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Knowledge-Based Dynamic Structuring of Process Control Systems

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Abstract: *A dynamic-structure system is one that has the flexibility to change the system configuration automatically so as to operate in an optimal manner. A conceptual model for a dynamic-structure system is presented in this paper. In this model, the interchangeable components of the overall system are grouped together. Their activity levels are evaluated by an intelligent preprocessor that is associated with the group. A knowledge-based task distribution system evaluates the activity levels and makes decisions as to how the components operating below capacity should be shared with workcells that have similar components that are overloaded. Associated decision making can be effected through fuzzy logic and particularly the compositional rule of inference. A simulation example is given to illustrate the application of dynamic structuring.*

INTRODUCTION

Considerable attention has been given to the use of decentralized or distributed control in complex, large-scale systems [1]. When various control functions in a large system can be ranked into different levels, a hierarchical control approach may be useful [2,3]. Also, in some situations, the components (both hardware and software) that perform the ranked functions could be arranged in a hierarchical manner. Published work has been limited to hierarchical systems which are designed to possess fixed structures, and these structures do not change during operation of the system. This is the case, for example, in the systems described in [4] and [5].

A dynamic-structure system is one which has the flexibility to change its communication and control structure automatically so that the architecture in which the system is integrated could be altered without having to redesign the system. Even though the design, analysis, implementation, control, and operation of a fixed-structure system is usually simpler than those of a dynamic-structure system, it is generally less efficient and nonoptimal. For example, if two workcells have components that could be easily shared, it makes sense to share a component that operates well below its capacity with a workcell that has an overloaded component of the same type. Such sharing would be possible only if the system structure has the necessary flexibility to communicate with and control the shared component regardless of which workcell the component is associated with at a particular instant. Underlying here are the advantages of a dynamic-structure system [6].

Different levels of knowledge, expertise, and intelligence may be associated with different functions of a hierarchical control system, and dynamic structuring will have to rely on such knowledge. Specifically, intelligent preprocessors may be necessary to evaluate, interpret, and transform various types of information available within and without the system. Furthermore, system restructuring decisions have to be made "intelligently" through a suitable knowledge system, by taking into consideration the available, preprocessed information. This is the basis of knowledge-based dynamic structuring. This paper will describe a model for a knowledge-based dynamic-structure system. An illustrative example will be drawn from the fish processing industry to indicate the utility of the model.

KNOWLEDGE-BASED HIERARCHICAL SYSTEMS

A system that has the flexibility to automatically change its structure should possess proper control means to provide that flexibility. Since a system of this type has to be able to provide a variety of different services during operation, it tends to be complex in general. Consequently, the task of controlling such a system would be intractable unless the associated architecture of control and communication is properly organized.

A layered architecture can facilitate the operation of a complex, flexible system [7,8]. Since the higher layers generally deal with low-resolution, imprecise, and incomplete information, more intelligence would be needed in the associated decision making process [9]. In contrast, in the lower layers, as in servo loops,

information (e.g., signals from feedback sensors [10]) is used directly, without subjecting to intelligent preprocessing, in taking control actions. A hierarchy of intelligence may by identified in this connection [11].
Specifically, "Knowledge" may be interpreted as *structured information*, within the context of computer-automated process control. Various means such as logic, semantic networks, frames, and production systems may be employed to represent and process knowledge. Next, "Expertise" may be treated as *specialized knowledge*, and relates to in-depth knowledge that is needed to handle specialized situations. At the top level in this hierarchy rests "Intelligence" which cannot be defined precisely, but may be interpreted as the capacity to acquire and apply knowledge, thereby displaying some intelligent behavior. This is a somewhat circular interpretation. Intelligent characteristics include the ability to perceive, reason, learn, and make inferences, particularly in imprecise, vague, or fuzzy situations, and making use of incomplete information. It follows that, some intelligence is needed to gain knowledge from information, and to gain expertise by specializing that knowledge. This hierarchy is schematically represented in Figure 1. This is not a strict hierarchy because the separation of the knowledge layer and the expertise layer is somewhat fuzzy. The intelligence itself is fortified through the act of preprocessing of information and knowledge, with varying degrees of incompleteness, imprecision, vagueness, and fuzziness. Preprocessing may include perception, reasoning, learning, and inference. It is the "outward appearance" of the hierarchical system in Figure 1, that is considered intelligent. Associated root-level computations would be hardly classified as intelligent.
As an example in the process automation domain, one could model the execution of a routine task as knowledge-based and responding to a critical situation as expertise-based.

