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MANUFACTURING RESEARCH:

SELF-DIRECTED CONTROL

January 1991

Interim Report for the Period January 1988 - December 1990

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Recent progress in the development of self-directed systems suggest that we may soon be conducting engineering design and material science using systems (i.e., machines) which augment the process of scientific discovery - conjecturing hypotheses, conducting experiments and discovering new knowledge about the process of design and fabrication materials. Tantamount to the technological advances which will make such systems feasible is an overriding economic impetus to improve our nation's competitiveness in a growing and soon global marketplace. It is the econmic importance of global, international competitiveness which will sustain the development of self-directed systems and the direction will be simply that of continually improving product quality in less time and at less cost.

Process Control, Material Processing, Artificial Intelligence, Knowledge Based Systems

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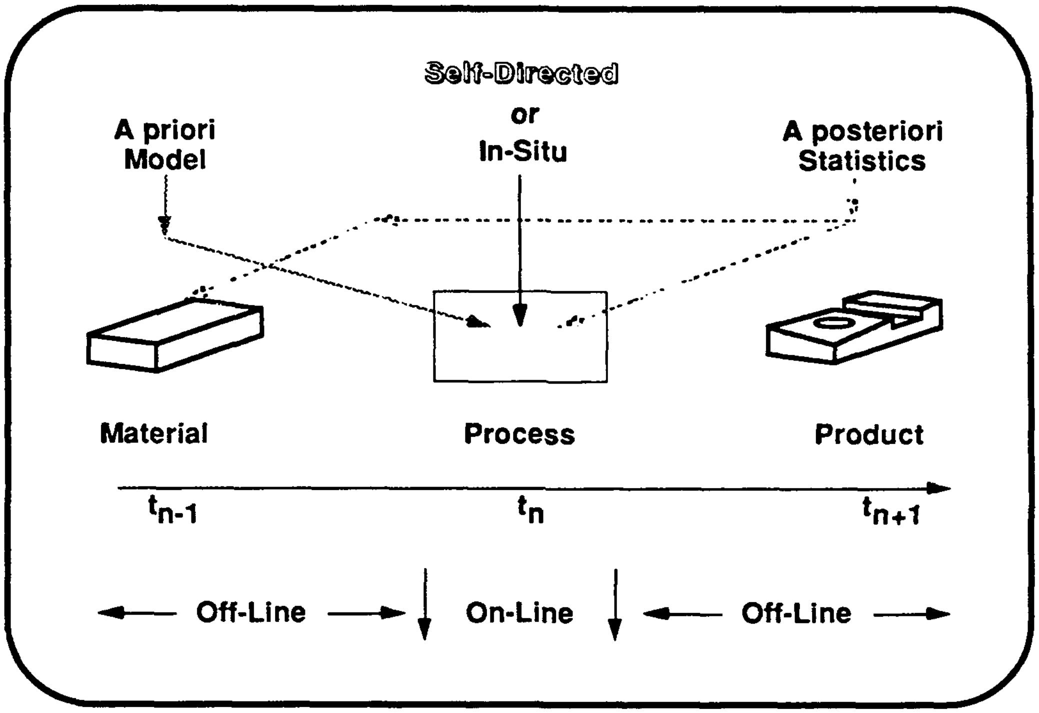
Manufacturing Research



SELF-DIRECTED PROCESS CONTROL

COMPOSITES **METALS**

SEMICONDUCTORS

WORKSHOP PROCEEDINGS
22-23 MAY 90

FOREWORD

As intelligent systems research begins to mature, it is becoming clear that the power of such systems lies in their ability to self-direct (autonomous control path generation), and self-improve (autonomous acquisition and application of new knowledge). Recent progress in the development of self-directed systems suggest that we may soon be conducting engineering design and material science using systems (i.e., machines) which augment the process of scientific discovery - conjecturing hypotheses, conducting experiments and discovering new knowledge about the process of design and fabrication of materials.

Tantamount to the technological advances which will make such systems feasible is an overriding economic impetus to improve our nation's competitiveness in a growing and soon global marketplace. It is the economic importance of global, international competitiveness which will sustain the development of self-directed systems and the direction will be simply that of continually improving product quality in less time and at less cost.

As we begin to compete in a global marketplace, the essence of product quality - improved design cycle time, life-cycle design, process repeatability, process yield, etc. has become central to manufacturing and therein intelligent systems research. It is for that reason that product quality has been embodied in our definition of intelligent manufacturing - systems which employ a product directed philosophy which when manifested in a manufacturing system enable on-line or in-situ generation of an improving product-process cycle.

SELF-DIRECTED SYSTEMS

In order to define further what is meant by 'intelligent systems', it is necessary to distinguish them from conventional systems. Very simply, conventional systems are typically a priori model driven, i.e., a mathematical model of the process is created, applied to the process and left undisturbed until product quality is determined unacceptable. Counter to such a philosophy is the development of systems which exhibit 'in-situ' adaptation, i.e., the systems are directly coupled to the product and thereby emphasize and are directed in real-time by product quality.

Intelligent systems are goal-driven in terms of product parameters of interest rather than state-driven in terms of following some prescribed model. The difference is expressed both in the modeling paradigm and the independent variable. In a state space model, the process is defined as a function of time (process time) irrespective of product. In a goal space model, the process is defined as a function of events (goals) regarding the product during processing. The distinction is one of adaptability.

A goal-driven system is adaptive and must be trained (off-line) by an expert to watch for and respond in-situ (on-line in real-time) to the occurrence of product goals during the process. A state-driven system is not intended to adapt and instead is forced to act in accordance with an a priori or off-line prescribed schedule of predetermined and time specific process states.

In-situ generation of a process cycle means the system has the autonomy to reason, i.e., make process-path decisions during the process. Therein, a goal-driven system must be capable of coupling these decisions (goals) together and creating its own processing path (from initial conditions through to end-goal conditions) in response to varying product parameters and process conditions.

A goal-driven system not only responds to when an event occurs but also to the many different combinations of events occurring during a process. Together, the capability to adapt and to reason about the occurrence of events, regardless of when they occur, in what combination or duration, establish the autonomy of a self-directed system. The benefit of such autonomy is a more consistent product and very often reduced processing time.

The technical advantage of self-directed over conventional systems is the real-time generation of a processing path. As a result, the process paths over time for the same identical process are usually slightly different from each other but always tailored to achieving desired product-quality goals. The economic advantage is usually a combination of improved design cycle time and reduces life-cycle design costs when applied to the design activity, and reduced processing time, improved process repeatability, and process yield when applied to material processing.

Steven R. LeClair, Maj, USAF

SELF-DIRECTED CONTROL WORKSHOP

UNITED STATES AIR FORCE
WRIGHT RESEARCH AND DEVELOPMENT CENTER
MATERIALS LABORATORY
WRIGHT-PATTERSON AFB, OH 45433-6533

22-23 MAY 1990

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PROCESSING NOISY INFORMATION USING NEURAL NETS

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ABSTRACT

A probability neural net (PNN) was developed which could be configured as a classifier as well as an estimator. The ability of fast-learning makes PNN an ideal Artificial Neural Net (ANN) for desktop systems implementation. A technique to form a reduced-size PNN training set to reduce the complexity of the net for QPA application was also discussed.

THE PROBABILITY NEURAL NET

INTRODUCTION

Artificial Neural Nets (ANN) models propose how the human brain might process information. ANNs have been developed into a variety of configurations. Despite this diversity, ANN paradigms that emerge from the basic characteristics of biological neural systems have a great deal in common. The brain is characterized by the massively parallel local processing and distributed organization of neurons. This study follows this biological inspiration closely in seeking for useful functions to develop an ANN for QPA autoclave application. Our effort in the development of a neural data processor has resulted in a PNN system which can be summarized as follows: 1) It is a statistical net which employs Bayesian approach to perform nonlinear decision making, 2) It is parallel, and thus can process data rapidly, 3) it is distributed ,so that PNN is robust, and can tolerate local failures. In addition, PNN is a fast-learning net which requires only one-pass to extract all the information available in the teaching set. This feature makes PNN an ideal low cost ANN which is superior to other nets for many applications.

