Design and Development of an Intelligent Simulation Training System for Process Control Operators

Richard K. Lowe* & Thomas E. Nielsen
(Curtin University; CBT Simulation Technology Pty. Ltd.)
Australia

Introduction

This paper reports the development of a knowledge-based simulation system for training process control operators. The project utilises cognitive tutoring principles that are implemented by way of a research-based model of expert performance in the content domain. A number of complementary learning modules are used to support trainees' construction of a mental model of the fundamental control loops underlying effective process control operation. The staged simulation environment is designed to expose learners to the special challenges of dealing with a dynamic problem solving situation while at the same time carefully limiting the cognitive demands imposed. To appreciate the purpose of the process control training system reported in this paper, it is necessary to understand the type of setting for which it is designed. We will introduce the concept of process control by considering the example of an electric power plant. This example allows us to illustrate a typical setting and to characterise the performance demands faced by process control operators.

Process Control: An Example

Ensuring a continuous and well-regulated supply of electrical power to consumers 24 hours each day requires that the process of power generation is maintained within strict limits. In a steam-driven electric power plant, the generators that produce electricity are turned by pressurised steam flowing from jets onto turbine blades attached to the generators. To keep this type of power plant operating safely and properly, there needs to be careful control of:

- the *temperature* of the steam supplied to the turbines,
- the *flow* of steam leaving the jets that turns the turbines,
- the *pressure* of the steam as it leaves the jets,
- the *level* of water in the tanks supplying the steam boilers.

In modern power plants, these four *process variables* of temperature, flow, pressure and level are monitored continuously by electronic sensors installed at relevant parts of the plant. This sensing equipment is complemented by a range of electronically operated control devices which automatically perform functions such as changing the temperature, regulating the flow, varying the pressure and maintaining the water level. For each critical function, there are also alarms that will be triggered automatically when any one of the process variables goes outside its permitted range of values.

Information gained from the monitoring of process variables by means of electronic sensors distributed around the power plant is fed back to the central control room. The operator in the control room views this status information which is displayed diagrammatically on computer screens. Alarm information is displayed in a similar way. Further, the control room operator can remotely adjust settings on the various control devices that alter the process variables out in the plant. The operator may take manual control to exert faster control or to override an alarm. This procedure of adjusting settings in response to monitoring and alarm information is carried out via dynamic interaction with the displayed graphic information. The type of control system described here is known as a *Distributed Control System* (DCS) because an operator working in the single location of the central control room is able to exercise control over many individual aspects of the process that are in reality widely distributed throughout the plant.

Although the above example used a power generation process to illustrate the concept of a distributed control system, such systems are widespread across a diverse range of industries. These include oil and gas, mining, manufacturing and various utilities. Despite the dissimilarity of these various enterprises in terms of the outputs they produce and the specific details of the processes they use, the underlying DCS approach remains very similar from industry to industry. It always involves monitoring process variables and carrying out adjustments in response to information depicted on a dynamic computer display. For this reason, the skills required to be a DCS operator can be considered as highly generic.

Overview of Process Control Training System (PCO_CBT)

The PCO_CBT training system was developed as a interactive simulation for delivery via personal computer in either stand-alone format or as a hands-on supplement to an instructor-led course. It was designed to develop generic skills in process control, rather than focusing on developing the specific skills needed for a particular industry. The training addresses four basic control loops that operators must typically master (temperature, flow, pressure and level). These are treated by means of interactive simulations that give trainees experience of working in a simplified process control environment in which the cognitive load is carefully limited to a manageable level while retaining the essential dynamic problem-solving approach required for such operations.

The main modules comprising the training are Introduction, Preliminary Training, Job Oriented Simulation Training, and Reference. Figure 1 shows that the instructional environment resembles the sort of control room context which a trainee might encounter if being given more conventional one-to-one training by an experienced process control operator. This control room display serves as a 'home' for the system and the basis of all activity. Secure navigational support is provided by requiring the trainer to travel between modules by way of this control room home panel. Note that trainees work from 'job cards' which specify the overall task to be completed (as would be used in a real plant). They are also given relevant information via an alarm panel (shown on left of the display) and guidance or feedback via a 'mentor'.