A MODEL FOR DYNAMIC STRUCTURING

Proper integration is crucial for efficient and cost-effective operation of a process control system. Since redesign of the system architecture and re-integration of the system are costly and time consuming, it is desirable to consider a flexible system whose structure could be automatically reconfigured according to various process requirements.
A model for a dynamic-structure system was conceptually proposed in [6], and is schematical represented in Figure 2. In this architecture, the workcell components of the processing system are grouped in such a manner that the functions of the components within each group are similar and they are interchangeable without affecting the functionality of a workcell. In a general sense, both hardware devices and software modules may be considered as workcell components. Each workcell component has a controller that manages its operation. Also, each component has one or more sensors that will provide the necessary information to an "Intelligent Preprocessor" which will determine the activity level of the particular component. In a fixed-structure system, the task distribution amounts to allocating tasks to various workcells in the system, and the constituent components of the workcells themselves are permanent. For a dynamic-structure system, however, a more intelligent task distribution system (TDS) would be needed. Here the TDS has to routinely monitor the activity levels of the workcell components, as provided by the corresponding intelligent preprocessors. It will then redistribute the constitution of the workcells by sharing some components that operate below their design capacity with workcells having components in the same group that are overloaded. These restructuring decisions are transmitted to the system restructuring controller (SRC) which activates the necessary communication and control links and provides the control strategies to effect the component sharing.
The activity levels of the components in a workcell with a given structural configuration, depends on the process load of the workcell. If the workcell load (or demand) changes due to reasons such as supply-demand variations (e.g., new orders, new raw material), the activity levels of the workcell components will change. It follows that the load levels of the workcells have to be provided as inputs to the TDS, and these inputs will trigger the decision-making process for workcell restructuring, on the basis of the component activity levels.
Reasoning associated with the restructuring decisions could be quite complex. For example, when more than one overloaded component and more than one component operating below capacity are present within a group, there arises a so-called conflict resolution problem. Here, the decision of which components should be shared with which workcells should be made by taking into consideration various factors such as the degree of overload and under-capacity, workspace geometry (e.g., proximity of a component to the workcell with which it is expected to share), ease of sharing, and the speed of restructuring. An intelligent (or knowledge-based) TDS is needed for this purpose. Each context in the decision making process could be considered fuzzy, and the associated decisions can be determined by applying the compositional rule of inference [12].
Analytical representation of the dynamic structuring model may be facilitated by the formulation given now. The activity levels A of the workcell components may be given by

$$A(\underline{w}, g, c) = \underline{F}(g) \times \underline{S}(\underline{w}, g, c) \tag{1}$$

where c = identifier for a component in a workcell; g = identifier for the component group to which c belongs; $\underline{w}$ = the set of workcells among which c is shared; $\underline{S}$ = sensory signals from component c for determining the activity level; $\underline{F}$ = intelligent preprocessor for a group of similar components that infers the activity level of a component; $\otimes$ = a suitable transitional operator.

The intelligent preprocessor ($\underline{F}$) is typically a knowledge-based reasoning system. The associated variables of knowledge representation could be fuzzy and the knowledge base itself might be expressed as a set of linguistic statements. In this case $\underline{F}$ may be interpreted as a multidimensional membership function [9]. The sensory signal $\underline{S}$ from the workcell components are crisp and of high resolution. The context that is needed by $\underline{F}$ to infer the activity level would be higher level information of lower resolution. For example, peak values, averages, standard deviations, correlations, trends, and times of certain critical values could be involved. The transitional operator $\otimes$ can be quite subjective [9] and should be interpreted depending on the particular component and the specific need. For example, in many situations, $\otimes$ could be a knowledge processing operation such as the application of the compositional rule of inference to a fuzzy rule base.

