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MENTAL MODELS, STRATEGIES, AND OPERATOR INTERVENTION IN SUPERVISORY CONTROL

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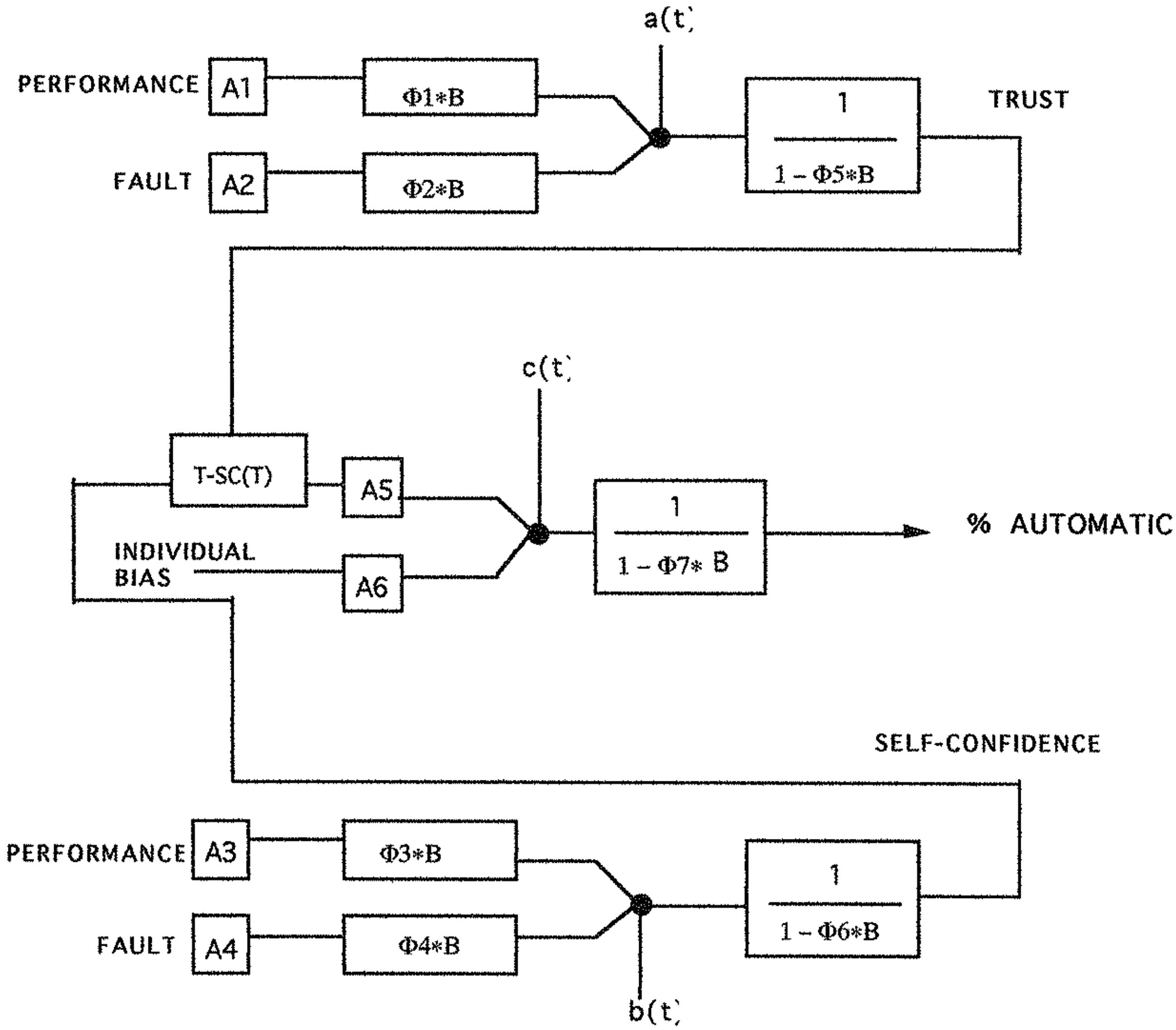
Abstract

Recent work has led to qualitative and quantitative models of operator intervention in supervisory control of continuous and discrete human machine systems> These models however apply to data pooled over operators and task conditions . Close examination of data show large individual differences in strategies of monitoring and control which are correlated with quality of performance. These strategies seem to be related to operators' mental models of the plant which they are controlling. We propose a new approach to identifying those aspects of a system which are likely to be incorporated into mental models of novice operators, based on the work of Conant, and describe some preliminary results of applying this method.