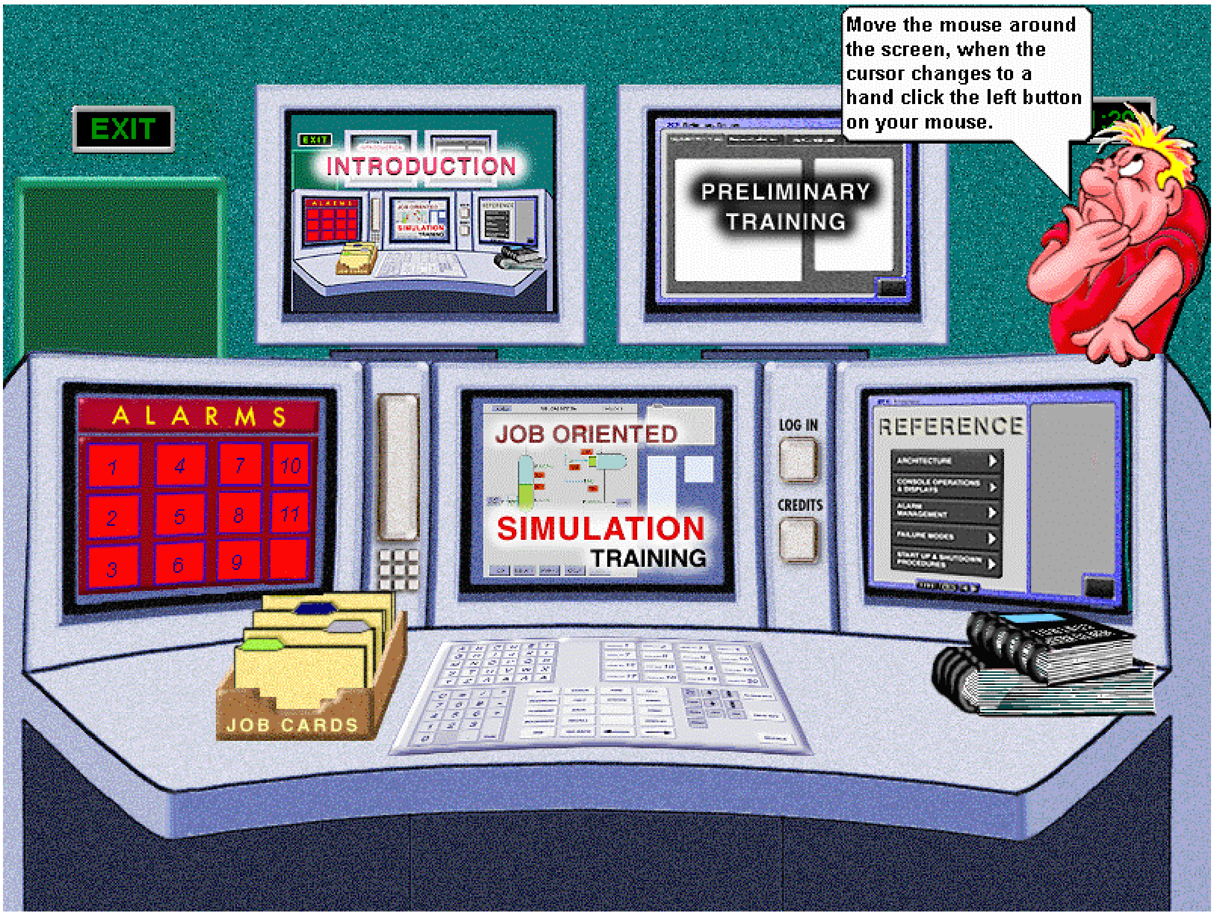

Figure 1. Control room display ('home') showing module entry points, job cards and mentor

