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# DEALING WITH THE DILEMMA OF DISPARATE MENTAL MODELS

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## Abstract

The integration of diverse and disparate operational support agents for real-time complex plant process management is investigated. This is motivated by the increased sensor density and complexity inherent in today's nuclear and chemical plants which lead to operator information overload. Such plants are best understood by a functional decomposition into sub-systems and components, typical of the engineering approach. Thus, computer-based aids must be based on such a functional decomposition. This, however, is not the mental model employed by the operator and leads to a dilemma: the system needs to be functionally decomposed along the lines of the physical or engineer's mental model, whereas, this is an inappropriate model for the operator. Some mechanism is needed to bridge the gap. Herein, a solution to this dilemma is proposed: concurrent scorecarding based on the blackboard paradigm.

## 1. INTRODUCTION: The Problem Domain

The proper design of real-time process plant user interface tools for nuclear and chemical process plants naturally requires the incorporation of the relevant characteristics of the physical plant. One of the most obvious features is its distributed architecture. Plant operations are diverse and multifaceted. Events can happen anywhere in the system. The breadth and depth of plant operations required that the plant be ENGINEERED by decomposition into layered sub-systems (functional abstraction, otherwise known as piece-wise refinement).

In operations, operator overload, response time, etc., necessitate procedural responses. The operator is never left with an open ended question. For instance, if the plant state is unknown, there is a definite procedure to follow. At any given moment, there are a limited number of alternatives to choose from. Successful plant operations are, by definition, procedural and pre-enumerated.

The overall control strategy used at the plant is of central importance. For the most part, regulations require that the human remain 'in the loop', ie, in control. The operator has at his or her disposal many tools to enhance

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performance but the operator is very much in the driver's seat. This is so not just because regulations require it. It is so also because operators, like engineers do not wish to divest their authority to a machine. Machines are tools, no matter how intelligent they appear to be. This issue has been referred to as the machine-centred approach vs. the human-centred approach [1].

Process plants operate, of course, in real time and require real time control. To respond to real events in a complex plant, analysis is required. Much of the control is automatic but a significant role is played by the operators who must reason about the situation at hand. The right side of Figure 1 illustrates the roles played the human operator with respect to the plant and plant control. It is not just a question of being fast. Rather, bounding the solution time is the issue. Can a sufficiently good solution be found within the time required? The heuristics, however, are not well delineated and human operators will remain for the foreseeable future.

## 2. COGNITIVE ISSUES: Problem Solving Strategies

The mental model of the designer or engineer as developed in Rasmussen's book [2] is one that is based on functional decomposition. Problem solving strategies here relies on a deeper than average understanding and use of specific knowledge. The user, however, is the operator, not the design engineer. The operator's mental model of the plant is closer to that of a technician - the plant is a collection of many systems, most of which are treated with generic algorithms for fault diagnosis and treatment of event symptoms, irrespective of the system in question. Rasmussen's figure (reproduced in part on the left side of Figure 1) illustrates this generic algorithm. The generic algorithm for problem solving is to observe and identify the state of the situation, interpret, evaluate, plan actions and execute the actions. Rasmussen notes that shortcuts can be taken at any stage. In fact, most of what we do involves shortcuts to some degree. ALL problem solving is covered by this figure but the technician often employs strategies and tactics that do not rely heavily on a detailed knowledge of system and component behaviour. That is, short cuts to Rasmussen's full solution path are taken.

Expertise is composed of both knowledge and the ability to manipulate that knowledge. It has been observed and is widely recognized in the literature that it is the vast knowledge-base that exemplifies the expert rather than raw inferencing capability. The nuclear reactor environment is a case in point; operator actions require mostly procedural knowledge and moderate inferencing capability. The knowledge-base (composed of facts and heuristics) is then very important. The knowledge-base is necessarily system or component specific. This leads to the paradigm of message passing as a means of allowing disparate agents (models or codes or humans, etc.) to interact. It is at this level that one is concerned about how the operator or engineer interacts with the system being controlled. The result of this is that the objects being manipulated (the

