Project No. E-24-607

Date: 7/28/82

Original

Project Director: Dr. W. B. Rouse

Sponsor: Office of Naval Research; Arlington, VA 22217

Type Agreement: SFRC No. N00014-82-K-0487

Award Period: From 6/1/82 To 5/31/86 (Performance) 5-31-86 (Reports)

Sponsor Amount: $397,098 ($121,166 partially funded through 6/30/83) Contracted through: GTRI/ONR

Cost Sharing: N/A

Title: Evaluation of the Abilities of Marine Engineering Personnel to Detect, Diagnose, and Compensate for System Failures

ADMINISTRATIVE DATA

1) Sponsor Technical Contact:
   Leader Psychological Sciences
   Division, Code N00014
   Office of Naval Research
   800 North Quincy Street
   Arlington, VA 22217

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   Thomas A. Bryant
   ONR-RR
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   Phone: (404) 881-4213

Defense Priority Rating: N/A

Security Classification: Unclassified

REstrictions

See Attached SFRC Supplemental Information Sheet for Additional Requirements.

Travel: Foreign travel must have prior approval — Contact OCA in each case. Domestic travel requires sponsor approval where total will exceed greater of $500 or 125% of approved proposal budget category.

For equipment, Title vests with Sponsor, but none originally budgeted.

COMMENTS:

Advance Payment Pool Agreement applies to payment provisions.

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Date 1/8/87

Project No. E-24-607

School/UK ISYE

Includes Subproject No.(s) N/A

Project Director(s) W. B. Rouse GTRC X

Sponsor Office of Naval Research; Arlington, VA 2217

Title Evaluation of the Abilities of Marine Engineering Personnel to Detect, Diagnose, and Compensate for System Failures

Effective Completion Date: 5/31/86 (Performance) (Reports)

Grant/Contract Closeout Actions Remaining:

[ ] None
[ ] Final Invoice or Final Fiscal Report
[ ] Closing Documents
[ ] Final Report of Inventions
[ ] Questionnaire to P. I.
[ ] Property Inventory & Related Certificate
[ ] Classified Material Certificate
[ ] Other

Continues Project No.

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Other Ina Lashley, Angela Jones

Russ Embry
October 8, 1982

Dr. Henry M. Halff
Code 442
Office of Naval Research
800 North Quincy
Arlington, VA 22217

Dear Henry:

Enclosed please find four copies of our quarterly report for the period June 1, 1982 - August 31, 1982.

Sincerely,

William B. Rouse
Professor and Director

WBR:j

CC: F. Cochran, ISyE
   L. H. Bowman, OCA
   ONR Resident Representative
   ONR Branch Office
   J. Hollan, NPRDC
   N. J. Kerr, NASA Memphis
   W. Scanland, NASA Pensacola
   J. McBride, NPRDC
   R. Sasmor, ARI
   H. F. O'Neil, Jr., ARI
   J. Orphansky, IDA
   A. R. Fregly, AFOSR/NL
   R. Blanchard, NPRDC
   P. J. Andrews, NAVSEA
   W. Rizzo, NTEC
   J. Yasutake, AFHRL/LRT
EVALUATION OF THE ABILITIES OF MARINE ENGINEERING PERSONNEL
TO DETECT, DIAGNOSE, AND COMPENSATE FOR SYSTEM FAILURES

William B. Rouse
Principal Investigator

Quarterly Report
For the Period June 1, 1982 - August 31, 1982

For

Contract N00014-82-K-0487
Work Unit NR 154-491
(June 1, 1982 - May 31, 1985)

Center for Man-Machine Systems Research
Georgia Institute of Technology
Atlanta, GA 30332
(404-894-3996)
Progress During the Reporting Period

The only accomplishment during this reporting period was negotiation and signing of the subcontract with Marine Safety International Inc. to provide access to their full-scope engine room simulator and trainees as well as provide needed technical information for development of the low and moderate fidelity simulations of the engine room environment. Because these negotiations involved some temporary snags, no work was begun on the project until the subcontract was signed on August 31, 1982.

Schedule for Next Quarter

The project team will start work on September 15, 1982. It includes William B. Rouse (Principal Investigator), T. Govindaraj (Assistant Professor), David Su (Ph.D. Student), and Annette Knaeuper (M.S. Student). Prof. Rouse and Ms. Knaeuper will focus on the extension of the model of human problem solving for application to the engine room environment. Prof. Govindaraj and Mr. Su will focus on the development of the low and moderate fidelity simulators. In addition, Prof. Rouse will, of course, direct the overall project.

During the next quarter, efforts will be directed towards developing an Apple II-based low-fidelity engine room simulator involving a hierarchical representation of the system embodied in Marine Safety's full-scope simulator. Efforts will also be directed towards design of the Pascal software for an initial version of the model of human problem solving.
Problems Encountered

The schedule has slipped due to the extended negotiations with Marine Safety. Hopefully, this slippage will be temporary.

Departures From Proposed Work

None

Accomplishments During Reporting Period

It seems reasonable to claim that the formalization of a solid working relationship with government (ONR), industry (Marine Safety), and academia (Georgia Tech) is worth noting.
EVALUATION OF THE ABILITIES OF MARINE ENGINEERING PERSONNEL
TO DETECT, DIAGNOSE, AND COMPENSATE FOR SYSTEM FAILURES

William B. Rouse
Principal Investigator

Quarterly Report
For the Period September 1, 1982 – November 30, 1982

For

Contract N00014-82-K-0487
Work Unit NR 154-491
(June 1, 1982 - May 31, 1985)

Center for Man-Machine Systems Research
Georgia Institute of Technology
Atlanta, GA 30332
(404-894-3996)
Progress During the Reporting Period

As proposed, the research has proceeded in two directions: simulator development and modeling. Considering simulator development, the operation of the high-fidelity engine room simulator being built at Marine Safety International (MSI) was studied. From the detailed manuals and figures obtained from MSI, the essential components that should be considered for the low and moderate fidelity simulator were initially identified. Even though all the details thus far considered may not be necessary for the low fidelity simulator, gathering such information is essential for obtaining a hierarchical representation that will be useful throughout this project. The initial hierarchical representation of the engine room simulator consists primarily of water/steam, fuel, and lube oil subsystems. This representation is being used to define the level of information required for the low fidelity simulator.

Methods appropriate for representing dynamic systems were also reviewed with the moderate-fidelity simulator in mind. Use of graph theoretic techniques have been investigated. It appears that the various subsystems of the engine can be represented in terms of graphs. Appropriate subsystems may be investigated by selectively connecting certain nodes. The breadth and depth to which failures or events affect other components can possibly be studied by using appropriate distance metrics.

The suitability of using techniques from artificial intelligence (AI) for representing dynamic systems, as well as the human's knowledge of dynamic systems, has also been
considered. Preliminary investigations indicate that AI techniques may be rather inefficient and slow for a complex system such as the simulator. The appropriateness of various concepts will be studied further by using an example of a simple dynamic system such as an automobile.

The modeling efforts are proceeding by attempting to extend the previously-developed, three-level, rule-based model of human problem solving to dynamic environments and applying it to describe human behavior in a process control environment for which experimental data is already available. During the current reporting period, most of the effort has been focused on outlining conceptual issues to be resolved and reviewing ideas from cognitive science and artificial intelligence that may be useful.

**Schedule for Next Quarter**

Now that the technical documentation from MSI has been reasonably digested, the next step involves interaction with the MSI technical staff to eliminate misunderstandings and fill in many missing details. Documentation of MSI's high-fidelity simulator will then be produced in a form that will serve as the basis for the development of the low and moderate fidelity simulators. The correctness of this transformed and extended documentation will then be assured.

The modeling efforts during the next quarter should proceed to the point of having an initial operational model that can at least observe a dynamic process and decide if the process outputs
agree with the model's expectations. This seemingly simple idea (i.e., expectations) is actually quite subtle and currently a topic receiving considerable thought within this work.

**Problems Encountered**

While the last quarter encountered schedule delays, this quarter proceeded more as had been expected at this stage of the work.

**Departures From Proposed Work**

None.

**Accomplishments During Reporting Period**

Nothing definitive.
March 7, 1983

Dr. Henry M. Halff
Code 442
Office of Naval Research
800 North Quincy
Arlington, VA 22217

Dear Henry:

Enclosed please find four copies of our quarterly report for the period December 1, 1982 - February 28, 1983.

Sincerely,

William B. Rouse
Professor and Director

WBR:j

CC: F. Cochran, ISyE
L. H. Bowman, OCA
ONR Resident Representative
ONR Branch Office
J. Hollan, NPRDC
N. J. Kerr, NASA Memphis
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H. F. O'Neil, Jr., ARI
J. Orlansky, IDA
A. R. Fregly, AFOSR/NL
R. Blanchard, NPRDC
P. J. Andrews, NAVSEA
W. Rizzo, NTEC
J. Yasutake, AFHRL/LRT
Progress During the Reporting Period

Most of the relevant information has been collected for the low fidelity simulator design. The information provided by Marine Safety International (MSI) has been collated and organized in a form suitable for the design. A visit by Rouse and Govindaraj to MSI was extremely helpful for gathering more information, and for clarifying a number of issues concerning the operation of a marine powerplant. Discussions with the staff of MSI has provided us with a good understanding of how the powerplant operates, and how the full fidelity simulator works. Information on a large number of failures that can be induced, and the effect of these failures on various components and subsystems have been collected. This is essential for the design of low and moderate fidelity simulators, to determine the symptoms when a simulated failure occurs, and for providing feedback to the subject interactively.

Some information necessary for the simulation of powerplant dynamics has also been obtained. This concerns primarily the thermodynamical equations and parameters. This information is being organized into a form suitable for dynamic system simulation.

A low fidelity simulator has been designed to run on the Apple II microcomputer, compatible in format with FAULT. Even though this is built upon work done previously, getting the simulator to run could be considered as an important accomplishment for this quarter. Information about the full fidelity simulator and various failures have been organized
suitably to improve computational performance. Since a large number of gauges and indicators (nearly 600) are involved, various schemes for arranging this information were tried.

LISP programs have been written to simulate dynamic systems with the intention of using these for qualitative simulation. The programs can simulate a simple second order system, as well as a network of tanks (tanks connected by pipes carrying fluid). Dynamical equations are currently used for simulation. States of the second order system have been quantized to observe the qualitative behavior when a step input is used. Deviations from desired values are viewed as "normal", "small", "medium", and "large". This has been done to observe the qualitative behavior in terms of the extent and number of oscillations before reaching steady state. This step is expected to be helpful for trying various schemes for qualitative simulation.

The initial version of the model of human problem solving has been programmed in Pascal. It is being tested with a process plant simulator (PLANT). The model is able to operate PLANT, when no failures occur, and it is also able to classify and compensate for familiar failures (i.e., valve or pump failures), when there is a moderate time interval between them.

Rules are being added to enable the model to operate when familiar and infrequent failures (i.e. tank rupture and safety system failures) occur, and when the plant is out of balance and a re-start must be performed. The model should be able to operate PLANT (with familiar and frequent failures, and familiar and infrequent failures) by the beginning of April.
Schedule for Next Quarter

The next quarter will be devoted to gathering information from MSI, modifying the low-fidelity simulator, and pilot testing it. Also, the efforts on qualitative simulation for use in the moderate-fidelity simulator will be pursued further. Finally, the model will continue to be refined and tested in the process plant environment.

Problems Encountered

None

Departures from Proposed Work

None

Accomplishments During Reporting Period

Initial versions of the low-fidelity simulator and model of human problem solving were programmed and are now running and being extended.
June 8, 1983
March 7, 1983

Dr. Henry M. Halff
Code 442
Office of Naval Research
800 North Quincy
Arlington, VA 22217

Dear Henry:

Enclosed please find four copies of our quarterly report for the period March 1, 1983 — May 31, 1983.

Sincerely,

William B. Rouse
Professor and Director

WBR:j

CC:  F. Cochran, ISyE
     ONR Resident Representative
     ONR Branch Office
     J. Hollan, NPRDC
     N. J. Kerr, NAS Memphis
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     A. R. Fregly, AFSOR/NL
     R. Blanchard, NPRDC
     P. J. Andrews, NAVSEA
     W. Rizzo, NTEC
     J. Yasutake, AFHRL/LRT
     G. S. Malecki, ONR Arlington

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EVALUATION OF THE ABILITIES OF MARINE ENGINEERING PERSONNEL
TO DETECT, DIAGNOSE, AND COMPENSATE FOR SYSTEM FAILURES

William B. Rouse
Principal Investigator

Quarterly Report
For the Period March 1, 1983 - May 31, 1983

For

Contract N00014-82-K-0487
Work Unit NR 154-491
(June 1, 1982 - May 31, 1985)

Center for Man-Machine Systems Research
Georgia Institute of Technology
Atlanta, GA 30332
(404-894-3996)
Progress During the Reporting Period

The development of the low-fidelity simulator progressed substantially this quarter with several rounds of iteration between our group and Marine Safety International (MSI) to clarify and resolve a wide variety of technical issues. Pilot testing of this simulator should take place this summer at MSI in New York.

The foundation for the development of the moderate-fidelity simulator also progressed this quarter. The approach that seems to be emerging involves using decoupling and reduced-order models to simplify the system dynamics. Further, a mixture of algebraic and symbolic models may be used to provide a "qualitative" simulation suitable for use on a microprocessor. An initial version of this simulation should be running by the end of next quarter.

The model of human problem solving in dynamic environments (KARL, which connotes Knowledgable Application of Rule-based Logic) was extended during this quarter to have explicit "expectations" concerning the evolution of a system's state. This ability now makes it such that KARL must explicitly deal with the tradeoff between devoting attention to continued system operation and devoting attention to diagnosing the source of unacceptable deviations from expectations. Rules for making this tradeoff are being developed by analyzing experimental data obtained during a recent process control experiment in another project. The concept of "expectations" is also an important prerequisite for KARL to deal with unfamiliar failures. By the end of the next quarter, KARL should be able to tradeoff operational and diagnostic goals as well as deal with unfamiliar failures.
Schedule for Next Quarter

As noted above, the next quarter will be devoted to:

1. Completing the first version of the low-fidelity simulator, pilot testing it at MSI in New York, and modifying the simulator on the basis of the data collected.

2. Developing an initial version of a portion of the moderate-fidelity simulator which will include a "qualitative" simulation of at least a portion of a marine powerplant.

3. Extending KARL to tradeoff operational and diagnostic goals and deal with unfamiliar failures in a process control environment.

4. Basic human factors engineering assessment of the controls and displays of MSI's high-fidelity simulator to identify potential inadequacies which will serve as components in the human error analyses that will be performed in conjunction with later experiments.

Problems Encountered

None

Departures from Proposed Work

None

Accomplishments During Reporting Period

The low-fidelity simulator is approaching credibility. The theoretical basis for the moderate-fidelity simulator is emerging. The model of human problem solving in dynamic environments now has "expectations" concerning how its environment is likely to evolve.
September 21, 1983

Dr. Henry M. Halff  
Code 442  
Office of Naval Research  
800 North Quincy  
Arlington, Virginia 22217

Dear Henry:

Enclosed please find four copies of our quarterly report for the period June 1, 1983 - August 31, 1983.

Sincerely,

William B. Rouse  
Professor and Director

CC: F. Cochran, ISyE  
ONR Resident Representative  
ONR Branch Office  
J. Hollan, NPRDC  
N. J. Kerr, NAS Memphis  
W. Scanland, NAS Pensacola  
J. McBride, NPRDC  
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J. Yasutake, AFHRL/LRT  
G. S. Malecki, ONR Arlington
EVALUATION OF THE ABILITIES OF MARINE ENGINEERING PERSONNEL
TO DETECT, DIAGNOSE, AND COMPENSATE FOR SYSTEM FAILURES

William B. Rouse
Principal Investigator

Quarterly Report
For the Period June 1, 1983 - August 31, 1983

For

Contract N00014-82-K-0487
Work Unit NR 154-491
(June 1, 1982 - May 31, 1985)

Center for Man-Machine Systems Research
Georgia Institute of Technology
Atlanta, GA 30332
(404-894-3996)
Progress During the Reporting Period

The development of the initial version of the low-fidelity simulator was essentially completed during this reporting period. All that remains to be done is the expansion of the data base to include a wider variety of failures. This should have minimal, if any, effects on the simulation software.

Pilot testing of the low-fidelity simulator is scheduled to take place during the first week of November at Marine Safety International (MSI) in New York. This test had been scheduled for the June-August period, but was delayed due to the facilities at MSI not being ready for trainees.

An initial version of the moderate-fidelity simulator is running on the VAX-11/780 in LISP. This is the first milestone in developing a "qualitative" simulation involving a mixture of algebraic and symbolic models. The overall propulsion system is modeled with a state variable formulation based on the physical principles of a steam propulsion system. The subsystem models will be based on symbolic representations.

An initial assessment was completed of basic human factors aspects of the controls and displays of MSI's high-fidelity simulator. This assessment was based on photographs and engineering drawings. The results definitely need to be confirmed and extended by visiting MSI. This visit is planned for October in conjunction with a meeting to plan the November pilot test of the low-fidelity simulator.
The first version of the rule-based model KARL (Knowledgable Application of Rule-Based Logic) was completed in conjunction with Annette Knaeuper's M.S. thesis which will soon be issued as a Center report. For the process control simulation studied, KARL was found to match subjects' choices of rules and action sequences fairly well. Perhaps of most interest was an analysis of mismatches between KARL and subjects which indicated that subjects knew KARL's rules but had different priorities. This is particularly interesting because the explanations of performance offered by these highly-trained subjects (i.e., "experts") differed from the way they actually did the task; they were able to explain what they knew, but they did not necessarily use this knowledge. This would seem to have significant implications for the design of expert systems.

Schedule for Next Quarter

The highest priority for the next quarter will be pilot testing of the low-fidelity simulator and modifying it as necessary. The goal is to have this simulator become a regular part of MSI's training program by early 1984 to allow collection of a substantial amount of performance data for similar and dis-similar problems on the low and high fidelity simulators.

The next quarter should also result in substantial progress on the symbolic modeling of subsystems for the moderate-fidelity simulator. Also, the basic human factors assessment of the high-fidelity simulator will be completed at MSI.
In the modeling area, KARL will be extended to be a more sophisticated planner and deal more consciously with unfamiliar failures. The idea has also emerged to use KARL as an online instructor and perhaps operational aid. An initial experimental evaluation of this idea will be performed during the next quarter. The current hypothesis is that assistance from KARL in situation assessment will substantially improve subjects' performance.

**Problems Encountered**

The experimental work at MSI has proceeded more slowly than anticipated. This is due to the completion of their simulation facility being delayed and changes in their personnel. This loss of time will hopefully be made up over the next six to twelve months. Fortunately, the simulator and model development efforts at Georgia Tech have proceeded a bit more quickly than anticipated and, therefore, resources have not been spent in simply waiting for MSI's facility.

**Departures from Proposed Work**

The aforementioned delay of the pilot test is a departure from the original schedule. The planned evaluation of the rule-based model as a potential training device and operational aid represents an unanticipated addition to the research plan.
Accomplishments During Reporting Period

The completion of the initial version of the low-fidelity simulator and having a version of the moderate-fidelity simulator running are important steps in the research plan. However, the results with KARL are more intriguing, at least at this point in time. In particular, the idea that well-trained subjects would explain what they would do in specific situations in one way and then, when faced with these situations, behave in a different way was initially quite puzzling. Certainly, as later testing showed, subjects did not lose their knowledge somewhere between training and operational evaluation. What did appear to happen, however, was that subjects had different priorities (e.g., attitudes toward risk) when asked what they would do versus required to actually do it. The implication is that expert systems should include not only the expert's facts but also his or her value structure.
January 3, 1984

Dr. Henry M. Halff
Code 442
Office of Naval Research
800 North Quincy
Arlington, Virginia 22217

Dear Henry:

Enclosed please find four copies of our quarterly report for the period September 1, 1983 - November 30, 1983.

Sincerely,

William B. Rouse
Professor and Director

cc: F. Cochran, ISyE
   ONR Resident Representative
   ONR Branch Office
   J. Hollan, NPRDC
   N. J. Kerr, NAS Memphis
   W. Scanland, NAS Pensacola
   J. McBride, NPRDC
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   A. R. Fregly, AFOSR/NL
   R. Blanchard, NPRD
   P. J. Andrews, NAVSEA
   W. Rizzo, NTEC
   J. Yasutake, AFHRL/LRT
   G. S. Malecki, ONR Arlington
EVALUATION OF THE ABILITIES OF MARINE ENGINEERING PERSONNEL TO DETECT, DIAGNOSE, AND COMPENSATE FOR SYSTEM FAILURES

William B. Rouse
Principal Investigator

Quarterly Report
For the Period September 1, 1983 - November 30, 1983

For

Contract N00014-82-K-0487
Work Unit NR 154-491
(June 1, 1982 - May 31, 1985)

Center for Man-Machine Systems Research
Georgia Institute of Technology
Atlanta, GA 30332
(404-894-3996)
Progress During the Reporting Period

The low-fidelity simulator for the marine engine room at MSI has been completed. Realistic failures provided by marine engineers at MSI have been incorporated in the data base for use in experiments. In addition, the schematics used to aid troubleshooting have been made to conform closely with the structure of the high-fidelity simulator. In particular, these schematics are based on the piping diagrams of the high-fidelity simulator. This aspect should improve the face-validity of the low-fidelity simulator considerably, in addition to improving the correspondence between different levels of fidelity. Experiments using this low-fidelity simulator are scheduled to begin during the first week of January 1984 at MSI.

Human factors evaluation of the full fidelity simulator has been completed based on detailed measurements of the high-fidelity simulator obtained during our last visit. This evaluation included testing the extent to which various controls and displays comply with good human factors guidelines and practice. This analysis will be used later to estimate the extent to which errors could have been induced by poor design and/or placement of controls. Possible errors resulting from inadequacies in the design can easily be compared to those resulting from experiments where experienced marine engineers identify the cause of failures using the symptoms provided.

A framework for modeling the dynamics of large interconnected systems has been developed. Characteristics of the components and subsystems have been identified and classified in terms of property lists. Each component is characterized in terms of its inputs, outputs, and the loops (circuits) of which it is a part. The methodology for the propagation of changes in states and controls of the system has been developed. For each type of dynamic system (thermal, mechanical, etc.) symbolic and qualitative dynamics
will be developed so that states can be updated whenever changes occur. After the details are worked out and the marine engine dynamics implemented, this will be incorporated in the moderate-fidelity simulator.

The first version of the rule-based model KARL (Knowledgeable Application of Rule-based Logic) was completed as reported in the Center report 83-3. For the process control simulation studied the analysis of agreements and disagreements between subjects' and KARL's choices of actions showed that subjects did not fully use their operational knowledge in various situations. From this the idea emerged to use KARL as an online instructor and perhaps operational aid.

This idea has been realized in that KARL can now function as an online observer of the process and subjects' control behavior. KARL only intervenes when subjects are inconsistent with their instructions. The display of an explanation is optional and subjects are allowed to proceed ignoring KARL's warning of inconsistency. KARL does not explicitly tell the subjects what to do in specific situations but provides a general explanation of what type of actions are appropriate after subjects have implemented their choice. This explanation is derived from the rules implemented in the model.

Furthermore, subjects are allowed to change their prior action choice after they received an explanation. Experiments using KARL as an operational aid are planned for the next quarter.

Since there are not yet data for the marine propulsion system simulation the second test of the model will be pursued using a communication network simulation and experimental data obtained from a different project. Currently the rules for this task are being developed and the implementation of the rules into the model shall show the general applicability of the model.
Schedule for Next Quarter

Two experiments will be conducted in January 1984. The first will involve an evaluation of the low-fidelity simulator. Four chief engineers will serve as subjects. Data collection will occur at MSI. While informal evaluation of this simulator using three subject-matter experts has provided considerable useful information, it is anticipated that this first formal experiment will provide definitive and reportable results.

The second experiment to be conducted in January will involve the use of KARL as an online instructor and operational aid. The plan is to run eight subjects in the PLANT simulation using KARL to assess situations, monitor consistency, and provide explanations. These subjects will run as a "fifth" group within the experimental design used by Morris in her experiments with PLANT which provided the data for earlier work with KARL. This experiment will be conducted at Georgia Tech. The next quarter should also result in an operational version of the moderate-fidelity simulator that combines a state variable description of the overall system and symbolic descriptions of various subsystems. Pilot testing of this initial version will be conducted at Georgia Tech in the latter part of the quarter.

Problems Encountered

Delays at MSI continue to be problematic. Delays in moving the Center's computer equipment (due to Georgia Tech) into its new facility has also been inconvenient relative to scheduling experiments. However, with a January 5th experiment planned at MSI and a January 9th hook-up of the VAX by DEC, these problems will hopefully soon be things of the past.

Departures from Proposed Work

As noted in the previous quarterly report, the schedule continue to slip, although not dramatically. Fortunately, unanticipated additions to the research
plan such as the upcoming experiment with KARL have allowed productivity to remain high.

**Accomplishments During Reporting Period**

Much of this quarter was devoted to planning and preparing for experiments. The data which will emerge during the next quarter should enable reporting of significant accomplishments.
March 30, 1984

Dr. Henry M. Halff  
Code 442  
Office of Naval Research  
800 North Quincy  
Arlington, Virginia 22217

Dear Henry:

Enclosed please find four copies of our quarterly report for the period December 1, 1983 - February 29, 1984.

Sincerely,

William B. Rouse  
Professor and Director

cc: F. Cochran, ISyE  
ONR Resident Representative  
ONR Branch Office  
J. Hollan, NPRDC  
N.J. Kerr, NAS Memphis  
W. Scanland, NAS Pensacola  
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EVALUATION OF THE ABILITIES OF MARINE ENGINEERING PERSONNEL TO DETECT, DIAGNOSE, AND COMPENSATE FOR SYSTEM FAILURES

William B. Rouse
Principal Investigator

Quarterly Report
For the Period December 1, 1983 - February 29, 1984

For

Contract N00014-82-K-0487
Work Unit NR 154-491
(June 1, 1982 - May 31, 1985)

Center for Man-Machine Systems Research
Georgia Institute of Technology
Atlanta, GA 30332
(404-894-3776)
**Progress During the Reporting Period**

An experiment was conducted at Marine Safety International using the low fidelity simulator. For the first time, marine engineers not previously involved with the development of this simulator were used as subjects in a controlled experiment. Four chief engineers (three from Texaco and one from the Merchant Marine Academy) participated. The objective of this experiment was to try the simulator for realism and to identify any problems prior to starting the regular experimental program. Another important objective was to observe the problem solving strategy of senior marine engineers and obtain feedback that would help improve the simulator.

A total of 13 failures were used in the experiments for each subject. Analysis indicated that the subjects when presented with symptoms for a failure seemed to follow a hypothesis-and-test routine until the failed component was identified. In some cases they could not identify the failed component. Difficulties in identifying the cause of the failure were sometimes traced to the lack of information provided to the subjects. It was felt that detailed symptoms and schematics would help greatly. The low fidelity simulator has now been enhanced using better schematic diagrams, and by providing additional information along with the systems. Additional failures have been incorporated into the training program being designed. Experiments on a bi-monthly basis are scheduled to start in April.
A thorough literature review on simulators used for training as well as related training issues has been completed. This report will be published as a technical report shortly.

Work on the moderate fidelity simulator has progressed steadily with the incorporation of additional information into the property lists. The simulation for propagating events has been refined. This incorporates the methodology for the propagation of changes in states and controls of the system mentioned in the last quarterly report. Schemes for identifying the system and component type using input and output information have been developed, and are being tested for implementing in the simulator. A preliminary version of this simulator is expected to be ready by the end of April.

As noted in the last quarterly report, the rule-based model KARL (Knowledgeable Application of Rule-based Logic) can now function as an online observer of a process control simulation and subjects' control behavior. Substantial changes were made in the display layout and in the interaction options of subjects and aid. KARL now provides: 1) situation assessment, 2) optional consistency assessment and feedback, i.e., a general explanation of what type of action is appropriate, and 3) performance feedback (i.e., encouraging or warning).

Subjects are allowed to change their prior action choice if there is an inconsistency or, overlook the inconsistency and proceed. The experiment using KARL as an operational aid will be performed during the next quarter.
The second test of the model, i.e., using a communication network and experimental data obtained from a different project, is currently being pursued. Most of the rules of this task have been developed and are currently being tested by comparison with subjects.

An improved structure for KARL has been developed. The basic structure has been maintained; however, all rules will be embedded in a knowledge base (problem-dependent) that is absolutely separated from the interpreter (problem-independent) of the program. The programming language is LISP. In order to test this new structure, the process control simulation that was used in earlier experiments was reprogrammed in LISP. This new KARL will be an improved, extended, and generalized version of KARL that will hopefully also allow adding and deleting rules while performing a task, i.e., include some form of learning mechanism.

Schedule for Next Quarter

Beginning in April, experiments will be conducted at Marine Safety International on a bi-monthly basis. The current plan is to look at the relationships among TASK, FAULT, the low-fidelity simulator, and the high-fidelity simulator in the April, June, and August experiments. Starting in August (perhaps as a pilot test), and continuing thereafter, the moderate-fidelity simulator will become part of the experimental protocol.

As noted in the previous section, the experimental evaluation of KARL as an online instructor and operational aid was delayed and will start in April. This will allow assessment of the impact of an
online 'coach', especially in terms of transfer once the coach is taken away. In parallel, work is proceeding on making KARL more general with increased abilities for adaptation and learning.

Problems Encountered

While delays have plagued us throughout this project, MSI's high-fidelity simulator is finally operational and training begins on a regular basis in April. Further, the somewhat painful transition between buildings at Georgia Tech is complete. Therefore, the unusual and inordinate delays appear to be past.

Departures from Proposed Work

Other than the delays, work is proceeding as proposed, with the moderate-fidelity simulator somewhat behind schedule and the model of human problem solving considerably ahead of schedule. We anticipate that the rate at which experimental data will be collected over the next year will more than compensate for its paucity thus far.

Accomplishments During Reporting Period

First experiment (mostly a pilot test) at MSI completed.
LIBRARY DOES NOT HAVE

Quarterly Report March 1, 1984-May 31, 1984
EVALUATION OF THE ABILITIES OF MARINE ENGINEERING PERSONNEL TO DETECT, DIAGNOSE, AND COMPENSATE FOR SYSTEM FAILURES

William B. Rouse
Principal Investigator

Quarterly Report
For the Period June 1, 1984 - August 31, 1984

For

Contract N00014-82-K-0487
Work Unit NR 154-491
(June 1, 1982 - May 31, 1985)

Center for Man-Machine Systems Research
Georgia Institute of Technology
Atlanta, GA 30332
(404-894-3996)
PROGRESS DURING THE REPORTING PERIOD

Experimentation with the low-fidelity simulator continued during this period. Development of the moderate-fidelity simulator also progressed. Work on the model of human problem solving has been temporarily halted due to the departure of Annette Knaeuper. We anticipate work starting again by January 1985.

Low-Fidelity Simulator

During this period, the failures used for experiments were reviewed both at Georgia Tech and MSI. FAIL was modified slightly to improve the realism by removing the Alarm command and incorporating a new command called Look. Look simulates the actions of going into the engine room to look at, listen to, or directly investigate suspected components. In addition, the subjects were also asked to rate the difficulty and familiarity level of the failure on a five-point scale at the end of each failure run. Then subjects were shown summary statistics of their performance for the failure. Work on the fault diagnosis model described in the previous quarterly report was continued. Results from two experiments at MSI were analyzed using the refined model structure. The preliminary conclusions of the experiment and model results seem valid. These conclusions as well as the robustness of the model will be tested in experiments scheduled for September, October and November, where some subjects with slightly reduced experience levels are scheduled to participate.

Moderate-Fidelity Simulator

The model structure for dynamic systems described in the previous quarterly report has been used to build up details for the simulator. A
number of primitives were identified for which the detailed structure will be worked out. Specific lists of components for various paths in the loops have been identified and classified into appropriate groups. A working paper was prepared that describes the model structure and model details, and forms part of the annual report. Due to the large number of components, most of which are not essential to the simulation process, a simpler system with reduced number of components has been approximated for testing the model of the dynamic system.

SCHEDULE FOR NEXT QUARTER

The Fall quarter will involve several experiments at MSI - all of the data for David Su's Ph.D. thesis will be collected by December. The prototype moderate-fidelity simulator will be tested.

PROBLEMS ENCOUNTERED

Small delay due to change of personnel.

DEPARTURE FROM PROPOSED WORK

Only the aforementioned delay.

ACCOMPLISHMENTS DURING REPORTING PERIOD

Mainly continued development and data collection.
EVALUATION OF THE ABILITIES OF MARINE ENGINEERING PERSONNEL TO DETECT, DIAGNOSE, AND COMPENSATE FOR SYSTEM FAILURES

William B. Rouse
Principal Investigator

Quarterly Report
For the Period September 1, 1984 - November 30, 1984

For

Contract N00014-82-K-0487
Work Unit NR 154-491
(June 1, 1982 - May 31, 1985)

Center for Man-Machine Systems Research
Georgia Institute of Technology
Atlanta, GA 30332
(404-894-3996)
PROGRESS DURING THE REPORTING PERIOD

Experimentation with the low-fidelity simulator continued during this period. Development of the moderate-fidelity simulator also progressed. As noted in the last quarterly report, work on the model of human problem solving has been temporarily halted due to the departure of Annette Knaeuper. We anticipate work starting again by January 1985.