The approach used in the Job Oriented Simulation Training emulates the usual training situation in which inexperienced operators are trained by attempting to perform actual control tasks under the supervision of an experienced mentor. During training, the trainee's knowledge and capacities are engaged and developed from the outset when they choose a job to do or an error condition to correct. The different jobs or error conditions trainees can choose range across various types of process variables and levels of complexity. For example, a job may require the trainee to modify or adjust a temperature or pressure to maintain production targets while staying within agreed safety boundaries. From the outset, the trainee interacts with the simulated process control system and is helped to learn appropriate responses to changing operational conditions in a dynamic and time-driven environment. Individual jobs in the simulation have been broken down into a number of key tasks (sub-procedures). Various alarm conditions and fault scenarios require the application of these tasks to correct the error condition. Figure 2 shows a typical display presented to the trainee during the Job Oriented Simulation Training. The learner's task is to interpret the abstract representation of the control loops depicted (left hand side of the display), read the information provided in the faceplates (bottom right) and monitor the trend data as adjustments are made (top right).

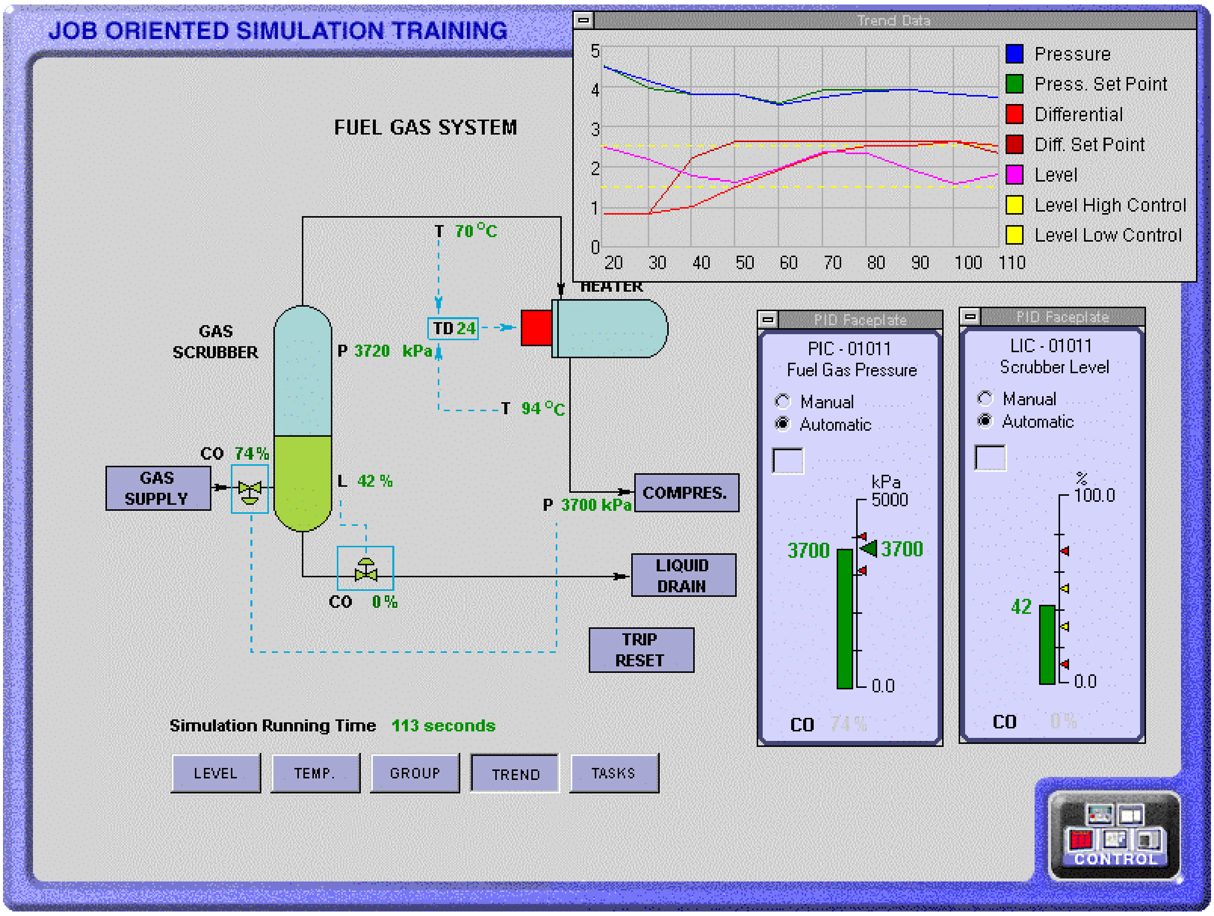

Figure 2. Job Oriented Simulation Training display showing loops, faceplates and trend data.

Expert advice and feedback is provided by way of an on-screen mentor (paralleling the situation that might exist with a supervisor in real life). Involvement of the mentor has been carefully designed to be context-sensitive so as to maximise correction of errors at the point of need while minimising possible disruptive effects. The mentor functions by having the knowledge of an expert process control operator encapsulated in "if-then" rules. For example, if a condition exists where an alarm is about to go off, the user is prompted via the expert rules to correct the situation by taking appropriate actions. Because the learner's interactions with the system are continually monitored in this fashion, guidance is both timely and relevant. This highly contextualised linking of conditions and actions is designed to provide opportunities for trainees to develop appropriate and properly situated mental models of problem solving in a dynamic process control environment.

Process Control as a Dynamic Task