Introduction

A fundamental characteristic of supervisory control of industrial systems is the decision by operators to intervene in the operation of an automated system in order to exercise manual control of the process. In recent years work from several laboratories (Lee and Moray, Muir, Parasuraman, Riley,) has led to quantitative and qualitative models of operator intervention. Typical of these models are those developed by Lee (op. cit.) in which performance characteristics (such as the efficiency of production) and task characteristics (such as the magnitude and frequency of faults) were found to affect the trust and self-confidence of operators, which in turn affected the probability that they would switch between manual and automatic control. If we speculate slightly beyond the data analysis performed by Lee we arrive at the model shown in Figure 1 which summarises the characteristics of intervention in continuous process control (a simulated pasteurisation plant).



FLOW CHART MODEL OF OPERATOR INTERVENTION IN SUPERVISORY CONTROL OF CONTINUOUS PROCESSES (PASTEURISATION PLANT)

(AFTER LEE AND MORAY)

Figure 1

This model can be also represented as time series equations allowing us to predict the proportion of time spent in each mode:

$$\text{Trust}(t) = \Phi5(\text{Trust}(t\text{-}1) + \text{A1Performance}(t) + \text{A1}\Phi1(\text{performance}(t\text{-}1) + \text{A2}(\text{Fault}(t) + \text{A2}\Phi2\text{Fault}(t\text{-}1) + a(t) \quad (1)$$

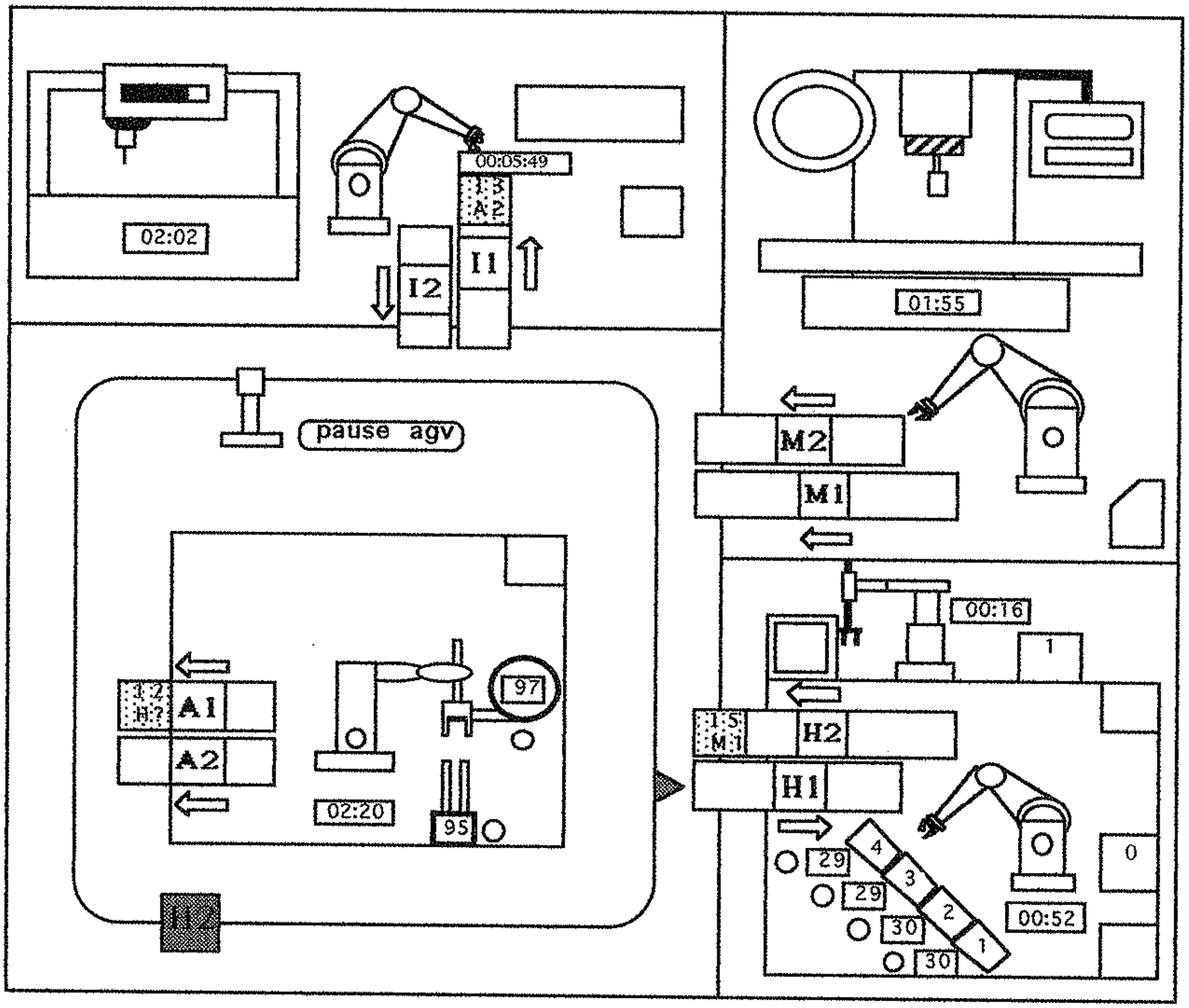
$$\text{SC}(t) = \Phi6(\text{SC}(t\text{-}1) + \text{A1Performance}(t) + \text{A1}\Phi3(\text{performance}(t\text{-}1) + \text{A2}(\text{Fault}(t) + \text{A2}\Phi4\text{Fault}(t\text{-}1) + b(t) \quad (2)$$