Low Fidelity Simulator

Three experiments were conducted during this period. The data from the September experiment were analyzed. A paper describing the human diagnostic process using data from April, June, and September experiments has been completed for submission to IEEE SMC Transactions. A preliminary version of this paper was presented at the IEEE SMC Conference in October, 1984.

Protocols have been collected during the October and November experiments. In October, subjects were asked to describe verbally the operation of the powerplant. In November, subjects were asked to think aloud while diagnosing. Recordings of these protocols are being transcribed for detailed analysis.

The protocols are expected to help better understand how the subjects reason from given symptoms. The reasoning process is assumed to be a function of the acquisition, structuring, and retrieval of the system knowledge. How the structuring and retrieval of system knowledge affect the inferential process during diagnosis is being investigated.

Moderate-Fidelity Simulator

For the marine powerplant with reduced number of components, most of the simulation details have been worked out. During this quarter, all the relevant states for the components that make up the system have been identified. The components themselves have been classified according to
their types. The types are: Heat Exchanger, Gain, Capacitor, Controller, Transducer, Source, Sink, Source-Sink, Phase Changer, Conduit, and Reactor. Except for the Heat Exchanger, the types correspond to primitives. Each component has, in addition to its type, input and output states and parameters defined as properties. The primitives have been modified where necessary to handle the states and parameters accessed from appropriate lists.

Preliminary details for the display of information concerning abnormal states and events have been finalized. Mechanisms for creation of events and failures, storage of historic information for abnormal conditions, and human operator actions have been formulated. The simulator should be ready when all the above components are integrated using appropriate control structure. It is expected that the simulator will be operational during the next quarter. With some "fine tuning" and additional refinement, the moderate-fidelity simulator is expected to be incorporated in experiments at MSI starting in April 1985.

SCHEDULE FOR NEXT QUARTER

The Winter quarter will involve completion of the analysis of the data from several experiments at MSI. This data and that from earlier experiments will constitute the bulk of the data for David Su's Ph.D. thesis. The prototype moderate-fidelity simulator will be tested.

PROBLEMS ENCOUNTERED

As noted in the last quarterly report, there has been a small delay due to change of personnel.

DEPARTURE FROM PROPOSED WORK

Only the aforementioned delay.

ACCOMPLISHMENTS DURING REPORTING PERIOD

Mainly continued development and data collection.
EVALUATION OF THE ABILITIES OF MARINE ENGINEERING PERSONNEL
TO DETECT, DIAGNOSE, AND COMPENSATE FOR SYSTEM FAILURES

William B. Rouse
Principal Investigator

Quarterly Report
For the Period December 1, 1984 - February 28, 1985

For

Contract N00014-82-K-0487
Work Unit NR 154-491
(June 1, 1982 - May 31, 1985)

Center for Man-Machine Systems Research
Georgia Institute of Technology
Atlanta, GA 30332
(404-894-3996)
PROGRESS DURING THE REPORTING PERIOD

The data collected in six experiments using low fidelity simulator were compiled and analyzed. A paper describing the diagnostic process and the experimental results, which was originally presented at the IEEE SMC Conference in October 1984, was revised; it has been submitted to IEEE SMC Transactions for review. The moderate fidelity simulator is progressing, with more details being worked out. Experiments could start sometime in May or June 1985.

Low Fidelity Simulator

Data from three experiments conducted during September, October, and November 1984 were analyzed. Based on this analysis, an earlier paper presented at IEEE SMC Conference in October 1984 was updated and revised. This paper has been submitted to IEEE SMC Transactions.

The general results from these experiments are twofold.

1) Good IFS (Initial Feasible Set) results in good fault diagnosis performance.
2) BD (Breadth-Depth) strategy results in better performance than BL (Balanced) strategy.

The fact that both IFS and Strategy Used affect the performance is significant. It seems to imply that in a complex system, problem solving ability is affected by both context-free (IFS) and context-specific (Transition Strategy) factors.

Protocols collected during October, November 1984 and January 1985 were transcribed. Preliminary analysis of these protocols showed that there were two types of knowledge employed by the subjects: symptom knowledge and system knowledge.
Symptom knowledge is rule-based, whereas system knowledge is organized hierarchically with the higher level abstracted toward system functionality and lower levels having direct physical correspondence. The data including protocols are being analyzed to further understand and model the diagnostic process.

**Moderate-Fidelity Simulator**

Components of the marine power plant were earlier identified and classified into a number of types corresponding to primitives. During this quarter, states and parameters for the primitives were refined and tentative control structures were designed. These enabled simulations of various subsystems and simple events and failures. These simulations run slower than real time so that effects of failures could be observed. Various means of storing historic information on abnormal conditions and human operator actions were tried.

Computational experiments with the model continue to be performed to choose appropriate control structures and parameter values. A number of simple display formats were also tried along with the simulations. It is expected that the simulation details will follow the structure developed thus far except for the display formats. More sophisticated displays will be possible with the availability of Xerox Dandelions.

**SCHEDULE FOR NEXT QUARTER**

Work on developing a suitable model for problem solving and diagnostic performance is expected to progress. This model will incorporate data from all six experiments including some protocol information from the latter experiments. David Su is expected to complete a major portion of his Ph.D. dissertation which will include experimental data and model details.
Symptom knowledge is rule-based, whereas system knowledge is organized hierarchically with the higher level abstracted toward system functionality and lower levels having direct physical correspondence. The data including protocols are being analyzed to further understand and model the diagnostic process.

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**SCHEDULE FOR NEXT QUARTER**

Work on developing a suitable model for problem solving and diagnostic performance is expected to progress. This model will incorporate data from all six experiments including some protocol information from the latter experiments. David Su is expected to complete a major portion of his Ph.D. dissertation which will include experimental data and model details.
The arrival of a Xerox Dandelion and a Dandy-Tiger within the next few weeks should help design better displays than were originally anticipated. Conversion of programs from Franz Lisp on the VAX to Interlisp-D is expected to be completed relatively quickly. Slight delays may occur due to the need to learn the features of a new system. It is hoped that experiments with the moderate fidelity simulator could start as early as May or June 1985.

The work on modeling of human problem solving will begin again in April with the addition of Ph.D. student Janet L. Fath to the project staff. Janet will focus on developing the "online coach" concept for application with the moderate fidelity simulator. The emphasis will be on integrating our previous notions with the much wider body of knowledge on intelligent tutoring and extending this body of knowledge to dynamic environments where time constraints may very significantly affect the viability of tutoring strategies.

PROBLEMS ENCOUNTERED

No new problems.

DEPARTURE FROM PROPOSED WORK

Increased emphasis on concept of "online coach".

ACCOMPLISHMENTS DURING REPORTING PERIOD

Mainly continued development and data collection and analysis.
EVALUATION OF THE ABILITIES OF MARINE ENGINEERING PERSONNEL TO DETECT, DIAGNOSE, AND COMPENSATE FOR SYSTEM FAILURES

William B. Rouse
Principal Investigator

Quarterly Report
For the Period March 1, 1985 - May 31, 1985

For

Contract N00014-82-K-0487
Work Unit NR 154-491
(June 1, 1982 - May 31, 1986)

Center for Man-Machine Systems Research
Georgia Institute of Technology
Atlanta, GA 30332
(404-894-3996)
PROGRESS DURING THE REPORTING PERIOD

During this period, David Su completed the analysis of the data collected at Marine Safety International over the past year, and developed the concept of "hypothesis frames" to account for the observed diagnostic behavior of the experienced subjects studied. T. Govindaraj's work on the moderate-fidelity simulator proceeded with efforts focused on rehosting the software on the Xerox Dandy-Tiger. Also, during this period, Janet Fath began work in the area of online training in dynamic environments.

Low Fidelity Simulator

Protocols and data collected up to January 1985 were analyzed. Large individual differences were observed. To explain for the deviation, we investigated a "micro" model for fault diagnosis that considered the formation of knowledge and the mechanisms behind the diagnostic actions. Two types of knowledge were identified: rule-based symptom knowledge and hierarchical system knowledge. The diagnostic process seems to proceed with frequent reference to these two types of knowledge. Characteristics of the diagnostic process were investigated. A conceptual entity called "hypothesis frame" was employed to account for observed characteristics. A hypothesis frame contains all relevant information about a particular failure. Each frame has four slots: symptom slot, component slot, inference slot, and flow slot. These slots put together all related symptoms, components, inferences, and flow types. The diagnostic process involves choosing an appropriate frame that matches the known symptoms, and evaluating the frame against the system state.
At the beginning of a diagnostic process, symptoms in the known symptom set are given. Symptoms in this set are used to match with the symptom-cause rules in the symptom knowledge base. Once an appropriate rule is found relevant, the corresponding hypothesis frame is elicited for evaluation. During the processing of a frame, inferences may be drawn from the inference slot to come up with some frames for processing. Observed heuristics are: physical closeness, best-matched frame, and direct mapping from symptoms. Four protocols were analyzed using this model. The model seems to fit the protocols reasonably well.

Details of this model will be presented at the IEEE Conference on Systems, Man, and Cybernetics in November.

Moderate Fidelity Simulator

Computational experiments were continued with the model. The parameters chosen for the various components for use by the primitives of the qualitative model appear reasonable. With the arrival of a Xerox Dandy-Tiger in May, a substantial amount of time was spent in trying to learn how to use Interlisp-D. The programs written earlier in Franz Lisp are not fully compatible with Interlisp-D. Various possibilities were explored for translating and transferring the large amount of data, primarily in the form of property lists, and programs. We expect to convert the files with help from LRDC, Pittsburgh.

Online Training in Dynamic Environments

Janet Fath started on this project during this quarter. Her goal is to pursue her Ph.D. thesis in the area of online training in dynamic environments. Prior to starting this work, she participated in the
development of two computer-based training systems, one for the Army and one for the nuclear power industry. She is attempting to generalize this experience by reviewing a variety of instructional frameworks within instructional science and cognitive psychology. A paper based on this review is being prepared for presentation at the IEEE Systems, Man, and Cybernetics Conference in November.

SCHEDULE FOR NEXT QUARTER

David Su is expected to complete his Ph.D. dissertation. In addition to the conference paper mentioned earlier, the dissertation will be published as a technical report. A paper will be prepared for submission to the IEEE Transactions on Systems, Man, and Cybernetics.

Display design for the moderate-fidelity simulator should proceed at an accelerated pace with the increased knowledge and experience gained on the Dandy-Tiger. It is likely that a preliminary version of the moderate fidelity simulator will be ready by the end of the next quarter.

Janet Fath plans to produce a draft dissertation proposal in the area of online training in dynamic environments.

PROBLEMS ENCOUNTERED

No new problems.

DEPARTURES FROM PROPOSED WORK

No new departures.

ACCOMPLISHMENTS DURING REPORTING PERIOD

Two papers and one report written. These items will be discussed in the forthcoming annual report.
EVALUATION OF THE ABILITIES OF MARINE ENGINEERING PERSONNEL TO DETECT, DIAGNOSE, AND COMPENSATE FOR SYSTEM FAILURES

William B. Rouse
Principal Investigator

Quarterly Report
For the Period June 1, 1985 - August 31, 1985

For

Contract N00014-82-K-0487
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(June 1, 1982 - May 31, 1986)

Center for Man-Machine Systems Research
Georgia Institute of Technology
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(404-894-3996)
PROGRESS DURING THE REPORTING PERIOD

During this period, David Su completed and successfully defended his Ph.D. dissertation. T. Govindaraj's work on the moderate fidelity simulator focused on the development of a graphical interface to the simulator on the Xerox 1108. Janet Fath's thesis efforts in ICAI also progressed.

Low Fidelity Simulator

Analysis of protocols and other experimental data was completed. A 'micro' model of expert fault diagnosis performance based on hypothesis frames, which was mentioned in the previous quarterly report, was completed. Description of this model and experimental results on which the model is based form an important part of Su's Ph.D. dissertation. The dissertation will be published as a technical report shortly. Also, a paper on the model has been prepared and will soon be submitted to IEEE Transactions on Systems, Man, and Cybernetics.

Moderate Fidelity Simulator

The programs for the moderate fidelity simulator written in Franz Lisp on the VAX 11/780 were ported to the Xerox 1108 with help from Jeff Bonar and Marty Kent at LRDC, Pittsburgh. Translations from Franz Lisp to Interlisp-D were also completed. The programs now run on the Xerox 1108. A graphical interface was developed for use in experiments. Marine engineers at Marine Safety International, who form our subject pool, will access the powerplant via this interface. The interface consists of a menu using graphical icons for different subsystems. After a particular subsystem, e.g. boiler system, is accessed by buttoning an icon, the component states are easily investigated by buttoning the component. Menus that pop up when a component is selected is used to view the state. Refinements of this interface is continuing.
Online Training in Dynamic Environments

Work has continued on design specifications for an intelligent computer aided instruction (ICAI) program to be used in conjunction with the moderate fidelity marine powerplant simulation developed by Govindaraj. Particular attention has been paid to the definition of the components to be included in the ICAI program and the ways in which these components interact. Components of the ICAI of most interest are the student model and the instructional strategies.

Important aspects of the student model which are under consideration are the form of student knowledge representation, including the representation of error knowledge, and the model of learning which will determine when the student model is to be updated. Student knowledge will be represented hierarchically as facts. Error knowledge, though viewed hierarchically, will be generated through the use of rules of error generation. To update the student model, a simple model of learning will be assumed which will be based on the number of times a student is exposed to certain knowledge and the number of times the student demonstrates understanding of that knowledge.

A review of current ICAI and CAI literature revealed that there exist many instructional strategies or "principles of instruction." Very few of these strategies, however, are theoretically derived. Instead, the majority of instructional strategies employed are products of the ICAI author's own common sense. Therefore, although many individual strategies have been identified, there is apparently no coherent set of instructional strategies. Thus, as of this time, it has not yet been decided which instructional strategies to use.
SCHEDULE FOR NEXT QUARTER

Display interface design for the moderate fidelity simulator will continue with the addition of more details for various subsystems. Appropriately designed gauges and status indicators will be incorporated into the output portion of the display interface. The simulator is expected to be ready for preliminary experiments soon.

Janet Fath's work in the next quarter will be devoted to better refining the student model and instructional strategies to be used. Knowledge representation and error treatment will continue to be major concerns. Once all components have been sufficiently specified, efforts to program working models on the Xerox 1108 will begin. Furthermore, instructional strategies will be chosen, based on the model of student learning.

PROBLEMS ENCOUNTERED

No new problems.

DEPARTURES FROM PROPOSED WORK

No new departures.

ACCOMPLISHMENTS DURING REPORTING PERIOD

Dave Su's dissertation completed.
February 20, 1986

Dr. Michael Shafto  
Code 442  
Office of Naval Research  
800 North Quincy  
Arlington, Virginia  22217

Dear Mike:

Enclosed please find four copies of our quarterly report for the period  

Sincerely,

William B. Rouse  
Professor and Director

cc:  F. Cochran, ISyE  
J. Hollan, NPRDC  
N.J. Kerr, NAS Memphis  
W. Scanland, NAS Pensacola  
J. McBridge, NPRDC  
R. Sasmor, ARI  
H.F. O'Neil, Jr., ARI  
J. Orlansky, IDA  
A.R. Fregly, AOSR/NL  
R. Blanchard, NPRDC  
P.J. Andrews, NAVSEA  
W. Rizzo, NTEC  
J. Yasutake, AFHRL/LRT  
G.S. Malecki, ONR Arlington
EVALUATION OF THE ABILITIES OF MARINE ENGINEERING PERSONNEL TO DETECT, DIAGNOSE, AND COMPENSATE FOR SYSTEM FAILURES

William B. Rouse
Principal Investigator

Quarterly Report
For the Period September 1, 1985 - November 31, 1985

For

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(June 1, 1982 - May 31, 1986)

Center for Man-Machine Systems Research
Georgia Institute of Technology
Atlanta, GA 30332
(404-894-3996)
PROGRESS DURING THE REPORTING PERIOD

During this period, T. Govindaraj's work on the moderate fidelity simulator progressed as did J. L. Fath's efforts on online training in dynamic environments. This progress is discussed in this section. Also presented are tentative schedules for the remaining nine months of this contract.

**Moderate Fidelity Simulator**

Development of the moderate fidelity simulator continued with the addition of subsystem schematics. More complete details about components and their interconnections were used to enhance the subsystem schematics developed earlier. Information stored in the form of property lists was used for building the subsystem schematics and for establishing linkages so that components of most subsystems could be investigated. A simple graphics editor was designed and used for building the subsystem schematics. Procedures were written to access most of the state values for display. A number of gauges were redesigned so that qualitative state values could be displayed. The interface for the simulator is nearing completion.

After the interface is completed, the major task that remains is the tuning of parameters to ensure temporal fidelity of simulation. This task is expected to be completed soon so that pilot experiments can be conducted during this quarter. A tentative schedule for the remaining nine months of this contract are as follows:

(For each task, the planned completion date is shown in parenthesis.)

(1) Completion of the moderate fidelity simulator (February 15)
   - Incorporate data collection procedures
   - Exercise the failures by investigating the gauges
- Design a display for symptoms found during investigation

(2) Experiments (March 21)
- FAIL and Moderate Fidelity Simulator
- Protocols for a subset of problems
- Subjective ratings

(3) Analysis of experimental results (April 26)
The following performance measures will be used: speed, number of actions, success rate, accessibility of gauges and components, efficiency of commands (e.g., how many commands are repeated), ease of use.

(4) Preparation of journal articles

1. Qualitative approximation and simulation methodology (March 3)
2. Experiments results and model outline (May 24)

Online Training in Dynamic Environments
Continued effort in this quarter has been devoted to better specifying the design for an intelligent computer aided instruction (ICAI) program to be used in conjunction with the moderate fidelity marine powerplant simulation developed by Govindaraj. The design has now been sufficiently specified to enable work to begin on an online tutor to be implemented on a Xerox 1108. As a first step in the development of the working ICAI system, instruction for the tasks of using the 1108 and gathering information for the marine powerplant simulation will be programmed.
An experiment has been tentatively scheduled for April, 1986. Goals for the proposed experiment include:

1. To pilot test the 1108 and information gathering sections of the instructional program, particularly the student modeling section.

2. To enable refinement of the student model with respect to the type of errors made and various learning models.

3. To test various teaching strategies.

Subjects for the experiment will be recruited from a population of approximately 150 Naval ROTC students from the Georgia Tech campus. Three levels of marine powerplant experience are found in the subject population:

1. licensed marine engineers,
2. sophomore level students with classroom training and shipboard experience, and
3. freshman level students with classroom training.

The experiment in April may, however, concentrate on the freshman level student.

A tentative schedule for the remaining nine months of this contract is presented below:

1. Familiarization with 1108 and marine powerplant simulation/Jan. 1986 (2 weeks)
2. Task analysis of 1108 use and information gathering with the simulated powerplant/Jan - Feb 1986 (3 to 4 weeks)
   - identify 'what', 'how' and 'why' knowledge
   - structure the knowledge in terms of a discrete control model
3. Encode the knowledge base on the 1108 using the programming technique of frames/Feb 1986 (3 to 4 weeks)

4. Determine and implement instructional strategies / Mar 1986 (1 week)

5. Determine and implement student model characteristics / March - Apr 1986 (4 to 6 weeks)
   - learning model
   - errors

6. Identify and encode supplemental instructional material / Mar - Apr 1986 (2 weeks)
   - text screens
   - exercises
   - others help or instructional messages

7. Run experiment / Apr 1986 (2 weeks)

8. Data analysis and interpretation / May 1986 (2 weeks)

9. Final report / May 1986 (2 weeks)

SCHEDULE FOR NEXT QUARTER

See the two lists in the previous section.

PROBLEMS ENCOUNTERED

No new problems.

DEPARTURES FROM PROPOSED WORK

No new departures.

ACCOMPLISHMENTS DURING REPORTING PERIOD

Mental models report was accepted by Psychological Bulletin, subject to a variety of minor revisions. Relationship with Georgia Tech WRUTC Unit was established, providing a rich and interesting subject pool for Janet Fath's experiments.
April 15, 1986

Dr. Michael Shafto  
Code 442  
Office of Naval Research  
800 North Quincy  
Arlington, Virginia 22217

Dear Mike:

Enclosed please find four copies of our quarterly report for the period December 1, 1985 - February 28, 1986.

Sincerely,

William B. Rouse  
Professor and Director

Enclosures

cc: F. Cochran, ISyE  
  J. Hollan, NPRDC  
  N.J. Kerr, NAS Memphis  
  W. Scanland, NAS Pensacola  
  J. McBridge, NPRDC  
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/eml
EVALUATION OF THE ABILITIES OF MARINE ENGINEERING PERSONNEL
TO DETECT, DIAGNOSE, AND COMPENSATE FOR SYSTEM FAILURES

William B. Rouse
Principal Investigator

Quarterly Report
For the Period December 1, 1985 - February 28, 1986

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Georgia Institute of Technology
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(404/894-3996)
PROGRESS DURING THE REPORTING PERIOD

During this period, T. Govindaraj's work on completing the moderate fidelity simulator progressed as did J. L. Fath's work on modeling the student and teacher for online training using the simulator. This progress is discussed in this section.

Moderate Fidelity Simulator

The interface to the marine powerplant simulator was completed. Symptoms of a failure, subsystem schematics, components, and gauges are accessed by buttoning a mouse on appropriate icons and figures. Efforts to ensure the consistency and correctness of interconnections between components in various subsystems were begun. This is essential to obtain appropriate fidelity levels and correctness of simulation results. Consistency checks resulted in reclassifications of some components into appropriate primitive types and resetting of relevant parameter values. Property values and records were adjusted and modified where necessary. This process, along with parameter tuning and exercising possible failures, is being continued.

Online Training in Dynamic Environments

The teacher model that is currently under development for use in the online training program includes both a domain model and a set of instructional strategies. The student model is to be based on the domain model, but will allow for the possibility of errors. Work during this period concentrated on developing the domain and student models. In particular, the backwards reasoning portion of the domain and student models was a major concern. A test
version of the backward reasoning model is to be combined with the forwards reasoning model as the basis for the domain and student models. These models will then be incorporated into a prototype instructional system and used in a pilot study of the online training program.

SCHEDULE FOR NEXT QUARTER

Parameter tuning and simulator testing will be completed. A preliminary version of the student and teacher model along with instructional strategies will be programmed and incorporated into the simulator. Pilot experiments using Navy ROTC instructors and students as subjects are planned.

PROBLEMS ENCOUNTERED

No new problems.

DEPARTURES FROM PROPOSED WORK

No new departures.

ACCOMPLISHMENTS DURING REPORTING PERIOD

The moderate fidelity simulator is substantially complete. Preliminary details of the student and teacher model have been outlined.
EVALUATION OF THE ABILITIES OF MARINE ENGINEERING PERSONNEL
TO DETECT, DIAGNOSE, AND COMPENSATE FOR SYSTEM FAILURES

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INTRODUCTION

Following in the wake of the aviation industry, efforts to introduce automation in the marine industry are increasingly evident. Most of these efforts have been pursued in hopes of improving energy efficiency, increasing abilities to operate in confined waters and low visibility, and reducing the size of the crew. An example of trends in the latter direction is the relatively recent emergence of unmanned engine rooms.

Considering the engine room in more detail, various automatic controls have been introduced for regulating engine rpm and the flows of steam, feedwater, fuel oil, lube oil, etc. In addition, several automatic changeover systems are now utilized for activating backup pumps, generators, etc. In general, these automatic devices have eliminated many manual tasks for marine engineering personnel, at least during normal operations or "standard" abnormalities.

However, as in many other domains, the introduction of automation into the engine room has resulted in the engine system becoming increasingly complex. The marine engineering personnel who monitor this system now must be concerned with the possibility of many more types of failure and combinations of failures. This can be particularly problematic when the automation itself fails and its subsequent compensatory response to its own failure appears to be rather unpredictable.

Partially in response to this increase in system complexity, the marine industry has increased efforts in the direction of training. Typically, these training programs utilize full-scale, high-fidelity simulators and attempt to provide the trainee with one or two weeks of highly concentrated experience with a wide variety of system failures.
Because the development of a high-fidelity engine room (or bridge) simulator requires a multi-million dollar investment, training centers tend to have a single simulator which greatly restricts class size and makes the program very expensive. While the industry views this as a necessary evil, this may not be the case because:

1. It is not clear what problem solving skills are necessary for detecting, diagnosing, and compensating for failures in the engine room.

2. It is not clear that full-scale, high-fidelity simulators provide a more effective and economical environment for learning these skills than possible with lower fidelity simulators.

The primary goal of the research program whose first-year progress is reviewed in this report is to pursue these issues and provide an understanding of human problem solving in the engine room environment, particularly in terms of the abilities of trainees to learn problem solving skills as a function of the level of fidelity of the simulator.
FIRST-YEAR PROGRESS

The problem outlined in the Introduction is being pursued by both theoretical and experimental investigations of human problem solving abilities in simulated supertanker engine room environments. The theoretical aspects of the investigation involve the use of an evolving model of human problem solving in dynamic environments. The experimental studies involve three simulated engine room environments, ranging in fidelity from fairly low to very high, where professional marine engineering officers are being used as subjects for all formal experiments.

Model of Problem Solving

The modeling effort is an outgrowth of earlier work on human problem solving behavior. Prior to the start of this ONR project, this effort had reached the point that the model had been tested extensively in various static troubleshooting situations. It also had been extended conceptually so as to apply potentially to dynamic operational situations. However, this conceptualization had not been operationalized and tested.

Under ONR support this year, this extended version of the model has been programmed (in Pascal on a VAX-11/780) and initially tested. Since data from the engine room simulations (discussed below) is not yet available, the programming and testing of the model is being pursued using a process plant simulator and experimental data obtained from a different project. The initial results of this effort are reported in Knaeuper and Rouse (1983) which is included in the Appendix of this report.

This progress with the modeling is important in several ways. First of all, few if any models or theories of human problem solving deal explicitly with dynamic operational environments.
Thus, they need not be concerned with the important role of expectations and the need for planning in operating dynamic systems. Further, they do not have to consider the tradeoff between operational goals and problem solving that is inherent with many dynamic systems. The model discussed in Knaeuper and Rouse (1983) explicitly considers issues such as these and, once validated, should be a valuable means of identifying potential avenues for training and/or aiding of problem solvers.

Another important aspect of the progress on the model is the fact that its rule-based nature is such that the context of the problem solving is embedded in the rules rather than the rule-processing mechanisms. Thus, for example, the model "knows" that, regardless of context, operation of dynamic systems requires multiple tasks and that expectations concerning the evolution of the system's state depend on the task being performed. In other words, the model has to "know what it is doing" independent of the context. This "all context in rules" notion will allow straightforward transfer of the model to the marine engine room domain as data becomes available, as well as transfer to other domains such as are being studied in other projects in the Center.

**Simulator Development and Evaluation**

As noted earlier, this research is utilizing three engine room simulators involving low, moderate, and high fidelity. The high-fidelity simulator is available via subcontract to Marine Safety International (MSI). The low and moderate fidelity simulators are being developed as part of this research project. These three simulators will be used to assess the relationships among a wide variety of measures of problem solving performance which will provide insights into what is learned with each type of simulator and what level of fidelity is necessary for alternative problem solving training objectives.
This year has focused on developing the low-fidelity simulator and researching the conceptual basis for the moderate-fidelity simulator. The basic differences between these two simulators is that the moderate-fidelity simulator will respond dynamically, allow trainees to make control inputs, and provide some conventional display instrumentation. Both simulators are being programmed in Pascal on an Apple II Plus.

The low-fidelity simulator has received the most attention thus far. This simulator was designed on the basis of the specifications of the MSI simulator. As information was gathered about the MSI simulator, it quickly became apparent that an Apple II based simulation could not include the 500 gauges, etc. associated with the real system. As a result, the initial version of the low-fidelity simulator which is now running incorporates a variety of features (e.g., multiple pages of displays and alarms) to allow simple simulation of a complicated system. A description of this simulator and initial results of a small pilot experiment are discussed by Govindaraj and Su (1983) and is included in the Appendix.

Work on the moderate-fidelity simulator also progressed this year. It was quite clear at the outset that the dynamics of the real system would have to be approximated for use of an Apple II to be feasible. The current plan is to employ decoupled, reduced-order, qualitative dynamics. The approach that is emerging involves a mixture of control theory, fuzzy set theory, and artificial intelligence (Govindaraj, 1983).

All of the simulation issues are being considered in the framework of attempting to define the general concept of simulator fidelity. Thus far, it appears clear that fidelity is a multi-dimensional concept involving at least physical, structural, and dynamic aspects of trainee-simulator interaction. From this
perspective, the low-fidelity simulator is low, moderate, and low on the three dimensions; the moderate-fidelity simulator is moderate on all three dimensions; and the high-fidelity simulator is high on all three dimensions.

One other aspect of the simulators deserves special note. One of the primary indices of problem solving performance that will be assessed in the planned experiments is the types and frequencies of human errors. In order to identify the contributions of human engineering design deficiencies to human error, a human factors evaluation or audit of the controls and displays of the high-fidelity simulator is in progress and will soon be completed. The relationships between design deficiencies and human errors will be determined in later experiments and will hopefully serve as useful inputs for design principles and guidelines.
REFERENCES


APPENDIX
QUALITATIVE SIMULATION OF COMPLEX DYNAMIC SYSTEMS:
AN APPLICATION TO A MARINE POWERPLANT UNDER SUPERVISORY CONTROL*

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ABSTRACT

An investigation of the possibility and effectiveness of qualitative simulation for training marine engineering personnel to detect, diagnose, and compensate for failures is discussed. Low, moderate, and full fidelity simulators will be used in the training. The moderate fidelity simulator will use qualitative simulation of system dynamics. Details of the qualitative simulation are discussed including a review of several modeling methodologies. Low, moderate, and full fidelity simulators are also described, and an outline of research in progress is provided.

INTRODUCTION

Complex dynamic systems such as marine powerplants are operated in supervisory control mode since most of the functions are automated. Appropriate power levels are maintained by the automatic control systems as long as there are no problems during operation. When a problem arises, the supervisory crew must be able to detect problems quickly, identify the causes and correct the problems. Where full correction is not possible, compensation for problems is desired so that the system can be safely managed until the problems can be fully identified and corrected. While formal procedures can be developed for dealing with many types of possible situation, all possible contingencies cannot be anticipated. Therefore the operation of a large, interconnected dynamic system such as a marine powerplant sometimes depends on the problem solving skills of the crew members.

Various means could be used to develop problem solving skills. One possibility is to provide the operators with on-the-job training via a considerable period of time on the equipment they are expected to use. This is rather expensive, especially for training marine engineering personnel. First, the ships are expensive to operate, and it is therefore difficult to preempt other productive operations for the purpose of training. Second, and perhaps equally important, the real system cannot be made to function in a degraded mode intentionally. This would endanger the ship's operation, as well as the crew's safety. It is obvious that alternative methods are preferable. One possible approach is to let the trainees be apprentices on a

real ship, and let them observe how an expert solves problems. This is a very inefficient process, however. Further, faults seldom occur in most automated systems, and cannot be simulated in such an environment. Hence, training with the real system tends to be both inefficient, and limited in effectiveness. One of the best alternatives for training is through the use of training simulators.

Simulators can be designed at various levels of complexity and realism relative to the systems they represent. The degree of realism and closeness with which the simulators resemble the actual systems can be formalized in terms of the concept of fidelity of simulation. Typically, the higher the fidelity of the simulator, the higher will be the cost. However, for training purposes, it may not be necessary to have a simulator with the "highest" fidelity possible in all aspects. Depending on the skill requirements, certain aspects of the simulation can be provided with high fidelity, with others at low or moderate fidelity levels. In fact, enhancing certain functions, and approximating some others may be useful for training.

The primary concern of the research described here is the design of training simulators to be used to teach the general problem solving skills associated with failure management. The long term goal is to design simulators to enable transferability of training at relatively modest costs. To this end, low and moderate fidelity simulators are being developed for a marine powerplant to train marine engineers in the detection, diagnosis, and compensation of system failures.

SIMULATOR FIDELITY ISSUES

Background

Research issues in simulator fidelity were the topic of a recent workshop in which researchers in the area of training participated [1]. Various simulator and training techniques in use were discussed, and fidelity issues were debated. Baum [2] presented hypothetical relationships between "physical" and "functional" fidelity versus the degree of simulator effectiveness. Even though these relationships have been used for a number of years, they appear to lack a firm experimental or theoretical basis.

A good discussion of simulator fidelity and its relevance for training is discussed by Montague [3]. Examples are provided to show that physical fidelity ("physical isomorphism") is not always necessary, and at times counterproductive for training purposes. The inability to specify fidelity in terms of actual training requirements is attributed to the lack of good mental models. Mental models such as those developed by researchers in cognitive science are discussed at some length. How these could possibly be used is described. Montague recommends that specifications of knowledge and experience required to attain specific performance levels be used to define training task fidelity.

Orlansky [4] maintains that fidelity is only one of many features that influence the effectiveness of a training device. He suggests that the effectiveness of a given fidelity level be measured in terms of the performance on the job rather than at school. While fidelity itself is not explicitly defined, the possible relationship of different amounts of fidelity
to training effectiveness is discussed.