Process control operators, such as those working within DCS contexts, perform their duties in a highly dynamic task environment (Decourtis, 1993; Wallach, 1995). As with other dynamic tasks such as driving a motor car (Aasman, 1995; Donges, 1978) or controlling air-traffic (Lee, Anderson & Matessa, 1995), process control requires operators to respond in real-time to a continually changing set of task conditions. Many of these changes in the nature of the task are due to alterations in process variables that occur independently of the operator or that are beyond the operator's immediate control.

With fresh information continually being presented as the DCS screen is updated, the operator who is monitoring the state of process variables via the display is required to interpret on-going changes and respond appropriately. In effect, the operator is faced with a labile problem solving situation in which the givens of the problem and the nature of the solutions can vary from moment to moment. As each new set of conditions arises, the operator is placed in a fresh problem-solving context and must make decisions then take actions within a very limited time frame.

Rather than simply being fixed problems that can be dealt with by making a finite set of choices, dynamic tasks can be considered to be control problems (Brehmer & Allard, 1987). As such, these tasks are qualitatively different from the static problem solving situations that have been extensively studied by cognitive psychologists in recent years. For example, in domains such as physics (Chi, Glaser & Rees, 1982) and computer programming (Davies, 1994), the nature of the overall problem is defined at the outset and does not change. A satisfactory outcome can be obtained if an appropriate set of steps is followed through to the solution. However, this is clearly not the case with process control.

The immediacy of the task demands in process control are such that there can be little or no time for deliberation on the part of the operator. As with driving a motor vehicle, skilled performance needs to be a largely automatic process that involves significant unconscious control of behaviour. The time imperative for continuous interactive adjustment to the system does not allow for lengthy decision-making processes or extensive introspection. Nevertheless, process control cannot be carried out effectively in a purely intuitive manner. The choices of actions made by a skilled operator in the control room from moment to moment must ultimately be related to their likely physical consequences within the plant itself. This suggests that skilled process control involves the operator constructing some type of mental representation of the situation depicted on the DCS displays and basing decision-making on that representation.

