. THREAT instruction condition.

Figure 5. THREAT model predictions (——), RANDOM model predictions (----), and observed probabilities of firing (o) at the jth most-threatening target. Number of targets (k) = 2 to 16. (Note: Values shown for err and rnd = squared errors for THREAT and RANDOM models respectively.)

For the latter, the probability that the jth ranked of the targets is the one fired at is simply 1/k. Although the same engagements were used for testing, the range and threat models were fit to different probability distributions; namely, those induced by the two presumed target rankings. Simple comparisons of goodness of fit may therefore be misleading. It is perhaps more revealing to compare each model's error relative to the random model's error, when predicting the same data. Results are summarized in Table 2 and discussed below. (Note that the RANGE and THREAT models refer to the ranking model of equation (1), as based on the range and threat ranks respectively.)

1. For the NORMAL condition, the squared error for the range model was only 13 percent of that for the random model; the comparable error ratio for the threat model was 67 percent. Thus, the range model was a better predictor of performance in the NORMAL condition. Inspection of Figures 4a and 5a reinforces this finding. The fit of the range model in Figure 4a is qualitatively more satisfying than that of the threat model in Figure 5a. It appears that the range strategy is a reasonable description of the operator's normal processing mode.

2. For the THREAT instruction condition, the squared error for the threat model was only 12 percent of that for the random model; the comparable error ratio for the range model was 70 percent. Thus, the threat model was the better predictor in the THREAT condition. This is also seen in the superior fits of Figure 5b vs. those in Figure 4b. It is reasonable to conclude that the operator was able to adopt a threat strategy when instructed to do so.

Table 2

Errors in Predicting the $p_j(k)$ Distributions

Item	NORMAL Condition Range Model	NORMAL Condition Threat Model	THREAT Condition Range Model	THREAT Condition Threat Model
Strategy Model:				
Squared error	906.89	2,701.18	1,726.82	1,317.27
Average error	0.83	1.43	1.21	1.06
Random Model:				
Squared error	7,130.69	4,004.69	2,483.45	10,547.45
Average error	2.32	1.74	1.45	2.99
Ratio[a]	0.13	0.67	0.70	0.12
Number of cases[b]	1,319		1,176	

[a]Strategy model squared error/random model squared error.

[b]Total number of display updates in which 2-16 targets were eligible and a launch was made.

Test for Strategy Shift

To determine whether increased workload produced an identifiable shift in the operator's strategy, the 0.25 and 0.40 target rate conditions were analyzed separately. The result was that the relative fits of the models were the same as for the combined data reported above. Thus, there was no gross change in strategy for moderate vs. high workload engagements.

A more detailed test for strategy shifts was made by separately analyzing performance for low load displays (2-5 eligible targets) and high load displays (10-16 eligible targets), regardless of the actual target rate. A shift in strategy from threat to range would be most likely in the THREAT instruction condition. Here, the average error for the threat model increased from 1.04 at low load to only 1.10 at high load--hardly an abandonment of the threat strategy. The average error of the range model increased from 1.09 at low load to 1.25 at high load; a decrease would be expected if there was a switch to the range strategy. In the NORMAL condition, the error for each model also increased. Thus, while there was some degradation in executing the strategies at high loads, there was no evidence for a shift in strategy.

DISCUSSION

Detailed data collection, together with a rather simple mathematical model (based only on rank-order information), proved useful in making inferences about an operator's threat assessment strategies. A random engagement strategy was clearly rejected. A range strategy reasonably described the operator's normal processing mode and reinforces, in an interactive and dynamic task, the earlier results of Rigney and DeBow (1967).

When instructed to do so, the operator gave ample evidence of adopting the optimal but more complex threat strategy. However, it resulted in poorer performance (increasing ship's vulnerability), since it could not be executed as rapidly as the nonoptimal range strategy. The operator's preference for the simpler range strategy can be interpreted as an optimal use of nonoptimal resources--a good example of well-advised coping.

Of course, it is preferable that the proper strategy be executed at a high rate. This is precisely the goal of so-called automated subsystems (e.g., those in Aegis), but even these depend on human monitoring and intervention (RCA, 1984). Thus, operators will continue to require supplemental displays and aids. In particular, there is a need for a display format that codes threat directly; that is, without demanding complex cognitive transformations by the user. Barnes (1983) has compared two such formats in the context of airborne electronic warfare.

Regarding possible strategy shifts, none was detected either between low vs. high workload engagements or between low vs. high density displays within engagements. This is not to say that the operator rigidly executes his adopted strategy. Indeed, adaptability to task difficulty is evident in the observed $p_1(k)$ distributions (Figure 3), and has prominence in the model via the parameter $\underline{a}$ in Equation (1). To the extent that the model accurately reflects human performance, it suggests that the operator spends less and less time in search and decision processes as target density increases.

Note that the values obtained for the parameter $\underline{a}$ imply more persistence in using the prescribed threat strategy ($\underline{a}$ = 0.41) then the unprompted range strategy ($\underline{a}$ = 0.72). This seems inconsistent with the difficulty of the former, as it should degenerate toward

randomness more quickly and yield thereby a larger value of a. However, the explicit instruction to use a threat strategy may have induced its greater persistence. The obtained values of b yield estimates of 3.0-3.3 for the size of the restricted set of targets, consistent with the expectation based on human information processing limits.

It is worth remarking that no "pure" strategies were observed; significant target clustering was generally the case. This tendency was strongest in the NORMAL condition, in which the operator used a range strategy tempered by clustering of targets based on bearings. While clustering incurs a cost (the increased likelihood of overlooking a better target), the higher processing rate that it affords makes it a major heuristic for coping with high workload demand. In this regard, a standard practice in NTDS AAW operations is one of "sectored responsibility"; that is, an individual operator is assigned a single bearing sector of 90-120 degrees in extent. This division of labor obviously reduces the adverse effects of an operator's tendency to cluster targets based on proximities in bearing. The current results thus support the NTDS "sectoring" practice.

CONCLUSIONS

1. It was demonstrated that a simple mathematical model based on the rankings of the target stimuli can provide suitable tests of the information processing strategies used by an operator.

2. No evidence was obtained for a shift in processing strategy as workload increased; rather, the effect of workload may be to limit the depth to which the operative strategy is pursued.

3. The strategies used by "experts" are not necessarily optimal; they may not be the best guidelines for automated algorithms.

RECOMMENDATIONS

It is recommended that, in continued exploratory research on AAW decision making, particular attention be given to the following:

1. Inclusion of additional dimensions of threat, such as the lethality of the opposing platforms' weapons.

2. Identification of information processing strategies in more complex AAW scenarios.

3. Development and evaluation of decision aids for threat assessment.

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