As the discussion above shows, no consensus seems to exist as to what constitutes fidelity or how it can be measured. One possibility is to characterize fidelity in terms of training effectiveness and transfer of training. This would reduce the concept of fidelity to be mainly an intervening variable which need not be defined rigorously.

Transfer of training and measurement issues are discussed in papers by Valverde [5], and Blaiwes and colleagues [6]. However, these measurement techniques do not appear to provide a means of measuring simulator fidelity. Adams [7] presents detailed arguments to point out the difficulty of evaluating training devices including simulators. Measuring the transfer of training, as well as the rating methods in which persons experienced on the actual equipment rate the simulator, are shown to have problems. He suggests that these evaluation procedures are unnecessary if the simulators are designed on the basis of scientific principles. An example of such a principle is that human learning is dependent on knowledge of results. Designing simulators on a firm scientific basis would bypass the question of simulator fidelity altogether, since it ceases to be an issue any longer.

Dimensions of fidelity

The issue of defining fidelity and studying its implications can perhaps be clarified if one begins with the premise that fidelity is a multi-dimensional concept. This allows a partitioning of the problem of defining fidelity into more manageable subproblems, from both a conceptual and measurement perspective. This approach is advocated in this paper.

Traditionally fidelity in simulators was synonymous with the physical similarity of the simulator to the actual system. A "good" simulator looked, and felt like the real equipment it was meant to simulate. This implies that the simulator had, at the least, the same number and types of displays and controls as the real system. Physical fidelity is concerned with the variables that are presented, the form in which they are presented (pictorial, verbal, etc.), and in how much detail they are given. If this requirement is only partially satisfied, the simulator lacks full physical fidelity. Another important consideration is the environment. For instance, noise, vibration, and thermal conditions similar to the real life environment should be provided where high physical fidelity is a requirement.

These requirements imply that simulators with high physical fidelity are usually rather expensive. However, the need for this high level of face-validity is often difficult to demonstrate. Even though a good correspondence between the simulator and the actual system provides a realistic environment with little deviation from the actual work environment, its contributions may not be clear. Possibly, a less detailed representation that provides only a limited number of essential controls and displays could provide an adequate training device. (Montague [3] provides some evidence in support of this.) This would imply that low or moderate physical fidelity levels may sometimes be acceptable.

Structural fidelity refers to the nature of relationships between various subsystems that make up the system. Feedback and feedforward relationships, and coupling through system states, inputs, and outputs are relevant.
Hierarchical relationships including the different levels of abstraction, and the details within a given level are important factors to be considered. Structural fidelity also deals with the aggregation of the detailed system elements and the levels of abstraction required to represent the system.

Dynamic fidelity refers primarily to the evolution of the system states over time, and their presentation to the operator. Dynamic fidelity is affected by the state representation and the level of approximation of the relationships among state variables as well as provision of the ability to control the system, and the feasibility for system reconfiguration. Dynamic fidelity issues are the primary focus of this paper. Other issues are included for the purpose of placing the problem in the proper perspective.

It is worthwhile noting that the three dimensions of fidelity defined here (i.e., physical, structural, and dynamic) offer a rather different perspective than the more traditional notion of engineering versus psychological fidelity. Basically, the point of view advocated in this paper is that psychological fidelity is multidimensional in and of itself, and that engineering fidelity is a related but different concept, one that is not pursued in this paper.

Measuring fidelity

Physical fidelity could possibly be quantified by using some simple pattern matching techniques. Controls and displays that form the man-machine interface could be compared at the simulator and at the actual system. Number, type, relative distances and configurations, are some of the primary factors that could be used in the determination of similarity measures. Techniques from syntactic pattern recognition could be useful [8,9].

Graph theoretic methods may be useful for measuring structural fidelity [10,11]. Suitable hierarchic representations may be necessary for this. Distance measures for nodes and arcs in the simulator and the system could be used to quantify the relationships between various parts of the systems. Since graph theoretic methods are widely used in pattern recognition [12], measures for structural and physical fidelity may be related and similar to each other.

Control theoretic measures could be useful for measuring dynamic fidelity. Among others, these could include measures of errors for important variables, response times, and the operational effort required. Analytical measures such as controllability and observability may also be useful. Methodologies from optimal control theory [13] and system identification [14] appear to be relevant for dynamic fidelity measures. Appropriate techniques are being explored.

An important consideration in defining and measuring fidelity is the impact of context and purpose. The environment and the purpose for which the simulator is to be used have a strong influence on fidelity. Also, fidelity of simulation appears to be closely determined by the context in which it is used. Therefore, context free measures of fidelity may be difficult to derive.
For example, even though it may seem desirable to have good "physical" fidelity in a simulator used for problem solving training, physical fidelity may not influence problem solving performance greatly; availability of the required information may be more crucial than the format and face-validity. In contrast, in training for another aspect of training in the same environment (e.g., rapid execution of emergency procedures), high physical fidelity may be absolutely essential.

**Summary**

Features that affect fidelity may be viewed from a man-centered and a machine-centered viewpoint. The former would include the various human abilities and limitations that affect fidelity, including sensory, perceptual, and cognitive aspects. The latter aspect would include factors such as the level of detail, and nature of structural representation, hierarchical relationships among the different subsystems, and accuracy of dynamical representation. The human and the machine aspects are interdependent and both have psychological implications. Therefore, these aspects should not be considered independently. The machine aspects greatly affect the cognitive factors. For example, if certain subsystems and their interconnections are not explicitly provided by the simulator, the trainee may have to compensate for these by inferring their states. Hence, a lack of these functions could reduce the fidelity.

Apart from the issues which are based mostly on system characteristics, another method of studying fidelity is in terms of its use and effectiveness. Since the purpose of simulators is in training, one might say that a simulator has high fidelity if the training on the simulator is transferred well to the actual system. The level to which the training can be transferred can be a measure of fidelity. Unfortunately, the effectiveness of transfer of training can be difficult to assess, particularly if one attempts to isolate long term effects independent of other variables.

**APPROACHES TO DYNAMIC FIDELITY**

The primary concerns of this paper are the dynamic fidelity issues when a large, interconnected system is simulated. Such a system has traditionally been simulated in high fidelity. This could possibly be due to the influence of engineers who were responsible for the design of the actual system as well as the simulator. Nothing short of the complete dynamics was considered acceptable for the simulator. Also, since manual control was still prevalent in most systems, physical motions including noise and vibration were provided in the simulation. However, these requirements may be unnecessary for problem solving in supervisory control where information such as time histories of primary variables may be sufficient. It appears that concepts from two rather different domains could prove useful for modeling the dynamics for the simulators. One is from control theory, based on aggregation, decoupling, and order reduction techniques. The other is the use of mental models in cognitive science. The latter has been proposed in artificial intelligence research for representing systems and devices. Details of these two approaches are discussed below.
Aggregation, decoupling, and order reduction

In general, various components of a large scale system interact with each other via inputs, states, and outputs [15]. When two systems in series are connected to each other only via inputs and outputs, the outputs of the predecessor become the inputs to the successor. The individual systems in such a case are decoupled. Otherwise the systems are coupled, whether they are in series or in parallel, since the states of one system are also affected by the other system. This coupling makes it impossible to study the different systems separately. Differential equations of fairly high order are required to represent coupled systems. Large matrices required for storage and manipulation of system equations make the computations slow and difficult. These considerations also impose constraints on the size of the system that can be modeled on a computer. In addition, high order coupled systems are rather difficult to visualize for modeling and manual control. Hence simpler representations are desirable.

Complexity of a large scale system can be reduced if the system equations are approximated through aggregation [16,17]. Components are aggregated so that the total number of subsystems is reduced and the overall structure is simplified. Minor components are lumped together to obtain a smaller number of possibly loosely coupled subsystems. After aggregation, the individual subsystems are coupled primarily through inputs and outputs. Coupling through the states is weakened or eliminated entirely.

In weakly coupled systems, individual subsystems can be decoupled so that they can be studied independently. In physical systems, the decoupling can be done so that the subsystems represent components which are only loosely coupled with the rest of the system. The system representation is thus simplified, and the computational load is reduced.

Order reduction methods can be used to further simplify high order decoupled systems [18,19,20]. In reduced order models of dynamic systems, the order of the differential equations is reduced so that only dominant modes are retained. For example, in systems where fast response is important, relatively slow modes are simply discarded. (In other cases it may be appropriate to retain the slow modes and eliminate the fast modes.) In a complex, interconnected system with time constants at different orders of magnitude, this type of simplification may be rather difficult to implement. In such cases, a combination of suitable aggregation, decoupling, and model reduction techniques can be used.

When human operators control a system other types of simplifications and approximations may be appropriate. This arises due to the inability of the human to fully utilize the state and output variables. It is desired to obtain reduced order models that are compatible with possible internal models of the system that the human operator has in a supervisory control situation. Manual control models such as the crossover model or the optimal control model cannot be used since we are not concerned with predicting human performance [21]. The possibility of developing a suitable simulation of the physical system that may also aid in the development of cognitive models for a dynamic system is being investigated. A simple model structure suitable for representing a wide variety of complex dynamic systems is desired.
"Cognitive" models

Investigators in artificial intelligence, cognitive science, and psychology have done research in mental models of simple systems. Representative examples of various attempts at modeling are papers by Kieras [22], Rieger [23], de Kleer and Brown [24], Stevens [25], Johnson-Laird [26], and Gentner and Stevens [27]. The cognitive models described in these papers deal with models of devices. Usually no dynamics is involved. Only the sequence of operations are described without regard to their exact time relationships. The following discussion will illustrate the nature of these modeling approaches.

Kieras [22] describes mental models that people have about devices, based on descriptions of functions and components. He provides a survey, where experts and non-experts were asked to describe simple electronic devices such as radios. He concludes that people's knowledge of devices consists of major categories such as what the device is for, how it is used, its structure in terms of its subdevices, its physical layout, how it works, and its behavior.

Rieger [23] proposed a "common sense algorithm" (CSA), that provides a data structure for modeling cognition and information processing. The structure is defined in terms of five "building blocks": Wants, Actions, States, Statechanges, and Tendencies. These five are used to construct 25 primitive links. The goal of this approach was to express the "dynamics of just about everything" using the primitives. The CSA was used for modeling the operation of a reverse-trap toilet, and the sawing of a board in half.

Mental models of physical mechanisms are developed by de Kleer and Brown [24] using certain "esthetic principles". They employ qualitative simulations, referred to as "envisionments", as a means of generating mental models. Envisionment follows from the device structure, and results in "causal attribution". The mental model is described as a combination of envisionment and causal attribution. Esthetic principles are then identified that are useful in evaluating mental models of physical devices as well as for help in forming the mental models. A qualitative model is given for a buzzer. Detailed description of a buzzer mechanism is given, and a plausible mental model of its functions is discussed.

Both the CSA approach and the models based on the esthetic principles appear to have a number of drawbacks for modeling dynamic systems. These models could be possible means of explaining what appears to go on in the mind. However, even for fairly simple devices, these model descriptions become enormously complicated and large. Coupled with the growth of the model size is the problem of whether or not the humans are actually capable of managing such complex, detailed models. At this point in time, experimental evidence in favor of these models appears rather limited.

Attempts at using such "qualitative" models for describing dynamic systems have been made in connection with the design of training simulators. Such a simulation is described in connection with a steam powerplant [25]. This is helpful for understanding device structures. Simulation models of components have been built. The simulation appears to be very useful for training, by taking the trainee step by step through the dynamical behavior.
Summary

The inherent "robustness" and the formal structure of the cognitive models are attractive. However, they appear to complicate the problem and greatly increase the number of states and, consequently, computational requirements. Possibly, these models provide a means of representing a physical device, though not necessarily a good method for representing a complex, interconnected dynamic system with continuous states. Real time simulation of these models would be extremely difficult, if not impossible.

On the other hand, control theoretic approaches provide a means of simulation without compromising rigor and computational convenience and efficiency. No qualitative behavior is available, however. What is needed is a modeling approach that incorporates the desirable features of both of the above methods for real time simulation.

PROPOSED MODELING APPROACH

Basic requirements

The issue of primary interest at this point is the simulation of the dynamics so that a simple representation is possible. The simplified model may not be appropriate for control purposes or for predicting the numerical values of any of the system variables as a function of time. However, it should be sufficient to explain the qualitative behavior of the entire system or any of the subsystems.

When a particular component or element fails, it may take some time for the problems to be felt by the entire system. The problems propagate through the system in a sequential order in the beginning. When a number of components have been affected, the system could degrade at a faster rate. Usually the operator uses the sequence in which the events happen at various parts of the system as a clue to detect and isolate the problem. Hence the dynamic simulation must preserve the order in which events occur when a problem begins. The sequence of actions required to isolate and identify the event should be the same for both the simulator and the actual system. Also, the response for a given input must be the same in both cases. Since the detailed state information may not be necessary for comparison, or for producing the same outputs, reduced order representation may be acceptable.

All the important variables that could aid in the detection of the fault must be provided in the simulation. The level of approximation will determine the extent and depth to which the fault isolation and detection can be carried out. With an appropriately simplified dynamics it should be possible to simulate the overall, gross qualitative nature of changes.

Basic methods

Linearized dynamics about some steady state will be used for modeling a dynamic system. When transient operations are possible, as in startup and shutdown phases of complex systems, a number of operating points can be established about which the system equations are linear.
Large dynamic systems such as those considered here have a number of interacting loops. Within any loop, there could be coupling between subsystems and modes, characterized by various degrees of interdependence. For modeling purposes, large systems will be decoupled so that interactions between loops is minimized without compromising the "dynamic fidelity". Within a loop, various modes will be decoupled to the extent possible.

Approximations to the actual dynamics are to be achieved by the elemental combinations of first and second order systems. A first order system can be described in terms of a time constant and a gain. In a discrete time representation, the time constant can be expressed simply as the number of time intervals required for steady state after a step input has been applied. A second order system can similarly be explained by the number of cycles before a suitably defined steady state is reached. This would combine the damping and the natural frequency. For a second order system, it seems plausible that the number of cycles before steady state can describe the response appropriately. Higher order systems can be approximated by various combinations of these "elemental" systems.

The possibility of modeling the system using a combination of dynamical and symbolic models is being explored. An appropriate scheme would be to use conventional dynamic system models for subsystems that require frequent state changes. Subsystems where changes in variables are small and infrequent could be modeled using symbolic structures. The higher levels will have some form of "knowledge representation", where semantic, verbal representations of dynamics will be used. The idea is to obtain a mix of algebraic and symbolic operations that result in reduced storage and computational requirements.

Yet another possibility is the use of fuzzy set theory. Fuzzy set theory has been found useful for designing controllers [28,29,30,31]. Under manual control, operators develop control laws from experience with the systems over a period of time. Heuristics are necessary since such systems tend to be rather slow and complex. The fuzzy controllers link the control laws expressed using linguistic expressions and numerical values of control required to operate the system. Such a link between qualitative representation of control laws and quantitative values of control suggests that fuzzy set theory may be useful for modeling of dynamic systems. A model based on fuzzy set theory can also provide system states and outputs in a form compatible with the mental models that the human operators use to control the system.

Overall scheme

For simulating the dynamics, the basic structure of a subsystem will have three parts. The first part will be used to convert and transform the states and other system variables for use in the qualitative representation. This is a "pre—processor" that quantizes the states roughly so that the generic model of dynamics can handle it. The central, second part will be "generic" dynamics made up of simple combinations of first and second order systems. The third part will transform the results of the qualitative dynamics back to quantitative state and system variable values as necessary. This is a "post—processor" that transforms the qualitative dynamic states into a suitable quantitative form. It is seen that the first and the third parts form the interface of the subsystem with the dynamics part. The quantitative values of the states are perhaps rough quantizations that preserve the order.
and sequence relationships among various system variables. The pre-, and post-processors are in some sense inverses or complements of one another.

An application

An application of these methods to modeling the dynamics of a marine powerplant is being pursued. A typical marine powerplant uses an oil-fired boiler to produce steam. The steam drives a series of turbines. The turbines are used to derive mechanical energy to drive the propellors, pumps, and compressors, and for electricity generation. Water for the boilers is distilled from the sea. The water-steam system forms a closed loop, with any leaks being compensated for by the addition of distilled water. Air is taken from the atmosphere, pre-heated by exhaust gases, and used to burn the fuel oil in the burner. The hot gases are then used in the boiler to generate steam, as well as to superheat the steam coming out of the boiler. Before exhausting into the atmosphere, the hot gases pre-heat the water entering the boiler. Fuel oil is preheated by auxiliary steam before coming into the burner. Since there are a number of mechanical subsystems such as turbines and pumps, a lube oil loop is used. This is a closed loop, where the lube oil goes through the bearings and other elements, picks up heat, and gets cooled by water. Failures in any element of the four major systems (water, air, fuel, and lube) could affect the operation of the powerplant.