Further complicating factors involved in the learning of dynamic tasks such as process control arise from the inherent unpredictability of the situation the learner is dealing with. This means that it is typically impossible to do a look-ahead search, or to carry out extensive backtracking due to uncontrolled changes in the task environment. In addition, there are temporal characteristics of a dynamic skill that need to be considered, such as the time taken for changes to occur in the process environment and the time taken to complete tasks within the operating environment (see Brehmer, 1990). To perform process control effectively, the operator must take proper account of these temporal aspects. Trainee operators therefore need to be given the opportunity of learning to handle these aspects during their instruction. These additional demands all increase the complexity of the task for which operators must be trained.

Expertise in DCS Operations

As with performance in other complex problem solving domains (e.g. Lowe, 1993), some aspects of the skills involved in process control are largely implicit and therefore unlikely to be revealed during an expert's explicit explanation. However, carefully designed investigations have allowed researchers to infer many of the underlying cognitive structures and mental activities that underpin expert performance. The expertise exhibited by skilled operators in many fields is associated with their possession of extensive stores of domain-specific knowledge. Part of this stored knowledge consists of the more fact-like, inert knowledge that is available for explicit recall (*declarative knowledge*). However, of particular interest to process-oriented expertise (such as skilled DSC operation) is the *procedural knowledge* that concerns the sequences of actions to be performed in order to carry out a process successfully.

Expertise in DCS operation has been studied by Nielsen and Kirsner (1994) and characterised in terms of its proactive nature (a response to the complex dynamic environment involved). From these investigations, a computer model has been developed which represents such expertise in terms of production rules ("if-then" condition-action combinations) and follows on from the extensive work of Anderson (1993a) on this form of knowledge characterisation. This external modelling of DCS expertise has led to a proposal that skilled DCS operators may possess knowledge structures that allow them to model process control functions in a fashion somewhat analogous to the operation of the computer model. According to this proposal, these knowledge structures would include the mental equivalent of production rules and be the basis on which expert DCS operators constructed their highly flexible mental models of the system's behaviour.

It is important to note that although we may ultimately be speaking of implicit procedural knowledge when the operator reaches the stage of fluent, automatic performance, it is not sufficient to rely on a purely procedural approach during training. Such reliance would simply lead to the development of a set of low-level conditioned routines rather than the higher-level flexibility that characterises expert performance. In the initial stages, the trainee passes through a phase in which appropriate knowledge is dealt with in explicit, declarative form. However, the training must also provide opportunities for adequate practice in sufficiently authentic situations to enable the trainee to develop the necessary automaticity.

The main function of the DCS training system discussed in this paper is seen as being to help trainee process control operators develop the capacity to build suitable mental models of the situations they were required to handle. A similar approach has recently been used with some success to improve trainee meteorologists' capacities to make weather map predictions (Lowe, 1995). A fundamental requirement for designing instruction based upon such approaches is for the design team to have a clear, explicit conception of the knowledge structures that underlie the model-building capacities of expert performers in the domain. However, this conceptualisation on its own deals only with the nature of the desired outcome of instruction. It does not give any guidance about what instructional processes are likely to be effective in promoting that outcome. We also need to consider the way in which characteristics of the learning situation itself may interact with the development of expertise.

Challenges for Training: Developing Expertise in Process Control

One approach to training DCS operators might be to use a straightforward simulation that closely resembles the actual situations which such operators would typically be expected to encounter. However, it can be seen from the discussion in earlier parts of this paper that this approach may be ineffective due to the undesirably high cognitive processing demands it would make on the learner (see also Sweller, 1993). Faced with a conventional simulation of this type, the learner's response is likely to be primarily one of survival. That is, the actions taken would be a result of the learner's attempts to cope with the immediate exigencies of the situation, rather than efforts directed towards the building of an expert-like knowledge representation.

Coping strategies such as the focusing of processing resources on some aspects of a task while paying less attention to other aspects are often adopted in situations of high task demand. This type of cognitive load-shedding would be a possibility if multimedia-based training in process control was to rely upon high demand real-time problem solving tasks. Sweller (1988) has suggested that the cognitively-demanding nature of problem solving activity itself may mean that it is not the most efficient way to acquire expert knowledge representations.