PNN is based on the estimation of probability density functions (PDFs) of an input pattern for the various classes in the input space. The Bayesian strategy is used in the PNN algorithm to compare the PDFs of the input pattern for all the pattern classes. The input pattern is then assigned to the class in which the PDF of the input has the maximum value. Mathematically, the Bayes strategy of classification is described by the following rule: if $f_i(x) > f_j(x)$ for all i<>j, then input pattern x belongs to i-th pattern category. In the above statement $f_i(x)$ is the probability density function of the n-dimensional input pattern x belonging to the i-th pattern category. Specifically, by denoting the total number of the patterns in the i-th teaching pattern category as m_i, PDF can be described by the following equation[3]:

$$f_i(x) = \frac{1}{(\sqrt{2\Pi\sigma})^n} \frac{1}{m_i} \Sigma \exp \left(\frac{-(x-x_{ij})^t (x-x_{ij})}{2\sigma^2} \right)$$

(1)

where x represents the input pattern, x_{ij} is the j-th teaching pattern in the i-th pattern category, and σ a smoothing parameter. A parallel, distributed implementation for (1) has been successfully developed, and its structure is sketched in Figure 1. Note that this PNN unit can be easily connected to a MAXNET to form a classifier. It can also be modified into an estimator. These two configurations are shown in Figures 2a and 2b, respectively. When configured as an estimator, PNN utilizes PDFs as weight functions for the input category. It then incorporates the observation with the information in the teaching set to generate an estimation. In this sense the PNN estimator is analogous to a Kalman filter.

Evaluation of PNN

In order to evaluate PNN the back propagation net (BPN) was also used for comparison. There are two reasons for the use of a BPN: 1) BPN is one of the most successful ANNs for a large variety of applications, 2) Both PNN and BPN depend on mathematical logic rather than biological simulations in their search of solutions in the solution space. The following three examples have been conducted on a10MHz IBM PC clone to illustrate the use of PNN in a variety of applications.

Parity Detector

A BPN and a PNN were configured into two 4-bit parity detectors. A set of sixteen teaching examples was formed to train both nets. The a priori knowledge about the optimal configuration of a BPN application is in general not available. However,this information is made available to BPN so that the net contains four hidden units. Since the BPN requires a recursive learning process, a number of 5000 iterations was imposed to stop BPN from inefficient learning. Various values of 1< s <4 were used for PNN. With this specification it has been discovered that while it took only a few milliseconds to train a PNN, it required about 23 minutes for the BPN to complete a learning process. In a typical trial of 10 runs the BPN has learned successfully in 6 runs, while the PNN suffered from no failure at all.

Thermocouple Data Processing

A data file from a typical QPA autoclave[2] run consists of several hundreds of samples. QPA system operation requires real-time information related to the velocity and the acceleration of temperature during the curing process. QPA is a self-directing material processing system. Each process run is somehow different due to material and layup variability. Therefore, the QPA information embedded in the QPA file affords an unique opportunity for the training of PNN. Since every hidden unit in PNN represents a teaching example, it is required to develop a technique which can be used to construct a reduced size of teaching set from the QPA file so that PNN can be efficiently trained. In this study an unsupervised learning process was used to form a reduced-size training set. Thermocouple readings were utilized to generate cluster information in the classification space. In addition, a phase diagram (dT/dt vs. d^2T/dt^2) the optimal cluster size utilized in the PNN algorithm smoothing parameter in (1). The the teaching set. The rational for the formation of teaching clusters assumes that the patterns of the same class in the classification space are closer to each other than to patterns of a different class.

A BPN with 30 hidden units was also implemented to process a QPA file which consisted of 321 data points. It was soon concluded that BPN was not adequate for thermocouple data processing. This was due to the fact that BPN required a time-consuming recursive training procedure. In addition, BPN often failed to generate a satisfactory solution. On the other hand the fast-learning PNN estimator needed only one-pass to generate a satisfactory solution. It was estimated that PNN was faster than BPN by a factor of at least 4 (10^4) in this application. Figure 3a depicts the performance of the PNN estimator which was used to estimate the temperature acceleration of the composite material. Figure 3b showed the result of a differentiator for comparison. It is obvious that PNN has a better smoothing effect than than its conventional counterpart. Recently, the number of teaching groups used in the PNN for the estimation of temperature acceleration has been reduced from 13[1] to 7. This progress represents approximately a 50% reduction of hardware implementation for the autoclave PNN system.

Thermopile Data Processing

Currently thermopiles have been used for the study of utilizing the "apparent thermal diffusivity"[4] to infer the state of the QPA curing process. Preliminary results showed that the dynamics of the apparent thermal diffusivity can be used to infer qualitatively the release of reaction heat and the occurrence of accelerated reaction of the curing laminate in the QPA system. In addition, thermopile is better than the dielectrometer in the detection of complete cure. This is due to the fact that the apparent thermal diffusivity is independent of temperature, while the loss factor from the dielectrometer is affected by the laminate temperature. Due to the potential of the thermopile for the improvement of the current QPA system, a feasibility study of PNN for thermopile data processing has been initialized recently. A moving data window of size 6 was used to form the input port of the PNN estimator. A preliminary conclusion for this study can be summarized as follows: 1) Similar to the case of thermocouple data processing, PNN can be trained rapidly to estimate the dynamics of the apparent thermal diffusivity, therefore is useful for the detection of the reaction heat and accelerated reaction, 2) Pnn is sensitive to the sudden change of the dynamics of the apparent thermal diffusivity. An interpretation for the surge of apparent thermal diffusivity is currently under study. The use of three thermocouple readings from different laminates as inputs to a PNN might be able to avoid the degeneracy of information. This situation is particularly true when all these three readings are close to one another. A progress in this area might enable us to simplify the QPA data acquisition system and to enhance its overall performance, which would represent a breakthrough of the QPA research.

CONCLUSIONS

PNN's speed, accuracy, and flexible classification and estimation functionality make PNN an ideal artificial net for QPA and other related applications. Except BPN, the explicit structure of PNN. alleviates time-consuming trial-and-error procedure construction. In general, the development of a ANN is very expensive, while its delivery is inexpensive. The quick turn-around makes PNN an ideal tool which is more cost-efficient than other nets.

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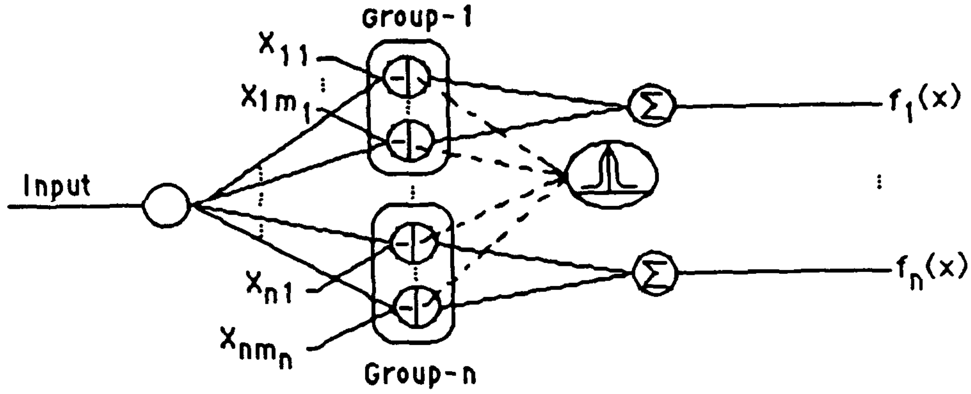

Figure 1. Structure of Probability Neural Net.