$$\%\text{Auto} = \Phi7\%\text{Auto}(t\text{-}1) + \text{A5}^*((\text{T-SC})(t)) + \text{A6}^*(\text{Individual Bias}) + c(t) \quad (3)$$

which can be combined to give:

$$
\begin{aligned}
\%\mathrm{Auto} = {} & \\
& \Phi 7\%\mathrm{Auto}(t-1) + A5^*((\Phi 5(\mathrm{Trust}(t-1) + A1\mathrm{Performance}(t) + A1\Phi 1\mathrm{Performance}(t-1) \\
& \quad + A2\mathrm{Fault}(t) + A2\Phi 2\mathrm{Fault}(t-1) + a(t) - \Phi 6\mathrm{SC}(t-1) + A1\mathrm{Performance}(t) \\
& \quad + A1\Phi 3\mathrm{Performance}(t-1) + A2\mathrm{Fault}(t) + A2\Phi 4\mathrm{Fault}(t-1) + b(t)) \\
& \qquad + A6^*(\mathrm{Individual\ Bias}) + c(t)
\end{aligned}
\tag{4}
$$

For an interpretation of the coefficients see the original papers by Lee and Moray.



UIUC-CIM: A SIMULATED DISCRETE MANUFACTURING PLANT USED BY HISKES (1994)

Similar results were reported by Hiskes (1994) using a simulation of a computer integrated manufacturing discrete process, although it was not possible to develop a predictive model at the level of detail reached by Lee because of the nature of the process. His system is shown in Figure 2.

Among Hiske's results were the following:

1. Effect of faults on intervention:
   14 out of 14 operators used automatic control less on the second day, (mean decline = 16.5%,) when faults occurred. ($P < 0.001$)

2. Effect of faults on trust:
   12/14 operators showed a decrease in trust on the second day when faults occurred. ($P \approx 0.01$)

3. Effect of faults on (T - SC):
   12/14 operators showed a decline on in the value of (T-SC) with no change in self-confidence.on the second day. ($P \approx 0.01$). Note that faults only occurred when automatic scheduling occurred, and hence there was nothing in the expeeriment to cause SC to vary. Once manual scheduling occurred there were almostn no faults seen.

Individual Differences in Strategy: the Role of Mental Models

The above results, while being very satisfactory as far as they go, rely on the pooling of data over many subjects and many trials or, where the notion of trial is not applicable, over many events during operations. However, if we examine more closely the details of moment to moment behaviour, it is apparent that there is great variability in how operators perform these tasks. (It should be emphasiseed that while many of the operators appear to reach asymptotic performance, others do not, and there is a need for research both into the acquisition of these skills and into the stability of strategies.)

In an unpublished pilot experiment for those of Hiskes, Moray, Phillips and Quaid found the results shown in Table 1.

What is noteworthy here is that when faults were rare or very rare, nonetheless some operators chose to use manual control of the discrete manufacturing process even though the scheduling algorithms were effective. In this experiment and those of Hiskes,, faults only occur during automatic operation, and hence operators can preempt the possibility of faults at the cost of considerable workload. This kind of strategy has appeared in some of our later work. It appears that some operators decide, once the system shows any faults at all, that is worth their while to undertake very considerable manual intervention, probably in order to prevent the possibility of faults occurring. This seems to be true even when the probability of a fault is very low indeed, less than one fault per production run of 35 minutes. But not all operators do this. There is great variation between individuals.