A simplified version of the powerplant comprising of the water/steam loop and the air loop will be simulated using the modeling concepts discussed above. The major components of the reduced system are shown in Figure 1. Each of the individual subsystems shown will be replaced by modules with approximate dynamics.

```
<---- Boiler <------ Economizer <-- Regulator <-- Pump <-----
| Steam | | Water |
<----- Superheater -------> Turbine ------> Condenser ---->
| Furnace | Air |
<------<---- Air Heater <----
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Figure 1. Air and Water/Steam Loop of a Marine Powerplant

A qualitative model for the dynamics will be used in a moderate fidelity simulator of the marine powerplant. This moderate fidelity simulator will be compared to a high fidelity simulator and a low fidelity simulator in transfer of training studies. These studies will focus on the problem solving performance of marine engineering personnel.

The high fidelity simulator consists of a replica of an engine and control room with the associated control and display panels. The engine dynamics is simulated on a mini-computer to a high level of detail. Simulated equipment such as burners, boilers, and plumbing are seen from the engine room.
as it would be on a real ship. Environmental conditions such as heat, humidity, and vibration are also simulated. Hence it is apparent that this has high fidelity along any reasonable dimension that one uses.

The low fidelity simulator will have a limited amount of information displayed, in a format somewhat different from the real equipment [32]. Information will be provided using system schematics. Symptoms corresponding to the failures or problems will be presented on a video display terminal. No dynamics is involved. The subject can check for the status of gauges and other displays through the computer interface. Display status stored in advance for each of the failure situations will be provided. The subject cannot control the system. Hence it is seen that this has no dynamic fidelity, low physical fidelity, and moderate structural fidelity. The latter is given through the system schematics.

Comparing the moderate-fidelity simulator to the low and high fidelity simulators, the simplified dynamics and qualitative response to operator's control inputs of the moderate-fidelity simulator provide an intermediate level of dynamic fidelity. Structural fidelity is maintained at the moderate level of the low-fidelity simulator. Physical fidelity is improved by providing a limited number of displays.

SUMMARY AND CONCLUSIONS

This paper has been concerned with the development of qualitative models of the dynamics for large, interconnected systems. Such models will be incorporated in the design of moderate fidelity simulators used for training in problem solving. The qualitative models of dynamic systems are also expected to be helpful in representing the mental models that supervisory controllers have of systems.

Preliminary work has been completed in deriving the appropriate equations for the dynamics. Approximate equations for dynamics will be derived for the major components of the marine powerplant. The suitability of the approximations will be evaluated by comparison of the simulation results between two sets of dynamics. The first set will use the actual system equations for the perturbed states. The second set will involve the approximate models. For various events that are characteristic of the subsystems, the overall system response will be presented to human operators. They will be asked to use these system responses to correctly detect and diagnose faults. If the approximation is functionally correct, the fault diagnosis performance on either of the systems will not differ from each other. The approximation will be modified if necessary until a reasonable performance agreement is achieved between the two models of dynamics. Transfer of training studies will then be conducted using the simulators at low, moderate, and high fidelity levels.

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REFERENCES


TRAINING SIMULATOR DESIGN FOR A MARINE ENGINE ROOM
AT DIFFERENT LEVELS OF FIDELITY*

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ABSTRACT

A marine powerplant on a large supertanker is a complex system made up of a number of interconnected subsystems where most functions are automated. A human operator manages the system in supervisory control mode, intervening only when an event occurs requiring his action to restore normal operations. For training marine engineering personnel to detect, diagnose, and compensate for failures, simulators at different fidelity levels are being developed. A low fidelity simulator uses information displayed on an Apple II computer terminal in conjunction with system schematics provided on paper. Details of the low fidelity simulator are described, and the results of a pilot experiment are discussed.

INTRODUCTION

Complex dynamic systems such as marine powerplants are normally run by automatic control systems. The control systems can handle routine operations as long as there are no problems during operation. Intervention by supervisory personnel is required only to detect problems, identify the causes, and correct the problems. Where full correction is not possible, compensation for problems is desired so that the system can be safely managed until the problems can be fully identified and corrected. While formal procedures can be developed for dealing with many types of possible situation, all possible contingencies cannot be anticipated. Therefore the operation of large, interconnected dynamic systems such as marine powerplants sometimes depends on the problem solving skills of the crew members.

Problem solving skills of supervisory control operators can be developed efficiently and effectively using training simulators. Simulators can be designed at various levels of complexity and realism relative to the systems they represent. The degree of realism and closeness with which the simulators resemble the actual systems can be formalized in terms of the concept of fidelity of simulation. Typically, the higher the fidelity of the simulator, the higher will be the cost. However, for training purposes, it may not be necessary to have a simulator with the "highest" fidelity possible in all aspects. Depending on the skill requirements, certain aspects of the simulation can be provided with high fidelity, with others at low or moderate fidelity levels. In fact, enhancing certain functions, and approximating some others may be useful for training.

The primary concern of the research described here is the design of

training simulators to be used to teach the general problem solving skills associated with failure management. The long term goal is to design simulators to enable transferability of training at relatively modest costs. To this end, low and moderate fidelity simulators are being developed for a marine powerplant to train marine engineers in the detection, diagnosis, and compensation of system failures.

SIMULATOR FIDELITY ISSUES

Background

Research issues in simulator fidelity were the topic of a recent workshop in which researchers in the area of training participated [Hays, 1981]. Various simulator and training techniques in use were discussed, and fidelity issues were debated. Baum [1981] presented hypothetical relationships between "physical" and "functional" fidelity versus the degree of simulator effectiveness. Even though these relationships have been used for a number of years, they appear to lack a firm experimental or theoretical basis.

A good discussion of simulator fidelity and its relevance for training is discussed by Montague [1981]. Examples are provided to show that physical fidelity ("physical isomorphism") is not always necessary, and at times counterproductive for training purposes. The inability to specify fidelity in terms of actual training requirements is attributed to the lack of good mental models. Mental models such as those developed by researchers in cognitive science are discussed at some length. How these could possibly be used is described. Montague recommends that specifications of knowledge and experience required to attain specific performance levels be used to define training task fidelity.

Orlansky [1981] maintains that fidelity is only one of many features that influence the effectiveness of a training device. He suggests that the effectiveness of a given fidelity level be measured in terms of the performance on the job rather than at school. While fidelity itself is not explicitly defined, the possible relationship of different amounts of fidelity to training effectiveness is discussed.

As the discussion above shows, no consensus seems to exist as to what constitutes fidelity or how it can be measured. One possibility is to characterize fidelity in terms of training effectiveness and transfer of training. This would reduce the concept of fidelity to be mainly an intervening variable which need not be defined rigorously.

Transfer of training and measurement issues are discussed in papers by Valverde [1973], and Blaiwes and colleagues [1973]. However, these measurement techniques do not appear to provide a means of measuring simulator fidelity. Adams [1979] presents detailed arguments to point out the difficulty of evaluating training devices including simulators. Measuring the transfer of training, as well as the rating methods in which persons experienced on the actual equipment rate the simulator, are shown to have problems. He suggests that these evaluation procedures are unnecessary if the simulators are designed on the basis of scientific principles. An example of such a principle is that human learning is dependent on knowledge of results. Designing simulators on a firm scientific basis would bypass the question of simulator fidelity altogether, since it ceases to be an issue any longer.
Dimensions of Fidelity

The issue of defining fidelity and studying its implications can perhaps be clarified if one begins with the premise that fidelity is a multi-dimensional concept. This allows a partitioning of the problem of defining fidelity into more manageable subproblems, from both a conceptual and measurement perspective.

Traditionally fidelity in simulators was synonymous with the physical similarity of the simulator to the actual system. A "good" simulator looked, and felt like the real equipment it was meant to simulate. This implies that the simulator had, at the least, the same number and types of displays and controls as the real system. Physical fidelity is concerned with the variables that are presented, the form in which they are presented (pictorial, verbal, etc.), and in how much detail they are given. If this requirement is only partially satisfied, the simulator lacks full physical fidelity. Another important consideration is the environment. For instance, noise, vibration, and thermal conditions similar to the real life environment should be provided where high physical fidelity is a requirement.

These requirements imply that simulators with high physical fidelity are usually rather expensive. However, the need for this high level of face-validity is often difficult to demonstrate. Even though a good correspondence between the simulator and the actual system provides a realistic environment with little deviation from the actual work environment, its contributions may not be clear. Possibly, a less detailed representation that provides only a limited number of essential controls and displays could provide an adequate training device. (Montague [1981] provides some evidence in support of this.) This would imply that low or moderate physical fidelity levels may sometimes be acceptable.

Even though it may seem desirable to have good "physical" fidelity in a simulator used for problem solving training, physical fidelity may not influence problem solving performance greatly; availability of the required information may be more crucial than the format and face-validity. This suggests that structural and dynamic factors may be more important.

Structural fidelity refers to the nature of relationships between various subsystems that make up the system, including feedback and feedforward connections, and hierarchical relationships. Similarly, the evolution of the system states over time, and their presentation to the operator can be characterized by dynamic fidelity. Structural and dynamic fidelity issues are discussed in detail in [Govindaraj, 1983].

Additional Considerations

Features that affect fidelity may be viewed from a man-centered and a machine-centered viewpoint. The former would include the various human abilities and limitations that affect fidelity, including sensory, perceptual, and cognitive aspects. The latter aspect would include factors such as the level of detail, and nature of structural representation, hierarchical relationships among the different subsystems, and accuracy of dynamical representation. The human and the machine aspects are interdependent and both have psychological implications. Therefore, these aspects should not be considered independently. The machine aspects greatly affect the cognitive
factors. For example, if certain subsystems and their interconnections are not explicitly provided by the simulator, the trainee may have to compensate for these by inferring their states. Hence, a lack of these functions could reduce the fidelity.

Apart from the issues which are based mostly on system characteristics, another method of studying fidelity is in terms of its use and effectiveness. Since the purpose of simulators is in training, one might say that a simulator has high fidelity if the training on the simulator is transferred well to the actual system. The level to which the training can be transferred can be a measure of fidelity. Unfortunately, the effectiveness of transfer of training can be difficult to assess, particularly if one attempts to isolate long term effects independent of other variables.

SIMULATION OF A MARINE POWERPLANT

Major Systems of a Marine Powerplant

A typical marine powerplant uses an oil-fired boiler to produce steam. The steam drives a series of turbines. The turbines are used to derive mechanical energy to drive the propellers, pumps, and compressors, and for electricity generation. Water for the boilers is distilled from the sea. The water-steam system forms a closed loop, with any leaks being compensated for by the addition of distilled water.

Air is taken from the atmosphere, pre-heated by exhaust gases, and used to burn the fuel oil in the burner. The hot gases are then used in the boiler to generate steam, as well as to superheat the steam coming out of the boiler. Before exhausting into the atmosphere, the hot gases pre-heat the water entering the boiler.

Fuel oil is preheated by auxiliary steam before coming into the burner. Since there are a number of mechanical subsystems such as turbines and pumps, a lube oil loop is used. This is a closed loop, where the lube oil goes through the bearings and other elements, picks up heat, and gets cooled by water. Failures in any element of the four major systems (water, air, fuel, and lube) could affect the operation of the powerplant.

Low, Moderate, and Full Fidelity Simulators

Simulators at low, moderate, and full fidelity levels will be used to study the problem solving performance of marine engineering personnel. Experiments will be conducted in which the subjects must identify the component or subsystem that caused a given failure for the symptoms provided. Transfer of training between simulators at various levels of fidelity will be investigated.

The high fidelity simulator consists of a replica of an engine and control room with the associated control and display panels. The engine dynamics is simulated on a mini-computer to a high level of detail. Simulated equipment such as burners, boilers, and plumbing are seen from the engine room as it would be on a real ship. Environmental conditions such as heat, humidity, and vibration are also simulated.
In the moderate fidelity simulator, a qualitative model of simplified dynamics will be used for the marine powerplant. A limited number of control inputs and displays will provide a moderate level of physical fidelity. Structural relationships between various subsystems will be provided using schematic diagrams.

The low fidelity simulator will have a limited amount of information displayed, in a format somewhat different from the real equipment. Information will be provided using system schematics. Symptoms corresponding to the failures or problems will be presented on a video display terminal. No dynamics is involved. The subject can check for the status of gauges and other displays through the computer interface. Display status stored in advance for each of the failure situations will be provided. The subject cannot control the system.

The full fidelity simulator has high fidelity along any reasonable dimension that one uses. On the other hand, the low fidelity simulator has no dynamic fidelity, low physical fidelity, and moderate structural fidelity. The moderate fidelity simulator has an intermediate level of dynamic fidelity, since a qualitative response to operator's control inputs is provided, while the structural fidelity is maintained at the moderate level of the low-fidelity simulator. The limited number of displays improves the physical fidelity over the low fidelity simulator.

THE LOW FIDELITY SIMULATOR

Overview

The remainder of this paper is devoted to discussion of the low-fidelity simulator. Discussion of the moderate-fidelity simulator can be found in Govindaraj [1983].

The primary component of the low fidelity simulator is an APPLE II Plus computer, used to accept inputs from the subject, and to display powerplant status and other relevant information (Figure 1). In addition, a number of diagrams provide system schematics at various levels of detail. A typical schematic is shown in Figure 2. A list of gauges and alarms provides the numerical codes required for checking their status (Table 1).

<table>
<thead>
<tr>
<th>Operation</th>
<th>Symptoms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gauges</td>
<td>Cr</td>
</tr>
<tr>
<td>Alarms</td>
<td>SF</td>
</tr>
<tr>
<td>Indicators</td>
<td>DF</td>
</tr>
<tr>
<td>Cutoff</td>
<td>SF</td>
</tr>
<tr>
<td>Record</td>
<td>SF</td>
</tr>
<tr>
<td>Initial Condition : Steering at sea</td>
<td></td>
</tr>
<tr>
<td>Symptoms : High salinity alarms sound</td>
<td></td>
</tr>
</tbody>
</table>

Figure 1. Screen Layout
Figure 2. Feedwater Flow

Table 1. Command List
The simulator resembles FAULT [Hunt and Rouse, 1981] very closely. FAULT is an interactive context-specific troubleshooting simulator. In FAULT, the user is given a hardcopy form of the network representation of the system of interest, and a statement of the symptoms which reflect the fact that some component or part in the system is malfunctioning. By interacting with the CRT terminal, the problem-solver must gather information in order to identify which of the components or parts has failed. Problem solving performance is judged by the total cost to identify the failed component, calculated from the costs of all actions. The cost for each simulated action corresponds to the actual cost of performing such an action on a real system.

Display Interface

At the start of a trial, initial conditions and the symptoms of a failure are shown on the display (Figure 1). For example, the initial condition could be "Steaming at sea", and the symptoms of failure could be "Vacuum pump fail alarm sounds". The user may request more information by typing in appropriate commands.

A subset of the actual alarms, status indicators and gauges (384 out of approximately 500) is used in this simulator. The alarms refer to the six panels of annunciators in the middle section of the full fidelity simulator. Each panel contains a number of indicators which are lighted as necessary to display the states of components and/or subsystems. Displays other than gauges and meters are classified into 12 groups by their location and function. Each group is identified by a name. Alarms and status indicators are given in groups while gauges are shown individually because approximately the same effort is required to locate the former in a group or the latter separately.

All actions and their associated costs are displayed at the lower left portion of the screen. Cost for each action reflects the time involved to obtain the relevant information on the real system. The number of steps and the total cost are the objectives to be optimized. At the end of a trial, the subject's number of steps is displayed along with the number for an experienced user for the same problem. This provides the subject with a standard for comparison.

Only the alarms and the status indicators that are activated by the given failure are shown to the user to simulate the illuminated tiles in the real system. The user can only diagnose and identify the failed component by designating the number shown beside the chosen component on the schematics. The schematics are color coded to indicate the components which are common to more than one diagram.

Operator Inputs

Each of the six possible actions are described below.

1. GAUGES (G):
   A qualitative description such as LOW, HIGH, NORMAL or ABNORMAL will be shown instead of the actual readings of the gauges. When appropriate, the time history of the gauge of interest can also be provided. For example, a message like "Pressure drop to 300 lb in 10 min" could give the subject some idea about the changes of the system states over time.
2. ALARMS (A):
This option displays the alarm status of a particular subsystem. Only those illuminated tiles in the real system are shown in the right half of the display. If none of them is turned on, an "ALL ARE NORMAL" message will appear. When more than 22 alarms are on at one time, the last line displays: "MORE ON NEXT PAGE. PRESS ENTER". The subject presses either the "ENTER" key, or types any one of the commands if viewing the next page is not desired.

3. INDICATORS (I):
The status indicators of the subsystem are shown on request. The content and format are similar to "ALARMS".

4. DIAGNOSIS (D):
The users can check their conclusions and/or test their hypotheses using this option. All the failures can be traced down to the physical component level using the numbers on the system schematics.

5. QUIT (Q):
This option is used to terminate the diagnostic process without completion.

6. RECALL (R):
Since all the actions and their responses are stored, they can be reviewed using the RECALL option. No extra cost is charged for doing this.

A PILOT EXPERIMENT

A pilot experiment has been conducted on the low fidelity simulator using two relatively inexperienced subjects. The discussion below is based on the observations made as they proceeded with the diagnostic process.

First, the subjects tended to identify or locate a component or subsystem using the keywords from the given symptoms. In a number of cases they immediately tested this component using the D option. If this test showed that the cause of the failure was elsewhere then the next move was to decide on the search direction, either upstream or downstream, based on their knowledge of the system. Often the subjects tested the first component in the chosen direction. The diagnosis was continued by checking gauges and indicators for system status. The subjects seemed to develop hypotheses, and either tested them using the D option, or modified them by asking for more information. This process was repeated until the faulty component was correctly identified.

The nature of actions taken by the subjects can best be illustrated with an example. In one of the failures used in the experiment, the symptom was: "Condenser Vacuum Low Alarm Sounds". The subjects started at the schematic that has the condenser, and continued to the feedwater flow schematic because "Vacuum" was also involved. In this case, a component upstream of the condenser is likely to have caused the problem. According to the feedwater flow schematic, there are four possible routes coming into the condenser. Typically, a subject checked the status of the condenser system in order to learn more about the states of the system. Therefore he was likely to type 19, and the system responded by showing the status of the subsystem on the right half of the display. Proceeding in this manner it was determined that the atmospheric drain tank float had failed.
From these discussions it is seen that the relationship between the symptoms and the faulty component played an important role in determining the cause of the fault. The symptoms as well as the faulty component could be in the same subsystem, or in a different subsystem. If more than one subsystem was involved the subjects seemed to devote more effort to deriving hypotheses and gathering information, resulting in more actions. Occasionally, the subjects checked the lower left window to check if a particular option had already been tried. It should be emphasized that these observations are based on the results of a pilot experiment with a small number of problems and a small number of subjects and, therefore, the results are not at all conclusive.

Additional problems are being developed where failures occur at different levels of complexity. Complex failures involve more than one of the four major subsystems. Experiments will soon be conducted involving marine engineering personnel. This should lead to the identification of features in the simulation that are helpful in problem solving.

SUMMARY AND CONCLUSIONS

The primary concern of the research described in this paper has been the design of training simulators for a marine powerplant. Marine powerplants are complex systems with a number of interdependent subsystems. Operation of such systems in supervisory control requires good problem solving skills. We are designing simulators at various levels of fidelity so that the general problem solving skills can be taught efficiently and effectively.

Fidelity of simulators appears to be strongly dependent on the context in which the simulator is used. Key factors that determine fidelity are discussed in this paper. Possible dimensions along which the levels of fidelity can be defined are identified. Low, moderate, and full fidelity simulators useful for training in problem solving were briefly described.

Details of the low fidelity simulator were given. Preliminary experiments have been conducted on the low fidelity simulator using a number of hypothetical failures. More experiments are planned with problems of varying levels of difficulty. Experiments will be conducted using experienced marine engineering personnel to study the transfer of training between the different levels of simulators. It is expected that this will lead to a better understanding of the factors that determine fidelity, and hence better design of training simulators.

ACKNOWLEDGEMENT

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REFERENCES


Baum, D. R., "A Framework and Topics for Empirical Research on Training


Orlansky, J., "Research on the Fidelity of Simulators", in [Hays, 1981], pp.143-151.

A MODEL OF HUMAN PROBLEM SOLVING
IN DYNAMIC ENVIRONMENTS *

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ABSTRACT

Human problem solving is considered in terms of the effects of the environment being dynamic. For example, the impact of having to operate a system while also trying to diagnose failures is discussed as well as several related issues. A general structure is proposed for modeling human problem solving in such environments. A realization of this general structure within a particular rule-based computer program is discussed. Results are presented from applying this program to modeling human problem solving in a process control task.

INTRODUCTION

During the past ten to fifteen years a wide range of models of human problem solving behavior has been developed. Some models focus on the pattern recognition nature of human behavior in problem solving tasks. For example, familiar scripts (Schank and Abelson, 1977) or frames (Minsky, 1975) may evoke a sense of having seen a particular type of problem before. Other models use a strategic approach, e.g., symptomatic versus topographic strategies (Rasmussen, 1978). However, most of the models developed thus far focus on a single aspect of problem solving. What is needed is a model that, at least conceptually, captures the whole of problem solving, and at the same time, can be operationalized within specific task domains.

The purpose of this paper is to discuss human problem solving in dynamic environments and to represent a general structure for modeling human problem solving in such environments. Finally a realization of this structure within a particular rule-based computer program is discussed.

RULE-BASED MODELS

Rule-based models, especially production systems, have become a fairly popular medium for modeling human problem solving. They excel in flexibility,
modularity and expandability (Davis and King, 1977). Within the production system formalism it is possible to express different levels of knowledge as well as different problem solving strategies.

All production systems consist basically of two parts: 1) a set of rules, and 2) a control structure for administering the rules. Each rule also consists of two parts. The left-hand side describes a situation to which the rule applies. The right-hand side describes an action to be taken or information to be gained as a result of employing the rule. Most often, this sort of rule is referred to as an if/then rule, a situation/action(situation) pair or simply a production.

The rules may be either context-specific, i.e., they refer directly to the state of the specific problem, or they may be context-free, i.e., they refer more generally to any problem with a given structure. Another distinction should be drawn between left-hand driven or pattern-directed models and right-hand or goal-driven models. The former results in a bottom up or forward chaining behavior, whereas the latter results in a hypothesis testing or backward chaining behavior.

Rule-based models seem quite appropriate for modeling the human problem solver in dynamic environments. Before representing the modeling approach, however, the nature of dynamic processes and the role of the operator in such environments will be discussed.

PROBLEM SOLVING IN DYNAMIC ENVIRONMENTS

Most of the well-known rule-based systems such as MYCIN (Shortliffe, 1976) and DENDRAL (Feigenbaum et al., 1971) deal with static problems. The design of a model of a dynamic task requires consideration of additional issues.

While an operator is controlling a dynamic process, there are four general tasks, which may have to be performed simultaneously: 1) transition tasks, such as start-up, shut-down, take-off, and landing, 2) steady-state tuning, 3) detection and diagnosis of failures, and 4) compensation for failures. To perform these tasks, the operator has to know: 1) how the process will evolve if left alone, 2) what the effect will be of implementing control actions, and 3) what task is currently appropriate. (For a detailed discussion of the complexity of controlling dynamic processes, see the recent review report by Morris (1982).)

While the operator performs a transition task, control is often fairly proceduralized. A certain sequence of actions is often known which will lead to the desired outcome. This is clearly a goal-driven situation and a model for this task should be right-hand driven.

Steady-state tuning involves actions oriented toward optimizing performance. This calls for a pattern-directed approach, where the appropriate action depends on a multitude of factors that can only be perceived as a pattern. Procedures are of great value for this task, since the merits and consequences of various approaches may be considered in advance and the one(s) most likely to achieve a given set of goals may be selected.
The task of failure detection and diagnosis will necessarily be, at least partially, active at all times. Procedures may not be as valuable because it is rather difficult to anticipate all possible malfunctions. Thus, certain rules for failure detection must be monitored during transition tasks, steady-state tuning and compensation for failures. Once an abnormal condition has been detected then the diagnosis must begin. It is possible that the diagnosis task could be either pattern or goal-driven. If the process is not too complex the diagnosis could proceed from the left-hand side. In a more complex process it may be necessary to establish the integrity of certain critical plant functions in a more structured right-hand driven manner.

Failure compensation would, in most cases, be fairly proceduralized. Once the cause of a disturbance has been diagnosed then, if it is a familiar failure, an appropriate action can be performed. However, if it is an unfamiliar failure, alternative approaches to failure compensation may have to be considered.

There are some rules that apply to all four tasks and others that apply to only one task (Hunt, 1982). For example, rules for a fairly proceduralized transition task, such as start-up, may be utilized when operations have been cut back during failure diagnosis and have to be restored again. Furthermore, as mentioned above, there are rules for failure detection whose preconditions have to be monitored during all four tasks.

Considering coordination among the four tasks, the human occasionally will proceed hierarchically from goal to subgoal to function to task (i.e., in a linear fashion). More often, however, he or she will skip from task to task and from goal to goal in an opportunistic manner (Hayes-Roth and Hayes-Roth, 1979). The latter reflects a more heterarchical strategy. The proposed model is capable of reflecting both hierarchical and heterarchical behavior.

A THREE-LEVEL MODEL OF HUMAN PROBLEM SOLVING

Rouse (1982) has proposed a general and potentially widely applicable model of human problem solving. This model assumes that problem solving occurs at three levels of cognitive activity.

1. Recognition and Classification. At this highest level the human has to identify the context and category of the problem. The operator first attempts to map the observed state of the problem to an appropriate frame. Failing to recall an appropriate frame, the operator has to classify the situation by its structure, perhaps through analogy to problems with similar structures.

2. Planning. At this level the operator has to decide upon a course of action. Either the situation (i.e., observed state) is familiar and an appropriate script can be applied, or the human must use an approach based on problem structure in order to develop a new plan.

3. Execution and monitoring. Actual problem solving occurs at this lowest level. Familiar aspects of the current state may be utilized or, if state patterns are not familiar, the execution may rely on features of the structure, in a manner similar to that for the other two levels.
Thus, the model operates on three different levels and on each level with either a state-oriented or a structure-oriented approach depending on the knowledge of the model relative to the patterns displayed. The basic mechanism of this proposed model is such that humans are assumed to have a clear preference for proceeding on the basis of state information rather than using structural information. This reflects an assumed human preference for pattern recognition over more analytical thinking.

In order to realize an operational model of human problem solving based on this general conceptual framework, a control mechanism for the coordination of goals and tasks has to be implemented. Humans often get caught up in the tasks that they are performing and lose sight of their goals. In addition, because of the dynamic nature of the task, goals may be preempted, temporarily or permanently, before they are reached. The next section describes a possible control structure that allows representation of these phenomena.

REALIZATION OF A RULE-BASED MODEL

In the preceding section a general model of human problem solving was discussed. This model, in form of a rule-based computer program, is currently being developed. While the rules which the model utilizes naturally depend, to a great extent, on the specific problem to be solved, one particularly important goal of this research has been to give the model a generally applicable structure. With such a structure the model should be easily adjustable to different dynamic problem solving environments.

Structure of KARL

KARL (Knowledgeable Application of Rule-based Logic) is a rule-based computer program, a model which consists of a set of production rules, i.e., the knowledge base, and a control structure. A simplified flow-chart of KARL is given in Figure 1.

The production rules are embedded in a framework, which represents the four tasks associating with controlling a dynamic process, as well as the three levels a human generally operates on while controlling a dynamic process. The control structure consists of two modules: 1) a pre-processing module, where the necessary information about the system's state is processed in order to identify the current task the model is performing (CURRENT-TASK), and 2) a branching mechanism that accesses the portion of the knowledge base containing the rules the model requires in order to perform the current task (CONTROL).
The knowledge base consists of four subsets, each of which is associated with one of the four general tasks. These subsets deviate somewhat from the tasks discussed earlier. FAILURE contains rules for diagnosis and correction of failures. TRANSITION contains a rather proceduralized sequence of rules. TUNING contains rules for normal operating conditions and failure compensation. Finally, PROCEDURES contains standard sequences of rules, each of which is applicable to particular operating situations. These procedures describe situations where the system state requires a certain action sequence in order to restore stable system operation.

Each module, except for PROCEDURES, is divided into the three levels observable in human problem solving behavior. After the classification of a situation (CLASS), different possible actions are evaluated (PLANning), from which an appropriate one is then executed (EXEC).

Functional Aspects of KARL

Referring to Figure 1 the information flow through KARL can be explained. The control process passes information about the system's state to the model and prompts it for an action command. In INTERFACE this state information is converted into a form suitable for the rules embedded in the knowledge base. In CURRENT-TASK the model determines the current task by means of current state information and, in particular, by knowledge about the system gained from previous state information acquired and subsequent actions. At this point, CONTROL branches to one of the four modules in the knowledge base.
As mentioned above, the model works both hierarchically and heterarchically. The rules in FAILURE, TRANSITION and TUNING have been constructed in such a way that, with the starting point at the top (CLASS), either a rule in a lower level of operation is invoked (i.e., from CLASS to PLAN, from CLASS to EXEC or from PLAN to EXEC), or a rule in another phase is invoked (i.e., from TRNS-CLASS to FAIL-CLASS or from TUNG-EXEC to PROCEDURES).

PROCEDURES is not divided into these three levels, since it is assumed that for a given situation the commands to be given are specified until the system is stabilized. This does not mean, however, that a predetermined command sequence is given. Applying a procedure means that basic actions are known that will return the system to stable operation. These are determined by invoking rules which contain knowledge about which command is to be given when. However, while the model is following a procedure, a failure may occur so that the procedure may be preempted in order to perform failure diagnosis and correction. While failure diagnosis and correction take place, CURRENT-TASK and CONTROL take care of "remembering" the current operating task.

It should be noted that the proposed model is not intended to be an "Expert System" such as MYCIN (Shortliffe, 1976). MYCIN has been designed to diagnose and prescribe treatment for real medical conditions to the best of its artificially intelligent ability. Towards this end the designers have combined human reasoning abilities with the rapid retrieval and calculating abilities of the computer to create a problem solver that often out-performs its human counterparts.

However, the goal for KARL is not that it should out-perform humans but that it matches human performance, both good and bad. A model that accurately represents both the efficient and inefficient elements of human performance would be of great value in the design of decision aids and/or development of effective training programs.

PERFORMANCE OF KARL IN A PROCESS CONTROL TASK

Currently, KARL is being tested in a process control simulation that was developed for studying human problem solving. This simulation environment was chosen because of the availability of extensive data on human problem solving in this simulator.

PLANT.

PLANT (Production Levels And Network Troubleshooting) is a computer-based simulation of a continuous, fluid processing plant through which generic raw material is transformed into generic finished product. The PLANT operator's task is to supervise the flow of fluid through a series of tanks interconnected by valves so as to produce an unspecified product. The operator's goal is to maximize production given the "physical" limitations of the system (such as tank or valve capacity or reliability of system components).
Tanks are organized in columns, where tanks in the left-most column receive input and tanks in the right-most column produce output. In general, the flow through the system is from left to right, and any pair of connected tanks behaves as a second order system. Tanks are connected by valves, which may be opened and closed by the operator via appropriate commands. Furthermore, the operator controls the input to and output from PLANT by specifying the number of units of fluid per tank to be pumped in and pumped out, respectively.

Since pumps, valves, and tanks, may fail in different ways, several diagnostic commands are available to the operator. Furthermore, there are commands for failure compensation, such as sending a "repair crew" to the site of the failure.

Safeguards incorporated into the system inhibit loss of control of the system and prevent system damage. For example, valves are closed automatically, i.e., tripped, when the amount of fluid flowing through them is too great. The operator can recover from trips by reducing input and output and diligently reopening valves until flow is stabilized. For more detailed information about PLANT see Path (1982) and Morris (1983).

Assessing the Model Performance

The ultimate goal for any model of human behavior is to duplicate the behavior of the human being modeled (Hunt, 1981). The degree of success obtained is highly dependent upon the performance measures used to evaluate the model. One might develop a model for solving problems such that it matched human performance very well in terms of overall production obtained. However, the model might use strategies completely different from those of humans. Since the goal of the proposed model is to match human behavior in terms of problem solving approaches, rather than to match only the final problem results, emphasis was placed on the sequence of actions taken by the model in comparison to the subjects. An overall evaluation of the model running by itself was also performed.

A large quantity of data was available from experiments performed by Morris (1983). A sample of this data was used to develop the rules of the model and to evaluate the resulting model behavior and performance. Specifically, data for all 32 subjects in sessions 8 through 11 of the experiment of Morris (1983) was utilized for the comparison reported here.

Comparison with subjects

An overall evaluation of the model was performed by comparing the total production achieved by the subjects and by the model. In order to compare the actions of the model and those of the subjects, the model was used to select the action it would have made in each situation that the human subject viewed. Then the action actually taken by the subject was read from a data file. The actions for the model and the subjects were then recorded in a data file for later analysis. Finally, the problem was updated with the action selected by the subject. This process was repeated until the problem was solved.

The subject's choice was used for updating since, otherwise, any deviation of the command sequences of model and subjects would have resulted in divergent system states and inherently different command sequences. To avoid this problem the model always selected actions according to the situation
viewed by the subject. This was assured by always implementing the subject's choice.

**Total Production**

To compare the model with the subjects on total production the model was allowed to run by itself, without being updated using the subject's actions. It should be noted that production was never used by the model to make a decision. Table 1 shows the total average production for KARL and for all 32 subjects from four instructional groups who received different amounts and types of information about PLANT.

Morris (1983) found that there was no significant difference in total production achieved among the four instructional groups. However, there was wide variability within groups, and it can be said that the model succeeded quite well in matching the average or typical behavior for all four groups. A more detailed analysis, including analyses of other measures, can be found in Knaeuper (1983).

<table>
<thead>
<tr>
<th>Groups</th>
<th>Production runs (average production: subjects/KARL)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>A</td>
<td>147,715.9</td>
</tr>
<tr>
<td>B</td>
<td>145,872.8</td>
</tr>
<tr>
<td>C</td>
<td>174,725.6</td>
</tr>
<tr>
<td>D</td>
<td>161,398.9</td>
</tr>
<tr>
<td>Mean</td>
<td>157,428.3</td>
</tr>
<tr>
<td>KARL</td>
<td>171,240.0</td>
</tr>
</tbody>
</table>

Table 1: Total Production: Comparison of Subjects and KARL.

**Action-by-Action**

For an initial analysis and evaluation of the model two subjects of each group were selected at random and action-by-action comparisons between model and subjects were performed. Table 2 shows how the model compared to the subjects in four production runs. Although the numbers in Table 2 do not come close to 100% matching they still reflect a successful initial model. If one considers that the model was not individually adjusted to each subject, a match of 25% to 55% is a fairly good start.

There are some rules within KARL which are not applicable for some subjects, and in those cases the model fails to match the subject's choice. However, it was not the idea to make every action a special case with its own rule. Nevertheless, for some of the poorer subjects or subjects with limited knowledge about the system, a different set of production rules have to be implemented.
It was found that some rules are too strict to match several subjects. For example, the model contains a rule which proposes that if the system is stable, i.e., all valves are opened and the height differences are within a specified range, then output and input to the system should be some high, optimal value. However, some subjects appear to be conservative and do not like to bring the system to its limits. In these cases the model continues to give the action command for optimal input and output, but the subject never goes that far. This behavior was observed very often and resulted in a degradation of the match. Another source of mismatch that was found involved subjects doing much more fine tuning than the model.

These initial results, which are in the process of being extended and refined (Knaeuper, 1983), lead to several interesting behavioral interpretations. First, not all subjects appear to know, or at least utilize, all of the information provided in their instructions, despite of the fact that a written examination administered by Morris (1983) indicated subjects had learned their instructions. Second, some subjects appear to be conservative in terms of not operating as close to the limits of production as is possible and tuning the process much more than necessary. These results, if validated during subsequent analysis, provide some interesting avenues for training and/or aiding of operators.

<table>
<thead>
<tr>
<th>Groups</th>
<th>Production runs (same actions [%])</th>
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<td></td>
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<td>1</td>
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<td>C</td>
<td>5</td>
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<tr>
<td></td>
<td>6</td>
</tr>
<tr>
<td>D</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>8</td>
</tr>
</tbody>
</table>

Table 2: Action-by-Action Comparison of Subjects and KARL.

SUMMARY AND CONCLUSION

KARL, a model of human problem solving behavior in dynamic environments, was presented. Its general structure and functional aspects were discussed and an evaluation was performed by applying this model in a dynamic process control environment. At this point in time, only initial results of the validity and usefulness of the model are available. However, further research is in progress. Some of this work will involve testing the usefulness of the model in different problem environments. Further, the model's potential for making errors in the same way and for the same reasons as humans will be studied.
ACKNOWLEDGEMENTS

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REFERENCES


EVALUATION OF THE ABILITIES OF MARINE ENGINEERING PERSONNEL
TO DETECT, DIAGNOSE, AND COMPENSATE FOR SYSTEM FAILURES

William B. Rouse
Principal Investigator

Annual Interim Report
For the Period June 1, 1983 - May 31, 1984

For

Contract N00014-82-K-0487
Work Unit NR 154-491
(June 1, 1982 - May 31, 1985)

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Georgia Institute of Technology
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INTRODUCTION

Following in the wake of the aviation industry, efforts to introduce automation in the marine industry are increasingly evident. Most of these efforts have been pursued in hopes of improving energy efficiency, increasing abilities to operate in confined waters and low visibility, and reducing the size of the crew. An example of trends in the latter direction is the relatively recent emergence of unmanned engine rooms.

Considering the engine room in more detail, various automatic controls have been introduced for regulating engine rpm and the flows of steam, feedwater, fuel oil, lube oil, etc. In addition, several automatic changeover systems are now utilized for activating backup pumps, generators, etc. In general, these automatic devices have eliminated many manual tasks for marine engineering personnel, at least during normal operations or "standard" abnormalities.

However, as in many other domains, the introduction of automation into the engine room has resulted in the engine system becoming increasingly complex. The marine engineering personnel who monitor this system now must be concerned with the possibility of many more types of failure and combinations of failures. This can be particularly problematic when the automation itself fails and its subsequent compensatory response to its own failure appears to be rather unpredictable.

Partially in response to this increase in system complexity, the marine industry has increased efforts in the direction of training. Typically, these training programs utilize full-scale, high-fidelity simulators and attempt to provide the trainee with one or two weeks of highly concentrated experience with a wide variety of system failures.

Because the development of a high-fidelity engine room (or bridge) simulator requires a multi-million dollar investment, training centers tend to have a single simulator which greatly restricts class size and makes the program very expensive. While the industry views this as a necessary evil, this may not be the case because:

1. It is not clear what problem solving skills are necessary for detecting, diagnosing, and compensating for failures in the engine room.
2. It is not clear that full-scale, high-fidelity simulators provide a more effective and economical environment for learning these skills than possible with lower fidelity simulators.

The primary goal of the research program whose progress is reviewed in this report is to pursue these issues and provide an understanding of human problem solving in the engine room environment, particularly in terms of the abilities of trainees to learn problem solving skills as a function of the level of fidelity of the simulator.

The problem outlined in this Introduction is being pursued by both theoretical and experimental investigations of human problem solving abilities in simulated supertanker engine room environments. The theoretical aspects of the investigation involve the use of an evolving model of human problem solving in dynamic environments. The experimental studies involve three simulated engine room environments, ranging in fidelity from fairly low to very high, where professional marine engineering officers are being used as subjects for all formal experiments.
MODEL OF PROBLEM SOLVING

The modeling effort is an outgrowth of earlier work on human problem solving behavior. Prior to the start of this ONR project, this effort had reached the point that the model had been tested extensively in various static troubleshooting situations. It also had been extended conceptually so as to apply potentially to dynamic operational situations. However, this conceptualization had not been operationalized and tested.

Under the first year of ONR support, this extended version of the model was programmed (in Pascal on a VAX-11/780) and initially tested. Since data from the engine room simulators (discussed below) was not yet available, the programming and testing of the model was pursued using a process plant simulator and experimental data obtained from a different project. The results of this effort are reported in Knaeuper and Rouse (1984).

This progress with the modeling was important in several ways. First of all, few if any models or theories of human problem solving deal explicitly with dynamic operational environments. Thus, most models of human problem solving need not be concerned with the important role of expectations and the need for planning in operating dynamic systems. Further, they do not have to consider the tradeoff between operational goals and problem solving that is inherent with many dynamic systems. The model discussed in Knaeuper and Rouse (1984) explicitly considers issues such as these.

This initial modeling effort produced two conclusions that have been pursued in detail during the past year. First, in comparing subjects' control behavior to the model, it appeared that subjects did not fully utilize the information provided by written instructions, even though a written test indicated that they had learned the information. In particular it was noted that people only partially followed available operational procedures and thus did not achieve as much system output as was possible. This result led to the idea of using the model as an online method for testing subjects' use of instructions and providing appropriate feedback to subjects.

Second, the model was found to be excessively proceduralized and
inflexible in certain situations. The planning aspect of the model needed considerable elaboration. Further, the model should be able to adjust its behavior and augment/modify its knowledge while it is controlling a system. In order to add and delete rules while the model is performing a task (i.e., to include some form of learning mechanism), a new improved structure was designed. This new version of the model has not yet been programmed, but an outline of the new structure is described in this report.

A Model-Based Approach for Online Aiding and Training

The model of human problem solving has been used as an online observer of a process control simulation and subjects' control behavior. An experiment was conducted in the hopes of gaining insights into the reasons for subjects' failure to follow procedures completely, and to assess the potential benefits of supplying subjects with an online operational aid in addition to written instructions. A further issue to be pursued was to investigate the applicability of a rule-based system for monitoring and supporting humans as an online aid. A description of the experiment and discussion of the results can be found in Knaeuper and Morris (1984) which is included in the Appendix of this report.

A Rule-Based Model That Learns

The new improved structure of the model will be such that all rules are embedded in a knowledge base (problem-dependent) that is absolutely separated from the interpreter (problem-independent) of the problem. The programming language is LISP. The basic structure of the model as described in Knaeuper and Rouse (1984) has been maintained.

The knowledge base will still be divided into three general tasks (i.e., transition, tuning, and failure management) and three general levels of behavior a human usually operates on when he controls a dynamic system (i.e., classification, planning, and execution). Thus, the knowledge base will contain nine main parts plus one part for general rules that determine the current task. Each part will be constructed as a list of rules, for example, the list of rules for Tuning-Classification might be as follows:

(setq rules-tuning-classification
  ((RTUCQ1
    (IF (diffbetwcolumns greater 15)
Each list will contain structure-oriented rules with variables (e.g., \(x, y, z\)) that can be bound to values if the situation requires. This will create a new rule. The structure-oriented rules will also be stored in a separate list and then be added to the appropriate list in the knowledge base. Similarly, rules can be deleted. If an action results in a deteriorated system state then the rule that triggered that action might be deleted.

In addition to the rules in the knowledge base there will be a list of facts concerning the current system state. This facts list will be updated each iteration (i.e., each time an action is taken). The stored facts are used to fire rules. The facts list might look as follows:

```
facts
   { (current input 150)
   (current output 150)
   (valve AD closed)
   (valve AF closed)
   (valve AD inrepair)
   (repair crew busy till iteration 120)
   (average_height equal 45)
   (last command equal rva-d) 
   ( : : : )
   ( : : : )
```

A control function will access the appropriate part of the knowledge base as is determined by CURRENT TASK. CURRENT TASK uses functions of the interpreter to test rules in the rulescurrenttask list.

The interpreter will consist of several functions. For example: TESTIF, a function that loops through all elements in a rule's IF part, testing each with RECALL, a function that looks for facts in the facts list. USETHEN, a function that is called if TESTIF returns T, uses REMEMBER, a function that adds new facts onto the facts list. TRYRULE glues TESTIF and USETHEN together and returns T only if all the facts in
the IF part are on the facts list and at least one of the facts in the THEN part is not on the list. In addition to these basic functions some functions have to be written to allow forward chaining, i.e., working from facts to conclusions, and backward chaining, i.e., working from hypotheses to facts.

Once programmed this version of the model will allow additions/modifications of the model's knowledge and adjusting of actions. Starting off with a minimum set of rules in each part of the knowledge base, the model should be able to build its knowledge base during the course of actions.

Recently, the idea has emerged of using the model in parallel to a human operator, as a means for identifying rules. A separate program will create rules dependent on the human subject's actions, the observable state and additional state information inferred by the model. The created rules will then be added to the model's knowledge base. After several sessions of observation, the model should converge to a good description of the human operator being observed. Such a model might then be used to analyze subject's control behavior and/or used to aid and support the human in his course of actions (i.e., in a similar way to that described in the previous section).
As noted earlier, this research is utilizing three engine room simulators involving low, moderate, and high fidelity. The high-fidelity simulator is available via subcontract to Marine Safety International (MSI). The low and moderate fidelity simulators are being developed as part of this research project. These three simulators are being used to assess the relationships among a wide variety of measures of problem solving performance which will provide insights into what is learned with each type of simulator and what level of fidelity is necessary for alternative problem solving training objectives.

This year has focused on evaluating the low-fidelity simulator and developing the moderate-fidelity simulator. The basic differences between these two simulators is that the moderate-fidelity simulator will respond dynamically, allow trainees to make control inputs, and provide some conventional display instrumentation.

**Low-Fidelity Simulator**

The low-fidelity simulator is programmed in Pascal on an Apple II Plus. This simulator was designed on the basis of the specifications of the MSI simulator. As information was gathered about the MSI simulator, it quickly became apparent that an Apple II based simulation could not include the 500 gauges, etc. associated with the real system. As a result, the low-fidelity simulator incorporates a variety of features (e.g., multiple pages of displays and alarms) to allow simple simulation of a complicated system. A description of this simulator and initial results of a small pilot experiment are discussed by Govindaraj and Su (1983).

After extensive pilot testing and modifications, two experiments were conducted with the low fidelity simulator at Marine Safety International, one in April and the other in June. Five marine engineers from TEXACO participated as subjects in the first experiment. Each subject went through 18 problems on the low fidelity simulator -- FAIL (FAULT-based Aid for Instruction and Learning). Based on the data, a fault diagnosis model has been developed. The model and experimental results are summarized below and detailed in Su and Govindaraj (1984) which is included in the Appendix.
Fault diagnosis is a backward reasoning process going from symptoms to causes. The symptoms may be obvious or non-obvious. Obvious symptoms are those presented via audio alarms or flashing lights to attract the operators' attention. Examples of non-obvious symptoms are abnormal gauge readings and system status indicators which are available only through checking. Only obvious symptoms were presented to the subjects in FAIL; information on non-obvious symptoms had to be requested. The relationship between obvious symptoms, non-obvious symptoms and causes is analogous to an inverted tree with the obvious symptoms at the root and the causes forming the leaves. Each set of symptoms may be a result of several sets of causes. A set of causes is the collection of components which are suspected to be responsible for the observed symptoms.

The diagnostic process is to find a path from the root to the correct leaf, i.e., the faulty component. This process can be further broken down into two stages. In the first stage, the subjects tried to gather more information about the system and formed a feasible set of symptom-cause pairs that may cause the failure to happen. Hypotheses were formed based on this feasible set. Once a hypothesis was formed, the subjects moved into the second stage in which the newly formed hypothesis was evaluated. If the hypothesis could not be confirmed, the subjects shifted back to the first stage to form new hypotheses.

Two factors were observed to be related to the performance which was measured using the total number of actions, cost and time. The first was the initial feasible set which reflected the subjects' knowledge about the given failure. The second was the transition strategy used for shifting from stage to stage. Two types of strategy were identified: breadth-depth strategy vs. balanced strategy.

Subjects using the breadth-depth strategy conducted a broad search for hypotheses and did thorough checking once a hypothesis was formed. Subjects using the balanced strategy did not conduct a broad search for hypotheses and did not seem to evaluate any single hypothesis thoroughly. They tended to form hypotheses quickly and maintain several hypotheses at the same time.

The data seem to indicate that subjects who had good initial feasible sets and used the breadth-depth strategy performed better than subjects who
had bad initial feasible sets and used the balanced strategy.

The model was also used to analyze the data from the second experiment in June in which four marine engineers participated as subjects. Similar results were obtained. These results seem to indicate that both context-specific (initial feasible set) and context-free (transition strategy) factors affect human fault diagnosis performance. However, the sample size is relatively small to draw any definitive conclusion at this time. Three more experiments are scheduled for September, October, and November.

**Moderate-Fidelity Simulator**

Various features that were developed earlier for the moderate fidelity simulator have been consolidated to result in a unified structure which is detailed in Govindaraj (1984) in the Appendix. The simulator is viewed as a combination of subsystems in various loops. Using property lists for components forming the subsystems, various loops and paths for signal and mass/energy flow have been formalized. Components have been classified into various generic types such as heat-exchangers. Primitives for generic types have been developed. Each primitive performs a specific function. Using functional descriptions for the primitives, the state evolution process has been refined to a two-step process. During the first step, individual components are considered. From the previous state values and the operator inputs and event-related changes to the component, new states are calculated. In the second step, the state values are propagated along various loops. Any state values thus propagated form inputs to various components in the first step. This continues until all subsystem states are updated for each cycle. When the cycle is complete, each component uses its inputs and states to calculate the next state as described earlier. When appropriate means of handling operator inputs and providing system information to the operator are developed, this simulator should be ready for experiments.

All of the simulation issues are being considered in the framework of attempting to define the general concept of simulator fidelity. Thus far, it appears clear that fidelity is a multi-dimensional concept involving at least physical, structural, and dynamic aspects of trainee-simulator interaction. From this perspective, the low-fidelity simulator is low,
moderate, and low on the three dimensions; the moderate-fidelity simulator is moderate on all three dimensions; and the high-fidelity simulator is high on all three dimensions. The overall issue of simulator fidelity and transfer of training is reviewed in a recent report by Su (1984).

One other aspect of the simulators deserves special note. One of the primary indices of problem solving performance that will be assessed in the planned experiments is the types and frequencies of human errors. In order to identify the contributions of human engineering design deficiencies to human error, a human factors evaluation or audit of the controls and displays of the high-fidelity simulator was completed. The relationships between design deficiencies and human errors will be determined in later experiments and will hopefully serve as useful inputs for design principles and guidelines.
PUBLICATIONS

Journal Article:


Conference Papers:


Technical Reports:

Su, Y-L., A review of the literature on training simulators: transfer of training and simulator fidelity (Tech. Rept. 84-1), Atlanta, GA: Center for Man-Machine Systems Research, Georgia Institute of
A MODEL-BASED APPROACH FOR ONLINE AIDING AND TRAINING IN PROCESS CONTROL

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ABSTRACT

This research addressed the feasibility of adapting an existing rule-based system as an online "coach" for controlling PLANT, a simulation of a generic process plant. KARL, a rule-based model capable of controlling PLANT, was adapted to provide three types of information to subjects: 1) situation assessment (i.e., which operational procedure, if any, was applicable for a given situation); 2) guidance in following procedures (i.e., feedback whenever subjects' actions were inconsistent with available procedures); 3) performance feedback (based upon changes in the system's stability). Subjects received this information online while controlling PLANT. Compared to subjects in an earlier experiment who controlled PLANT without the benefit of the coach, these subjects maintained a generally more stable system, scored higher on a paper-and-pencil test of system knowledge, and were more successful in diagnosing an unfamiliar failure of the PLANT safety system. Careful analysis of these results in light of previous research with PLANT indicated that the reasons for these differences were not as straightforward as they might appear. This experiment is viewed as illustrating potential benefits and subtleties of using a rule-based model as an online coach.
INTRODUCTION

As systems increase in complexity, the question of how persons should be trained to operate them becomes more important. The amount of training required for someone to become proficient at controlling a complex system may be quite extensive, and it is necessary to consider a number of issues when developing such a training program. These issues include the content and format of instructional material and the structure of the program. Because of inherent human limitations, it may also be necessary to consider provision of some kind of performance aid, in addition to appropriate training.

Many reports are available which directly or indirectly address issues relevant to training (Morris & Rouse, 1984b). Some are directed at obtaining an understanding of how people solve problems, either in the laboratory or in contact with an actual system. Others investigate the effects of various training approaches upon performance. Often there is a discussion of the human's "mental model" of the system being controlled (Rouse & Morris, 1984).

One study in particular served as a basis for the present research. Morris investigated the effects of different types of instruction upon subjects' ability to control PLANT, a computer-based simulation of a generic fluid production process.
(Morris, 1983; Morris & Rouse, 1984a). The PLANT operator's task is to supervise the flow of fluid through a series of tanks interconnected by valves so as to maximize production. This may be done by opening and/or closing valves and adjusting input and output, via commands entered at the terminal keyboard. A number of failures may occur in PLANT, so there are several diagnostic and repair commands available as well.

The primary comparison in Morris' research was between two different types of instruction: 1) operational procedures, and 2) a description of dynamic principles and functional relationships in PLANT. Four groups of subjects were compared, distinguished on the basis of the combination of written instructional materials they received (i.e., principles, procedures, neither principles nor procedures, or both principles and procedures). Instruction was found to have no effect upon subjects' achievement of the overall goal of production, in that there were no differences between groups with respect to this measure. However, those groups receiving procedures were found to control the PLANT in a more stable manner, even though all groups had been told to maintain stability.

An interesting aspect of this research was an investigation of subjects' ability to deal with two unfamiliar failures: a tank rupture, and failure of the PLANT safety system. (The failures were unfamiliar in that, although subjects knew they
could occur, they had not experienced them before.) Almost all subjects repaired the tank rupture; however, only half of the subjects in each group successfully diagnosed the safety system failure. This was surprising, because subjects with an understanding of the functioning of the system (as described in the principles) should have been better able to make that diagnosis.

As a result of these findings, it was suggested that one of the reasons a knowledge of principles failed to help many subjects deal with the unfamiliar failure was that those people did not realize that they were in an unusual situation, and thus did not realize that they should use their knowledge. In other words, they failed to make an accurate assessment of the situation. This notion was indirectly supported by the fact that those persons who did repair the unfamiliar safety system failure also maintained a more stable system in general; since the effect of the safety system failure was to make the PLANT appear more unstable, maintaining a stable system may have enabled subjects to detect the presence of an unusual situation more readily.

Some useful insights into subjects' behavior were gained by comparing their performance to that of KARL (Knowledgeable Application of Rule-based Logic), a model capable of controlling PLANT (Knaeuper, 1983; Knaeuper & Rouse, 1984). KARL is a
rule-based model patterned after a general model of human problem solving proposed by Rouse (1983), which suggests that problem solving is accomplished in three stages: 1) recognition and classification, 2) planning, and 3) execution and monitoring. These three stages essentially define KARL's structure. When controlling PLANT, KARL accesses a knowledge base consisting basically of information contained in written information available to subjects (i.e., operational heuristics and procedures, and information about dynamic principles and functional relationships).

When the performance of subjects and KARL was compared, it was noted that KARL consistently achieved higher production and maintained a more stable system than did subjects. It was also interesting to examine differences in the courses of action chosen by subjects and KARL in solving problems in PLANT. Basically, two rather systematic differences were found. First, the levels of system input and output chosen by subjects were not as high as those chosen by KARL (and suggested by procedures); subjects were more conservative in this respect. Second, KARL adjusted input and output much more frequently than did subjects; this reflected heuristics within KARL which were directed at maximizing production, which were not a part of operational procedures.

Considering some of the apparent difficulties experienced by
subjects in making an accurate situation assessment and following procedures, and the benefits derived from using KARL as an off-line analysis tool, an idea emerged. Why not make it possible for KARL to analyze subjects' actions online and provide advice, thus functioning as an online "coach"? It seemed that such an approach could prove to be useful for both training and aiding.*

DESCRIPTION OF THE COACH

In light of the factors noted above, the decision was made to provide subjects with three types of information. In the context of PLANT, this information was displayed on the terminal near the area where normal operating messages were displayed. The first type of information was related to situation assessment. Specifically, a message informing the subject which procedure was currently applicable was shown (e.g., "Procedure 5"). If no procedure applied, the following message was displayed: "No procedure applicable; Normal tuning".

Subjects also received guidance in following procedures. KARL monitored subjects' actions, and provided feedback if a given action was inconsistent with the applicable procedure. For

* Of course, one could view this approach as simply a special case of "expert systems". This issue is discussed later in this paper.
example, the following message might appear: "Your action (cva,e)* is inconsistent with Procedure 5. Keep all valves open until the system is stable again. Type 'y' for change." As may be ascertained from the last portion of the message, subjects had the option of overriding KARL or changing their actions to be consistent with KARL's recommendations.

The third type of information supplied by KARL was performance feedback, or information about the degree to which subjects' actions were succeeding in remedying problems in the system. This information was supplied because of the length of time required for the consequences of actions to become manifest. These messages were based upon changes in PLANT stability over a period of 10 time units, and consisted of the following: "Instability extreme", "Instability excessive", or "Instability improving".

The process of enabling KARL to supply such messages was relatively straightforward. However, when an attempt was made to control PLANT with KARL as an assistant, a number of problems became apparent. For example, KARL's advice as to what actions should be taken was not always consistent with procedures. This could be attributed to the nature of KARL's approach to PLANT.

* cva,e = close the valve between tanks a and e
Although the information in the procedures was contained in KARL's knowledge base, KARL also employed several heuristics when controlling PLANT, which occasionally preempted the action recommended in procedures.

Another problem was related to KARL's situation assessment. During the course of PLANT operation, situations would occasionally arise which were "borderline" conditions with respect to the applicability of various procedures. KARL's decisions as to which procedure applied were based upon fixed values of state variables. In borderline situations, normal fluctuations of these state variables caused KARL to change the situation assessment message rather frequently (e.g., every other time unit).

A third source of difficulty was KARL's "persistence" in reporting actions which were inconsistent with procedures. The PLANT operator was given the option of overriding KARL and implementing an action against KARL's recommendations. However, the consequence of thus failing to conform was to receive another message. KARL did not know how to concede; in short, KARL was a nag.

These problems were remedied in two general ways. First, it was necessary to inhibit the display of all messages which were not procedure-oriented. Second, thresholds for prompts were
incorporated. For example, if a subject failed to comply with one of KARL's suggestions, KARL did not make the same suggestion again for five time units. As another example, "hysteresis" was introduced into the situation assessment thresholds to avoid the aforementioned problem of borderline conditions.

An experiment was conducted to evaluate the effectiveness of KARL as an assistant. Two general issues were of interest: 1) the feasibility of adapting a rule-based system (which was not originally designed as an aid) to support human problem solving, and 2) the effects of an online coach upon humans' performance.

METHOD

Subjects

Junior and senior undergraduates at Georgia Institute of Technology served as paid volunteer subjects. All eight of them were majors in industrial and systems engineering, and had completed courses in physics, dynamics, calculus, and differential equations.

Experimental Procedure

The experimental procedure in this experiment was almost identical to that used in the research described earlier (Morris, 1983; Morris & Rouse, 1984a). Training provided to subjects in this experiment was equal to the group receiving instruction in
both principles and procedures in the earlier experiment, with the exception that aiding was available.

Subjects served in a total of 13 sessions each, with the average length of each session being approximately 60 to 75 minutes. Generally, training was accomplished during the first eight sessions, in which subjects read instructional materials and practiced controlling PLANT. A discussion of principles governing PLANT was provided during session 3, and operational procedures were made available for the first time in session 5. KARL was used as an online coach during sessions 5-8, and supplied the three types of aiding information described earlier.

Sessions 9-13 were considered experimental sessions, in that no further instruction was provided by the experimenter, and no questions from subjects were answered. As with the earlier experiment, unfamiliar situations (i.e., a tank rupture and a safety system failure) were introduced in sessions 10 and 12, which were counterbalanced across subjects. The coach did not provide guidance in following procedures during sessions 9-12; subjects received only information related to situation assessment and overall performance feedback. No information from the coach was available during session 13. At the end of session 13, subjects completed a paper-and-pencil test of knowledge about PLANT and the coach, based upon material contained in the written instructions.
RESULTS

In order to assess the effects of aiding, the performance of subjects in this experiment was compared via analysis of variance to performance of the group receiving both principles and procedures in the earlier PLANT research. (In the following presentation, these groups are referred to as the aided and unaided group, respectively.) Thus, performance measures were used as dependent variables in two-way analyses with one between-subjects factor (aiding) and one within-subjects factor (session).

As with the earlier research, the experimental manipulation had no significant effect upon total production achieved, although the mean for the aided group was slightly higher (344.6 vs. 320.2 units of production per time unit). There was also no significant effect of aiding on the number of automatic valve trips experienced (an indication of PLANT stability). However, as with total production, the mean for the aided group was slightly better (i.e., lower) (0.497 vs. 0.605 trips per time unit).

Aiding also failed to have a significant effect upon another measure of PLANT stability: variance of fluid levels in the system. Once again, the trend was in the expected direction, in that the mean for the aided group was lower (12.44 vs. 15.27).
Two performance measures were significantly affected by aiding. Aided subjects kept a higher percentage of valves open (92% vs. 87%, $p < .04$), and generally maintained a higher level of input into the system (116.8 vs. 106.9 units per time unit, $p < .04$). The practical significance of these results is presented later.

Assessing subjects' performance during unfamiliar situations, there was no effect of aiding upon subjects' repair of the tank rupture (15 of the 16 subjects did so). However, it was found that seven out of eight subjects in the aided group repaired the unfamiliar failure of the PLANT safety system, whereas only three of the eight unaided subjects found that failure. This difference in proportions was found to be statistically significant ($p < .04$).

Differences in scores on the test of PLANT knowledge were examined. Although overall scores did not differ significantly, it was found that the aided group scored significantly higher on the section of the test related to dynamic principles (83% vs. 69%, $p < .05$).

Finally, the actions selected by subjects were compared to actions which would have been selected by KARL in the same situation. This comparison was similar to that reported for the earlier experiment (Knaeuper, 1983; Knaeuper & Rouse, 1984).
There was no significant difference in the degree to which actions chosen by aided and unaided subjects agreed with those selected by KARL.

DISCUSSION AND CONCLUSIONS

As noted in the introduction, this research was prompted by two issues: 1) the feasibility of adapting a rule-based model as an online coach, and 2) the effects of such assistance upon subjects' ability to control PLANT. With regard to the second issue, none of the statistically significant effects the coach had upon subjects' performance were related to primary performance measures. Although mean performance for the aided group was better with all measures, the only significant effects of aiding were upon the secondary performance measures of number of open valves and level of system input. These measures indicate that subjects did what they were told to do. Although all subjects (in this research and in the earlier experiment) were instructed to keep all valves open and maintain a relatively high level of input and output, apparently the coach's presence caused them to follow these instructions more closely.

Whereas it is fairly easy to provide an explanation for subjects' following instructions more closely, explaining why more subjects in the aided group were able to diagnose the safety system failure is not as straightforward. Three possibilities are suggested by the data. First, since failure of the safety
system resulted in automatic closing of valves at random, the ability to maintain more valves open in general may have assisted subjects in detecting the presence of an unusual situation. Once detected, it should have been easy to determine that the cause of the unusual situation was failure of the safety system, since only two unusual failures were possible.

Judging from the available evidence, however, it is difficult to imagine that this is a sufficient account of what happened. A look at the performance of all subjects supplied with procedures in the earlier experiment conducted by Morris (i.e., those with procedures only, and those with both procedures and principles) reveals that there was no difference in the number of valves kept open by persons who repaired the safety system and those who did not (89% vs. 88%). Additionally, a subsequent examination of logs kept by the unaided group during the time the safety system had failed indicated that at least six of the eight people felt that something was wrong; yet, only three of these successfully diagnosed the failure, and the others attributed the problem to deficiencies in their control actions.

Another possible explanation may be found in the fact that the aided group scored significantly higher on the test of information related to dynamic principles. Perhaps an increased knowledge of the functioning of the system enabled the aided group to diagnose the unfamiliar failure. This explanation also
seems inadequate. There was no difference in the test scores of unaided subjects who repaired the safety system and those who did not (69.3% vs. 69.2%).

The third explanation for aided subjects' success in diagnosing the failure of the safety system is that somehow providing them with the coach made the difference. During the session in which the safety system failed, two types of aiding messages were provided: situation assessment and performance feedback. The situation assessment consisted of informing subjects which procedure, if any, applied. There were no messages such as "unfamiliar situation". Performance feedback was related to changes in the stability of the system. When the safety system failed, it is possible that subjects received conflicting messages, such as "No procedure applicable" and "Instability extreme". Apparent conflict such as this may have served as a cue that something was wrong, and could have suggested to subjects that the problems in the system were not the result of poor control actions.

These ideas about the role of the coach in the unfamiliar situation are purely conjecture at this point. It seems likely that a combination of all of these factors (i.e., increased system stability, knowledge of the functioning of the system, and assistance in situation assessment) contributed to subjects' success. An understanding of factors affecting the human's
ability to deal with an unfamiliar event could have important theoretical and practical implications, and further investigation of this issue is warranted.

Finally, another question arises with regard to the results of this research: Why did aided subjects score higher on the test of dynamic principles? Since the primary difference in the way the two groups were treated was the presence or absence of the online coach, it would appear that this was the reason for the difference in the test scores. This is counterintuitive, however, because the focus of the aiding was on following procedures, and not on understanding the functioning of the system. Therefore, interpretation of this result must be delayed until the research can be replicated, using a larger number of subjects and controlling for potential differences in abilities.

Considering the feasibility of adapting a rule-based model as an online coach, this research has served to emphasize the complexities and subtleties of model-based online aiding and training. As noted by other researchers (Clancey & Lestinger, 1982; Jackson & Lefrere, 1984), answering the questions of what advice and feedback to provide, as well as when they should be provided, is far from straightforward. This point is particularly supported by the results reported here where subjects benefited along several dimensions by having an online coach, but did not become more like the coach in the process
(i.e., there was no increase in agreement between the subjects' and model's choices of actions). Thus, the results of being coached can be more than, or at least other than, simply gaining the coach's expertise. This has profound implications for the current view of "expert systems" as a panacea for training and aiding.

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REFERENCES


FAULT DIAGNOSIS IN A LARGE DYNAMIC SYSTEM:
DESIGN OF A TRAINING SIMULATOR AND EXPERIMENTAL RESULTS

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Abstract

To investigate the relationship between levels of simulator fidelity and fault diagnosis performance, simulators at low, moderate, and high fidelity levels are being used. This paper describes research involving a low fidelity simulator of a marine powerplant. It is designed to run on Apple II plus personal computers. Using this simulator, called FAIL (for FAULT-based Aid for Instruction and Learning), two experiments were conducted in which a total of nine marine engineers participated as subjects. Based on data collected, the diagnostic process can be broken down into two stages: (1) hypothesis formation stage and (2) hypothesis evaluation stage. In the first stage, the subjects tried to gather information about the system and formed a feasible set of symptom-cause pairs. Once a hypothesis was formed based on this feasible set, the subjects moved into the second stage in which the hypothesis was evaluated. If the hypothesis could not be confirmed, the subjects shifted back to the first stage to form new hypotheses.

Two factors appeared to be related to the performance, which was measured using the total number of actions, cost and time. The first was the initial feasible set (IFS) which reflected the subjects' knowledge about the given failure. The second was the transition strategy for stage-shifting. Two types of strategy were identified: breadth-depth strategy and balanced strategy. Subjects using breadth-depth strategy conducted a broad search for hypotheses and did thorough checking once a hypothesis was formed. Subjects using balanced strategy did not conduct a broad search and did not seem to evaluate any single hypothesis thoroughly. They tended to form hypotheses quickly and maintain several hypotheses at the same time. The data seem to indicate that subjects who had good IFS and used breadth-depth strategy performed better than subjects who had bad IFS and used balanced strategy. These results seem to indicate that both context-specific (IFS) and context-free (transition strategy) factors affect the human fault diagnosis performance.

Introduction

The role of humans in the operation of large complex systems has become more supervisory than continuous control. An operator intervenes when an event occurs requiring actions to detect, diagnose, and compensate for failures, or when operating conditions change. Therefore, the operation of a large system sometimes depends on the problem solving skills of the operators. These skills can be developed efficiently and effectively using training simulators. Simulators can be designed at various levels of complexity and realism relative to the real systems. The degree of realism and closeness with which a simulator resembles the
actual system can be formalized in terms of the concept of fidelity of simulation.

The issue of defining simulator fidelity is discussed in a survey paper ([7]) in which the difficulty of defining fidelity and the components of fidelity were discussed in detail. A working definition of fidelity was proposed and used to classify simulators ([1]). Fidelity was treated as a three-dimensional concept: physical fidelity, structural fidelity and dynamic fidelity. Physical fidelity is concerned with the variables that are displayed and in how much detail they are given. This includes environmental factors such as noise, vibration and thermal conditions. Structural fidelity refers to the nature of relationships between various subsystems that make up the system, including feedback and feedforward connections, and hierarchical relationships. Similarly, the evolution of the system states over time, and their representation can be characterized by dynamic fidelity. Structural and dynamic fidelity issues are discussed in detail in ([1]).

In order to understand how simulator fidelity affects human fault diagnosis behavior, experiments are needed using simulators at different fidelity levels. This paper considers oil-fired marine powerplant simulators at high, moderate and low fidelity levels based on the definition presented above. A high fidelity simulator (HFS) is available at Marine Safety International (MSI), New York. This simulator has high fidelity along all three dimensions. A moderate fidelity simulator is being developed at Georgia Tech ([2]) in which the dynamics of major subsystems are represented qualitatively. Even though the physical fidelity of this simulator may be low, fairly high structural fidelity and moderate dynamic fidelity are achieved. A low fidelity simulator called FAIL (FAULT-based Aid for Instruction and Learning) has been developed that runs on an APPLE II computer. System information is displayed to the operator upon request. Schematic diagrams of important subsystems are provided on paper. Even though the dynamic fidelity is very low, the structural fidelity is close to the high and moderate fidelity simulators. A series of experiments have been conducted on FAIL and HFS. Analysis of results from FAIL are described in this paper. Data from HFS are, thus far, quite limited and analysis has not been completed.
The implementation details of FAIL and experiments where experienced marine engineers participated as subjects are described next. Description of model of fault-diagnosis based on the experimental results follows. Finally, the implications of experimental results are discussed.

The Low Fidelity Simulator — FAIL

This low fidelity simulator, designed to run on an APPLE II Plus computer, is used to accept inputs from the subject and to display powerplant status and other relevant information (Figure 1). In addition, a number of diagrams provide system schematics at various levels of detail. A typical schematic is shown in Figure 2. Also provided is a list of commands used interactively to check for the status of gauges, alarms and indicators.

The simulator evolved from FAULT (Framework for Aiding the Understanding of Logical Troubleshooting) ([3]). FAULT is an interactive context-specific troubleshooting simulator. In FAULT, the user is given a hardcopy form of the network representation of the system of interest, and a statement of the symptoms which reflect the fact that some component or part in the system is malfunctioning. By interacting with a CRT terminal, the problem-solver must gather information in order to identify which of the components or parts has failed. Problem solving performance is judged by the total cost to identify the failed component, calculated from the costs of all actions. The cost for each simulated action corresponds to the actual cost (or time equivalent) of performing such an action on a real system.

Display Interface

Using design concepts similar to those used in FAULT, FAIL presents failures to the subjects via a CRT terminal. At the start of a trial, initial conditions and the symptoms of a failure are shown on the display (Figure 1). For example, the initial condition could be "Steaming at sea", and the symptoms of failure could be "Vacuum pump fail alarm sounds". The subjects may request more information by typing in appropriate commands.
A subset of the actual alarms, status indicators and gauges (384 out of approximately 500) is used in this simulator. The alarms refer to the six panels of annunciators in the middle section of the high fidelity simulator. Each panel contains a number of indicators which are lighted as necessary to display the states of components and/or subsystems. Displays other than gauges and meters are classified into 12 groups by their location and function. Each group is identified by a name. Alarms and status indicators are given in groups while gauges are shown individually because approximately the same effort is required to locate the former in a group or the latter separately.

All actions and their associated costs are displayed at the lower left portion of the screen. Cost for each action reflects the time and effort involved to obtain the relevant information on the real system. The objective is to minimize the time required to diagnose the failure. At the end of a trial, the subject's total number of steps and cost are displayed.

The subject requests information about gauges, alarms and status indicators by typing in appropriate commands. Only the alarms and the status indicators that are activated by the given failure are shown to the subject to simulate the illuminated tiles in the real system. The subject keeps requesting information from the system until he is ready to diagnose. Then he identifies the failed component by designating the number shown beside the chosen component on the schematics. Gauges are also numbered. They are color coded on the schematics to avoid confusion with component numbers.

Operator Inputs

Each of the seven possible actions are described below.

1. GAUGES (G):
   A qualitative description such as LOW, HIGH, NORMAL or ABNORMAL is shown instead of the actual readings of the gauges. When appropriate, the time history of the gauge of interest can also be provided. For example, a message like "Pressure drop to 300 lb in 10 min" could give the subject some idea about changes of the system states over time. The cost associated with this action is 3 units.

2. ALARMS (A):
   This option displays the alarm status of a particular subsystem. Only those illuminated tiles in the real system are shown in the right half
of the display. If none of them is turned on, an "ALL ARE NORMAL" message will appear. When more than 22 alarms are on at one time, the last line displays: "MORE ON NEXT PAGE. PRESS "ENTER" TO SEE MORE". The subject presses either the "ENTER" key, or types "Q" to return to the command mode. The cost associated with this action is 2 units.

3. INDICATORS (I):

The status indicators of the subsystem are shown on request. The content and format are similar to "ALARMS". The cost is also 2 units.

4. DIAGNOSIS (D):

The users can check their conclusions and/or test their hypotheses using this option. All the failures can be traced down to the physical component level using numbers on the system schematics. The cost is 50 units.

5. LOOK (L):

This option simulates the action of going into the engine room to physically inspect a component. The subjects can observe the status of various components including noises, gauge readings and vibration. No complicated procedures are involved to inspect a component under this option. For example, to respond to a "LOOK" at the feedwater regulator, the system may indicate "open 10 V". If the components the subjects choose to "LOOK" at cannot be seen on a real ship such as "boiler tubes", "sea scoop" etc, the system responds with "not available". The cost is 5 units.

6. QUIT (Q):

This option is used to terminate the diagnostic process without completion. No cost is assigned to this option.

7. RECALL (R):

Since all the actions and their responses are stored, they can be reviewed using this option. No extra cost is charged for doing this.

Experiments

Chief Engineers from various fleets of a major petroleum processor who attended an MSI training course participated as subjects. All of them are experienced marine engineers. The training course is designed to improve their problem solving skills. It is two weeks long and consists of three parts: HFS training, lectures and laboratory training. FAIL was run as part of the laboratory training.

The subjects were seated before APPLE II Plus microcomputers in a room that accommodates eight people comfortably. This room is used exclusively for problem sessions using APPLE II computers. They were given a list of components, a set of schematics of the system and a command list. An instruction sheet was read to them after which a set of three failures were used in a demonstration to familiarize them with
FAIL. Since they had experience on FAULT, this brief training seemed sufficient. For each trial they were asked to find the solution by identifying the failed component while keeping the total cost to a minimum.

**Experiment 1:** Five subjects participated in this experiment (they will be referred to as S1, S2, S3, S4 and S5 later in this paper). They represented American, English, and Italian fleets. The failures used on HFS were different from those on FAIL. Each subject was given eighteen problems containing one failure each. The first three problems were used for training. Problems were presented to each subject in the same sequence. Subjects were allowed to spend as much time as they wanted on each problem. Trials were sometimes interrupted because of the HFS schedule. The sequence was continued later at the point where it was interrupted. Subjects were allowed to ask questions since some of them had language difficulties. The "L" command was not available for this experiment.

**Experiment 2:** Four subjects participated in this experiment (S6, S7, S8, S9). They represented American, English, and Italian fleets. A set of twenty-seven failures, which were different from those used in experiment 1, was used in this experiment. By repeating five of the failures, a total of thirty-two problems were presented. The sequence of problems given to each subject was different from the sequences of other subjects. The first three problems were used as training trials. The "L" command was available in this experiment.

In the following discussion, a model of fault diagnostic process on FAIL is proposed based on observations from the experiments. Then, this model is used to analyze the data to show the factors that affect fault diagnosis performance. Finally, the implications of these experimental results are discussed.

**A Model of Fault Diagnosis**

Fault diagnosis can be viewed as a backward reasoning process that goes from symptoms to causes. However, the knowledge accumulated from years of education is arranged in a forward reasoning format that goes