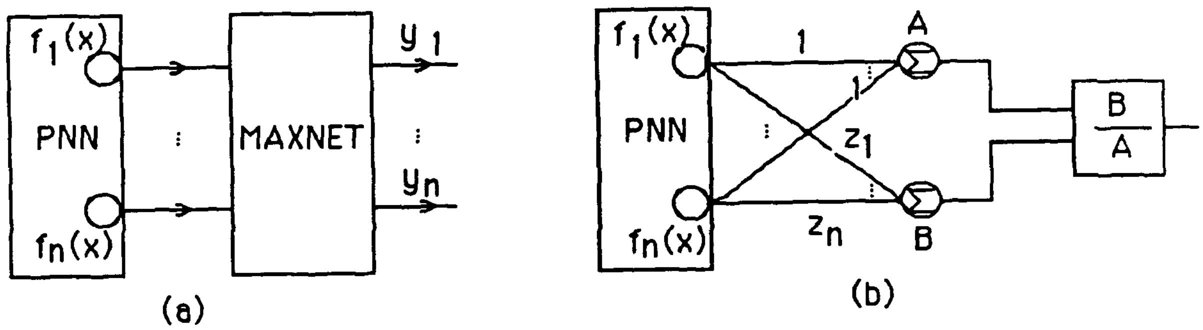

Figure 2. PNN Configurations: a) as a classifier. b) as an estimator.

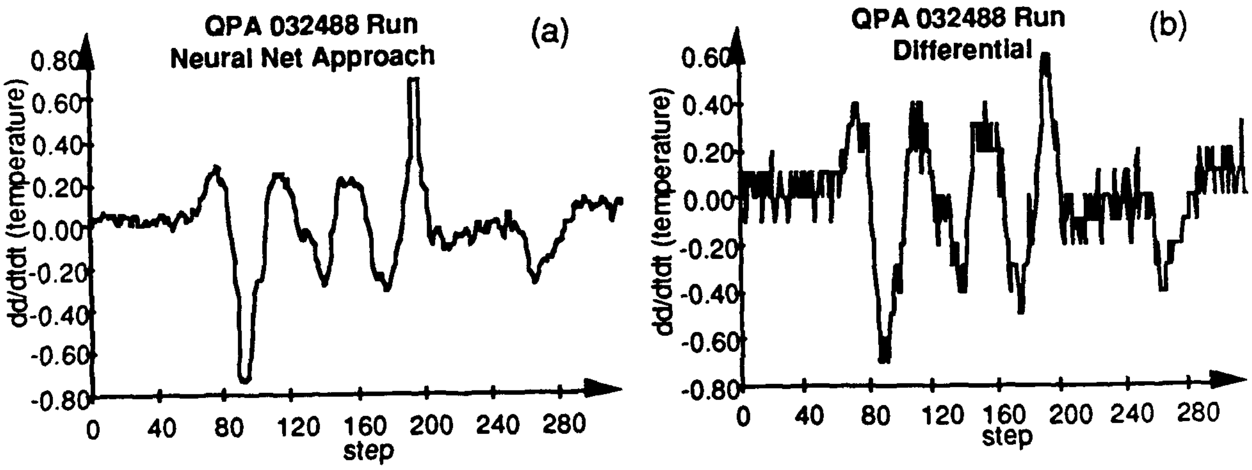

Figure 3. Temperature Acceleration: a) PNN output. b) Differentiator Output.

GRAPHICAL PROCESS KNOWLEDGE BASE DEVELOPMENT FOR QPAL

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INTRODUCTION

This paper describes work on a graphical knowledge base development tool for a second generation Qualitative Process Automation Language (QPAL) environment. The tool intendes to simplify knowledge base development within the new QPAL environment. Specifically, it will ease the task of encoding process control knowledge into the representational structures of a knowledge base.

The tool provides a knowledge base development environment superior to existing text-based QPAL software environment. Its features include: an underlying knowledge representation that is more flexible than QPAL, a graphical interface for quickly establishing various relations between knowledge structures and forming an overall picture of the process, and a syntax and completeness checker for detecting problems with syntax, naming, and knowledge base completeness. Because the knowledge base development tool uses a modified set of knowledge structures from QPAL, a new QPAL environment must be created to accommodate them prior to any real implementation.

KNOWLEDGE REPRESENTATION

A Limitation of QPAL

In the current version of QPAL, the Plan and Episode structures function as the primary descriptors for the overall control strategy. Plans allow the process to be decomposed into separate subtasks associated with the parent Schedule. Each subtask is a separate instance of a plan which contains a list of Episodes. Episodes capture the individual goals of the process and represent the lowest level of decomposition. Together, plans and episodes form a process decomposition containing two levels of control information. Plans separate conflicting process goals into nonconflicting, independent segments. Episodes define process goals in terms of states and specify the conditions needed to meet these goals.

The current version of QPAL is limited in its representational capability because the plan and episode structures require the user to decompose the process into two levels. Some processes may be too complex to represent in this manner. They may require a decomposition containing multiple levels of subtasks. Still, other processes which can be represented in the current version might be more easily represented and more understandable if broken down into multiple subtask levels. A control structure that is similar to plans and episodes, but allows a process to be decomposed into multiple control levels could greatly increase the representational power of QPAL and simplify knowledge base development.

New Structures

This section describes the modifications made to the existing QPAL knowledge structures which form a representation for the knowledge base development tool and the second generation QPAL environment. An alternative control structure is described which will preserve the representational capabilities of the present QPAL control structures and allow a process to be decomposed to any number of levels. A modification in the State structure is suggested as a part of this change. In addition, the Part structure is modified and renamed to assume additional roles in grouping associated controllers, tasks, and states.

A *Task* structure introduces the primary descriptor for the overall process control strategy. A task has start and end conditions specifying when the task begins and when the task ends. It can be defined in either of two possible forms which are referred to as *high level* and *low level.* A high level task allows a process to be decomposed into separate subtasks. Therefore, the goal of a high level task is to attain the goals represented within its subtasks. Of course, subtasks may also take on a high level form giving way to additional levels of decomposition. An example task decomposition of an airplane flight is shown in figure 1.

Low level tasks are the drivers of actions in the process. The goal of a low level task is to achieve, prevent, or maintain a specific process state. Influence rules associated with a low level task specify how the goal is to be achieved. They contain methods that *directly manipulate process controllers* if a specified condition is true.

The association of influence rules with task structures represents another change to the existing version of QPAL where influence rules or exciters and inhibitors are associated with state structures. This modification is introduced to maintain a consistent knowledge representation. Tasks are intended to describe goals and how they are to be achieved. Therefore, influence rules must somehow be associated with them since they specify controller methods for attaining a goal.

An *object* structure, introduced into the new representation, replaces the *part* structure in the existing version of QPAL. The new name refers to process objects or the objects undergoing change. Objects capture groupings of associated sensors, controllers, tasks, and states. For example, the task, Prevent HeaterFailure, the state, HeaterFailure, the controller, Heater, and the sensor, Temperature, might all be associated with an object, autoclave, as shown in figure 2.

In summary, tasks and states are the basic building blocks needed to represent a second generation QPAL process. State structures are the elemental descriptors of process events. They describe *when* process goals are to be achieved. Tasks describe *what* the goals of the process are and *how* they are to be achieved. Objects capture logical groupings of sensors, controllers, tasks, and states which are important to the semantics of the knowledge base.

