

**SENSOR FUSION:**  
**The Application of Artificial Intelligence Technology**  
**To Process Control**

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**ABSTRACT** At both the unit process and systems level of manufacturing there is a need to collect and understand aggregate (fused) data from multiple sources (sensors). The concept of fusing multiple-sense data is analogous to human sensory processing of vision, tactile, audio, thermal, etc. data. Evaluation of combined input from several senses produces a richer and more reliable perception of the environment than does evaluation of a single sense or separate evaluation of multiple sense data. The objective of understanding fused multiple-sense data is to improve awareness of current equipment/system states, anticipate future states and detect/diagnose faults. The approach presented in this paper to accomplish sensor fusion employs the use of Artificial Intelligence (AI) technology. The design is based on the parallel operation of three (3) inference systems, one for monitoring and understanding sensor data, another for control of the process and finally one for communication via a blackboard.  
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**INTRODUCTION**

Within the marketplace of candidate applications for AI technology, the field of manufacturing is considered to be very promising. Of particular interest are the functions of manufacturing planning, scheduling and control because, when considering the advantages afforded by AI techniques, the most significant benefit is associated with manufacturing decision making activities. From Bullers, Nof & Whinston (1980),

While computer technology can rapidly process large amounts of data by sophisticated logic, many of the necessary decisions must wait until human operators can sift through the data, become familiar with the system status, and select proper actions. This is where artificial intelligence techniques can provide better planning and control . . . . AI techniques can be used to develop decision aids that are capable of handling large streams of data as well as performing logic manipulation for conflict resolution, sequencing and resource allocation, etc.

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Figure 1 provides some perspective regarding the evolution of manufacturing planning, scheduling and control and the expected contribution from the application of AI techniques. The adaptive control example illustrates the state-of-the-art today, where (without AI) the control activity must rely on feedback. All is well as long as the environment is relatively stable and the priorities are fixed -- as the prescribed knowledge will adapt accordingly. But once the 'requisite variety' or the breadth of control is exceeded or the priorities are changed, the prescribed knowledge becomes inadequate and thus the ability to fuse and learn new knowledge becomes necessary. It is envisioned that AI will enable this next step in sophistication such that a machine can perform these activities much like a human, i.e. intelligent planning, scheduling and control.

### SENSOR FUSION

One such application of AI technology to manufacturing decision making activities is 'sensor fusion'. Although sensor fusion is very simply defined as the process of aggregating and understanding data from multiple sensors, its significance and scope are best realized by considering the capability to be emulated - human sense processing. Human understanding of the environment is accomplished by combining sights, sounds, touch, etc. Evaluation of these combined sense inputs produces a deeper and more reliable perception of the environment than does evaluation of any single sense or separate evaluation of each of them.

Although a sensor fusion system is intended to be a tool and thereby adaptable to any planning, scheduling or control activity, the real-time fusion of sensed environmental data for process control of materials will be the initial application. At the heart of the sensor fusion system is a concurrent symbolic processing system comprised of three (3) expert systems programmed in FORTH (reference Park 1986) operating on an IBM PC/AT class computer. In addition, the system has sensor and control interface components. The sensor interface provides an input stream of sensed data from the task environment. Typical sensed data includes temperature, pressure, resin flow rate, control settings, contact closure status, etc. The input stream provided by the sensor interface is coded in digital format suitable for direct input to the sensor parser.

Likewise, the control interface provides an output stream of data from the sensor fusion system. Aside from control messages to the process or other control systems, typical control data include annunciator indications to the process operator regarding the current process state, prediction of future states, and detection and diagnosing of faults.

### CONCURRENT SYMBOLIC PROCESSING SYSTEM

Each of the three expert systems performs a different part of the overall sensor fusion task: to communicate, parse, and analyze (as depicted in Figure 2).