Once the activity levels of the components are available, an input trigger such as a change in a workcell load should initiate the process of activity evaluation for workcell reconfiguration. This process may be formulated as

$$c(\underline{w}^*) = \underline{R} \otimes [\bigoplus_{c \in g} A(\underline{w}, g, c)] \qquad (2)$$

where $\underline{w}$ = the workcell association of component c prior to reconfiguration; $\underline{w}^*$ = the workcell association of c after the inferred reconfiguration; $\underline{R}$ = knowledge system for task redistribution; and $\otimes$ = combinational operation. Note that the operations implied by equation (2) have to be performed for all components that are overloaded and all other components that fall into the component groups to which the overload components belong. Again, the knowledge base associated with the decision making process of equation (2) could be a set of fuzzy linguistic statements, and accordingly $\underline{R}$ could be interpreted as a multidimensional membership function. Then the transitional operator $\otimes$ would correspond to the application of the compositional rule of inference. The combinational operator $\oplus$ too is subjective and situation-specific, and has to be performed separately for each component group. For example, it may constitute a simple comparison of activity levels of the components within a group and ranking them accordingly so as to pair say an overloaded component with one that operates below capacity. Finally, the new workcell configuration $\underline{w}^*$ will provide the necessary information for the SRC to activate the necessary communication and control links and to operate the workcells according to the new configuration.

EXAMPLE OF APPLICATION

An application in fish processing will be considered. Specifically, a system consisting of subsystems such as a fish cutting system, a grading system, and a packaging system will be reconfigured as workcells within a process plant, and will be implemented as a dynamic-structure control system. There exist many similarities in terms of hardware, software and processes in the subsystems. For example, system components such as sensors (including CCD cameras), image processing systems, actuators, grippers, and conveyors are similar. As a result, the nature of component interfacing, signal processing, and low-level control will be similar both in hardware and software. This means that there exists the prospect of sharing similar components among the workcells so as to reduce overloading and to achieve somewhat optimal operation.

Figure 3 presents a simulation example of dynamic structuring. The overall processing system consists of three workcells -- for cutting, packaging and grading, as shown. Each workcell has common components such as robots for fish handling and processing, automated guided vehicles (AGVs) for the transfer of raw fish, processed fish and waste, and vision stations for detection, gauging and quality evaluation of objects. The activity levels of the components are shown as percentages of their designed capacities, and are presented as solid bars, with the dotted region indicating the available excess capacity. Also, each workcell has a demand level in a given phase, which represents the load on the workcell to achieve the necessary productivity.

It is seen that in Phase 1, the components in all three workcells operate below their capacities. Then due to a drop in the supply of fish, the cutting demand drops by 25% and similarly the grading demand drops by 25%. But an accumulation of processed fish has occurred. Also, simultaneously a 50% increase in orders for processed and packed fish takes place driving up the packaging load by 50%. These result in associated changes in the activity levels of the workcell components, as shown by the Transition Phase. Now the workcells need to be reconfigured for improved operation. Possibilities of component sharing are indicated by broken lines in the Transition Phase. Once the reconfiguration is effected, in Phase 2, the activity levels of the components have changed, to achieve a somewhat balanced operation under the changed loading condition of the workcells. It is seen that, in Phase 2, none of the components are overloaded unlike in the Transition Phase. Also, an AGV has been completely released from the cutting workcell and has been allocated to the packaging workcell. Similarly, a robot has been completely released from the grading workcell and has been allocated to the packaging workcell.