BENEFITS

The new task and state structures provide a more flexible and understandable representational schema than their counterparts in the current version of QPAL. The new task structure replaces the schedule, plan, and episode structures and its recursive nature allows a process to be decomposed to any number of levels giving the user greater representational power and flexibility.

KNOWLEDGE BASE DEVELOPMENT ENVIRCNMENT

Text Editor & Interpreter

In the existing QPAL software, knowledge bases are developed in a text-based editor and then interpreted or compiled so that they can be executed by QPAL. Unfortunately, the text editor and interpreter slows the development process because of the extra burdens they place on the user. Entering knowledge structures in textual form is time consuming. The user must adhere to the QPAL syntax and be sure to declare structures before they are referenced by another structure. In addition, the user must function as a programmer, editing and recompiling whenever a modification is made to the knowledge base. This type of development environment can be quite cumbersome and inefficient. A knowledge base development tool is needed which will relieve the burdens of syntax and referencing off the shoulders of the user and in essence provide a quicker way to enter knowledge base information.

GRAPHICAL KNOWLEDGE BASE DEVELOPMENT TOOL

A graphical knowledge base development tool was developed for a second generation of the QPAL environment to provide a means for easier and more rapid knowledge base development. Graphical description windows are used in combination with textual windows containing record type fields to capture knowledge base information. This information is organized using the new structures: tasks, states, and objects, described previously and those structures that were left unchanged.

Graphical description windows provide a means of quickly representing specific relationships between knowledge base structures. Each structure type is represented as a different picture or icon and each relation type as a different line connection. A picture is created when a new instance of a knowledge structure is declared. A new connection can be formed when a relation must be established between two knowledge structures. These pictures and connections, allow the user to produce a meaningful and organized view of the process decomposition, process flow, and sensor and controller relationships to process objects. The views are discussed in more detail next.

The Process Description window captures the process decomposition and flow. Task structures and subtask connections pictures may be created and manipulated to fully represent a process decomposed into tasks and subtasks. A meaningful view of process flow can be formed using the task, state, inform, abort, and explain pictures and the relational connections: start condition, end condition, and trigger. A Process Description window containing a view of process flow for an airplane flight is shown in Figure 3.

Sensor and controller relationships to process objects are represented in the Sensor/Controller Assignments window. It allows pictures of sensor and controller objects and associated assignment connections to be created and manipulated. Together, these can be used to form an organized view of process objects and their assigned sensors and controllers.

The Process Description and Sensor/Controller Assignment windows also function as a definition and querying tool. Each knowledge base structure can be further defined by selecting the corresponding picture. The selection causes a textual window to be opened which holds the details of the knowledge structure.

Textual windows contain record type fields for entering attribute values and statements of knowledge structures. A text window for a state, for example, would include a field for the state name, a field for the process object that the state is associated with, and a field for the state conditions. Thus, to define a knowledge structure, the user must enter the appropriate information into the fields of the corresponding text window. The environment's syntax checker will insure that all fields are syntactically correct and structure names are not duplicated.

The syntax checker finds and informs the user of problems with syntax, naming, and knowledge base completeness. As the user enters information into the textual windows, the system automatically detects syntax and naming problems. If a problem is found, the user is informed immediately by an alert box and the cursor is placed in the appropriate field. Since naming problems jeopardize the integrity of the knowledge base, the syntax checker will be persistent in accepting only unique names. With other syntax errors the user has the opportunity to either correct the problem or come back to it later.

Upon request, a user can check knowledge base completenss. The check option finds and highlights incomplete and invaid knowledge base structure definitions. When QPA detects a problem, the system informs theuser through an alert box,opens a corresponding text window, and the cursor is places the cursor in the field where the error occurred.

BENEFITS

The graphical knowledge base development tool will prove to be a beneficial tool if implemented in the next generation QPAL environment. The tool provides an environment for quickly entering, and accessing knowledge base information. It frees the user from problems with syntax, naming, and referencing which can be a burden in a text-based development environment. In addition, the tool can potentially create executable knowledge structures without the need for a compilation step as in the present QPAL environment. These capabilities would clearly improve knowledge base development efficiency.

CONCLUSION

The benefits of the new representational structures, coupled with the graphical development tool, go beyond simplifying knowledge base development in the next generation of QPAL. The new task structures provide a more understandable and flexible representation. The graphical development tool provides a user friendly, picture-based environment which increases understandability, maintainability, and efficiency.

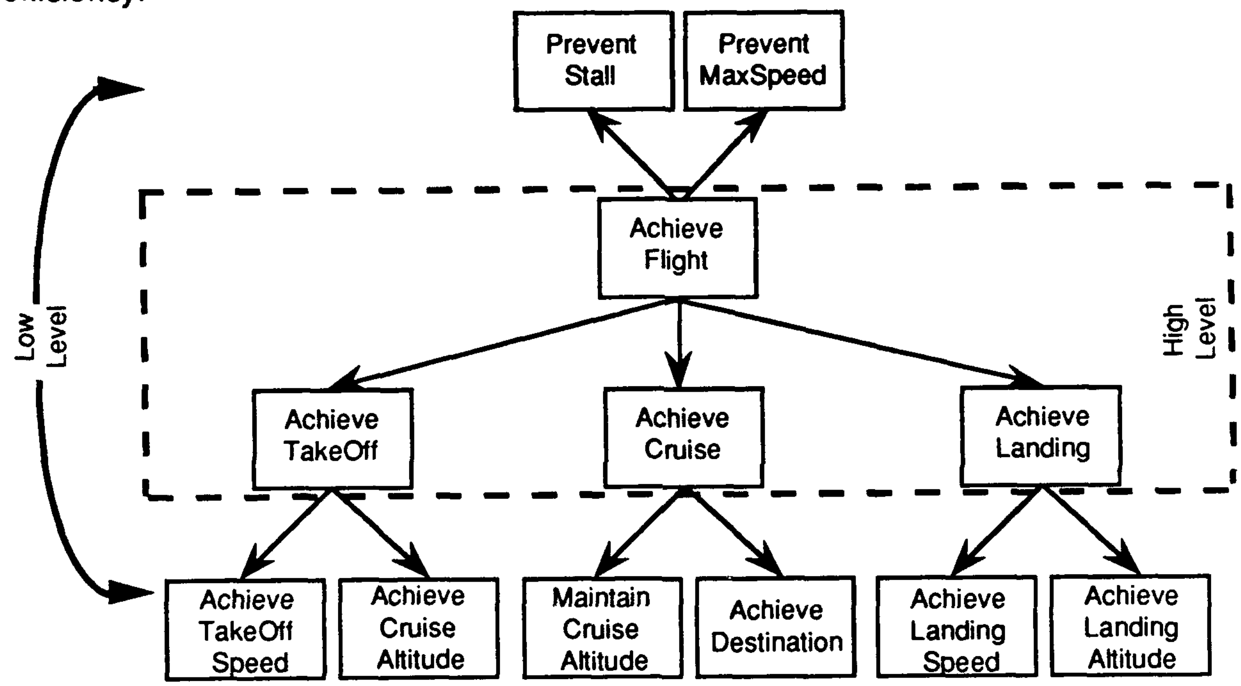

Figure 1. Example task decomposition of an airplane flight.