The specific results from studies of process control operators in a German power plant (Wallach, 1995; Wallach & Tach, 1994) appear to be consistent with the general concerns about cognitive load expressed by Sweller. Wallach has speculated that subjects who were given the dual tasks of learning and controlling the process achieved relatively poor results because of the effects of cognitive overload. If this was the case, it may be that DCS instruction would be more effective if, rather than being asked to cope with the demands of a full-blown control situation, learners were presented with a considerably scaled-down level of control demands. However, it would be important that the way in which the control demands were scaled down still required the operator to switch between the dual roles of (a) passively *supervising* an automated process and (b) actively *manipulating* process control variables in a direct fashion (see Reinartz & Reinartz, 1989).

This requirement is highlighted by the observations of Bainbridge (1987) who associated the increasing automation of processes with a decrease in the capacity of operators to intervene and take control. Such deficiencies in operator performance can be particularly pronounced at times when unexpected problems arise or significant increases in cognitive load are involved. Clearly a critical aspect of effective process control operator training would be that the learner is helped to develop the operational flexibility that is so fundamental to this complex job. This would be necessary both to equip operators with an appropriate set of skills and to facilitate transfer of those skills from the training situation to the context of everyday on-the-job performance.

Approach to Instructional Design

At the heart of the instructional design of the DCS training materials described in this paper is a knowledge-based system that models the performance of an expert process control operator. While in certain respects some its features resemble those of traditional simulation training, it goes beyond the preoccupation with surface fidelity that characterises most such approaches. This is partly because it deals with an abstracted working environment in which the reality of the equipment out in the plant is replaced by highly simplified two-dimensional symbolic representations. However, it is also because of the incorporation of an explicit model of process control performance. In contrast to many other model-based approaches, this system does not attempt to model the cognitive processes of the trainee but rather is derived from cognitive modelling of expert performers. As a consequence, its function is to act as a powerful resource for monitoring trainee actions while providing context-sensitive feedback to guide the learning process in an efficient manner.

With respect to the practical design of intelligent tutoring systems, Anderson (1993a, 1993b) has enunciated general principles intended to support the implementation of cognitive engineering approaches in computer-based instruction. These principles can have implications for design decisions taken at the micro level (computer programming of the rule base) or the macro level (development of practical instructional strategies). The following list summarises these principles:

1. Represent student competence as a production set.
   (The skill is decomposed into an accurate model).
2. Communicate the goal structure underlying the problem solving.
   (To be done through the interface as much as possible).

3. Provide instruction in the problem solving context.
   (Instruction is provided as each new set of production rules is introduced).
4. Promote an abstract understanding of the problem solving knowledge.
   (The conditions of the rules are sufficiently general to do this).
5. Minimise working memory load.
   (Do not present instruction while problem solving).
6. Provide immediate feedback on errors.
   (Cut down on time in error state).
7. Adjust the grain size of instruction with learning.
   (The grain size to reflect larger chunks built during problem solving).
8. Facilitate successive approximations to the target skill.
   (The tutor fills in some steps during early stages).

Wherever possible, the design of the present project was carried out in accordance with these principles. In some cases (such as point 1), the principles are concerned with the characterisation of the knowledge structures that underlie the desired performance outcomes. In others (such as point 5), the principles address the demands of the instructional situation by considering ways in which the learning which ultimately leads to the performance outcomes can be facilitated. For the design situation described here, strict adherence to Anderson's principles was not always possible and sometimes not even desirable because of the special nature of expertise in process control (including its dynamic character and the need to support construction of a coherent mental model). For example although representation of student competence as a production set certainly became the core of the design, it proved to be impractical to build in meaningful computer-based adjustments of the grain size of instruction with learning.