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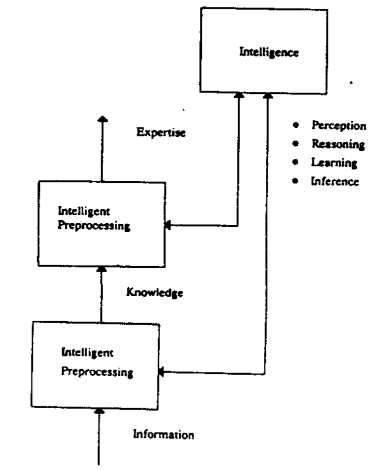

Figure 1. A Hierarchy of Intelligence

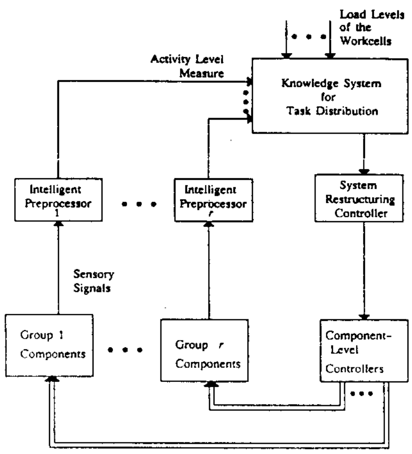

Figure 2. The Architecture of a Flexible Processing System with Dynamic Structuring

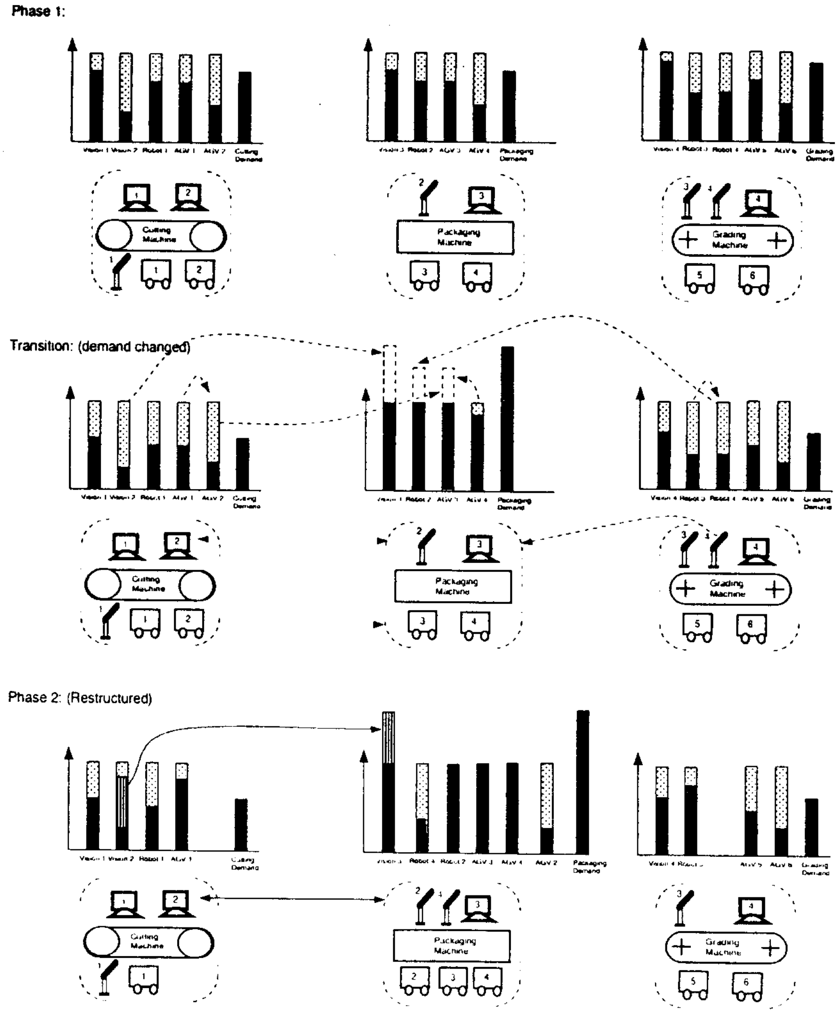

Figure 3. A Simulation Example of Dynamic Structuring

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