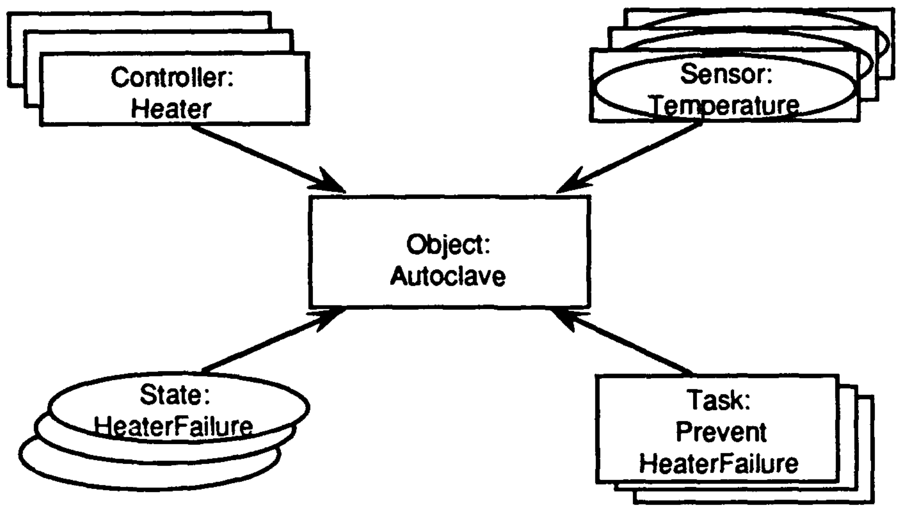

Figure 2. Example tasks, states, controllers, and sensors, associated with an Autoclave object.

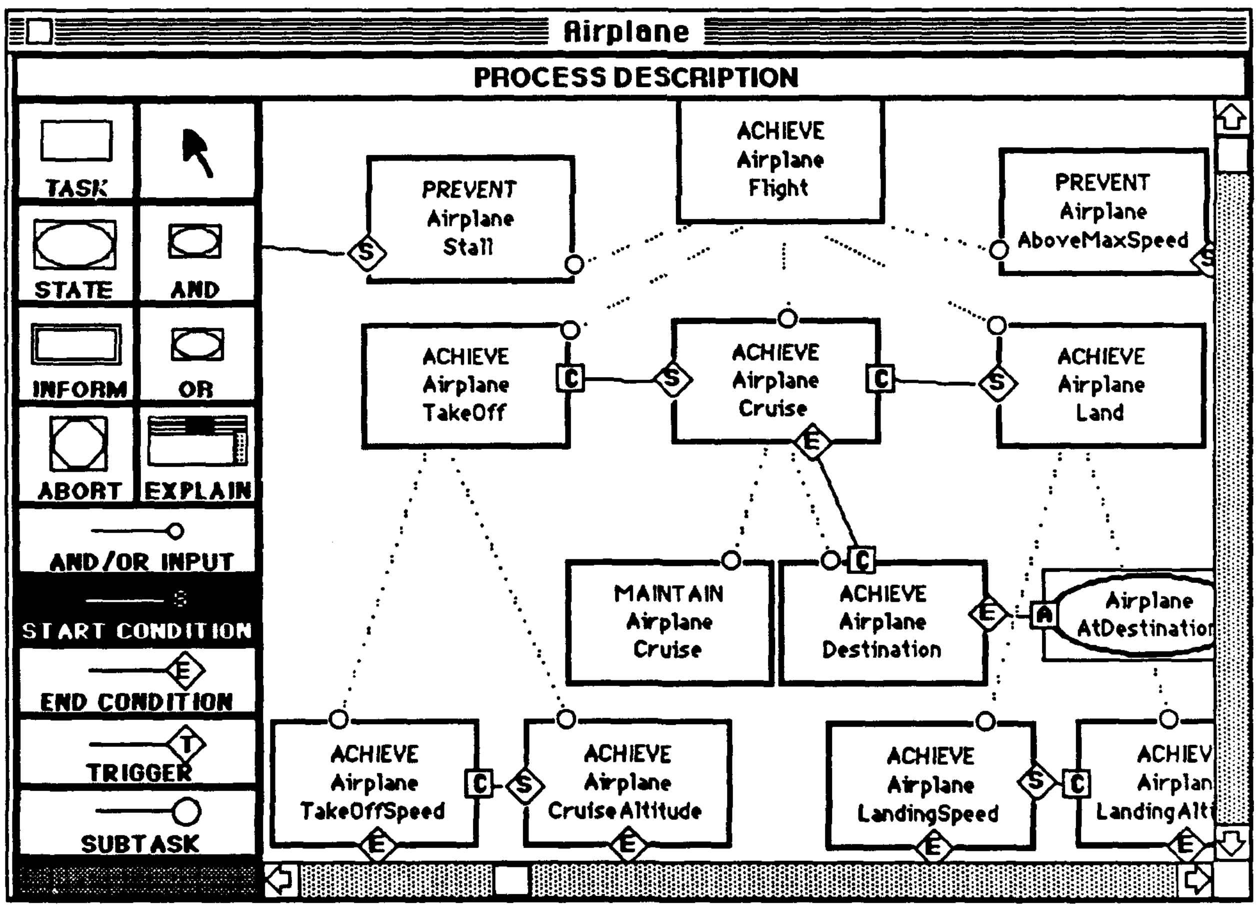

Figure 3. A Process Description window containing the process flow of an airplane flight.

SELF DIRECTED OPTIMIZATION

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INTRODUCTION

In order to remain competitive in today's markets a manufacturer needs to optimize all of its manufacturing processes in order to improve quality and reduce cost. This optimization is rarely done in the U.S.A. Manufacturing processes are left to run at non-optimal levels producing inferior products at higher costs. One of the reasons why manufacturing processes are not optimized is that there is a shortage of trained experts in the different fields required. If the optimization of a manufacturing process could be automated, then this would ease the problem of the shortage of trained experts.

The objective of my work is to develop an automated system that will optimize a manufacturing process with minimal interaction from human experts. I have combined some of the ideas from Evolutionary Operation (EVOP), Statistical Process Control (SPC), and Genichi Taguchi to develop an on-line automated optimization system that will interface to QPAL. This system is a Self Directed Optimizer (SDO). SDO is meant to be used during the manufacturing of a product to direct the process so that the process will provide both product and knowledge at the same time.

SYSTEM OVERVIEW

SDO is a software package that will run on any Apple computer that supports HyperCard. It is written in HyperTalk and is meant to be used with QPAL. The first step a user would take to use this package would be to supply the system with a list of process parameters and a list of measured response variables. The process parameters are specified in terms of QPAL controller or variable names. For each process parameter an initial value and an initial step size would also be specified (more about these later). The user would then enter the cost function to be minimized; this should approximate the cost of a individual part manufactured by the process. The cost function is a polynomial. Each term of the polynomial can either be one of the process parameters or one of the measured response variables. The exponent, scaling factor, and a target value (if one exists) can be set for each term.

Next the user would set two other parameters; the number of repetitions to use in each experiment and the size of the smallest difference between two trials that the system will consider significant. These two parameters along with the scale factor for the individual process parameters affect the rate at which the SDO system would find the optimum conditions. Once this information is entered, the SDO system would be instructed to start optimizing the process.

Each run of the process would be an experiment, with the SDO system directing the experimentation. First the SDO system would design an experiment. Then the SDO system would start a QPAL run with the proper settings for that experiment. When the QPAL run is complete, the measured response variables, if specified in terms of QPAL sensor names, would be automatically read into the SDO system. If they are not QPAL sensor names, the SDO system would prompt the user for their values. The SDO system would then analyze the results of the experiments and use this information to design the next experiment. This cycle would repeat until the user is satisfied that the optimum level has been achieved.

These experiments would allow the system to explore a small area near the working process and determine the direction to move the process in order to minimize the cost function. The area explored is small enough so that the quality of the products produced would not be significantly affected.

DETAILS OF OPERATION

The SDO system combines concepts from several sources. SDO is based on the concept of Evolutionary Operations. Concepts from SPC and Genichi Taguchi are also used. Evolutionary Operations and the other topics are briefly covered below.