from components (hence causes) to symptoms. Subjects were well versed in reasoning from a failed component to its symptoms based on the system topology and dynamics. Given sufficient information about the input conditions of a component, definite output states or influence on the downstream components can be derived if appropriate dynamics is used (see Figure-3). Knowledge of system dynamics is the basis of this forward reasoning process. Though the dynamics may be complicated, the reasoning from causes to symptoms is relatively straightforward. However, backward reasoning from symptoms to components cannot be accomplished by applying the system dynamics directly because rules of dynamics do not work in reverse time order. In this backward reasoning process, the counterpart of system dynamics, and hence the output (the cause), is unknown (See Figure-4).

When a failure occurs, the faulty component causes deviations from normal system states. Among these state deviations some are obvious and manifest themselves in the form of alarms, or other irresistible clues, while some are non-obvious and must be investigated. We call the first kind the "obvious" symptoms and the second kind the "non-obvious" symptoms. In most cases, the obvious symptoms are just alarms representing the non-obvious symptoms that exceed acceptable levels.

Obvious Symptoms, Non-obvious Symptoms, and Causes

Obvious symptoms are those presented usually via audio alarms or flashing lights to attract the operator's attention. Compensatory actions appropriate to these symptoms are often required to maintain the powerplant in an operating mode. However, these obvious symptoms alone may not provide enough information to diagnose the failures. The subjects need to gather more information in order to form a hypothesis about the faulty component and evaluate the hypothesis. To gather more information the subjects must interrogate the system for the non-obvious symptoms.

The relationship between symptoms and causes is dynamic since the symptoms could change with time. However, at any moment, a rather simple relationship between symptoms and causes seems to exist. That is, a set of obvious symptoms may be common to several sets of non-obvious symptoms each resulting from several different causes (Figure-5). A set of causes
is the collection of components which are suspected to be the cause of observed symptoms. It is possible that several different causes may result in the same set of non-obvious symptoms. A set of causes may take the form of a subsystem that is characterized by some clearly identifiable function. For example, it may be the "Condenser System" that removes heat from steam to reuse water. The "Condenser System" consists of several subsystems such as condensate system, circulating water system, condenser etc. Each subsystem can be further decomposed into smaller subsystems or components.

**Hypothesis Formation, Hypothesis Evaluation and Stage Shifting**

The apparent relationship between symptoms and causes actually resembles an inverted tree with obvious symptoms at the root and the causes forming the leaves. The diagnostic process is to find a path from the root to the correct leaf, i.e., the faulty component. This process can be further broken down into two stages. In the first stage, given obvious symptoms the subjects gather information about the system in order to find a set of possible causes that explain all the symptoms identified up to that point. This is like forming branches for the symptom-cause tree. After a set of possible causes is identified, the subjects shift into the second stage in which they try to identify a narrower set of causes and search through the hierarchy of the chosen set of causes to the faulty component. In other words, in the first stage, hypotheses about faulty subsystems are formed while in the second stage, these hypotheses are evaluated and tested. Subjects alternate between these two stages to arrive at the solution (Figure-5).

**Feasible Sets**

A preliminary step before any hypothesis can be formed is to search through the knowledge base to find related symptom-cause pairs. This is done to build new branches for the symptom-cause tree. The collection of these branches forms a feasible set of causes for the given failure. When members of this feasible set related to the failure are found, new hypotheses are formed. The feasible set is modified as the diagnostic process continues. Older branches are discarded if evidence gathered does not warrant further consideration. New branches are added as more elaborate reasoning is completed. Although each hypothesis may appear
reasonable, not every hypothesis is guaranteed to be correct. The failed hypothesis may provide insights into localizing the failure, and for forming new hypotheses.

Two factors affect the efficiency of a diagnostic process. They are the initial feasible set and the strategies that govern the transition from the hypothesis formation stage to hypothesis evaluation stage. The identification of the initial feasible set, the transition strategies and the analysis of the experimental results are discussed next.

Initial Feasible Set and Transition Strategies

The initial feasible set (IFS) consists of the symptom-cause pairs that the subjects considered before any hypothesis was formed and evaluated. It reflects the strongest symptom-cause pairs that are associated with the given obvious symptoms.

Initial Feasible Set

To study the relationship between the initial feasible set and overall performance, an operational definition and measure for initial feasible sets was necessary. It was impractical to ask the subjects what their initial feasible sets were. An operational criterion was to take the first three actions as the initial feasible set if no stage shifting occurred. Stage shifting was assumed to have occurred if a subsystem or a component was diagnosed as the cause of failure. If subjects transitioned to the hypothesis evaluation stage before their third actions, only the actions before transition were taken as the initial feasible set. According to this criterion, members of an initial feasible set might be a component checking, gauge reading or alarm status inquiry.

If the initial feasible set contained components that were related to the faulty subsystem or component, the set was rated as "good", otherwise "bad". This description of "good" and "bad" is used as a convenient gross measure without implying any measure of the amount of "goodness". Table-1 shows examples of initial feasible sets that were formed by subjects for Failure 1-6.
Since the faulty component was the gland seal regulator, the initial feasible sets formed by S1, S4 and S5 were rated as "good" and those by S2, S3 were rated as "bad".

Transition Strategies

Two types of strategy were observed to result in transitions from the hypothesis formation stage to the hypothesis evaluation stage. They were the breadth-depth strategy and the balanced strategy.

(1). Breadth-Depth Strategy (BD):
Subjects stayed in the hypothesis formation stage until further symptoms were found and hypotheses were formed. Then they switched into the hypothesis evaluation stage. They thoroughly tested these hypotheses before they gave up and went back to the hypothesis formation stage. In other words, they conducted a broad search for candidates and did thorough checking once a hypothesis was formed.

(2). Balanced Strategy (BL):
Subjects did not conduct a broad search for candidates in the hypothesis formation stage. They switched to the hypothesis evaluation stage although no obvious hypothesis was formed. They did not seem to evaluate any single hypothesis thoroughly. They tended to form hypotheses quickly and maintain several hypotheses at the same time.

To analyze the data, two difficulties must be resolved.

(1). how to distinguish the hypothesis formation stage from hypothesis evaluation stage?
(2). how to identify the dominant strategy?

The identification of stages was very difficult. The following criteria were used:

(1). If more than two actions for a particular subsystem were checked consecutively, then it was assumed that the subjects were in the hypothesis evaluation stage.

(2). If a hypothesis had been tested before, or a particular component or gauge had been considered before, then later related investigations were considered as entering hypothesis evaluation stage.

(3). Actions that could not be classified using the two criteria above were regarded as actions in the hypothesis formation stage.

Two more criteria were used to help classify the strategy as balanced or breadth-depth.

(4). If multiple hypotheses were observed, then more weight should be placed on balanced strategy.
If each hypothesis evaluation stage consisted of more than three related actions, then more weight should be placed on breadth-depth strategy.

The following examples illustrate how these criteria were used to identify stages and hypotheses. An asterisk before an action denotes that it is fault-related.

**Example 1: Bad IFS and BL**
Failure 1-13: condenser vacuum low alarm sounds
Subject: S1
Actions recorded:

1. G60 Main condenser level (IFS)
2. G36 Condensate pump pressure (IFS)
3. G34 Salt water service pressure (IFS)
4. * G27 Condenser vacuum pressure (fault related action)
5. * G35 Main cooling water pressure (fault related action)
6. D83 Sea scoop valve (hypothesis 1: circulating water)
7. D78 Main condenser (hypothesis 2: condenser)
8. D84 Sea scoop (hypothesis 1)
9. D80 Main circulator discharge valves (hypothesis 1)
10. G35 Main cooling water pressure (same as no. 5)
11. G19 Deaerator tank pressure (hypothesis formation)
12. G55 LP turbine exhaust temp (hypothesis formation)
13. G15 PORT FO to burners pressure (hypothesis formation)
14. I5 Salinity system (hypothesis formation)
15. G80 No. 1 Deaerating feedtank dump regulator
   (hypothesis 3: deaerator tank)
16. D82 Main circulator suction valve (hypothesis 1)
17. D87 Sea strainer (hypothesis 1)

Total number of actions: 17
Total cost: 323

**Example 2: Good IFS and BL**
Failure 1-13: condenser vacuum low alarm sounds
Subject: S2
Actions recorded:

1. * G35 Main cooling water pressure (IFS)
2. D81 Main circulators (hypothesis 1: cooling water)
3. R0 Recall
4. D83 Sea scoop valve (hypothesis 1)
5. D85 Sea high suction (hypothesis 1)
6. D86 Sea low suction (hypothesis 1)
7. D87 Sea strainer (hypothesis 1)

Total number of actions: 7
Total cost: 253

In example 1, actions 1, 2 and 3 were classified as the initial feasible set. Since none of them were related to the cause of the failure, this IFS was rated as "bad". Actions 4 and 5 were additions to the feasible set. These two actions were related to the fault directly. Action 6 showed the first hypothesis which was related to circulating water. Action 7 showed another hypothesis which was concerned with the condenser itself. Actions 8 and 9 tested the first hypothesis further. From action 10 to action 14 the subjects switched back to the hypothesis formation stage. Action 15 was related to action 11 and was thus regarded as the third hypothesis which dealt with the deaerating tank. In actions 16 and 17, the subject picked up the first hypothesis again and obtained the solution.

In example 2, the initial feasible set contained only one member which was related to the cause of the failure. Therefore the IFS was rated as "good". From action 2 onwards, the subject formed a hypothesis about the cooling water system and conducted thorough checking on it until action 7 when the solution was found.

In example 1 the subject maintained three hypotheses at the same time. He alternated among hypotheses. Therefore, it was classified as using a balanced strategy. In example 2 the subject maintained only one hypothesis and did thorough checking on that hypothesis. It was thus classified as using a breadth-depth strategy.

Analysis of Experimental Results

Experiment 1
Table-2 summarizes the relationship between the initial feasible set, strategy used and the overall performance. Failures not shown in Table-2 were too simple for subjects (i.e., immediate correct diagnosis) and, therefore, the data were not used.

In general, good initial feasible sets resulted in better performance in terms of total number of actions and cost. If bad initial feasible sets resulted in better performance than good initial feasible sets, compared across the subjects, it was regarded as a disparity (of the model). A disparity is designated by a "*" in Table-3. A "*" under "Cost" or "No. of Actions" means a disparity when cost or number of actions is used as performance measure. Several disparities were observed and are summarized in Table-3. Obviously there were some other factors not explained by the model that affect the overall performance. One of them was the transition strategy. It was assumed that subjects who adopted a BD strategy performed better than those who used a BL strategy in terms of total number of actions and cost. If the reverse relationship occurred, it is regarded as a disparity which is also designated by a "*" in Table-4. Considering the initial feasible set and strategy used together results in a better model, as shown in Table-5.

There were five disparities observed if IFS alone was used to explain overall performance (See Table-3) and four disparities if Strategy Used was used (See Table-4). Some subjects might start with bad initial feasible sets, but a better transition strategy could help smooth out the disadvantage. It was obvious (From Table-3 and Table-4) that the correlation between IFS and the overall performance as well as the correlation between Strategy Used and overall performance were high. However, each one alone could not explain performance very well. A better model could be derived if these two criteria were considered together. By considering these two criteria together, there are four different groups: (good IFS and BD), (good IFS and BL), (bad IFS and BD), and (bad IFS and BL). If the performance of the group with (good IFS and BD) was compared to that of the group with (bad IFS and BL), the disparities were reduced to one (Table-5).

Combining together (good IFS and BL) and (bad IFS and BD) as an intermediate group, we have one best group (good IFS and BD), one worst group (bad IFS and BL) and one intermediate group. The average
performance of these three groups were consistent throughout all the failures considered (See Table-6). The best group was consistently better than the intermediate group and the intermediate group was consistently better than the worst group.

Experiment 2

A similar analysis was done on the data from experiment 2. In addition to number of actions and cost, "Time" was also used as performance criterion. The results are presented in Table-7 through Table-10. Table-7 summarizes the data. Certain problems are not listed in Table-7. They are either very simple for the subjects or all the subjects used the same IFS and Strategy such that the current analysis does not apply. Table-8 and Table-9 list the disparities when IFS and Strategy Used are used as performance criteria respectively. There is no disparity if IFS and Strategy Used are considered together. However, due to the small sample size, the occurrences of "Bad IFS and BL" are relatively low. Table-10 lists the relationships among the best group, the intermediate group and the worst group. Even though some disparities are seen, in general the relationship holds.

The correlation between the three performance criteria "no. of actions", "cost" and "time" for each failure is fairly high except for problems 2-5, 2-7, 2-24, 2-26 and 2-27. See Table-11.

Discussion

Based on the data, it appears that the initial feasible set and the transition strategies greatly affect the diagnostic performance on a low fidelity simulator of a marine engine control room. The initial feasible set reflects the knowledge base of the subjects. The better the initial feasible sets are, the better is the performance. Although it is not clear how the initial feasible sets are formed, it is suspected that this may be affected by the knowledge of the system and the structure of the internal (mental) model linking the symptom-cause pairs.

However, a good initial feasible set in itself does not seem
sufficient to explain the observed performance. Good problem solving strategy also plays an important role. It was found that a breadth-depth strategy was more efficient than a balanced strategy. It is worth noting that strategies are context-free, while formation of the initial feasible set is context-specific.

The fact that both initial feasible set and the strategy used affected the performance is very significant. It seems to imply that in a highly specialized field, problem solving ability is affected by both context-free and context-specific factors. This agrees with the results and models of [4] and [5].

Further experiments are planned where in addition to FAIL the moderate fidelity simulator will be used. The modeling methodology described in this paper will be explored further and better models could emerge.
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<td>Recall</td>
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Action :G60

G12 C=3
I2 C=2
G27 C=3
L77 C=10
D105 C=50

---

Figure-1: Screen Layout
Figure-2: FUEL OIL SUPPLY SYSTEM
Figure-3: Forward Reasoning

Figure-4: Backward Reasoning
Figure 5: A Symptom-Cause Tree

Figure 6: Stages of Diagnostic Process
Failure 1-6: Low vacuum alarm sounds, vacuum steadily dropping on slowing to half ahead during maneuvering.

Faulty component: Gland seal regulator

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<tr>
<td></td>
<td>main cooling water</td>
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</tr>
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<tr>
<td></td>
<td>condensate pump pressure</td>
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Table-2: Relationship between IFS, Strategy Used and overall performance from experiment 1
### Table 3: Disparities when using IFS as criterion in experiment 1

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### Table 4: Disparities when using Strategy Used as criterion in experiment 1

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### Table 5: Disparities when using IFS and Strategy Used together as criteria in experiment 1

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<td>1-14</td>
<td></td>
</tr>
<tr>
<td>1-16</td>
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</tr>
</tbody>
</table>
Failure 1-6: A(2.52) > B(5.58) > C(8.5,185)
Failure 1-9: A(4.56) > B(9.5,187) > C(12,312)
Failure 1-11: A(8,223) > B(19.5,400.5) > C(-,-)
Failure 1-12: A(9.5,163) > B(13,217.5) > C(30,924)
Failure 1-13: A(6.5,253.5) > B(17,323) > C(-,-)
Failure 1-14: A(6.3,124.3) > B(12,311) > C(35,1030)
Failure 1-16: A(6,158) > B(-,-) > C(21,474)

where
> denotes better than
A denotes (good IFS and BD)
B denotes (good IFS and BL) and (bad IFS and BD)
C denotes (bad IFS and BL)
(x,y) denotes (avg no. of actions, avg cost)

Table-6: Relationships among groups from experiment 1
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Table-7: Relationship between IFS, Strategy Used and overall performance in experiment 2
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Table-8: Disparities when using IFS as criterion in experiment 2

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<th>Failure No.</th>
<th>No. of Actions</th>
<th>Cost</th>
<th>Time</th>
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</tr>
<tr>
<td>2-27</td>
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</table>

Table-9: Disparities when using Strategy Used as criterion in experiment 2
Failure 2-6: $A(1.7,52,132) > B(7,64,325) > C(-,-,-)$
Failure 2-11: $A(1.7,53,65) > B(7,78,324) > C(-,-,-)$
Failure 2-12: $A(3.55,133) > B(14,331,648) > C(-,-,-)$
Failure 2-14: $A(3,102,61) > B(10.3,139,216) > C(-,-,-)$
Failure 2-15: $A(5.5,62.97) > B(9,190,329) > C(-,-,-)$
Failure 2-16: $A(9,219,152) > B(8,161,141) > C(17,290,688)$
Failure 2-17: $A(3,78,165) > B(6,69,380) > C(16,280,1131)$
Failure 2-21: $A(5,106,83) > B(14,152,294) > C(30,550,1418)$
Failure 2-26: $A(3,102,189) > B(83,154,282) > C(-,-,-)$

where
> denotes better than
A denotes (good IFS and BD)
B denotes (good IFS and BL) and (bad IFS and BD)
C denotes (bad IFS and BL)
$(x,y,z)$ denotes (avg no. of actions, avg cost, avg time)

Table-10: Relationships among groups in experiment 2
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<td>0.96</td>
</tr>
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Table-11: Correlations between different criteria
Reference


QUALITATIVE MODELING FOR SIMULATION OF LARGE DYNAMIC SYSTEMS

Working Paper
July 1984

T. Govindaraj
Center for Man-Machine Systems Research
School of Industrial and Systems Engineering
Georgia Institute of Technology
Atlanta, Georgia 30332-0205

Abstract

Simulators of large dynamic systems are often used for training in the acquisition of troubleshooting skills. In such simulators a variety of information is presented to the human operator via displays. Unfortunately, the amount of information required to fully describe the state of a dynamic system is rather large. The operator cannot efficiently utilize all the available information. Even when a portion of the information is required to diagnose a problem, its effectiveness can be improved if some amount of preprocessing is done prior to display. This preprocessing could reduce the human's information processing load, thus enabling more reserve capacity to concentrate on problem solving. A particularly effective method of doing this is the generation of the state information in a qualitative form during dynamic system simulation. A qualitative modeling methodology which achieves this objective is described. The model starts by looking at the system as a combination of subsystems. Components make up a given subsystem. Individual compounds are subdivided further into a collection of primitives. Detailed structures are developed for the primitives. Using property lists for inputs and outputs, along with descriptions for primitives, methods for propagation of dynamics is developed. Pertinent details of the model structure and the means of state evolution are presented in the paper.

Introduction

Large dynamic systems such as steam powerplants of ships are made up of a number of interconnected subsystems. The subsystems perform certain unique functions involving energy and/or mass transfer operations. Such systems are mostly automated so that the human operator's responsibilities are limited to intermittent actions to effect changes in operational modes and for fault diagnosis and compensation when abnormal events and/or failures occur. Since such events occur rarely, human operators cannot be trained on actual systems. Training simulators are therefore valuable to impart troubleshooting skills. Simulators can be designed at various levels of fidelity with respect to the actual system. An important dimension of fidelity is the degree to which the dynamics of a simulator mimics that of the actual system. If a number of variables are displayed on a suitable graphics system, physical fidelity can also be improved to a great extent. On such a system, the state variables could be displayed in a qualitative, pictorial representation. In this paper a simulation methodology that combines qualitative models of dynamics with exact and quantitative representations is developed.
Qualitative Models for Supervisory Control

The primary emphasis of the research is the development of qualitative models of large dynamic systems. In addition to simulating the behavior of dynamic systems, development of these models may be beneficial for the conceptualization of mental models of devices and large systems. Since the system models are required to provide state variable representations in a descriptive, qualitative form similar to those used by the human operators, it is essential to understand the plausible structures used by the humans. It is expected that the experience and insights gained by the modeling process may be helpful for the understanding of mental models of large dynamic systems.

Preprocessing State Information for Supervisory Control

When a human operator is responsible for a highly automated system, the nature of workload imposed by the system differs from that of controlling a system where manual control skills are important. Cognitive skills for problem solving are important. During the operation of the system, the human operator observes the system status through a number of displays and alarms. The information is generally displayed either digitally or as continuous variables on appropriate instruments. With the exception of a small fraction of cases, however, the operator does not need this information with precision in order to make decisions and choose appropriate actions. The operator processes the displayed information by transforming it into approximate, qualitative form for comparison with the values generated by an appropriate internal (mental) model. The human's cognitive workload may be reduced if this transformation is performed by machine prior to display to the human. Reduction in human's workload can be beneficial to the overall system operation because more information can be handled by the human. When information is thus preprocessed, the operator's attention can be devoted to tasks requiring more cognitive processing, such as determining the cause of observed symptoms or taking compensatory actions when symptoms of a failure are noted.

One method of preprocessing the display information could begin by running the simulation with regular descriptions through the exact mathematical descriptions for the dynamics. The numerical information generated for the displays is processed by appropriate quantization to obtain qualitative descriptions for the states. This differs from the
conventional systems only by the addition of a preprocessor before the display. Another method of achieving this is by the use of qualitative models for dynamic systems so that the state information is inherently in a form usable by the human operator. The simulation methodology described here achieves this latter objective by designing the entire simulation by appropriate qualitative models for dynamics.

**Dynamic System Simulation**

Simulation of large systems qualitatively also has the additional advantage of simplifying the computations, since approximate equations are used. There is no need to perform numerical integration and other operations requiring highly accurate calculations. Since high precision is not required, speed and efficiency can be improved. In the remainder of this paper an oil-fired steam powerplant is used for model development. The simulation must be designed such that both normal and abnormal operations can be handled. Under normal operations, the simulated system response must follow that of the real system. The simulator must respond to the operator's control actions as well as failures of any of the components in a consistent manner. Real time response to changes in conditions is essential for use in training.

**Component Interconnections**

The overall system consists of a number of subsystems within interacting, but distinct, loops. Various loops are characterized by the flow of a particular fluid around a closed loop. The term fluid is used generically to mean either a conventional fluid such as air or water used in energy and/or mass transfer, or a "fluid" such as a signal. Individual loops contain a number of subsystems made up of components. Typically, a subsystem is made up of an ordered, purposive interconnection of a finite number of components to achieve a single specific objective or a set of objectives. Interaction between different loops occurs in components or subsystems. Figure 1 illustrates a situation where three interacting loops for water, steam and sea-water are shown. A single subsystem is also indicated in the figure. The condensate and feedwater subsystem is further subdivided into a number of components, three of which are shown in Figure 2.
Component Classification

A marine powerplant has a large number of components. The system being simulated has approximately 200 components. A component may be classified into "active" or "passive". An active component is one in which the fluid (or fluids) undergoes some phase changes such as a measurable chemical or physical change. Mass and/or energy transfers between fluids is common. For example, a burner is an active component where chemical changes occurring during combustion result in energy conversion and transfer of heat. A passive component on the other hand does not induce any major changes to the state of the fluid. Normally only a single input and a single output are involved in the case of a passive component. A valve that regulates fluid flow in a duct is a passive component. There are no phase changes; only the amount of flow is affected. These descriptions are not necessarily standard nor follow any commonly accepted terminology. These are used solely to explain the modeling process that follows.

Approximating System Dynamics

Dynamics of an actual powerplant is determined by a set of differential equations describing the thermodynamic and combustion processes. Since combustion takes place only at the burners in the furnace, appropriate equations can easily be handled. Thermodynamical processes, however, go on at a large number of components and subsystems. Differential equations describing the thermodynamic processes are nonlinear. Most parameters in the equations vary depending upon the states of the fluid. The complexity increases due to the interaction of a number of subsystems, each described by nonlinear differential equations. Even though the individual subsystems are of small order, the combination makes the problem rather large. Hence it is not practical to run the simulation using a large number of nonlinear differential equations with varying parameters. Besides it is not necessary to solve the differential equations exactly since only the qualitative form of the state are required by the human. Actual numerical values are not used for control or for problem solving except in a small number of cases. Even when numerical values are required, it is sufficient to provide the deviations from their normal operating conditions.
Similarity to Perturbation Approach

Hence the approach followed in the model is similar to that of the perturbation approach used in linearizing the nonlinear differential equations. This approach is common in the simulation of aerospace systems and other higher order nonlinear systems. When the steady state or nominal values are known, only the deviations from steady states are needed for a complete representation. This makes the equations linear about the operating point. Under normal operation with no failures, the (perturbed) state variables are zero or have extremely small values. When an event occurs, thus disturbing the equilibrium, state variables take on non-zero values. When certain key state variables exceed their predetermined values corresponding to a given phase, the system goes into another nominal state.

An event could be an intentional change in operating conditions or the failure of some components. In the former case, since the change is intended, the linearized (perturbed) states can be set to zero after a predetermined amount of time. When the system is made to change states by some intentional action, the simulation must also show changes in states that would normally appear to the operator before being reset to zero. The states are reset to zero, under normal operating conditions, only when the new steady state has been reached. When a failure occurs, the resulting state changes are to be construed as deviations from nominal, and hence should not be set to zero until corrective actions are taken.

When an event occurs, one or more components are affected. In the affected components the states deviate from their nominal values, which are then propagated through the entire system. Components downstream, and elsewhere when feedback loops are present, are affected in time. Similar situations result for operator actions. The qualitative nature of states, which are functions of quantized values of perturbed states, may result in the states diverging after some time even when the disturbances are temporary. Inherently stable systems should handle this situation in a routine manner. Periodic adjustments to states can be made when states diverge if exact representation is used in a simulation running in the background.

The entire system can be viewed as made up of connections of components through inputs and outputs. Individual components are defined in terms of primitives. The primitives are the smallest units which perform a specific operation or a class of operations. Detailed rules for
the primitives only for the primitives. The state variables passing through the primitives are characterized by "intensive" and "extensive" properties.

Simulation Details

Dynamics of the entire system is simulated in a two-step process. During the first step, individual components are considered. From the previous state values and the operator inputs and event-related changes to the component, new states are calculated. Figure 3 illustrates this step schematically. In the second step, the state values are propagated along various loops. Any state values thus propagated form inputs to various components in the first step.

Numerical values are used internally to represent the states. These are not necessarily in the same units as the actual state variables. The state values can be viewed as generalized forms of normalized state variables which can be easily converted to qualitative descriptions such as low, moderate, high, oscillating etc. In fact, for presentation to the subjects, the state values are converted to qualitative values. Since we deal with a stable system, the deviations are expected to decay exponentially to reach steady state values in a short time. When the system is functioning normally, the exponential reduction can bring the states to the equilibrium value of zero. When events occur, the stabilizing effects of the exponentials are not sufficient to bring the states to zero, resulting in symptoms of the failure. In the simulation, the exponential decay is handled by reducing the state values by a certain amount each time they are propagated.

The state propagation is via the inputs and outputs of the components. For each component, the components from which it receives input and the components to which it sends output are grouped together in property lists. Closed loops for various fluids are formed using these property lists. The names of all the loops are stored in appropriate variables in the form of a list. During the simulation, the program goes through the list from beginning to end traversing all the loops. New state values previously calculated are propagated. When the cycle is complete, each component uses its inputs and states to calculate the next state as described earlier.
Component Description via Primitives

To calculate new state values from inputs and current states, appropriate dynamical relationships must be set up. Components are classified into a number of generic components, which are then broken down into primitives. (For example, a condenser as well as an economizer can be classified as heat-exchangers.) The primitives are the simplest form of components performing a single operation or a function. Some of the most important (and occurring most often in the system) are: source, sink, resistor or gain, and transfer agent. A component such as a condenser would be broken down into two sets of sources and sinks, gains and conduits, and a transfer agent (Figure 4). Detailed structures are formalized only for the primitives. An example of a primitive is shown in Figure 5. Hence, the entire modeling process can be viewed as identifying and clarifying the hierarchy with the entire powerplant at the highest level and various primitives at the lowest level. When detailed structures are identified and developed for the primitives, the simulation becomes rather straightforward.

Human Operator Interface

There are a few more problems that have not yet been addressed. These concern the handling of operator inputs and providing system information to the operator. Operator inputs can be handled simply as changes in inputs to the appropriate components. Operator actions are expected to be in the form of qualitative variables. By the use of a table that gives the relationship between numerical values and descriptive values, operator actions can easily be converted. The same table can also be used to provide the status information to the human operator by converting the numerical values into qualitative states.

Summary

Research on modeling complex dynamic systems made up of a large number of interacting subsystems has been described. Using a steam powerplant as an example, a hierarchical representation where each subsystem is viewed as a suitably interconnected collection of components is described. The operation of a component is explained using a number of primitives, each responsible for a specific function. The dynamics of the overall system is simulated in a two-step process, where the steps concern state regeneration
and state propagation respectively. Hence the entire simulation is based on a qualitative model of system dynamics. Exact mathematical representation in terms of differential equations is not used.

The qualitative model of the dynamic system also provides the state variable values in a qualitative form which results in reduced information processing load by the human operator. Hence, this type of modeling approach should benefit the design of dynamic system simulators where human operators must interact with the system.
Water, Steam and Sea-water Loops

Figure 1
Condensate and Feedwater Subsystem

Figure 2

State Evolution

Figure 3
Component (Condenser)

Figure 4

Primitive (Resistor)

Figure 5
EVALUATION OF THE ABILITIES OF MARINE ENGINEERING PERSONNEL TO DETECT, DIAGNOSE, AND COMPENSATE FOR SYSTEM FAILURES

William B. Rouse
Principal Investigator

Annual Interim Report
For the Period June 1, 1984 - May 31, 1985

For

Contract N00014-82-K-0487
Work Unit NR 154-491
(June 1, 1982 - May 31, 1986)

Center for Man-Machine Systems Research
Georgia Institute of Technology
Atlanta, GA 30332
(404-894-3996)
INTRODUCTION

Following in the wake of the aviation industry, efforts to introduce automation in the marine industry are increasingly evident. Most of these efforts have been pursued in hopes of improving energy efficiency, increasing abilities to operate in confined waters and low visibility, and reducing the size of the crew. An example of trends in the latter direction is the relatively recent emergence of unmanned engine rooms.

Considering the engine room in more detail, various automatic controls have been introduced for regulating engine rpm and the flows of steam, feedwater, fuel oil, lube oil, etc. In addition, several automatic changeover systems are now utilized for activating backup pumps, generators, etc. In general, these automatic devices have eliminated many manual tasks for marine engineering personnel, at least during normal operations or "standard" abnormalities.

However, as in many other domains, the introduction of automation into the engine room has resulted in the engine system becoming increasingly complex. The marine engineering personnel who monitor this system now must be concerned with the possibility of many more types of failure and combinations of failures. This can be particularly problematic when the automation itself fails and its subsequent compensatory response to its own failure appears to be rather unpredictable.

Partially in response to this increase in system complexity, the marine industry has increased efforts in the direction of training. Typically, these training programs utilize full-scale, high-fidelity simulators and attempt to provide the trainee with one or two weeks of highly concentrated experience with a wide variety of system failures.
Because the development of a high-fidelity engine room (or bridge) simulator requires a multi-million dollar investment, training centers tend to have a single simulator which greatly restricts class size and makes the program very expensive. While the industry views this as a necessary evil, this may not be the case because:

1. It is not clear what problem solving skills are necessary for detecting, diagnosing, and compensating for failures in the engine room.

2. It is not clear that full-scale, high-fidelity simulators provide a more effective and economical environment for learning these skills than possible with lower fidelity simulators.

The primary goal of the research program whose progress is reviewed in this report is to pursue these issues and provide an understanding of human problem solving in the engine room environment, particularly in terms of the abilities of trainees to learn problem solving skills as a function of the level of fidelity of the simulator.

The problem outlined in this Introduction is being pursued by both theoretical and experimental investigations of human problem solving abilities in simulated supertanker engine room environments. The theoretical aspects of the investigation involve the use of an evolving model of human problem solving in dynamic environments. The experimental studies involve three simulated engine room environments, ranging in fidelity from fairly low to very high, where professional marine engineering officers are being used as subjects for all formal experiments.
MODELING PROBLEM SOLVING

The first-year of this program of research was devoted to operationalizing a proposed model of human problem solving in dynamic environments. The result was KARL (Knowledgeable Application of Rule-Based Logic), which was quite successful in mimicking subjects' problem solving in a process control task (Knaeuper and Rouse, 1983). During the second year, KARL was successfully applied as an "online coach" for the same process control task, with a variety of encouraging and somewhat surprising results (Knaeuper and Morris, 1984).

The third year of effort in the modeling area involved looking at model-based instruction from two perspectives. The notion of a student model is very much related to the concept of mental models. This relationship motivated an extensive review of research in mental models, with particular emphasis on instructional issues as well as knowledge representation and the nature of expertise (Rouse and Morris, 1985). A related, but much more specific, effort involved developing an approach to online, intelligent training in dynamic environments such as typified by marine propulsion systems (Fath and Rouse, 1985).* This approach is currently being extended and refined for application to instruction using the moderate-fidelity simulator.

*This paper is appended to this report.
SIMULATOR DEVELOPMENT AND EVALUATION

This research utilizing marine powerplant simulators at various levels of fidelity has progressed with more experiments using the low fidelity simulator, FAIL (FAULT-based Aid for Instruction and Learning). Development of the moderate fidelity simulator also continued. The high fidelity simulator could not be used for any rigorous experiments due to the short training periods available on it as well as the lack of facilities for recording observations or subject protocols without interfering with the training program at MSI.

Results from four experiments conducted this year along with two experiments conducted during the previous year were analyzed and models for fault diagnosis performance have been developed. The experimental results and the models are summarized below. More features and capabilities have been added to the moderate fidelity simulator. Based on the structure developed during the previous year, more properties have been added to make the simulator more realistic, increasing its structural fidelity. Details are provided below.

Low-Fidelity Simulator

From experimental results using FAIL, the model proposed for fault diagnosis based on the first two experiments was refined. Earlier observations concerning the relationship between the Initial Feasible Set (IFS) and diagnostic strategies were confirmed. From the series of six experiments, it is apparent that a good IFS results in good fault diagnosis performance. Also, a breadth-depth (BD) strategy where subjects conduct a broad initial search for possible causes of a failure, and then investigate the specific hypotheses formed thoroughly, leads to better performance than
a balanced (BL) strategy. The latter, BL strategy, is used by subjects who do not seem to investigate any one hypothesis thoroughly. Instead, they seem to hold multiple, concurrent hypotheses concerning the failed component.

These results and observations seem to imply that in a complex system, problem solving is affected by both context-specific (IFS) and context-free (Transition Strategy) factors. The data also revealed large individual differences in problem-solving strategies. To investigate these differences further and to get a better insight into the problem solving process, including how the reasoning process central to problem solving might be affected by the acquisition, structuring, and retrieval of the system knowledge, think-aloud protocols were gathered during the last two experiments.