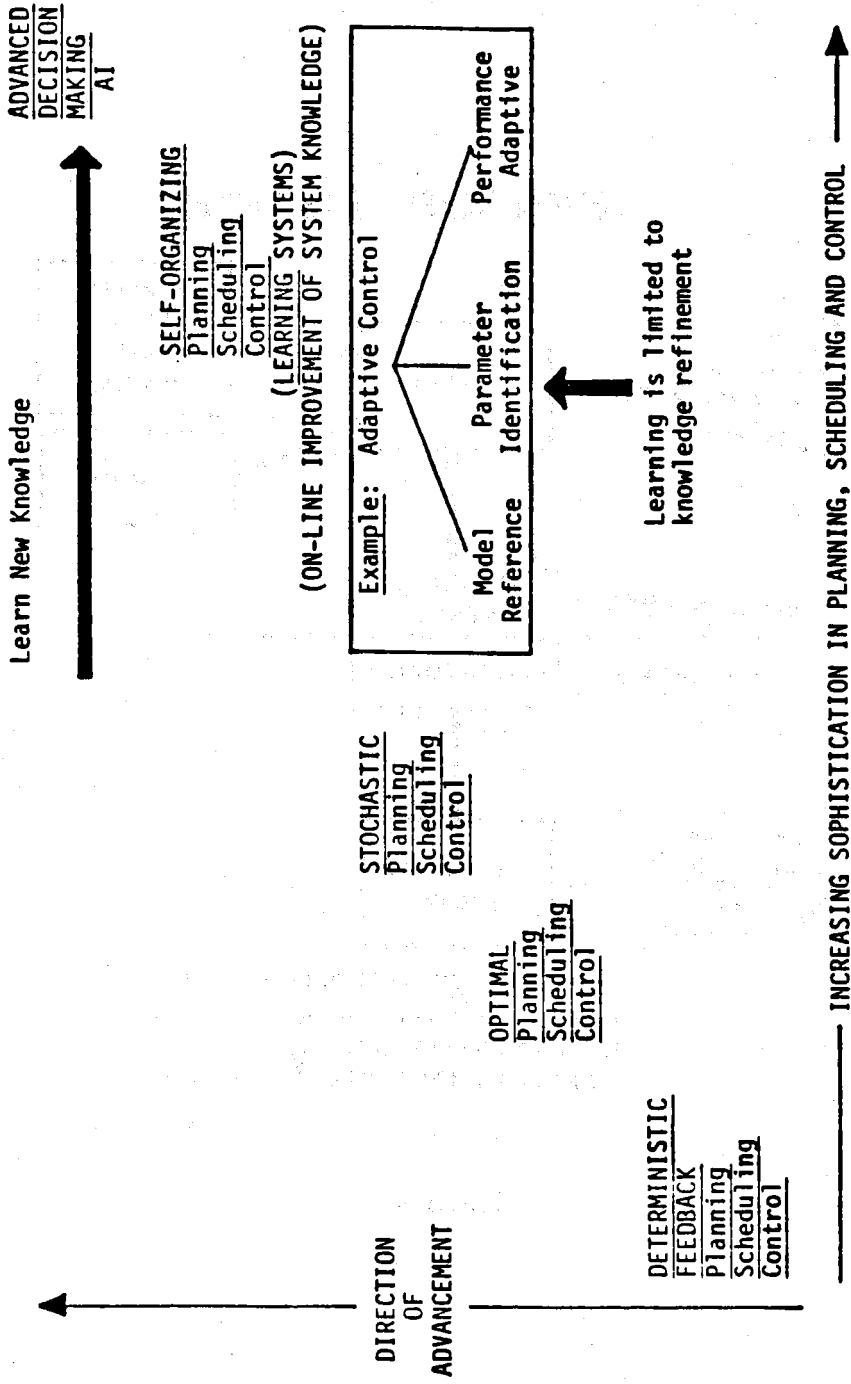


Figure 1. Increasing Sophistication on the Path to Intelligent Planning, Scheduling and Control.