Evolutionary Operation

Evolutionary operation is the basis for the automated optimization system I have developed. Evolutionary Operation was developed by George Box in the early 1960's. The main idea behind EVOP is that a process should be made to evolve towards the optimum conditions. This evolution takes place during the manufacturing of product and is accomplished by continuously performing experiments on the process, thus exploring the small area around the current working process. The results of this exploration are then used to guide the setting of the process parameters so that an improvement in the process is made.

The results of these experiments are not meant to be used only by the SDO system. A complete history of all experiments is maintained so that it can be examined by process operators and management in order to make further improvements.

Genichi Taguchi

Two of Genichi Taguchi's ideas are involved with SDO. The first is his quadratic loss function. SDO's cost function supports terms with this form, where the loss is proportional to the square of the distance the characteristic is from the its target value.

The second idea is Taguchi's approach to removing process variation. He removes process variation by selecting the setting of the process parameters that reduce the processes sensitivity to noise. This is done during the parameter design stage of his process design philosophy. Reducing the sensitivity of a process to noise is one of the goals of an SDO system. By using a term in the cost function that is of the form of Taguchi's quadratic loss, SDO will automatically determine the setting of the parameters that will reduce this sensitivity. SDO is performing Taguchi's parameter design.

Statistical Process Control

SPC techniques will be used to monitor the process and provide a signal to show when the process is out-of-statistical-control. SPC will perform the role of maintaining a level of quality once it is achieved. When an out-of-statistical-control signal is generated the process will be stopped and the proper corrective action taken by the operator in order to return the process to its minimum level of variation. Tools are provided by the SDO system which will help the operator determine if the out-of-control situation is caused by the SDO system or by some outside cause. ANOVA tools will allow the operator to determine the significance of the changes made to the different process parameters, then if a change to a parameter seems to be the cause of the problem, then the step size for that parameter could be reduced.

The Optimization Algorithm

The optimization algorithm searches the space formed by the set of process parameters entered by the user. An n-dimensional space forms with each of its axis corresponding to a different one of the n process parameters identified by the user. The space is broken into a set of points. Points are placed on a grid with the sides of each grid equal to the step size for that parameter. For example, consider the system in Figure 1, it has two control parameters: temperature and pressure. The space formed would be a plane with one axis temperature and the other pressure. If the step size of the temperature parameter is 5 degrees and the step size of the pressure parameter is 10 psi there will be points place as depicted in Figure 1. The goal now is to determine which of these point is the optimum point considering the cost function.

There are two factors that guide the experiment planing, the "working process" (Wp), and the current direction of optimization (Cd). The "working process" is the point that the process is currently operating at, this is the point from which every step of the optimization starts. The current direction of optimization is the direction in the parameter space that the optimum conditions are thought to lie in at the present time. The first step in the optimization algorithm is to design an experiment to explore the small area near the working process in the current direction, the experimental design is shown in Figure 1. After the experiment has been performed the cost function is evaluated at all of the experimental points. If the experiment involved any replicants the average value of the cost function is then determined at each experimental point. Next the algorithm determines the point with the maximum cost and the point with the minimum cost. Several actions are then possible depending on whether or not the difference between the maximum cost and the minimum cost is greater than some predefined threshold of significance.

If the difference is significant, then the minimum cost point becomes the new working process and the direction from the maximum to the minimum cost point is the direction for the next experiment to explore. The next experimental design is shown in Figure 2.

If the difference is significant then the working process will be moved in the current direction. This assumes that the last direction is still correct. It can be shown that this is normally the case and that the speed of optimization is improved by this action. The next experimental design is shown in Figure 3.

RESULTS

The system has been tested with a simple model of a process to determine the effects of noise and the other parameters on the rate at which it converges to the minimum solution. The optimization algorithm was analyzed and an equation was determined that predicted the expected rate at which the SDO system would converge on the minimum value. This equation was tested against runs of the SDO system, the equation predicted the actual results rather well. Based on the experimental and analytical results, three SDO parameters where found to have an affect on the rate at which the system converges. They are: the number of replicants used in each experiment, the significance level and the step size for the process parameters. The number of replicants used had a negative affect on the rate of convergence, that is as the number of replicants increased the rate of convergence decreased, therefor one replicant should be used. The best value for the significance level was determined to be about one standard deviation of the response. And the step size should be set at the largest value that can be used and still have the quality of the end product not significantly affected.

SUMMARY

SDO's main benefit allows a process to be optimized with little interaction from experts. The simulations to date show that this simple algorithm works as predicted even with a large amount of noise present. The next step applies the SDO system to a simulated composite curing process. This should indicate how the SDO system might work under actual conditions.

FUTURE DIRECTION

There are several enhancements which are possible with the current SDO system. First in the current system the step sizes for the process parameters can only be adjusted by the operator. An automated means of adjusting these would make the system even more independent of operator. Next, the speed of optimization might be improved by incorporating Taguchi's two step optimization algorithm into the system. Another useful feature for the system would be the ability to handle qualitative changes in the process, the current system handles only quantitative changes. And finally a discovery system could be created that would use the data collected by the SDO system to make changes at the rule level of the QPAL knowledge base.

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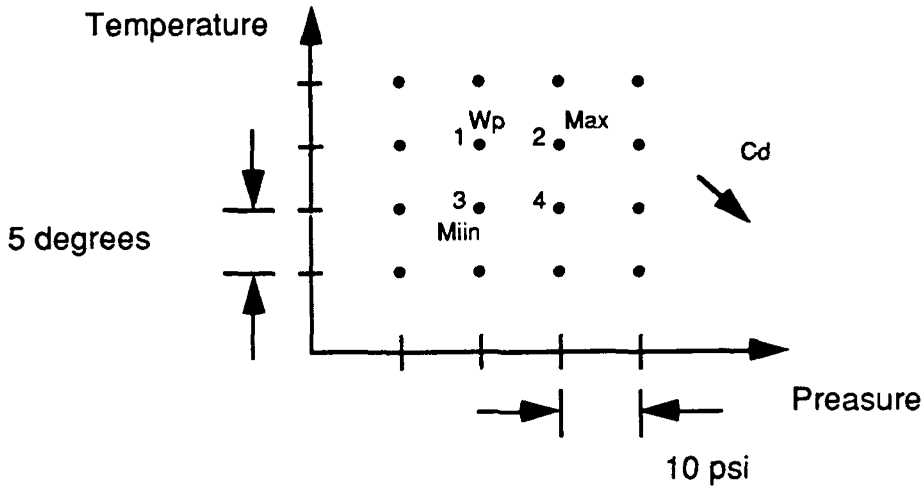