A 'micro' model of fault diagnosis has been developed from analysis of the protocols and observations. The subjects seem to employ two types of knowledge; symptom knowledge and system knowledge. Symptom knowledge is rule-based, whereas the system knowledge is organized hierarchically with the higher level abstracted toward system functionality and lower levels having direct physical correspondence. The diagnostic process seems to proceed with frequent reference to these two types of knowledge.

A conceptual entity called a "hypothesis frame" was used to account for the observed characteristics of protocol and experimental performance data. A hypothesis frame contains all relevant information about a particular failure. Each frame has four slots: symptom slot, component slot, inference slot, and flow slot. These slots put together all related symptoms, component, inferences, and flow types. The diagnostic process involves choosing an appropriate frame that matches the known symptoms, and evaluating the frame against the system state.
At the beginning of a diagnostic process, symptoms in the known symptom set are given. Symptoms in this set are used to match the symptom-cause rules in the symptom knowledge base. Once an appropriate rule is found relevant, the corresponding hypothesis frame is elicited for evaluation. During the processing of a frame, inferences may be drawn from the inference slot to come up with frames for processing. Observed heuristics are: physical closeness, best-matched frame, and direct mapping from symptoms. Four protocols were analyzed using this model. The model fits the protocol data well. More complete details are presented in Su and Govindaraj (1985) which is appended to this report.

Moderate-Fidelity Simulator

The hierarchical structure developed for the moderate fidelity simulator earlier was further enhanced with the incorporation of more complete details. The powerplant is viewed as an interconnected combination of interacting subsystems. The subsystems are made up of appropriate components. The individual components are further decomposed into primitives which form the generic, fundamental building blocks for the simulation. Equations of system dynamics are abstracted with sufficient detail at the primitive level. The primitives are: gain, capacitor, controller, transducer, source, sink, source-sink, phase changer, conduit, and reactor.

Each primitive performs a specific function, and system states evolve in a two step process. During the first step, the states of individual components are updated. The next step propagates the effects to other components downstream (and upstream where feedback connections are involved). The specific components that form various subsystems are characterized by parameters and states which govern the state evolution via primitives.
For each component, appropriate parameters, input and output states were identified. These are arranged as properties in property lists. The parameter values are tuned so that the occurrence of state changes follow the appropriate temporal sequence, characterizing temporal fidelity.

Component failures are characterized by suitable alterations of parameter and/or state value. Preliminary simulations were conducted in slower than real time, to observe the effects of failures. These were used to choose appropriate control structures for combining primitives and parameter values. Simple display formats were tried before the Xerox 1108 arrived. A display interface has been developed using the Xerox 1108, an example of which appears in the figures. Since the trainees/subjects are generally unfamiliar with computers, a simple mouse-based interface is used. The subjects choose icons that trigger the display of appropriate subsystems. Components with subsystems, as well as gauges associated with components (shown in a menu) are chosen using the mouse. Any item chosen is highlighted, and appropriate help is provided in the prompt window.

The interface will be further refined and experiments are expected to begin in the fall. This simulator has moderate to high structural and dynamic fidelity, and low to moderate physical fidelity. Experimental results are expected to provide further insight into the fault diagnosis performance behavior of experts on complex dynamic systems.
Welcome to the training program!
We have developed a simulator for an oil-fired steam powerplant, that provides symptoms appearing after a component has failed.

You are expected to identify the failed component.
You may investigate various subsystems using the mouse.
A particular subsystem can be displayed by selecting the appropriate icon.
Press and release the left button to activate a subsystem or a component.
You may start whenever you are ready.

Sponsored by the Office of Naval Research
The following settings will work:

NOROTATE? NIL
COMPRESS? T

Use these settings? yes
PUBLICATIONS

Journal Articles:


Conference Papers:


Technical Reports:


AN APPROACH TO TRAINING FOR OPERATION AND MAINTENANCE IN LARGE-SCALE, DYNAMIC ENVIRONMENTS

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Abstract

Though recent technological trends are towards complex, dynamic systems, little research is being done to explore appropriate training methods for operators and maintainers of such systems. Research results from cognitive psychology, along with knowledge requirements of the operators’ and maintainers’ tasks, can aid in the development of training programs. A general approach for training operators and maintainers in large-scale, dynamic environments is proposed.

Introduction

With recent technological developments, the number of problems associated with operating and maintaining large-scale dynamic systems is increasing. Examples of large-scale systems are communications networks, process control plants, and ships. System characteristics that are particularly problematic include the dynamic nature of both the operation and maintenance tasks and the greater degree of system automation.

Two major approaches exist for dealing with the problems created by large-scale, dynamic systems. One approach involves the design process and concentrates on developing operator-task interfaces and aids to simplify the operators’ and maintainers’ tasks. Although better interfaces and aids can help to simplify the operators’ and maintainers’ tasks, they cannot eliminate all the complexity associated with operation and maintenance of large-scale, dynamic systems. A second approach does not preclude the first. Instead, this second approach involves designing appropriate training programs to equip the operator and/or maintainer with the knowledge and skills required for coping with the complex problems required to perform the job.

A preliminary step in solving the training problems associated with large-scale, dynamic environments is to analyze the operators’ and maintainers’ tasks to reveal the types of knowledge that must be conveyed during training. The types of knowledge can be roughly categorized into knowledge of “what,” “how,” and “why.” These three categories can be further refined into two general classes: 1) system knowledge and 2) operational knowledge.

Knowledge to be Taught

Table 1 illustrates the “what,” “how,” and “why” of system knowledge. Many elements of system knowledge that are necessary for diagnosis are also required for other system activities. Knowledge of “what” is shown as ranging from details of system elements, such as names of parts and subsystems, to global response patterns, such as the normal starting and running sequence for a particular system. Knowledge of “how” is depicted as ranging from specific descriptions of how each subsystem or part works (and how each might fail) to general mechanisms of system response, that is, how particular operating sequences occur. Finally, knowledge of “why” ranges from concrete explanations of why specific parts or subsystems are necessary to abstract explanations of system functioning and reliability, based on general physical and mathematical principles.

Table 2 summarizes the “what,” “how,” and “why” of operational knowledge. In contrast to Table 1, Table 2 depicts knowledge that is extrinsic to the system as an engineering entity, but intrinsic to the diagnostic function of personnel who operate and maintain the system. As a result, the perspective in Table 2 is different from that in Table 1. Knowledge of “what” ranges from specific diagnostic situations that can arise with a particular system to general classes of diagnostic scenarios and criteria. Knowledge of “how” is depicted in Table 2 as ranging from procedures for dealing with specific system failures (e.g., clogged filter) to methodologies, such as experimental design.
or optimization, that would help in synthesizing and/or evaluating alternative procedures or diagnostic strategies. Knowledge of "why" ranges from system-specific explanations of the usefulness of a particular diagnostic procedure to explanations of diagnostic methods in terms of theories of probability, statistics, logic, etc.

Considering all of the types of knowledge shown in Tables 1 and 2, it should be apparent that no single individual is likely to be fully cognizant of all this information. For example, design engineers can be assumed to be steeped in system knowledge, including the more global, general, and abstract considerations that help them to devise and optimize system designs. In contrast, plant or operations engineers are usually well acquainted with operational knowledge, including the more global, general, and abstract methodological and theoretical aspects of operational planning and control. Comparing design and plant engineering, designers are well-versed in the lower right entries of Table 1 while the expertise of plant or operations engineers lies within the lower right entries of Table 2.

Considering operations and maintenance personnel, it seems reasonable to claim that their knowledge requirements, especially for troubleshooting, are more detailed, specific, and concrete and, therefore, emphasize the upper left entries of both Tables 1 and 2. Succinctly, operations and maintenance personnel tend to need less general/abstract and theoretical than design and plant engineers, but more breadth on a detailed/specific level covering both system and operational knowledge. Therefore, some types of system knowledge are necessary for proficient diagnostic behavior by operators and maintainers. However, system knowledge is not sufficient; some types of operational knowledge are also necessary. The implication of this conclusion is that the diagnostic training of operators and maintainers should be different than the training of design and plant engineers. While this conclusion is obvious, there nevertheless remains the notion in many training communities that more engineering-oriented training will assure better operators and maintainers. This can be problematic if engineering-oriented training displaces more operationally useful training; a better balance is needed.

Perhaps the best illustration of this point concerns knowledge of "why" and its relationship to proficient diagnostic behavior. While knowledge of "what" and "how" are necessary for proficient diagnostic behavior by operators and maintainers, a complete knowledge of "why" is not absolutely necessary. Although it may seem counterintuitive, few, if any, of a variety of experimental efforts in operations and maintenance environments [3, 4, 5] have succeeded in demonstrating any performance benefit, for diagnosis or other tasks, due to knowledge of "why," particularly if that knowledge is in terms of abstract principles or theories.

Therefore, it appears that the primary reason for including in a training program the more abstract type of knowledge of "why" is to motivate personnel and satisfy their curiosity. Nevertheless, from a performance perspective, it is very difficult to justify the "it's good for them" argument, especially if one is concerned with "why" at the level of theories of physics, chemistry, and probability and statistics. On the other end of the abstraction continuum, it is much easier to justify "why" in terms of explanations of operational requirements and procedures' usefulness. In other words, to be useful, knowledge of "why" must be operationalized and expressed at a level commensurate with the way in which it will be used.

To summarize, one can view Tables 1 and 2 as representing the range of potential components of trainees' knowledge. A very important consideration is the extent to which a diagnostic training program should attempt to provide a significant amount of each type of knowledge. In general, it appears that many diagnostic training programs, in a variety of industries, try to cover all aspects of system knowledge. In contrast, operational knowledge is given much less coverage, with "what" (in terms of situations) and "how" (in terms of procedures) usually being given much more attention than criteria, analogies, and strategies. It seems reasonable to claim that a more balanced approach is required.

### Implications of Cognitive Psychology for Problem Solving Instruction

Although most cognitive psychology research has been conducted in the fields of mathematics, computer programming and other static and relatively well bounded domains, some of the results of such research may be applied to the development of training for large-scale, dynamic systems. Frederiksen [7] offered suggestions for instruction in problem solving found in the cognitive psychology literature. Each of these suggestions is discussed below, with emphasis on the way it relates to training operators and maintainers of large-scale, dynamic systems. Further, each implication is described in the context of Tables 1 and 2. Since this paper is concerned with the training of system operators and maintainers, only the entries in the upper left diagonal are considered in the following discussion.

#### Teach the Knowledge Base

This suggestion relates directly to the discussion above of knowledge of "why" important in training. With respect to a large-scale, dynamic system, it should be noted that the amount of knowledge to be learned is vast and it may not be possible to teach it all in a training program.

#### Teach the Application of Problem Solving

Simon and Newell [8] stress the importance of
constructing an appropriate problem space, or internal memory representation, and list various sources of information which might be useful in doing so. The list contains information found both within the learner in the form of previous experience and programs stored in long term memory, and in external sources. Training should help to expand the learner's repertoire of experience and programs, but it should also teach the learner where to look for other useful information. System knowledge is available in a variety of documents such as manufacturer's specifications, design specifications, schematic drawings, and system manuals. Unless an operation and/or maintenance task is heavily proceduralized, external sources of operational knowledge are scarce. If written procedures are available, 'what' information for problem space construction can be found in the procedures' enabling conditions and 'how' information can be found in the procedures' actions. If the procedures are not written, the learner must search his own memory for information to form the problem space.

Teach General Problem Solving Strategies

If specific procedures are unavailable for solving some problem, general problem solving strategies must be used. These strategies are classified as "how" operational knowledge, but their applicability may be determined by certain "what" conditions. Examples of general models or strategies of human problem solving are described by Roue and Hunt [9].

Teach Pattern Recognition

Patterns of operational "what" information trigger "how" procedures, strategies and methodologies. In order to build up the larger library of patterns necessary for competent problem solving performance in large-scale dynamic environments, much practice is required. It is also helpful to teach general or common patterns rather than attempting to teach all possible patterns. Moreover, it is important to teach the pattern of normal operating conditions so that operators and maintainers will know when to start looking for a problem.

Teach Cognitive Processes or Procedures

Cognitive procedures are detailed/specific/concrete operational procedures used to deal with specific situations ("how"). Such procedures have been identified in the form of process models of competent performance or may be inferred by analyzing errors made while a student performs a task. When models of competent performance are used to specify the material to be taught, Resnick [10] warns that they must be used along with some description of the student's incoming knowledge in order to be most useful. Resnick also states that, since it might not be easy or possible to teach some procedures, it may be better instead to teach procedures which place the student in a position to invent the correct procedure on his own.

Though interesting and useful in well constrained environments, the approach of identifying all possible errors in a task may not be practical for use in large-scale, dynamic systems. DEBUGGY [11] diagnoses errors in subtraction by comparing students' answers with those generated using combinations of error rules. Since the list of primitive errors alone in DEBUGGY numbers 110, however, it would not be practical to attempt to identify all possible errors for larger, more complex environments.

There are two other problems connected to the teaching of cognitive processes. First, if left to their own invention, students may devise incorrect procedures. Second, it is conceivable that, by virtue of the sheer number of procedures connected with a large-scale, dynamic system, not all of them could be learned. Emphasis must then be placed on the detailed/specific/concrete operational knowledge of how to locate the appropriate written procedure and how to use it when it has been located.

Teach the Development of Knowledge Structures

Development of knowledge structures concerns the way in which new information in long term memory is represented and organized. Rumelhart and Norman [12] propose that all knowledge is represented in long term memory as procedures called schemata. When a human needs to know a specific fact, the procedures are interrogated. Thus, knowledge of "what" is embedded in knowledge of "how." New knowledge is organized in terms of old knowledge through the use of analogies. An hypothesis concerning use of schemata for training is that primarily system and operational procedures or "how" knowledge should be taught since knowledge of "what" may be derived from "how" knowledge. A second hypothesis is that, on the global/general/abstract level, useful operational analogies should be identified during training to ease the incorporation of new knowledge into the student's long term memory.

Use Models in Instruction

Models can be directly viewed by students as a demonstration of appropriate performance or they can be used covertly to manipulate the training environment. In the former case, a student may view an illustration of a concept or procedure to be learned and then attempt to duplicate the performance. In the latter, system and operational "what" knowledge might be most appropriately conveyed by using illustrative models. In the latter case, a model of the student's knowledge and one or more target models are used to make decisions regarding which information or training problem to present at any given time. A target model contains information the student should possess upon completion of the training program. A student model contains knowledge believed to be possessed by the student. Both system and operational "what" knowledge can be conveyed to the student through combined use of student and target models.

Of course, in a large-scale dynamic system, the development of one (or even several) illustrative and target models which can capture the important aspects of a task may be difficult. Moreover, once a set of partial models has been developed, they must be integrated into the training program so as to form a coherent and useful training environment. The difficulties involved in development and integration may limit the use of models in training for operation and maintenance of large-scale, dynamic systems.

Provide Practice with Feedback

Practice with feedback is important in both pattern recognition and procedural training. As was previously mentioned, training in pattern recognition is important for operational "what" knowledge of situations, criteria, and analogies. Practice with feedback helps students to recognize more readily the important patterns they may see during system operation and also allows them to recognize more readily when to perform the appropriate procedures. Further, practice with feedback helps students to gain proficiency in the operational "how" knowledge used in performance of procedures and use of strategies.

Teach Aptitudes

For the purpose of the domains in which the authors are working, it is reasonable to assume that all students have the aptitudes required to succeed as operators and maintainers of large-scale, dynamic systems. Therefore, problem solving aptitudes will not be discussed further here.

Summary

The relationships between the implications of
cognitive psychology for instruction and the knowledge to be taught to operators and maintainers in large-scale, dynamic systems are summarized in Tables 3 and 4. Information in Tables 3 and 4 can be used to formulate a general approach to training in large-scale, dynamic systems.

| Table 3. Implications of Cognitive Psychology on Instruction of System Knowledge |
|-----------------------------------------------|-----|-----|-----|
| **LEVEL** | **WHAT** | **HOW** | **WHY** |
| DETACHED/SPECIFIC/CONCRETE | TEACH THE KNOWLEDGE BASE | TEACH DEVELOPMENT OF PROBLEM STRUCTURE | TEACH THE KNOWLEDGE BASE |
| | TEACH DEVELOPMENT OF PROBLEM STRUCTURE | USE MODELS IN INSTRUCTION | |
| | TEACH PATTERN RECOGNITION | PROVIDE PRACTICE WITH FEEDBACK | |
| | TEACH COGNITIVE PROCESSES | USE MODELS IN INSTRUCTION | |
| | USE MODELS IN INSTRUCTION | PROVIDE PRACTICE WITH FEEDBACK | |
| | TEACH DEVELOPMENT OF KNOWLEDGE STRUCTURES | | |
| | TEACH GENERAL PROBLEM SOLVING STRATEGIES | | |
| | USE MODELS IN INSTRUCTION | | |
| | PROVIDE PRACTICE WITH FEEDBACK | | |
| | TEACH DEVELOPMENT OF KNOWLEDGE STRUCTURES | | |
| | USE MODELS IN INSTRUCTION | | |
| | PROVIDE PRACTICE WITH FEEDBACK | | |
| | TEACH PATTERN RECOGNITION | | |
| | TEACH DEVELOPMENT OF KNOWLEDGE STRUCTURES | | |
| | USE MODELS IN INSTRUCTION | | |
| | PROVIDE PRACTICE WITH FEEDBACK | | |
| GLOBAL/GENERAL/ABSTRACT | TEACH THE KNOWLEDGE BASE | TEACH DEVELOPMENT OF PROBLEM STRUCTURE | TEACH THE KNOWLEDGE BASE |
| | TEACH DEVELOPMENT OF PROBLEM STRUCTURE | USE MODELS IN INSTRUCTION | |
| | TEACH PATTERN RECOGNITION | PROVIDE PRACTICE WITH FEEDBACK | |
| | TEACH COGNITIVE PROCESSES | USE MODELS IN INSTRUCTION | |
| | USE MODELS IN INSTRUCTION | PROVIDE PRACTICE WITH FEEDBACK | |
| | TEACH DEVELOPMENT OF KNOWLEDGE STRUCTURES | | |
| | TEACH GENERAL PROBLEM SOLVING STRATEGIES | | |
| | USE MODELS IN INSTRUCTION | | |
| | PROVIDE PRACTICE WITH FEEDBACK | | |
| | TEACH PATTERN RECOGNITION | | |
| | TEACH DEVELOPMENT OF KNOWLEDGE STRUCTURES | | |
| | USE MODELS IN INSTRUCTION | | |
| | PROVIDE PRACTICE WITH FEEDBACK | | |

| Table 4. Implications of Cognitive Psychology on Instruction of Operational Knowledge |
|-----------------------------------------------|-----|-----|-----|
| **LEVEL** | **WHAT** | **HOW** | **WHY** |
| DETACHED/SPECIFIC/CONCRETE | TEACH THE KNOWLEDGE BASE | TEACH DEVELOPMENT OF PROBLEM STRUCTURE | TEACH THE KNOWLEDGE BASE |
| | TEACH DEVELOPMENT OF PROBLEM STRUCTURE | USE MODELS IN INSTRUCTION | |
| | TEACH PATTERN RECOGNITION | PROVIDE PRACTICE WITH FEEDBACK | |
| | TEACH COGNITIVE PROCESSES | USE MODELS IN INSTRUCTION | |
| | USE MODELS IN INSTRUCTION | PROVIDE PRACTICE WITH FEEDBACK | |
| | TEACH DEVELOPMENT OF KNOWLEDGE STRUCTURES | | |
| | TEACH GENERAL PROBLEM SOLVING STRATEGIES | | |
| | USE MODELS IN INSTRUCTION | | |
| | PROVIDE PRACTICE WITH FEEDBACK | | |
| | TEACH PATTERN RECOGNITION | | |
| | TEACH DEVELOPMENT OF KNOWLEDGE STRUCTURES | | |
| | USE MODELS IN INSTRUCTION | | |
| | PROVIDE PRACTICE WITH FEEDBACK | | |
| | TEACH PATTERN RECOGNITION | | |
| | TEACH DEVELOPMENT OF KNOWLEDGE STRUCTURES | | |
| | USE MODELS IN INSTRUCTION | | |
| | PROVIDE PRACTICE WITH FEEDBACK | | |
| GLOBAL/GENERAL/ABSTRACT | TEACH THE KNOWLEDGE BASE | TEACH DEVELOPMENT OF PROBLEM STRUCTURE | TEACH THE KNOWLEDGE BASE |
| | TEACH DEVELOPMENT OF PROBLEM STRUCTURE | USE MODELS IN INSTRUCTION | |
| | TEACH PATTERN RECOGNITION | PROVIDE PRACTICE WITH FEEDBACK | |
| | TEACH COGNITIVE PROCESSES | USE MODELS IN INSTRUCTION | |
| | USE MODELS IN INSTRUCTION | PROVIDE PRACTICE WITH FEEDBACK | |
| | TEACH DEVELOPMENT OF KNOWLEDGE STRUCTURES | | |
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| | TEACH PATTERN RECOGNITION | | |
| | TEACH DEVELOPMENT OF KNOWLEDGE STRUCTURES | | |
| | USE MODELS IN INSTRUCTION | | |
| | PROVIDE PRACTICE WITH FEEDBACK | | |

A Plan for Training in Large-Scale, Dynamic Systems
Cognitive psychology research can provide some general insight into the problems of training in large-scale, dynamic environments, but these results are not sufficient to develop a complete training program. It is also not clear whether there is enough similarity between task environments such as mathematics and large-scale, dynamic systems to justify using implications derived in the former environment for training in the latter. Thus, the applicability of the cognitive psychology research implications described above should be empirically tested in a more complex environment.

Domain of Study
This testing will be performed using a computer-aided training program for the qualitative, moderate fidelity marine powerplant simulation developed by Govindaraj [13]. The simulation possesses a high degree of cognitive fidelity when compared to an actual marine powerplant. Moreover, a somewhat constrained, computerized environment allows a degree of experimental control that is unattainable in real marine powerplants.

Two subject populations will be tapped for experimental studies. Initial subjects will be recruited from the Naval ROTC program at the Georgia Institute of Technology. Only those students who have completed at least one course in propulsion systems engineering will participate in the studies. The second population of subjects, and the one of primary interest, is the group of engineers who attend the marine powerplant training program at Marine Safety International.

General Approach
Design and development of the training program will involve the following steps:

Step 1. A cognitive task analysis will be performed to identify the necessary system and operational knowledge of "what," "how," and "why." Both detailed/specific/concrete and global/general/abstract knowledge will be considered with emphasis on the upper left diagonals of Tables 1 and 2.

Step 2. Sources of information to be used to define the problem structure will be identified. Distinction will be made between information students must learn and information which is to be accessed externally. Specific training for the "to be learned" information will be developed, but only the location and reasons for use of externally available information will be trained.

Step 3. General problem solving strategies will be taught which will be applicable to relevant areas of the system. Along with the general strategies, conditions of their use will be taught.

Step 4. Patterns of operational "what" information will be identified. Patterns of both normal and abnormal operating conditions will be identified and taught using the method of practice and feedback.

Step 5. Analysis of the operational procedures will be performed to determine which of them must be learned and which may be externally accessed. Practice will be given with both the "to-be-learned" procedures and in accessing the external information. Feedback will be given when it is appropriate.

Step 6. A possible teaching tactic will be to concentrate on teaching operational "how"
knowledge and then ask students to derive operational "what" information from their knowledge of procedures. Analogies will be employed wherever possible in teaching procedures, providing that it is reasonably certain that the student is competent in using the analogical domain.

Step 7. Models will be used in both capacities as described above. That is, models will be used to demonstrate system and operational "how" knowledge and to manipulate the training environment in teaching system and operational "what" knowledge.

Hypotheses

The list of general steps for design and development of a training program suggest many experimental hypotheses relevant to training programs. Two major hypotheses concern steps 6 and 7. An hypothesis related to step 6 is that teaching "how" knowledge will allow students to also learn "what" knowledge with little additional teaching effort. Thus, an experiment could be performed to test whether concentration should be made on teaching "how," using appropriate analogies as opposed to teaching "what" and "how" knowledge separately.

A second hypothesis, derived from step 7, concerns the use of models in training. Provided that adequate models of system and operational "how" knowledge can be developed an experiment could be performed that tests the relationship between levels of proficiency in the operation and maintenance tasks and performance in operating the qualitative simulation. Groups of Naval ROTC students and experienced marine powerplant operators and maintainers could be trained either with or without use of "how" knowledge models. The groups trained without the models could receive other training which includes the same general concepts as presented in the models, but not arranged in model form. Errors in operating and maintaining the simulated system may be used as a performance measure.

For the NROTC students, it might be expected that the group provided with the models would make fewer errors than those students who do not have the model. Two possible outcomes for experienced operators and maintainers, however, can be imagined. In the first case, members of the experienced group could perform equally well, either with or without the model. This result would indicate that the model has no effect since the experienced subjects were better than the model. In the second possible case, the experienced group that receives the model could perform worse in terms of making more errors than the no-model group. This result could be caused by confusion due to incompatibilities of the training model and the system and operational representation that the experienced operators and maintainers possess internally.

Conclusions

The steps described above to be used in developing a training simulation for a large-scale, dynamic environment are admittedly very general. Perhaps they are best described as general goals for the training system. They have been presented here in the hope of fostering a cognitively-oriented approach to solving some of the pressing problems of developing training systems in large scale dynamic environments.

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References

A MODEL OF EXPERT FAULT DIAGNOSIS PERFORMANCE

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Abstract

Models of fault diagnosis by expert human operators are classified into two types: macro and micro. Macro models describe general problem-solving rules or strategies that are abstracted from observations of experts' diagnostic behavior. Micro models consider the formation of knowledge and the mechanisms behind the diagnostic actions. This paper proposes a micro model of fault diagnosis on a marine powerplant simulator. Based on experimental data, including protocols, two types of knowledge were identified: rule-based symptom knowledge and hierarchical system knowledge. Diagnostic process seems to proceed with frequent reference to these two types of knowledge. Characteristics of the diagnostic process are discussed. A conceptual entity called hypothesis frame is employed to account for observed characteristics. Diagnostic process involves choosing an appropriate frame that matches the known symptoms, and evaluating the frame against the system state. This model of fault diagnosis performance is employed to explain protocol data.

Introduction

The level of fidelity required of a training simulator could depend on task complexity, experience and expertise of trainees and the training program. Even though it may be desirable to have simulators that have high fidelity in every detail, constructional and operational costs could be prohibitive. Specific aspects of a system's operation can be simulated with relatively high fidelity while keeping the overall fidelity, and hence cost, low. This paper describes research on fault diagnosis performance of expert marine engineers interacting with a low fidelity simulator of a marine powerplant.

Su and Govindaraj [1] proposed to employ three simulators at different fidelity levels to investigate how simulator fidelity affects fault diagnosis performance. A three dimensional approach was used to define fidelity [2]. In [1], a low fidelity simulator was used. Failures of marine powerplant control were presented, and expert subjects were asked to find the failed component. The fault diagnosis process was observed to consist of two stages: hypothesis formation and hypothesis evaluation. Two types of strategy were identified to control the transition between stages. Subjects using breadth-depth (BD) strategy conducted a broad search for hypotheses and did a thorough evaluation once a hypothesis was formed. Other subjects who used the balanced strategy (SL) tended to form hypotheses quickly and maintained multiple hypotheses at the same time. This kind of modeling approach to identify diagnosis patterns provides a macro model of fault diagnosis performance.

Macro model describes general problem-solving rules that are abstracted from observations of subjects' diagnostic behavior. A model proposed by Rouse and Hunt [3] that uses topographical rules (T-rules) and symptomatic rules (S-rules) is a typical example. These rules were employed successfully to classify the diagnostic behavior. They explained "what" has been performed, but not "how" and "why" a particular action was chosen or formed.

Contrasted with macro models, micro models consider the individual differences. Therefore, a micro model should specify the formation of knowledge and the mechanisms behind actions. Most Artificial Intelligence (AI) models can be classified as micro models since they usually deal with the knowledge representation and retrieval problems in a precise manner. For example, Schank's [4] approach to Memory Organization Package (MOP) not only specifies how memory is organized, but also describes the mechanism of reminding. Kolodner [5], [6] proposed a computer model of long term memory. Later she applied this model to medical diagnosis [7] which demonstrated the experience's role in acquiring expertise. She showed how medical knowledge is learned, modified, and generalized.

In this paper, we propose a micro model that deals with the knowledge formation and the mechanism for fault diagnosis behavior. Such a model could help identify the essential components of fault diagnosis behavior and hence choose appropriate simulator fidelity for training. A micro model might also reveal the weaknesses of human operators, and help develop better aiding schemes.

Kuipers and Kassar et al. [8] pointed out that in building an intelligent computer system dealing with causal reasoning, two types of constraints must be considered: computational constraints on knowledge representation, and empirical constraints on expert's reasoning process. Computational constraints require that a knowledge representation be computer implementable. Empirical constraints may direct the formation of the knowledge representation in a format that reflects how experts solve problems.

In the discussions below, the data and protocols from [1] are incorporated into a coherent model. Only empirical constraints are considered. Two types of knowledge and their structures are discussed. Then the characteristics of the diagnostic behavior on a marine powerplant are summarized. A conceptual entity called hypothesis frame will be employed to account for the observed behaviors. Finally, an integrated diagnosis model taking into consideration these two types of knowledge structures and the hypothesis frame will be described.

Experiments and Data

A low fidelity simulator of a marine powerplant, called FAIL (FAULT-based Aiding for Instruction and Learning), was used in [1]. FAIL displayed symptoms of powerplant failures. System state was frozen sometime after the failure occurred. Subjects were given the component list, command list and system schematics. They could interrogate the system state by issuing appropriate commands. They were asked to find the failed component as quickly as possible using the smallest number of steps. Six experiments, with different subjects in each experiment, were conducted. A total of twenty-eight marine engineers with ten to twenty years of experience participated as subjects. Each subject solved 21 problems. Protocols were taken in the last two experiments on some subjects. The characteristics of the diagnostic process from experimental data and protocols are summarized below. Then a model based on these observations is proposed.
Apparent Characteristics of the Diagnostic Process

1. Two types of knowledge were identified: symptom knowledge and system knowledge. In real diagnostic tasks, some actions were generated fairly quickly, suggesting a direct association between symptoms and causes. For example, given "fluctuation of fuel oil pressure," most engineers immediately diagnosed that there was water in the fuel. These associations can be represented in IF-THEN rules. Causes associated with a particular symptom seem to have high generality across subjects. For example, rule 1 in Table 1 lists the most popular causes that are associated with the symptom "vacuum low at reduced speed." Gland seal steam was referred to by 20 out of 27 subjects. Cooling water system and condensate pump system were referred to by 23 and 18 out of 27 subjects respectively (see [1]). These rules may be prioritized and partitioned into groups with similar characteristics.

System knowledge is well defined. Although there is no clear evidence of a homogeneous mental model about the system across subjects, there exist hierarchical models of subsystems and components. Knowledge about the system is organized on several abstraction levels. In general, modules on higher abstraction levels are more function-oriented, while modules on lower abstraction levels have clear physical correspondence. However, at lower levels, the relationships are not entirely hierarchical since certain components and subsystems may be common to more than one system. For example, a steam system module may be defined as a heat transfer unit, while a boiler itself may be defined as a collection of its major physical components.

2. Diagnosis proceeds in a hierarchical manner. Given symptoms, subjects start reasoning from a higher abstraction level and generate hypotheses using available information. Hypotheses generated in a higher level set the direction of diagnosis for a lower abstraction level. The following excerpts from protocols showed this hierarchical approach.

L217: Need to find out whether there is too much demand for the boiler.
L218: Whether the boiler pressure is dropping in the auxiliary system or the main system.
L219: In order to bring the pressure back, you might reduce the load.
L220: We have to come back to a reduced speed,
L221: To secure some other steam demand and find out the problem.
L235: Whether the temperature of the boiler is OK
L228: To see if it would have dirty tubes.

The subject first diagnosed the problem in terms of functional concepts like "too much demand on the boiler" (L217). Following this diagnosis of a high abstraction level, the subject suggested some remedial actions (L219, L220, L221). Then after assuring the boiler was not overloaded, the subject proceeded to further diagnose the problem using "too much demand on the boiler" as a guideline. He shifted attention to a gross but concrete subsystem called a "burner" (L223). To identify what was going wrong in burners, he moved down the hierarchy tree to the fuel line and air line inside a burner (L224, L225). At this moment, he checked the system state to find out the status of the fuel and air lines going into the burners. They were alright. So the subject came back to a higher abstraction level to resume another line of reasoning (L226, L227).

3. Diagnosis proceeds with backward and forward reasoning. It is commonly known that given symptoms, subjects search for symptom-cause pairs to proceed with the diagnostic process. This is a backward reasoning process which goes from symptoms to causes. However, it is observed that subjects also use forward reasoning to help formulate and eliminate hypotheses. Forward reasoning process allows the subjects to reason through the system dynamics over time starting from a component of interest. For example, a subject was observed to reason in the following manner.

E530: If cold water goes into the feedpump, it would cause the feedpump to flash the steam, and the pump would then lose suction.

In this case the subject mentally derived how the system would react if cold water goes into the feedpump. This is a forward reasoning process.

4. The symbolic descriptions of quantities are stated in qualitative terms. For example, high pressure, low vacuum, enough flow etc., are used to describe the system variables. Therefore, qualitative state descriptions seem adequate.

5. Knowledge appears to be chunked: relevant symptoms, inferences, and structures are grouped together mentally for easy access. Subjects showed great efficiency in evolving through system states qualitatively. For example, when asked about what would happen if the 358 line had problems, the subject responded quickly with the dialogue from line L135 to line L138 in Table 2.

Hypothesis Frame

The observations above lead to the construction of a useful conceptual entity called hypothesis frame. A frame as described by Minsky [10] is a general way of representing common knowledge. Frames contain information about many aspects of the objects or situations they describe. The "hypothesis frame" or prototype has been used for organizing disease types in medical diagnosis research. CENTAUR [11] and PIP [12] used
"hypothesis frame" as the main construct for representing the disease categories.

An application of the frame concept to fault diagnosis is to hypothesize the existence of a "hypothesis frame" which contains all relevant information about a particular failure situation. Each hypothesis frame may contain four slots: symptom slot, component slot, inference slot, and flow slot. Table 3 shows an example of hypothesis frame for condensate pump failure.

**Failure 19 (Vacuum drops at reduced speed) (S31)**

L100: First indication is a lot of vacuum loss.
L101: So, first thing I'll check will be the gland seal.
L102: (to see) if it has pressure after regulator.
L103: You know on board it is at least, say, 1 or 2 pounds.
L104: If that is OK, I believe. you check circulator maybe,
L105: to see that you have enough water going back into the condenser
L106: to keep the air ejector cool.
L107: Why the air ejector?
L108: Oh! If you talk about the vacuum pump... I am not quite familiar with the vacuum pump. Let us say the ....
L109: I know with the air ejector you lose vacuum that way.
L110: What else can be wrong?
L111: So, those are most common problems?
L112: Yes, I would think so, unless you...
L113: Assuming the condensate pump running normally, L114: that will be the first indication, the major cause.
L115: So, what else?
L116: Check level of condenser.
L117: Why! What do you want to find?
L118: You want to find out if it is normal, L119: if it is too high then... you see it could be getting water from somewhere else.
L120: What do you mean by somewhere else?
L121: Say. for example, condensate pump may not be functioning properly.
L122: Think aloud.
L123: It would be .... well. If the level is OK. then you look for something else.
L124: We just slow down.
L125: You assume everything else is OK.
L126: In other words. circulating water is fine.
L127: No reason for that, which you think probably will be ...
L128: I don't think it has any problem with the bleeds
L129: I don't know. The symptom is...
L130: Vacuum dropping when slowing down to 50 to full speed.
L131: Possibly the bleeds. you could lose it that way.
L132: Any other possibilities?
L133: Like I said, the dump could cause it,
L134: when you have problems with the 35# line.
L135: If that was the problem you hear the 35# make up and you hear the feedpump speed up a little.
L136: You definitely hear the 35# line making up
L137: from the high pressure steam coming into the low pressure steam
L138: where the low pressure dumping it into the condenser.
(S31 checked the 35# dump regulator and found the solution)

Table 2: Protocols from subject S31 while solving Failure 19. Lines begin with "E" was interruptions by the experimenter to keep conversation going. Lines begin with "L" were dialogue made by S31.