Conclusion

Instructional design typically involves some degree of optimisation in which competing demands arising from the nature of the content and the characteristics of learners must be reconciled. For the DCS operator training discussed in this paper, this reconcilation process was particularly challenging because of the complexity of the task involved, its dynamic character, and the abstract way in the information involved is represented. The learner is dealing with what could be thought of as a moving target. However, developing the capacity to deal with this target effectively relies on a the construction of knowledge structures that will permit the learner to generate and modify mental models of the depicted remote situation in order to take appropriate action.

A major challenge to the developer of instruction in this area is the lack of a comprehensive theoretical framework to guide design activities. In the project reported here, although we have taken a strongly theory-driven approach to the design of the instruction, it has been necessary to be quite eclectic in our approach. It may be that this is unavoidable in a domain such as DCS but the absence of coherent, principled approaches to guide the design of instruction for dynamic environments in general is a matter of some concern. In our future development of DCS operator training, we will be exploring possible approaches and design methodologies that can be used in this demanding area.

References

Aasman, J. (1995). *Modelling driver behaviour in SOAR*. Unpublished doctoral dissertation, Royal PTT, Netherlands.

Anderson, J. (1993a). *Rules of the mind*. Hillsdale, NJ: Erlbaum.

Anderson, John. (1993b). *Cognitive tutors: Lessons learned*. Hillsdale, NJ: Erlbaum.

Bainbridge, L. (1987). *Ironies of automation*. In. J. Rasmussen, K. Duncan, & J. Leplat (Eds.), New technology and human error (pp. 271-283). Chichester, UK: John Wiley & Sons.

Brehmer, B. (1990). Strategies in real-time dynamic decision making. In R. Hogarth (Ed.), *Insights into decision making* (pp. 262-279). Chicago: University of Chicago Press.

Brehmer, B., & Allard, R. (1987). Learning to control a dynamic task. In E. De Corte, H. Lodewijks, & R. Parmentier (Eds.), *Learning & instruction: European research in an international context* (pp. 275-284). Oxford, UK: Pergamon Press..

Chi, M.T.H., Glaser, R., & Rees, E. (1982). Expertise in problem solving. In R.J. Sternberg.(Ed.), *Advances in the psychology of human intelligence* (pp. 7-75). Hillsdale, NJ: Erlbaum.

Davies, S. P. (1994). Knowledge restructuring and the acquisition of programming expertise. *International Journal of Human-Computer Studies*. *40*, 703-726.

Decortis, F. (1993). Operator strategies in a dynamic environment in relation to an operator model. *Ergonomics*. *36*, 1291-1304.

Donges, E. (1978). A two-level model of driver steering behaviour. *Human Factors*. *20*, 691-707.

Lee, F. J., Anderson, J. R., & Matessa, M. P. (1995). *Components of Dynamic Skill Acquisition*.. Unpublished manuscript.

Lowe, R.K. (1993). Constructing a mental representation from an abstract technical diagram. *Learning and Instruction, 3*, 157-179.

Lowe, R.K. (1995, August). *Interactive animated diagrams for learning meteorological structures*. Paper presented at the 6th Biennial conference of the European Association for Research on Learning and Instruction, Nijmegen, Netherlands.

Nielsen, T.E., & Kirsner, K. (1994). A challenge for SOAR: Modelling proactive expertise in a complex dynamic environment. *Proceedings of the Singapore International Conference on Intelligent Systems (SPICIS-94).*

Reinartz, S.J., & Reinartz, G. (1989). Analysis of team behavior during simulated nuclear power plant incidents. In E. D Megaw (Ed.), *Contemporary Ergonomics*. London, UK: Taylor and Francis.

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*. *12*, 257-285.

Sweller, J. (1993). Some cognitive processes and their consequences for the organisation and presentation of information. *Australian Journal of Psychology*, *45*,. 1-8.

Wallach, D. (1995). *Knowledge, control performance and powerplants*. University of the Saar, Germany. Unpublished Manuscript.

Wallach, D. & Tach, W.H. (1994, June). *System knowledge, control performance and powerplants*. Paper presented at the first ACT-R workshop, Carnegie Mellon University, Pittsburgh.