## SENSOR FUSION

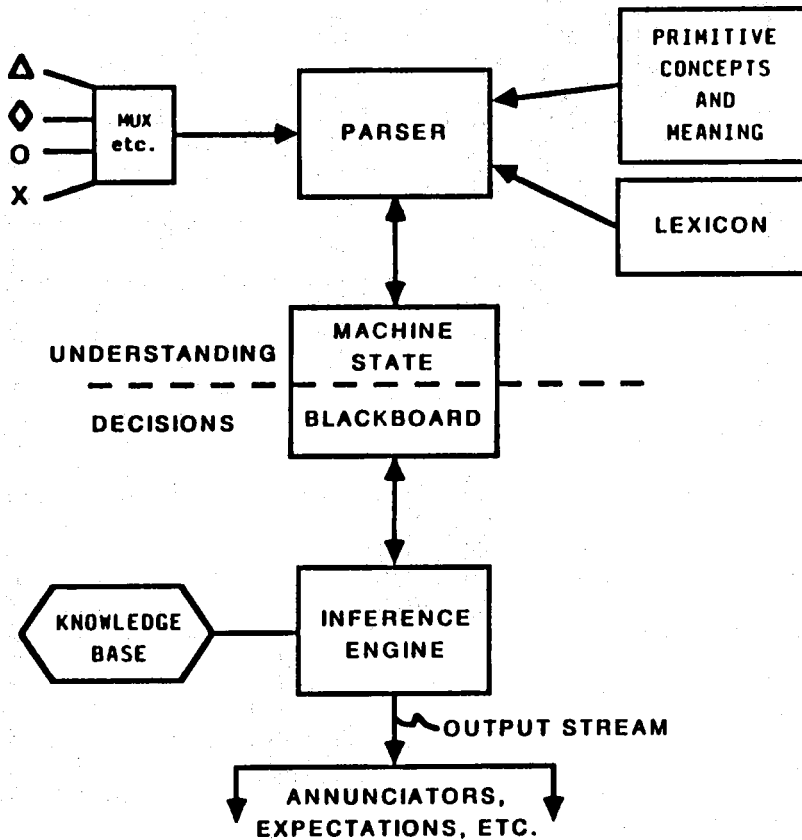


FIGURE 2

Communication is accomplished by means of a blackboard data structure where multiple independent 'knowledge sources' cooperatively interact by posting hypotheses for general use. The blackboard is the interface expert system which provides communications between the sensor interface, the control interface, the other two expert systems, and a user at the terminal. The blackboard expert system also provides the file management tools (e.g. storage and retrieval of data for recording process performance) necessary for the sensor fusion tool to operate as a complete process control system.

The sensor parser combines domain knowledge with a 'primitive' parsing strategy to transform an input stream of sensed data into memory structures useful for planning, control and diagnostic purposes. The memory structures built by the sensor parser are stored in the memory of the blackboard expert system. The sensor parser considers its data input stream as the 'natural language' of the domain environment. This parser applies knowledge of the task domain to select the correct semantic meaning of the input data from words in a lexicon (a dictionary of allowed words) built into the parser. If a given word is not found in the lexicon, a form of expectation processing is initiated to attempt disambiguation of the input data stream. During expectation processing the parser recognizes the potential meanings and establishes a set of knowledge based mini-expert systems called 'expectations' to watch for further inputs that will help select the correct meaning. Finally, failure to identify the meaning of the input stream indicates that a potential fault has been detected and the control actions may be outside the knowledge base available to the parser.

The analyzer is a domain expert system configured to execute user-supplied plans in order to control a task environment. The additional feature of on-line, continuous fault monitoring and diagnosis provides a means to eventual incorporation of 'learning' tools such that the sensor fusion system may be 'trained' on-line to deal with exceptional conditions.

The analyzer's input stream consists of task environment information 'posted' on the blackboard by the parser, and commands by the user at the terminal. The analyzer's output is a series of control messages posted on the blackboard.

The analyzer performs its task by asking questions from a list - running a goal driven inference process. This goal driven process uses knowledge based questions to query the data structure built (on the blackboard) by the parser. It will look for potential faults (states requiring action to be taken) flagged by the parser as well as signs of faults not flagged, and compare the parser data structure with other agents (numeric algorithms) if available. Fault detection, isolation and resolution tasks of the analyzer involve a combination of qualitative process theory and temporal reasoning strategies.

Qualitative process theory considers the primitive notions of a process - the actors, the objects, and the state changes involved. In analysis, the current data structure and the process history are compared with expectations based on a plan and knowledge of how a given task should progress. The end

objectives of the analysis are either control commands or expectation results. Control commands result in messages posted on the blackboard which are then executed by the blackboard expert system. Expectation failures result in the analyzer entering its diagnostic mode, which begins with a search for an explanation of the failure detected.

A separate part of fault detection involves correlation of current state information with past state information, and with 'current expected' state information. That is, at time sequence zero, the analyzer has no past state information, but it looks at current state information and remembers current state as the next past state and develops an expected future state. At time sequence one, the analyzer has a memory structure of the past state, a memory structure of current state information, and a memory structure of what it expected (at time sequence zero) the state would be (at time sequence one). Thus, the analyzer performs a sequenced, temporal reasoning process, looking at where it started, where it is, and where it thought it should be.

### KNOWLEDGE BASE DEVELOPMENT

The kernel or core knowledge base is planned to provide knowledge engineers with a powerful set of primitive concepts and tools on which increasingly complex layers of domain knowledge may be built. This set of primitives will provide a necessary link between the knowledge applied by a human expert and the behavioral capabilities of a computer.