PALLETS SCHEDULED MANUALLY

P(fault):	33%	20%	14%	11%
SUBJECT				
1	4	2	2	0
2	1	0	0	0
3	2	0	0	1
4	3	1	2	0
5	3	0	0	0
6	0	0	0	1
7	0	1	0	1
8	2	1	0	1
TOTAL	15	5	4	4

TABLE 1

Table 2 shows related results found by Hiskes. In his experiment, the probability of faults might either be constantly high, constantly low, progressively more frequent or progressively less frequent. In all cases there were very many redundant scheduling activities performed manually. That is, even when there was no immediate evidence that faults were occurring, and even when the probability of faults was quite low or very low, some operators began to take charge of all the scheduling actions so as to prevent possible faults from occurring in the first place.

These kind of results suggest that the operators have a well formed mental model of what will happen when faults occur, and use that model for tactical or strategic decisions for improving, even if not optimising, the system performance. But again, there is a very great variation in individual performance, strategies and tactics.

Such individual differences were also found by Lee in his continuous process control task. Here it was very clear that these differences were related to differences in performance. In particular he analysed the monitoring strategies used by several individuals, including one who was very effective when the plant was normal, and was also effective when faults occurred, and another who was poor even with the normal plant and very poor when confronted by faults. graphical representations of the monitoring tactics used by these two operators are shown in Figure 3.

Table 2 Summary Statistics On Redundant Scheduling In Simulated Discrete Manufacturing

CONDITION	FAULTS SEEN	ReS
Overall		
High Mean Fault Rate	31	25.8
Low Mean Fault Rate	96	1.2
High-High		
High Mean Fault Rate	7	23.1
Low Mean Fault Rate	25	1.6

> The Column marked ReS shows the number of times the operator rescheduled a pallet which had already been (apparently correctly) scheduled by the computer, in order to ensure that no errors would occur. In the condition where there were many faults which could occur (High-High) operators only saw 7, wheras where fewer faults occurred they saw more (25). This is because when faults occurred frrequently the operators realised that they only occurred when scheduling was done automatically. Hence they scheduled many pallets (23.1) redundantly to the destination already chosen by the computer. Those who saw relatively few faults did not form a mental model of how they arose, and so did not reschedule so many pallets. Hence paradoxically fewer faults were actually seen in the condition where more occurred.

Lee found marked indivudal diferences in the pasteurizere environment. He recorded the sequence of demands for information as an index of monitoring strategies, and found that good operators tended to look at many more parts of the system than poor operators during fault management, although there was little difference during the operation of the normal system. Poor operators showed inappropriate cognitive tunnel vision. We assume that the reason for these differences is that the operators have different mental models of the causality which is present in the plant, since there is no constraint on the order in which monitoring observations are made, and it is up to the operators to interpret the task demands in such a way as to monitor the process as efficiently as possible. Given that all operators saw the same system, why should they acquire such different mental models, and can we proceed further to describe the nature of these models?

Identifying "Empirically Normative" Mental Models

If there are many alternatives that operators "choose" for their mental models, why do we so often talk about "the" mental model which operators should have of a system which they supervise? I have argued elsewhere (Moray, 1989) that we should think of a mental model as a homomorphic mapping of the properties of a physical system into a representation in the mind. To say this is to say that the contents of a mental model are a partial representation of the original physical system. What are the features which one might expect to be carried over from the physical system into the mental model? Does it make sense to talk of a "normative" mental model which the operator "should" possess?

There is an obvious sense in which one might define such a normative model. For example, in the Optimal Control Model (OCM) approach to human performance modelling to which Henk Stassen has contributed so much, one speaks of the need to have a well defined model of the system as part of the Kalman filter. And while there are often several possible such models depending on the choice of the variables to be measured, the notion of the normative complete model is clear. If operators are to be optimal controllers, we expect them to possess one of these models. In particular, the dimensionality of such models is well defined - they require the minimal degrees of freedom which are necessary and sufficient to represent the dynamics of the system.

But when we observe operators monitoring and controlling very large systems, is it reasonable or even possible to expect them to have such complete mental models? There are very tight constraints on the rate at which they can sample state variables, due to the limitations of eye-movements and the time required to access computer displays, and dynamic short term working memory is very limited. If the bandwidth of the system is moderately high and the degrees of freedom large, then it is probably unreasonable to expect operators to develop complete, that is isomorphic, mappings into their mental models; and even the homomorphic models may be too large for them to construct. I have noted elsewhere (Moray, 1976) that there is empirical evidence, for example from the work of Iosif (1968,1969a,b) that operators seem to regard a large system as composed of subsystems within which variables are so tightly coupled that it suffices to sample only some of them to determine the state of the subsystem, and that in effect the number of subsystems, not the number of variables, is what determines the structure of the mental model. If then many systems are too complex to be completely mapped into the mental model, can we determine what is the most likely subset of variables to be modelled, so that we can still speak of a "good" and a "poor" mental model, relative to such a subset? Such a subset of information about a system is not normative, because it is acknowledged to be imperfect. But one might speak of the "empirically normative" model, and ENM, meaning that given the limitations of human information processing, this is what one would expect a good operator to be able to discover, even if, from a truly normative viewpoint such as OCM, it is acknowledged to be suboptimal.