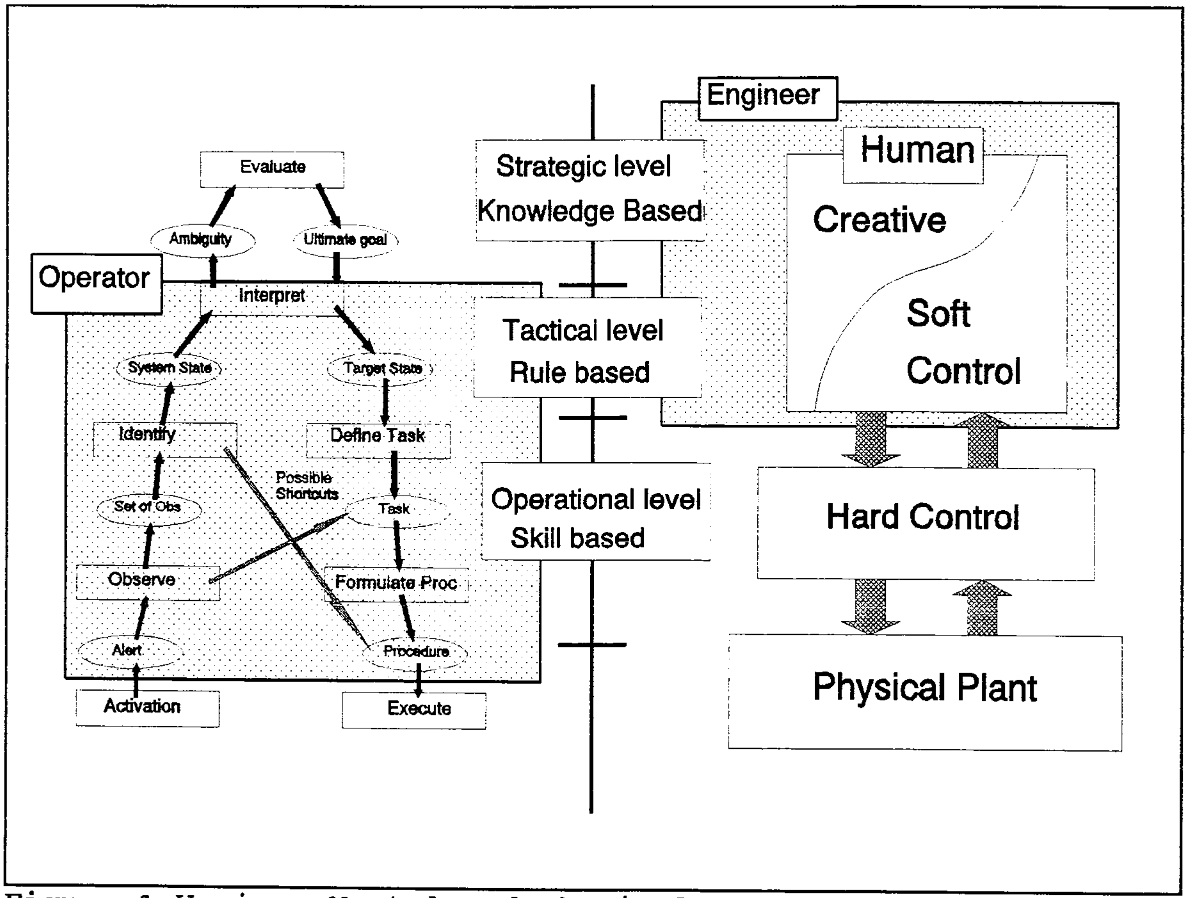

**Figure 1** Various Mental and Physical Models.

knowledge base) need to be defined before they can be manipulated (by the inferencing or procedural engine). But how we define these objects will depend on the mental model chosen. This leads to a dilemma: the system needs to be functionally decomposed along the lines of the physical or engineer's mental model, whereas, this is an inappropriate model for the operator. The plant is organized along the same hierarchial lines as the design engineer's mental model. That organization expects the human to provide the top level knowledge based control. The operator, however, spends much of the time at the rule based and skill based levels. Figure 1 illustrates this point. The issue is not a trivial one and, as such, deserves careful consideration in the design of operational support systems. No-one to date has demonstrated a schema to solve this dilemma. This mental model mismatch plus a machine-centred bias are arguably the leading causes of the failure of artificial intelligence based support systems.

## 3. THE SCORE CARD

We need to decouple the decision making process from the details of the solution. Thus, we pose the user interface in the users' terms: "What decision must I make and what factors influence that decision?" 'What decision' implies

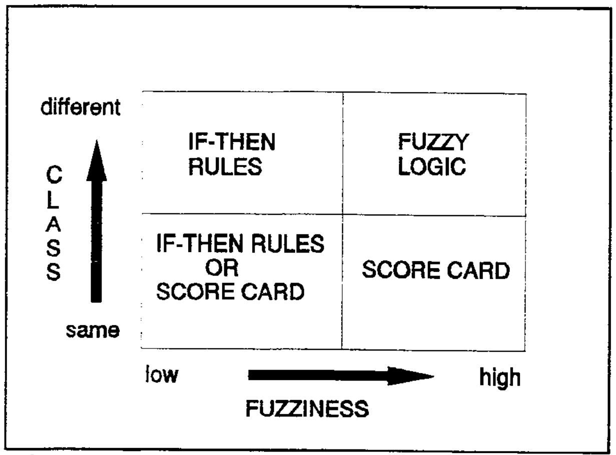

**Figure 2** Scorecard Domain

that the user must pick an option (ie., an object) from a pre-enumerated set. The 'factors that influence' are the attributes of the objects and if an appropriate decision is to be made, the attributes must be common amongst the objects (i.e., in the same class). Such clustering has been found to be a central feature for neural nets to be successful [3]. If a common set of attributes do not exist in the domain of an engineered system, then the set is ill-posed and the user cannot choose because there is no declared valid basis for reaching a decision in this case. The problem domain, then, is one involving clustered objects which are to be evaluated by weighing the pros and cons of each object. As illustrated in Figure 2, simple IF-THEN rules are appropriate if there is no fuzziness to the problem domain and can be applied whether clustering exists or not. To handle fuzziness, confidence factors would have to be added and this is deemed inappropriate if a more appropriate technique is available. One such technique that has proved successful is scorecarding. Our problem is clustered and fuzzy, exactly the domain for which scorecarding is the most useful.