Figure 1

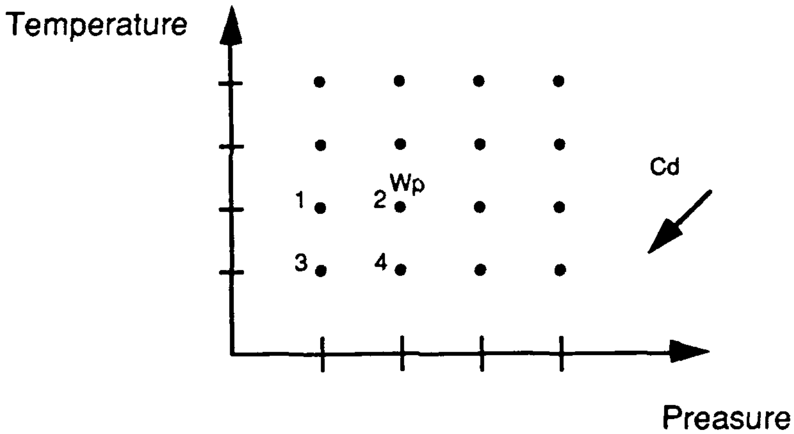

Figure 2: if max - min > significance level

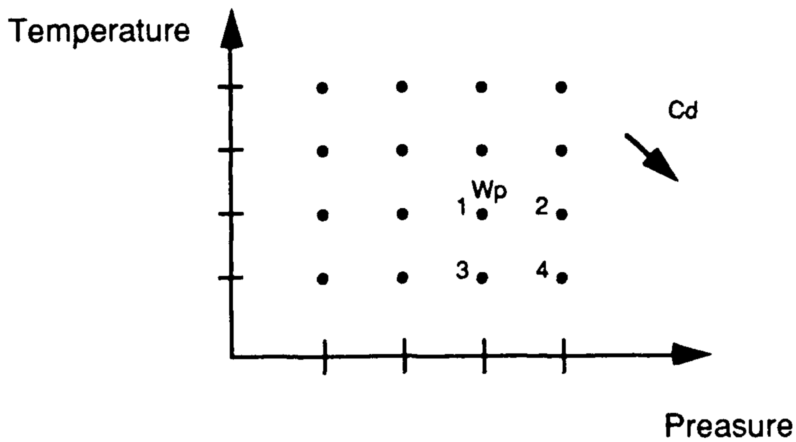

Figure 3: if max - min < signficance level

MANUFACTURING DATA: RELATIONSHIPS AND ANALYSIS

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ABSTRACT

The purpose of this work is to exploit the meaning behind manufacturing process data relationships in further exploration of the material or process, using various data analysis techniques. Semantic data relationships for the autoclave curing of thermosetting epoxy matrix composites have been identified. Currently, analysis techniques are being chosen and developed according to the goals of the data analysis. These goals are:

1) to find additional relationships among the data, and

2) to analyze future processing runs.

A method for building a system to aid manufacturing or materials specialists in data analysis is being established. This method is being used for prototype implementation. Prototype results will determine the level of success of the work, since it is here that we will discover whether or not identified relationships, selected analysis techniques, and the construction method are adequate for fulfilling the goals of the work.

THERE SEARCH ISSUE

This research is about the interpretation of manufacturing process data. The data may come from sensors or from human input. The interpretation is to be done by exploiting semantic data relationships when analyzing data.

PURPOSE

The purpose of this research is to assist materials or manufacturing specialists in learning about new materials and processes. Anticipated results will fall into two categories--the ability to find more relationships and the ability to analyze future processing runs. This is to be done by automating assistance in analyzing data, which may lead to the arousal or confirmation of specialists' suspicions about part quality and process variables or suggestion of new processes. The ultimate goal is to increase the possibility of making acceptable products efficiently and in a timely manner.

The process being used in this research is the autoclave curing of epoxy matrix composites. We are interested in analyzing process data from this process because of:

- the cost of manufacturing (we want to reduce this)
- the lack of expertise in processing (we want to increase this)
- the properties of the material (why composites are important)
    - strength
    - light weight
    - anisotropy
    - corrosion and damage tolerance
    - reduced radar cross-section

THE RESEARCH

The approach to this research is to find relevant kinds of data for this process, find the semantic relationships among these data, select appropriate analysis techniques and explore ways to synthesize the analysis techniques, develop a system construction procedure, and finally prototype analysis tool implementation. Inputs and outputs to and from the anticipated tool are depicted in Figure 1.

SEMANTIC RELATIONSHIPS

The word "semantic" refers to "meaning". Consider the difference between syntax and semantics. Briefly, "syntax" refers to a set of rules specifying how to put symbols together. "Semantics" are the mapping from those syntactic structures to objects in a domain. In other words, semantics are the meaning behind the syntax. For example, when writing a computer program, the programmer knows that certain words, numbers, spaces, etc. are used in a certain order. This is SYNTAX. SEMANTICS are what the computer program means, what it is trying to do, what its context is.

What does this mean to you?

1040

A name for a tax form? A measurement? A year? We could go on. Unless we know the context or unless we know associations between what the symbols mean and other symbols and their meanings, we don't really know if any of the potential meanings is the correct one. The syntax looks all right, but the semantics are missing. Note the two graphs in Figure 2. These two graphs look like they might plot the same process or an identical one. We might look at the graphs and decide that they display related processes. But we don't know whether what happens in the first graph affects what happens in the second graph. If the graphs are time and temperature graphs, they could be showing a correlation between two parts being processed in the same autoclave. One doesn't cause the other. The two graphs might also be showing an autoclave cooling down and a part cooling down inside the autoclave. If this were the case, one is causing the other. Knowing the context and relationships between data tells us whether or not this is a causal relationship.

The first steps in the research were to identify relevant kinds of data to analyze for this process, then identify the semantic relationships among these data. This was completed by reviewing literature and interviewing knowledgeable people in the field. The result is a database developed using HyperCard software on the Macintosh computer. Figures 3 through 5 show examples of information stored about each kind of data. These are "cards" of information about data; data relationships; and data definitions. The database serves two purposes--to allow the user to browse and learn about the data or the database or to seek certain kinds of information; and to use with real data which will then be used in analysis. Figure 6 shows the data represented in this database.

DATA ANALYSIS

Most people think of statistics when they think of data analysis. But we can look at data in other ways. We can look for patterns, contradictions to expectation, coincidences, or unexpected occurrences. In terms of semantics, we need to attach something to our data analysis procedures which takes them beyond what traditional statistics offers us. We need to take them past presentation of statistical results to what those statistical (or other analyses) results mean, given context and relationships.

Currently, this research has progressed to selection of functions for an analysis tool. A list of potential analysis functions was assembled then narrowed to include pattern identification, trend identification, causal relationship identification, irregularity/ inconsistency identification, processing outcome prediction, and showing of the "big picture" (e.g., processing steps, analyses, interpretation of analyses, conclusions). There is more than one way to perform each of these functions and various means of analyzing and displaying data to perform these functions are being explored.

To test the eventual analysis tool, data on the manufacture of A-10 aircraft leading edges will be provided by the Advanced Composites Program Office at McClellan Air Force Base. The data will be gathered in part using the Qualitative Process Automation system being developed jointly by Universal Technology Corporation and the United States Air Force.

CONCLUSION

Known relationships among data involved in the autoclave curing of epoxy matrix composites have been compiled into a HyperCard database. Data analysis techniques which will take advantage of these known relationships are currently being explored, with the eventual goal of providing manufacturing or materials specialists with a tool to assist them in learning more about this manufacturing process or the material involved.

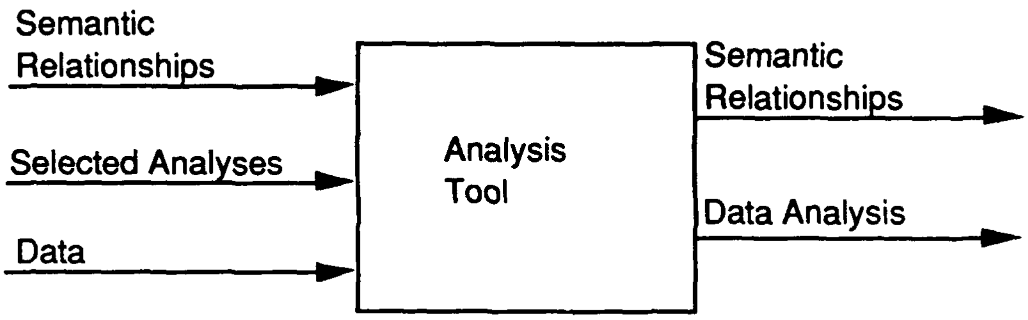

FIGURE 1. The Analysis Tool

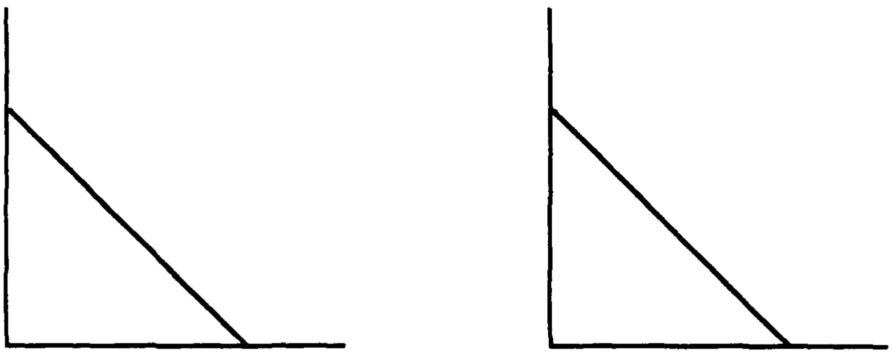

FIGURE 2. Two Graphs That Look The Same

DATA: **Conductivity, Thermal** (Bibliography)