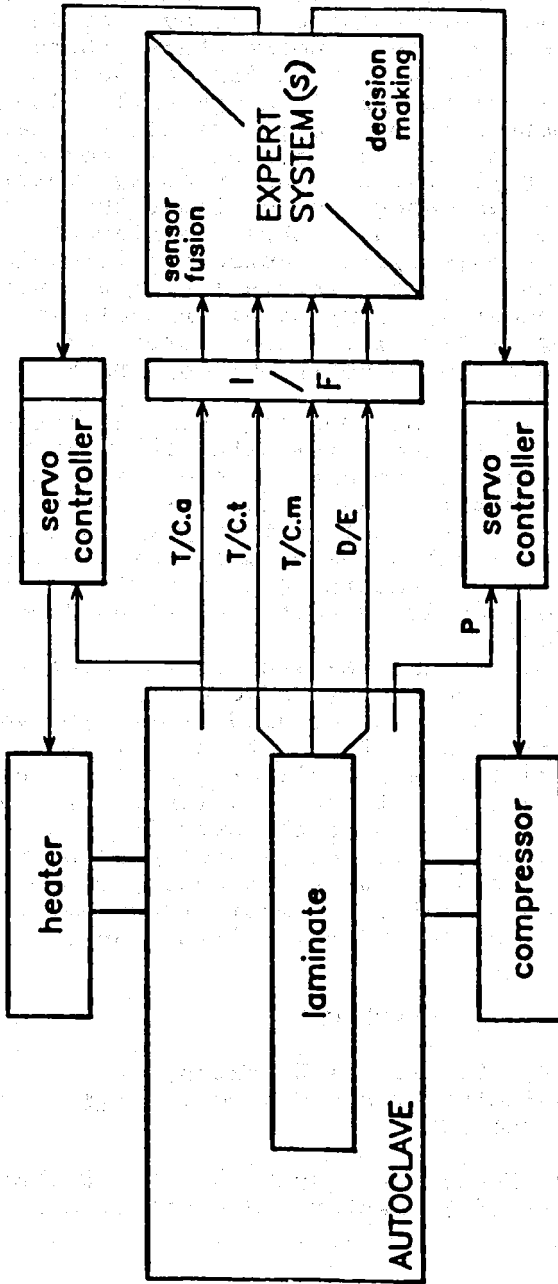
Knowledge is representable as any combination of the following: production rules, primitive lists, frames, knowledge networks, semantic networks, arrays, tables, etc. The kernel knowledge base will apply these structures to provide a 'meta knowledge base' - a knowledge base capable of reasoning about the knowledge involved in a sensor fusion task domain.

On top of the kernel knowledge base a knowledge engineer will layer such task domain knowledge as is necessary to reason within the task domain. Domain knowledge bases are to be constructed for each sensor fusion application and will include such knowledge as is needed to support parsing and fault diagnosis for the specific process environment.

### INTELLIGENT PROCESSING OF MATERIALS

Sensors and process models alone are insufficient for the processing of advanced and emerging materials. In large part these new materials have properties which are yet to be mathematically modeled and thus the application of heuristics is most appropriate.

The trial material for applying the sensor fusion tool is the autoclave curing of graphite epoxy laminates (reference Figure 3). This particular process was selected not so much because it is beyond the state-of-the-art in adaptive control technology but because it is on the leading edge of conventional model-based process control technology and it presents a relatively well understood yet challenging task for evaluation of artificial intelligence technology applied to process control.



SYSTEM CONFIGURATION

FIGURE 3

Currently the curing of graphite epoxy laminates is accomplished by prescribing a time, temperature and pressure pattern or cycle which is arrived at through simulation results of process models. The objective of applying a sensor fusion tool to this process will be to attempt control of the process without a prescribed time, temperature and pressure pattern, i.e. instead of dictating the process, use the graphite epoxy laminate cure behavior to automatically control the cure cycle.

It is conceived at this point that three different categories of inputs - autoclave, part lay-up and material should be monitored. Such a collection of inputs will allow the sensor fusion system to both encompass more 'requisite variety' and distinguish the effects of the corrective actions on the autoclave system, part lay-up and prepreg material. By considering these various categories of input the sensor fusion system will be able to handle three different sources of irregularities during a cure cycle: autoclave irregularity (e.g. faulty heating elements), part irregularity (e.g. variations in lay-up or bagging procedure), or material irregularity (e.g. off-specification prepreg material). The source of irregularity must be properly identified to apply the appropriate corrective action(s).

The short term goals of applying sensor fusion to the autoclave cure of graphite epoxy laminates is to improve control of desired part (in-process) conditions such as temperature and resin pressure. Ultimately, such control should be based on feedback measurements of critical part properties such as fiber volume, void volume, residual stresses and degree of cure. Since at present good sensors to measure part properties are lacking, the emphasis will be on measuring part conditions from which part properties can be inferred.

The long term goal of this research is to demonstrate that a direct relationship between the manufacturing process and the desired material properties can be used for improved process control. In the future, sensor fusion technology will be applied to other composite materials as well as metals, ceramics and electronics recognizing the basic commonality in all materials - that the product is a function of the starting constituent(s), the design and the process. If the desired part properties can be controlled and optimized during the process, rather than based on post process measurements, dramatic improvements in part development time, performance and reliability can be attained.

#### REFERENCES

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- Park, J., Rochester Paper on Expert-5. 86 Rochester Forth Conference, University of Rochester, Rochester, N.Y. 11-14 June 1986.