Scorecarding (the tallying of how well alternatives measure up for a number of attributes) is useful for reconciling judgements with facts, symbolic with numerics. As discussed in [4], the solution strategy centres around the elimination of alternatives that cannot be used for one reason or another, and the ranking of those that are left by the use of score cards. The specification of the scoring details is a knowledge engineering exercise that is not trivial but it is one that must be done in some form at some point in the design of any operator aid. Scorecards merely give form to the substance; but most importantly, the form is an appropriate one for decision making for all types of users, including operational support staff. User supplied attribute weights are used to generate the weighted sum to give the total scores used to rank the alternatives in the decision to be made. The score card approach provides a good way to perform the ranking since it emulates the expert methodology of weighing the pros and cons of the alternatives.

To illustrate the use of the score card, let us suppose that the operator must monitor the secondary side of a power plant, looking for signs of bad chemistry or condenser leaks. An array of alarms and measured data are available. The operator must choose from a finite number of possible states (no problem, bad chemistry exists, a leak exists, etc.). Now, of course, there is much more to a monitoring situation than this but the plant procedures are built around first determining which of the above states the plant is in. The presence of an alarm does not guarantee the existence of a plant state. Indeed, alarms can give conflicting indications. The detailed procedures determine how these data should be interpreted as attribute scores. Arbitrarily, a 0-1 scale is chosen. Weights can be assigned to each attribute to indicate its relative importance. For instance, a conductivity measurement might be less useful or reliable than a chlorine concentration measurement.

While the details of the scoring algorithms are of fundamental importance to the success of the scoring procedures, herein we are concerned with the use of the scores in reaching a decision. That is, we wish to delineate an appropriate score <u>evaluation</u> procedure, given a set of n attribute scores for each of m objects. We define the 'degree of closeness to the ideal' for the $i^{th}$ attribute of the $k^{th}$ object as $d_i^k$, where k = 0, 1, 2 ... m objects, and i = 0, 1, 2 ... n attributes.

The 'membership' function is defined [5] to be a measure of the closeness to the ideal as

$$L_p(\lambda,k) = \left[\sum_{i=1}^{n}(\lambda_i)^p(1-d_i^k)^p\right]^{1/p} . \tag{1}$$

where $\lambda_i$ is the derived weight for attribute i, and p is a parameter, typically between 1 and $\infty$.

We note that smaller is better in the membership function. When p = 1, equal weight is given to each attribute deviation from the ideal for each object regardless of the deviation size. When p = 2, increasing weight is given to larger deviations (a root mean square measure). When p = $\infty$, only the largest deviation is important since, in this case:

$$L_\infty(\lambda,k) = \max_i[\lambda_i(1-d_i^k)] . \tag{2}$$

It remains to define the algorithm for weight adjustment. We set the context

$$\tilde{\lambda}_i = \sigma_i = \sqrt{\frac{1}{m}\sum_{k=1}^{m}(d_i^k-\bar{d}_i)^2} , \tag{3}$$

dependent weight to the standard deviation of the scores, that is,
Finally, since the user may have supplied a priori attribute importance in the form of weights, say $w_i$, the final weights need to be calculated as the product of the context dependent and context independent weights (normalized),

$$\lambda_i = \frac{w_i\,\tilde{\lambda}_i}{\sum_{i=1}^{n}\tilde{\lambda}_i\,w_i}, \quad where \sum_{i=1}^{n}\lambda_i = 1. \tag{4}$$

The procedure is straightforward. Applying the above equations, $L_p(\lambda,k)$ is calculated for all objects and the best choice is that object with the lowest $L_p$ using the p that the user deems appropriate. This has been implemented for heat exchanger selection and the prototype performed very well, meeting or exceeding all expectations in ease of construction, ease of use, speed, and accuracy in emulating the human expert. It is currently being considered for a nuclear power plant application.

## 4. CONCLUSIONS

This implementation of scorecarding provides a means of dealing with disparate agents but it does not address the issues of real-time, asynchronous events or concurrency (ie multiple agents acting in parallel and sharing information during the solution). However, they are not precluded either. Such a technique clearly allows the user to remain in control since the aid simply presents the relevant information in a manner conducive to decision making, providing an automatic focus on the important issues and letting the user decide which path to actually follow.

## 5. ACKNOWLEDGEMENTS

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