We suggest that the work of Conant (1976) provides a way to approach this problem. Conant has shown, following the work of Ashby (1956), how one can use Information Theory to identify the natural decomposition of a complex system. By considering the flow of information between variables one can identify subsystems, defined as sets of variables between which there is tight coupling, while there is loose coupling between one subsystem and another. The tight coupling means that the value of one variable can stand, to some extent, proxy for the values of other variables within the subset, so as effectively to reduce the dimensionality of the system. this is of course what Iosif's operators seem to have discovered. One might proceed as follows. Take a record of the values of all the displayed variables in a system at a sampling rate sufficient to satisfy the sampling theorem, and perform a Conant analysis on the resulting history of the system. The result should be a "best empirical decomposition" of the system as a whole. Essentially this amounts to performing cross correlation among all the variables, and Conant's method allows one to compute cross-correlation and auto-correlation *functions*, not just point estimates. Moreover, one can make use of qualitative variables (such as colours) as well as quantitative variables. Given our knowledge of the rate at which operators can switch among displays, the size of working memory, etc., we can estimate which relationships are likely to be detectable by an operator. For example, even if there is a strong coupling between a change in one variable, perhaps under my control, and another variable, but with a lag of, say, several minutes, it will be extremely difficult for me to detect it.

Because of the ability of Conant's method to handle qualitative data, it is practical to use it to analyse systems such as those used by Hiskes. The analysis and modelling of discrete manufacturing systems is extremely difficult, since the causality is unlike that of continuous systems. For example, an intermittent fault in a discrete manufacturing system, such as the failure of an automated guided vehicle to stop at the correct place for some but not all pallets, is only visible from time to time. Its effect does not propagate through the system in the same way that a change in pump rate or heat supply propagate continuously in a petrochemical plant. Nonetheless, using variables such as the name of the p[lace where a product is to found at a particular time, Conant's method can in principle analyse the structure of such a system. Furthermore, in principle, the effects of the coupling of the operator to the system when he or she intervenes can also be detected.

One might then arrive at the representation of system causality which is most likely to be detected (as correlations among the values of displayed variables), and hence most likely to be mapped from the physical system into the mental model - the "empirically normative" mental model. in so far as operators do not even manage to acquire such a mental model, they are falling short even of what we can reasonably expect from them psychologically. Obviously, the discovery of such an ENM would be valuable for many purposes, such as guiding display design, assessing training, etc..

First Steps Towards ENM Methodology

In recent months we have been working with Conant on the first application of this approach. We have used the PASTEURISER simulation to trace the pattern of operator monitoring and intervention, and have tried to force operators' attention onto different parts of the system by the appropriate use of various faults. In addition we have used Conant's method to analyse the ENM of the PASTEURISER plant. Our hypothesis is that the best and most effective operator mental models approximate to the ENM of the system revealed by Conant's analysis, and that operators whose sampling pattern seems to be consonant with the aim of pasteuriser will be the most effective operators. If this is successful, this approach may offer new insights into the detection and analysis of mental models of supervisory control of complex systems. In effect, such an approach allows us to take seriously the notion of the "human-machine *system*" since Conant's method allows us to see how the structure of the total system seems to change as a result of the role played by the operator. The operator re-organises the system when he or she becomes coupled to it, and one must then assume that the mental model is not a model of the plant, but of the sytem of which the operator is a dynamic component. The operators in a sense model themselves, not just the plant. Examples of such an ENM for two operators are shown in Figures 4 and 5, in each case both when the plant is normal and when a fault has developed. Each arrow points from a significant source of infomation to a variable about which that source carries information. The "natural decomposition" of the system is different for the two normal cases although the physical plant is the same in each. The way in which the operator is coupled to the plant through observation and intervention however makes the two *systems* different. This is even more apparent in the natural decomposition of the faulty plant, where the responses of the two operators clearly differ, and as a result one can see that they are attempting to regulate the fault in quite different ways. We are currently developing this method further in collaboration with Conant.

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