Six different symptoms are associated with this failure. These point to proper rules in the symptom knowledge base. Eight relevant components are listed. These point to modules in the system knowledge base where the relationships among the components are placed in proper abstraction level. Components may point to modules of higher abstraction levels. This scheme facilitates the diagnostic process to reason from higher abstraction level and proceed in a hierarchical manner. The inference slot contains relevant inferences which may be derived from the system knowledge base. The flow slot indicates which type of flow is involved.

*Information in a frame may be updated. However, the mechanism of acquisition and modification of hypothesis frames is a complicated learning process, and will not be discussed here. Nevertheless we assume the existence of hypothesis frames and describe a model for the diagnostic process.*

**A Model for the Diagnostic Process**

At the beginning of a diagnostic process, there are certain known symptoms. As the diagnosis proceeds, this symptom set is updated. The updating process may not simply be the addition of new symptoms. Deductions may be drawn from symptoms. For example, while solving Failure 23 in which both feedpumps were heard to make noise, most subjects concluded that the fault was upstream of the feedpumps. The feedpumps themselves were not faulty because it is very unlikely that both

**Symptom slot:** (All are indexed back to proper rules in the symptom knowledge base.)

- condensate pressure low
- deaerator pressure low
- deaerator level low
- vacuum pressure low
- condenser level high
- LP turbine exhaust temp high

**Component slot:** (All are indexed into proper modules in the system knowledge base.)

- condensate recirculate control valve
- feedwater make-up control valve
- feedwater make-up regulator pressure transducer
- atmospheric drain tank
- deaerator feed tank
- main condenser
- condensate pump suction valve
- condensate pump discharge valve

**Inference slot:**

1. Condensate pump failure will cause low condensate discharge pressure.
2. Therefore more condensate remains in the condenser than normal condition.
3. This in turn causes condenser level to go high.
4. Once the level goes high, it loses vacuum and may be drawn from symptoms.
5. Low condensate discharge also causes the deaerator level and pressure to go low.
6. This in turn triggers the feedwater makeup control.
7. Which results in the atmospheric drain tank dumping water into the deaerator tank.

**Flow slot:**

*feedwater*

Table 3: Hypothesis frame for a condensate pump failure
pumps would go down at the same time. This new deduction about the system becomes a part of the known symptom set.

Symptoms in this set are used to match with the symptom-cause rules. The matching process can be speeded up using heuristics. An example of a heuristic is: "choose frames of higher priority". Rules in the symptom knowledge base are prioritized. Subjects have a tendency to choose the higher priority rules. In Table 2, given vacuum loss when slowing down the ship, S31 checked the gland seal steam system before the 35 line system. In fact, 13 out of 19 subjects observed checked gland seal before they checked the 35 line system. Another example of a heuristic is: "choose tighter rules whenever possible". It was observed that if only the vacuum loss symptom was given, different sequence of actions would be adopted. Most people checked the condensate system first instead of gland seal system which was the most preferred action when vacuum loss was paired with speed reduction.

Once an appropriate rule is found relevant, the corresponding hypothesis frame is proposed. During the processing of a frame, subjects interrogate the system to match the information in the slots. Any new symptoms found are fed back to the known symptom set. If new symptoms are found in the process of evaluating the hypothesis frame, these new symptoms and old symptoms may be used to search in the symptom knowledge base for tighter or higher prioritized hypothesis frames. However, if inferences drawn from frames are in conflict with observations from the known symptoms, then these frames should be discarded.

If no new symptoms or rules are found, subjects may resorted to another type of heuristics. Some observed heuristics are given below.

1. **Physical closeness**: If subjects failed to find any significant symptom from the system, they tended to search through subsystems or components that were physically close to the subsystem/component that they currently hypothesized to have failed. For example, while solving Failure 7 in which HP turbine vibration excessive alarm sounded and the engine noise level was higher than normal, S21 started from the superheated steam frame. Then he checked every component in sequence, starting from the burner and going all the way up to the FD fan. All these components were physically close, but not necessarily relevant, to this particular failure. Among 6 subjects who had difficulty with this failure, 4 had a tendency to process subsystems that were physically close.

2. **Pick a best-matched frame**: Investigate frames that are matched best. In Table 2, after failing to confirm the gland seal and circulating water frames, the subject tried to process the bleed frame. However, at first he was not convinced (L128). There should have been other symptoms preceding the loss of vacuum (L123) if bleed was the problem. Nevertheless this frame was chosen under the best-matched heuristic.

3. **Direct mapping from symptoms**: Investigate frames that contain the components or subsystems indicated in the symptoms. For example, 8 out of 21 subjects picked feedpump failure frame when presented with Failure 8 in which feedpump noises were heard.

Figure 1 presents this model in a flowchart-like schematic.

![Diagram of a Diagnostic Process](image)

**Figure 1: Flowchart of the diagnostic process**

**Locus of a Diagnostic Process**

The model proposed in previous sections is abstracted from experimental data and protocols. There are six pieces of protocols taken from four subjects (S31, S32, S33, S34). Four out of these were taken while subjects were solving Failures 8, 9, 19 and 23 respectively. The other two recorded subjects' description of how the powerplant works and the function of gland seal steam. The following is an interpretation of a diagnostic protocol in terms of the model outlined in the last section.

Table 2 lists an excerpt from protocols taken while S31 was diagnosing Failure 19 in which vacuum was dropping at reduced speed. S31 might take the vacuum dropping as a symptom. However, "at reduced speed" seemed to provide another piece of information. Therefore a "tighter" rule that considered both was preferred. He matched antecedents of the rules in the symptom knowledge base with these two known symptoms. If he had the rules in Table 1 in his repertoire, then rule 1 instead of rule 2 would be matched because rule 1 is tighter. Therefore he processed the gland seal regulator failure frame since this frame had the highest priority (L101, L102). Once the frame was brought into...
attention, he tried to match and evaluate the frame by interrogating the system about the information in the slots. This was a straightforward failure in which the gland seal steam pressure had to be low. So S31 checked this information with the system. However, the system responded that it was alright. Therefore he processed the third frame in the priority list — the condensate pump failure frame (L112, L113). This time instead of checking symptoms in the symptom slot, he followed the inference path in the inference slot (see Table 2) to reach an assertion that the condenser level must be high (L118, L119). So he checked it and found it was alright again. At this moment S31 was stuck and found no further symptoms to help continue the diagnosis.

After a slight pause, he seemed to pick up a frame that he thought was related but did not match the known symptoms well (L128). Here we could assume that he was applying the "pick a best-matched frame" heuristic. By using the information provided in the inference slot of the new frame (the 35# line system failure frame), he was able to make several qualitative inferences about the system changes quickly (L135, L136, L137). He checked the 35# steam dump regulator and found the solution.

Conclusions

A model for the fault diagnosis process has been presented based on the data from experiments and protocols. A conceptual entity called hypothesis frame was employed to account for the observations from data and protocols. Instead of reasoning from the dynamics and structure of the system, relevant information about a failure is "compiled-in" the frames. Therefore subjects could make quick and reliable inferences which would otherwise be impossible. Given symptoms of a failure, subjects would first try to match a frame from their repertoire of rules. Heuristics might be employed to make this matching process efficient. Once a frame was identified, subjects could use the information contained in the slots to make inferences or conduct evaluations. If more symptoms were found, subjects might use the new evidence to search for better hypotheses. If inferences drawn from frames are in conflict with known symptoms, these frames are discarded. The heavy indexing from frames to the system knowledge and symptom knowledge allowed the diagnostic process to start from related rules or subsystems if no new symptoms were found. Therefore, when no obvious frames could be processed, subjects could search in the system knowledge base for relevant information under the guidance of heuristics.

This model was applied to Failure 19 (S31). The results appeared to be reasonable. Although this model may be regarded as reasonable in organizing the observations of fault diagnosis performance from experiments and protocols, further refinements and testing are needed. Perhaps it can be employed to help training and aiding of fault diagnosis behavior or to develop intelligent diagnostic systems. Further examples and details of protocol analysis can be found in [13].

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References


HUMAN PROBLEM SOLVING IN DYNAMIC ENVIRONMENTS: STUDIES IN MARINE PROPULSION SYSTEMS AND PROCESS CONTROL

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INTRODUCTION

Background

This report summarizes the results of a four-year program of research on human problem solving in dynamic environments, with particular emphasis on marine propulsion systems and process control. To appreciate the importance of human problem solving in domains such as these, one need only review reports of inquiries into accidents in aviation [NTSB, 1973], process control [Parker, et al., 1974], and power production [Mason, 1979]. Human problem solving performance is usually found to be a central consideration in explaining accidents in complex, dynamic systems.

Of course, problem solving performance has been of keen interest to cognitive psychologists for at least three decades. More recently, researchers in cognitive science have begun to explore humans' understanding of various devices and simple systems. Thus, it would appear that psychology would have much to offer to those who design complex, dynamic systems.

However, there tends to be a "reality gap" between college sophomores attempting to explain how a thermostat works and a marine engineer trying to diagnose a failure, based on some subset of the several hundred gauges and indicators associated with his supertanker's propulsion system. Further, the marine engineer often has to keep the propulsion system running, and the ship moving, while failure diagnosis proceeds. Psychology has only recently been able to provide a modicum of assistance in understanding the performance of operators in complex, dynamic tasks such as supertankers, power and chemical plants, and aerospace systems. The purpose of the research summarized in this report was to advance the state of our knowledge in this area.

Many years of studying human performance in complex systems have led us to conclude that it is necessary to study trained personnel in realistic contexts. While complexity may have general characteristics, these characteristics only manifest themselves in specific contexts. Thus, we had to choose a particular context and we chose marine
engineering and, in particular, operation and maintenance of marine propulsion systems.

The Choice of Marine Engineering

There were three motivations for this choice. First, immediately prior to beginning this research, we had experienced a heavy dose of involvement in the maritime domain [Rouse and Reid, 1981; van Eekhout and Rouse, 1981; Rouse, 1982]. These experiences provided insights into the largely uncharted waters of human performance in marine engineering.

A second motivation for choosing marine propulsion systems was the fact that operation and maintenance of these systems often involves explicit tradeoffs between continued operations (e.g., "full speed ahead") and interruptions for maintenance. Our view is that managing this tradeoff is a central aspect of problem solving in dynamic environments. As noted earlier, psychology can provide little direct assistance in understanding how operators make these types of tradeoff.

The third motivation for choosing marine engineering was the availability of professional personnel to serve as subjects of study. Throughout the first three years of this research, Marine Safety International, Inc. (MSI) provided access to their instructional staff and trainees at their New York facility. More recently, the Naval Reserve Officer Training Corps (NROTC) unit at the Georgia Institute of Technology provided similar access. The use of the MSI and NROTC personnel is explained later in this report.

Overview

The summary of research results presented in this report is organized into three primary topics: modeling systems, modeling humans, and applications. The discussion of system modeling is concerned with the fidelity of simulation necessary to provide realistic task requirements to trainees or experimental subjects. The discussion of human modeling focuses on human problem solving performance relative to these task requirements. The
applications section deals with the use of system and human models to develop two intelligent "coaches" that provide online aiding and training. Evaluation of the impact of these coaches on human performance is also discussed.

Figure 1 represents a summary of the various components of this research program, as well as the relationships among these components. Several elements of this figure denote the primary products of this research:

1. Two substantial review reports were prepared, including one on simulator fidelity [Su, 1984] and another on mental models [Rouse and Morris, 1985, 1986].

2. Two simulators of marine propulsion systems were developed, including a low-fidelity simulator called FAIL [Govindaraj and Su, 1983; Su and Govindaraj, 1984, 1986; Su, 1985] and a moderate-fidelity simulator called Q-STEAM1 [Govindaraj, 1983, 1985, 1986].

3. A qualitative approximation methodology was developed [Govindaraj, 1986], with Q-STEAM1 being an example of how the methodology can be used.

4. Three models of human problem solving performance were developed, including two to explain performance using FAIL [Su, 1985; Su and Govindaraj, 1984, 1985, 1986; Govindaraj and Su, 1986] and another (KARL) to explain performance using the process control simulator PLANT [Knaeuper, 1983; Knaeuper and Rouse, 1983, 1985].

5. Two intelligent coaches were developed and evaluated, one involving KARL as an aid to using PLANT [Knaeuper and Morris, 1984] and another involving AHAB as an aid to learning to use PEQUOD, which is a version of Q-STEAM1 [Fath, et al., 1986; Fath, in progress].

These products, as well as the other elements of Figure 1, are explained in the sections that follow.

MODELING SYSTEMS AND TASK REQUIREMENTS

One of the original goals of this research was to study the effects of simulator fidelity on problem solving performance. Three levels of fidelity were planned: low, moderate, and high. The high-fidelity simulator was available at Marine Safety International (MSI) and included a complete control room, engine room, and simulated environment including noise, vibration, etc. The low and moderate fidelity simulators were developed in conjunction with
Figure 1. RELATIONSHIPS AMONG THE COMPONENTS OF THE RESEARCH PROGRAM
the research reported here, and are discussed in this section.

Our intention was to compare measures of performance, knowledge gained, and so on across the three types of simulator. This would enable an assessment of the effects of fidelity on performance. Unfortunately, this plan was undermined by two things. First, the high-fidelity simulator was fully operational much later than anticipated and, further, did not allow for a complete set of measurements as originally planned. Second, four years were required to develop the moderate-fidelity simulator, and it has only been fully available for the last several months. This delay was due, in part, to the unforeseen need to develop a simulation methodology prior to producing a specific simulator.

**Simulator Fidelity**

In the process of developing the low and moderate fidelity simulators, it was important to define precisely what "low" and "moderate" were to mean. This led to a general review of the topic of simulator fidelity [Su, 1984] and the conclusion that three dimensions of fidelity were important [Govindaraj, 1983; Govindaraj and Su, 1983]: physical, structural, and dynamic. Physical fidelity relates to the appearance of the simulator. Structural fidelity concerns the functional relationships embodied in the simulator. Dynamic fidelity concerns the response time of the simulator and the sequence of significant state changes. All three dimensions are, of course, referenced to the actual equipment system being simulated.

It was decided that the low fidelity simulator would have moderate structural fidelity and be low on the physical and dynamic dimensions. The moderate fidelity simulator was planned to be moderate on all dimensions. Finally, the high fidelity simulator at MSI would, by definition, be high on all dimensions.
Low-Fidelity Simulator (FAIL)

FAIL was an outgrowth of FAULT, a simulator developed by Hunt and Rouse for troubleshooting research [Rouse and Hunt, 1984]. FAULT represents an equipment system as a network of components, specified by connectivity and reachability matrices. Associated with each component are functional descriptions, logical descriptions (i.e., AND or OR), costs of various types of test, and the cost of replacement. The FAULT network, and associated information, is presented in a computer-based environment (e.g., APPLE II Plus) that enables the troubleshooter to make tests and replace components in an attempt to locate the source of the displayed symptoms.

While FAIL is based on the FAULT concept and also uses the Apple II Plus, it had to be modified considerably to enable simulation of the MSI propulsion system [Govindaraj and Su, 1983; Su and Govindaraj, 1984, 1986; Su, 1985]. The main reason for needing these changes was the requirement to simulate a propulsion system with several hundred gauges and indicators. This required an expansion of the FAULT action menu to provide access to "panels" for gauges, alarms, and indicators rather than actions associated with any particular display element. These panels in FAIL are organized in a manner that reflects MSI's simulator. Another addition was a "look" action to emulate going out to the engine room and, for example, checking for hot or vibrating pump motors. Of course, all of these changes required considerable analysis and knowledge engineering to complete the data bases that FAIL accesses.

It is important to note that one of the primary motivations for basing FAIL on FAULT was the fact that MSI has used FAULT for training since 1980. Thus, FAIL did not encounter any substantive instructor and trainee acceptance problems. Further, the MSI instructors were amenable and quite useful for validating the FAIL data bases via extensive pilot testing. The use of FAIL for a series of experiments is discussed in a later section of this report.
Moderate-Fidelity Simulator (Q-STEAM1)

As noted earlier, the purpose of the moderate-fidelity simulator was to provide a device of fidelity intermediate to FAIL and the MSI high-fidelity simulator. The fidelity was to be intermediate by providing increased levels of physical and dynamic fidelity relative to FAIL. We also hypothesized that a mixed quantitative/qualitative approach would be a useful way for trainees to transition from the sparse, qualitative environment of FAIL to the rich, quantitative MSI simulator.

Several approaches to developing the moderate-fidelity simulator were considered. Initially, we thought that we could just approximate the equations for MSI's simulator using various standard approximation methods. However, we soon discovered that MSI's simulator is not built upon equations derived from "first principles" in the way we thought. Instead, the simulator utilizes a great many look-up tables and function fits to assure that all the gauges, indicators, etc. display the correct values, but with little regard to the internal and unobservable dynamics of the system. We subsequently learned that many types of simulator work this way - - so much for academic approaches to simulation! The result was that there were no general equations available upon which to base approximations.

We also considered various approaches to qualitative modeling that have been developed in artificial intelligence and cognitive science. We quickly concluded that available methods were much too elementary and immature to be applied to the complex propulsion system of interest. This led to the development of the qualitative approximation methodology which, as indicated in Figure 1, was the means for producing Q-STEAM1.

The general approach involves a combination of control theoretic models and qualitative reasoning models [Govindaraj, 1983, 1985, 1986]. A system is described hierarchically in terms of unique subsystems, which are in turn composed of components, each of which is not necessarily unique to a single subsystem. Each component is described by one or more primitives, each of which has a structure and set of parameter values which can be adjusted to "tune" simulator behavior. The primitives currently in use include:
conduit, source, sink, source-sink, capacitor, heat exchanger, gain, controller, reactor, phase changer, and transducer.

The state of the system (e.g., temperatures, pressures, flows, etc.) are defined as perturbations from a nominal state. This enables the use of linear state equations. State changes which occur, for example, when failures occur are exponentially smoothed back to nominal as time progresses. All state updates and changes are performed quantitatively, but approximated qualitatively when displayed to the trainee or subject.

This qualitative approximation methodology was used to develop a simulator for the oil-fired steam propulsion system upon which MSI's simulator is based. This system involves approximately 100 components. It was modeled as having seven subsystems including: boiler, condensate, steam, fuel oil, gland seal, lube oil, and control air. Eight flow loops were modeled including: fuel oil, feedwater, steam, lube oil, air, gas, saltwater, and control air. The resulting simulator (Q-STEAM1) runs on a Xerox 1100 series LISP machine. The trainee/subject interacts with Q-STEAM1 via a direct manipulation interface that is similar in spirit to that of STEAMER [Hollan, et al., 1984, 1987].

MODELING HUMANS AND TASK PERFORMANCE

When we began the program of research reported here, we had just completed a six-year study of human problem solving performance in troubleshooting tasks [Rouse and Hunt, 1984]. This effort produced a series of models of human problem solving, culminating in a fuzzy rule-based model that represented troubleshooting actions as choices from fuzzy sets of rules [Rouse and Hunt, 1981; Hunt and Rouse, 1984]. Drawing on Jens Rasmussen's work on troubleshooting strategies [Rasmussen, 1974, 1981], the rules were organized into two classes: S-rules and T-rules (see Figure 1). S-rules are context-specific rules for mapping symptoms to hypothesized failures. In contrast, T-rules are context-free rules for searching the topography of the system of interest. In general, it was found that troubleshooting use S-rules if they can, and T-rules only if necessary. In other words, context-specific mappings
dominate context-free searching, probably because such mappings involve much less effort.

Following these studies of troubleshooting, a series of studies in dynamic environments such as flight management, ship control, and process control led us to propose a model for human problem solving in dynamic environments [Rouse, 1983]. This rule-based model also included the distinction between symptomatic and topographic strategies. This was accomplished by including state-oriented and structure-oriented rules for the three general tasks involved in detection, diagnosis, and compensation for system failures - recognition and classification, planning and commitment, and execution and monitoring. It was hypothesized that this three level organization would allow representation of the aforementioned central tradeoff when problems arise in dynamic environments, namely, continued operation in spite of problems versus reduced operation in order to resolve problems. As the research summarized here began, this three-level model (see Figure 1) had yet to be tested.

Troubleshooting Marine Propulsion Systems

In conjunction with his Ph.D. thesis, Dave Su used FAIL to study the troubleshooting performance of the marine engineers attending training courses at MSI [Su, 1985]. His first set of studies involved 28 marine engineers, with 10 to 20 years of experience. After each engineer had practiced with FAULT, which is a normal portion of MSI's course, they each solved 21 problems using FAIL. Each action that they took was recorded in a data file for later analyses.

Analysis of these data identified two distinct stages of troubleshooting: 1) hypothesis formation and, 2) hypothesis evaluation (see Figure 1). Hypothesis formation involves studying the symptoms presented by FAIL and forming an initial feasible set (IFS). Two hypothesis evaluation strategies were identified: 1) breadth-depth (BD) and, 2) balanced (BL). The BD strategy involves forming several hypotheses and then switching to in-depth evaluation of each hypothesis. The BL strategy is characterized by quickly switching from
hypothesis formation to hypothesis evaluation, and then broadly evaluating many hypotheses.

Several rules were developed for classifying a troubleshooter's IFS as good or bad, as well as for classifying the evaluation strategy employed as BD or BL. It was found that good troubleshooting performance was most often associated with good IFS and the BD strategy [Su, 1985; Su and Govindaraj, 1984, 1986]. One of the goals of Janet Fath's Ph.D. research, which is discussed in a later section, involves training marine engineers to develop good feasible sets.

Subsequent to the above studies, verbal protocols were collected at MSI to perform a much finer-grained analysis of troubleshooting performance. The goal of this effort was to model the formation of troubleshooting-related knowledge and the mechanisms underlying the action choices studied earlier. The analysis of these protocols lead to the following characterization of the diagnostic process:

1. Two types of knowledge are involved; symptom knowledge and hierarchically-organized system knowledge.
2. Diagnosis proceeds hierarchically.
3. Both forward and backward reasoning are involved.
4. Symbolic descriptions of quantities are stated in qualitative terms.
5. Knowledge appears to be chunked.

This characterization led to the development of a concept called hypothesis frames (see Figure 1). Frames include slots for symptoms, components, inferences, and flows. Evaluating a frame involves comparing the slots to available information from the system. Frames are invoked by rules that operate on symptoms. In the event that such rules are unsuccessful in identifying a frame, heuristics tend to be used such as physical closeness of hypotheses and symptoms, or choosing frames that are good but not perfect matches [Su, 1985; Su and Govindaraj, 1985; Govindaraj and Su, 1986].
The notion of hypotheses frames is quite powerful in that offers a possible explanation for how experienced troubleshooters can avoid explicit reasoning based on the dynamics and structure of the system, and instead retrieve relevant information that is "compiled" in the frames. Of course, at this point the hypothesis frames concept is simply a post-hoc description of a single set of data -- substantial experimentation will be needed to evaluate the validity and robustness of the concept. Nevertheless, it appears quite promising.

Problem Solving in Process Control

As her M.S. thesis, Annette Knaeuper developed a version of the three-level model of human problem solving and compared it to human problem solving performance in a process control task called PLANT. This task was used because Q-STEAM1 was not yet available and, equally important, an extensive data base existed for human performance using PLANT [Morris and Rouse, 1985].

PLANT was developed as a dynamic derivative of a troubleshooting simulator called TASK [Rouse and Hunt, 1984]. PLANT is a computer-generated network of tanks connected by pumps, valves, and pipes [Morris, et al., 1985]. Fluid enters from the left of the network at a constant rate and exits from the right of the network at a constant rate. These input and output rates can be set independently by the operator.

The operator's goal is to process as much fluid as possible through the network. This requires that all valves be kept open and all pumps running. However, random failures of valves and pumps tend to complicate this goal, particularly because these failures introduce transients that can lead to oscillations in the network. These oscillations can lead to excess levels and flows which will cause the automatic safety system to trip (i.e., close) valves and pumps to protect the system. Such trips, of course, lead to decreased production. As a result, the operator will try to diagnose and repair failures as quickly as possible. Thus, as emphasized earlier, problem solving in dynamic environments presents the central tradeoff of production versus maintenance.
The resulting rule-based model of problem solving with PLANT was called KARL [Knaeuper, 1983; Knaeuper and Rouse, 1983, 1985]. KARL's knowledge bases were organized according to the classification, planning, and execution levels of performance proposed earlier [Rouse, 1983]. The knowledge bases were also organized according to task dimensions of failure diagnosis, transition, tuning, and procedure execution. The knowledge bases were developed from the PLANT procedures drawn from previous task analyses (see Figure 1), as well as rules gleaned from expert operators of PLANT.

Beyond the structure dictated by the earlier modeling efforts, KARL also involved an important additional mechanism. Early experiences with KARL indicated that each update of PLANT state was faced as if it was a new problem -- KARL did not have a sense of what had been going on, as well as no expectations of what was likely to happen. This observation led us to provide KARL with an "internal model" of the dynamics and structure of PLANT. In this way, KARL formed expectations and, if the new state of PLANT did not differ substantially from these expectations, KARL assumed that no strategy changes were necessary. Without such expectations, KARL continually "re-thought" everything.

The performance of a Pascal version of KARL (which was later redesigned for LISP) was compared to Morris' data on the performance of 32 engineering students using PLANT [Morris and Rouse, 1985]. KARL was found to achieve roughly the same production as the average subject, while being a bit better in terms of stability. On an action-by-action basis, KARL and subjects agreed over 60% of the time. The majority of the mismatches were due to subjects not following instructions (which KARL faithfully followed), despite the fact that subjects had shown on a written test that they fully understood and could utilize these instructions. This result led to the notion of aiding subjects to follow procedures which is discussed later in this report.

In Search of Mental Models

At several points in earlier sections of this report, the concept of internal models or
mental models was noted. Dave Su's hypothesis frames and Annette Knaeuper's approach to providing KARL with expectations are two particularly salient examples. In general, the area of mental models continues to be a "hot topic" within cognitive science [Gentner and Stevens, 1983; Johnson-Laird, 1983].

The multi-disciplinary nature of our research group led to much discussion and debate on this topic, ranging from psychological validity to computational feasibility. As a result, we decided to review how different disciplines, ranging from psychology to engineering to architecture, conceptualize and utilize the mental models construct. The resulting product was a comprehensive review of the literature, as well a few new hypotheses and conjectures [Rouse and Morris, 1985, 1986].

In attempting to distinguish differences among disciplines' views of mental models, a two-dimensional characterization of different domains was developed. One dimension was the nature of mental model manipulation, ranging from implicit to explicit. The other dimension was the level of behavioral discretion, ranging from none to full. These two dimensions provide a rather clear explanation of, for example, why neuroscientists and policy analysts conceptualize mental models differently. The location of any particular domain within this two-dimensional space also has direct implications for appropriate choices of model identification methods.

This review also summarized the state of knowledge concerning issues such as model accessibility, forms and content of representation, the nature of expertise, cue utilization, and instructional issues. Instructional issues were given particular attention, including the impact on mental models of knowledge of theories and principles of system operation, the importance of guidance and cueing in the use of instructional information, and the effects of prior knowledge on biases and misperceptions within mental models.

This effort also resulted in several hypotheses and/or conjectures concerning fundamental limits in identifying mental models. One class of these limits concerns the inevitable biases that investigators bring to their research. Another class of limits relates to
statistical, logical, computational, and physical limits such as embodied in the uncertainty principle in physics. We are still actively pursuing the topic of fundamental limits in identifying mental models.

APPLICATIONS TO INTELLIGENT COACHING

The models of human problem solving discussed in the previous section are valuable for organizing one's thinking, computationally assessing the implications of hypotheses, and succinctly compiling experimental results [Rouse, 1980]. Beyond these uses of models in behavioral science research, these types of models also have very practical utility as online components for training and aiding. This notion is far from novel, as evidenced by the intelligent tutors discussed in Sleeman and Brown [1982] and several long-term efforts summarized in Volume 3 of Advances in Man-Machine Systems Research [Rouse, 1987]. However, there have been few, if any, robust applications of this idea in dynamic environments - - this section discusses two applications of this type.

We have chosen the intelligent "coaching," rather than tutoring, aiding, decision support, etc., to avoid limiting the concept to either training or aiding applications. In fact, it seems quite reasonable to claim that the intelligent coaching concept can be a basis for training and aiding in dynamic environments. The applications discussed in this section serve to illustrate this point.

KARL as a Coach for Process Control

As noted earlier, the comparison of KARL's performance with that of operators controlling PLANT led to the conclusion that the primary source of disagreement between the action choices of KARL and operators was that KARL closely followed PLANT procedures while operators did not adhere to the procedures to the same extent. Interestingly, a written test of operators' understanding of procedures indicated that they did know when and how to use them. This, obviously, leads to the question of why operators
chose to ignore their instructions, and how could they be coached so as to better utilize this information?

While this question subsequently received considerable attention [Mann and Hammer, 1986], our analysis initially focused on how KARL might prompt better use of procedures which, as indicated in Figure 1, were important components of KARL's knowledge base. We hypothesized three reasons why procedures might not be followed:

1. Operators might not realize that particular procedures apply in the current situation.
2. Operators may not realize that they are not following the applicable procedures.
3. Operators may abandon (or not even invoke) procedures if they do not perceive the situation as improving because of their using the procedures.

To support operators to overcome these potential problems, a coach called KARLAID was developed with the overall structure shown in Figure 2. KARL monitored the state of PLANT and chose, but did not implement, actions in the way described earlier. It is important to note that Karl's choices would tend to be the same as the operators with the possible exception of procedural compliance. Thus, KARL did not attempt to impose an "optimal" strategy, but tried to coach a human-like strategy.

KARLAID provided three types of coaching. First, situation assessment support was provided by displaying to operators the procedures that were currently applicable. KARLAID then compared KARL's hypothetical actions with operators' actual actions and provided performance monitoring by indicating whether or not operators' choices were consistent with the applicable procedures. Finally, KARLAID provided performance feedback that indicated whether PLANT stability was degrading, unchanged, or improving.

The design of the KARLAID interface, shown in Figure 2, proved to be an interesting challenge. Two particular problems were not initially envisioned. First, "chattering" could easily occur when the PLANT state was on the borderline between the entry conditions for two procedures. As a result, KARLAID might recommend procedure A, then shortly later
Figure 2. Architecture of KARLAID
B, and shortly later A again. Operators definitely did not like this.

Another problem was "nagging" where KARLAID would indicate that an operator's choice of action was inconsistent, but the operator chose to ignore this advice. In our initial version, KARLAID would continue to point out this problem rather than accept that the operator disagreed. This behavior was also not liked by operators.

The problems of chattering, nagging, and related behaviors were solved by putting "hysteresis" in the interface. Thus, KARLAID would not reverse recommendations in any short period of time and would accept operators' choices of actions without continual prompting, although KARLAID might eventually remind operators of poor choices if the impact of those choices lingered. These changes allowed us to proceed, but certainly do not represent a thorough analysis of the intelligent interface problem.

An experimental evaluation of KARLAID was performed [Knaeuper and Morris, 1984] by adding a fifth group to Morris' original experimental design for studying operators' performance with PLANT [Morris and Rouse, 1985]. By using subjects from the same population and the same experimental procedures, we were able to use Morris' data as the baseline. The results of this study were:

1. Use of KARLAID did not result in more PLANT production, but did lead to improved PLANT stability.
2. Operators who used KARLAID scored higher on a written test of system knowledge (i.e., principles as opposed to procedures), despite the fact that KARLAID was not designed to impart this type of knowledge.
3. Use of KARLAID was associated with substantially improved abilities of operators to diagnose unfamiliar failures, despite the fact that KARL could not diagnose these failures.

The first result was as we expected since procedural compliance in PLANT was known to have a greater impact on stability than production. The second and third results were unexpected and could be viewed as anomalous. Alternatively, we could conclude (and have) that operators may gain knowledge and abilities from interacting with a coach that go
beyond the explicit purpose and abilities of the coach. Recent studies in other domains support this hypothesis [Resnick and Mitchell, 1986; Zinser, 1986]. However, these indirect and subtle impacts of intelligent coaches need much more study before we can claim that they are predictable phenomena.

AHAB as a Coach for Marine Propulsion Systems

In conjunction with her Ph.D. thesis, Janet Fath is developing and evaluating an online coach for use with Q-STEAM1 [Fath and Rouse, 1985; Fath, et al., 1986; Fath, in progress]. She is using a simplified version of Q-STEAM1 called PEQUOD - - the online coach is called AHAB. The overall architecture of AHAB is shown in Figure 3. The primary components are the task model, the student model, and instructional strategies.

The task model for AHAB is roughly comparable to the operating procedures for PLANT as embodied in KARL. The task model was developed using the discrete control modeling methodology [Miller, 1985]. The model, therefore, includes a network representation of how an operator should troubleshoot PEQUOD, along with state transition functions that specify the conditions under which troubleshooting should transition between nodes in the network [Fath, et al., 1986].

The student model has the same structure as the task model, but allows for partial knowledge and the possibility of errors. The acquisition of knowledge (i.e., learning concepts and meta-concepts), as well as the importance of errors, is represented by a simple "strength" measure that counts the number of times that successful performance, which depends on particular knowledge elements, has occurred. Similarly, the strength of a particular error is represented by the number of times that error has occurred without subsequent successful performance.

The knowledge being taught includes concepts and meta-concepts. Concepts relate to Rasmussen's symptomatic and topographic strategies which, as shown in Figure 1, have been central to much of our work in human problem solving. Concepts associated with the
Figure 3. Architecture of AHAB
symptomatic strategy are types of system failures related to the generation, use, and condensation of steam in PEQUOD. Concepts associated with the topographic strategy have to do with the principles of conservation of mass and energy, as they may be used to identify blockages, leaks, and heating problems. Meta-concepts deal with the coordination of the symptomatic and topographic strategies in a problem-solving effort.

The instructional strategies include tutoring, which can occur both during and upon completion of a problem (i.e., diagnosis of a failure). Instruction also includes drill and practice which does not occur during problem solving and mainly involves context-specific question and answer methods. In general, AHAB assumes that operators are experienced with marine propulsion systems, but need coaching in problem solving.

At this point in time, a pilot test has been successfully completed using four NROTC instructors to solve problems using PEQUOD. This served to assure that the problems which NROTC students will experience with AHAB will be reasonable and within the scope of their previous training and experience. AHAB is soon to be pilot tested, again using NROTC instructors. A formal transfer of training experiment will occur within the next few months, involving two groups of ten NROTC students. Each student will have had classroom instruction in marine propulsion systems as well as at least one summer of shipboard experience. The goal of the experiment will be to assess the impact of AHAB's coaching abilities on end-of-training deviations between the task model and student model.

AHAB is envisioned as eventually being applicable in an operational shipboard environment, where it can serve as a coach for both training and aiding. While the current experiment will not assess the viability of AHAB functioning in this way, the results of this experiment should provide important insights that will influence such an eventual application.
CONCLUSIONS

The four-year program of research summarized in this report has produced many types of product. As shown in Figure 1, several reviews, simulators, methodologies, models and coaches have resulted. We hope that these products have significantly contributed to understanding of human problem solving in dynamic environments. However, as is common in such research programs, many new questions have arisen regarding qualitative simulation, identification of mental models, and intelligent coaching. We are enthusiastically working on these new problems, in hope that further contributions to understanding will be forthcoming.

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REFERENCES