B,D,A:* B, A

Dictionary

Click for definition

References: ASM, Chapman, Warnock, Hauwiller

Importance: Higher thermal conductivity means faster heat transfer.

Collectible? Where? By design before cure, testable after cure.

Manipulable? How? Manipulable in part design

Range, scale, type of data: Range for PAN (fiber precursor) axially is 8.5-70 W/m.k or 59-490 Btu.in/in.ft2.F (ASM 49)

Relationships & their implications: (Click on the box containing the relationship you want to see)

Evenness of Cure	Layup Materials	Tooling/ Molds

Comments:

1. Consists of thermal conductivity of resin, of fiber, and the proportions in the final material.

(Click to Return to "Resin" Menu)

(Click to Return to "Fibers" Menu)

* B=Before, D=During, A=After

(Click to Return to "Part Thermal Properties")

Figure 3.

Definition for: Conductivity, Thermal (k)

The ability of a material to conduct heat. Thermal conductivity is measured as the quantity of heat that passes through a unit cube of material in unit time when the difference between two faces is 1 degree. It is a constant for a given material.

Reference: ASM 23, Chapman

Click Here to Return to Data

(Bibliography)

Figure 4.

Definition for: Conductivity, Thermal (k)

The ability of a material to conduct heat. Thermal conductivity is measured as the quantity of heat that passes through a unit cube of material in unit time when the difference between two faces is 1 degree. It is a constant for a given material.

Reference: ASM 23, Chapman

Bibliography

Click Here to Return to Data

FIGURE 5

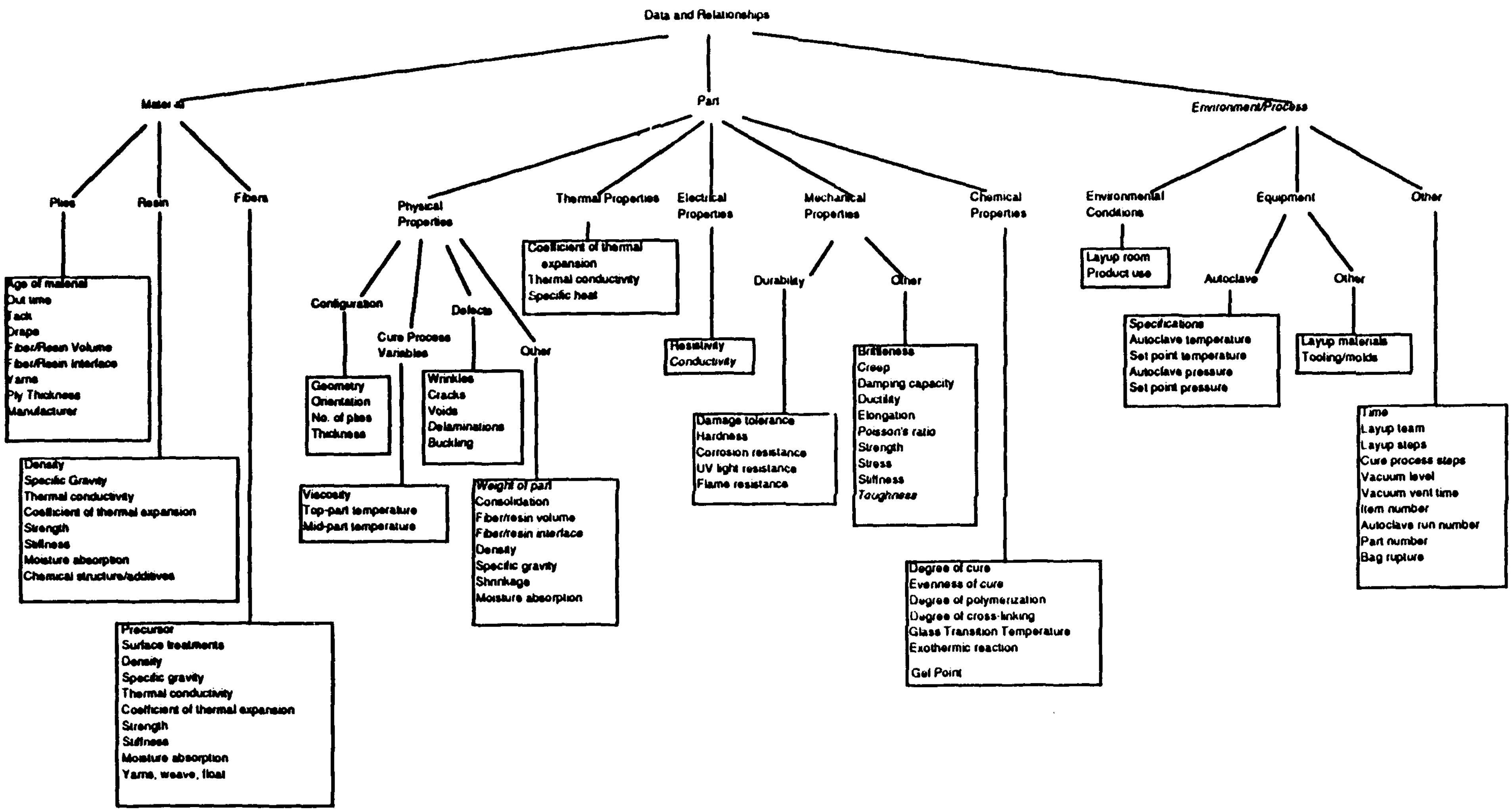

FIGURE 6. Data of Interest for This Process

APPLICATION OF QPA CONTROL TO END MILLING

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INTRODUCTION

One of the long range goals of machining control research is the development of a totally adaptive machining center. Such a machining center would utilize computer generated process operations to cut a part, and enable in-situ adaptation of those operations to obtain desired part tolerance. Intelligent closed-loop control of the machining operations is essential if an autonomous machining system is to be developed which can realize near optimal yields and cost effective production, even for lot sizes of one.

An autonomous system is desired because of the emphasis on quality for long production runs and adaptability to handle small batch operations. Adaptive machine control is essential to this overall system because of the large variations in the part/tool cutting geometry, and material properties. These variations make it very difficult to foresee and react to machining problems such as tool chipping, tool breakage, part tolerance and chatter. Without this capability, machining centers require close attention from skilled operators for diagnostics and machine adjustments. Especially prone to machining problems are aircraft parts made of aluminum and high temperature alloys. These parts typically require extensive contour milling, and as a result, large changes in the part geometry can occur, leading to undesired cutting conditions. These problems are intensified in flexible manufacturing systems (FMS) where only a few parts are being produced and the experience of cutting a part or a particular material is limited

QPA CONTROL OF END MILLING

Figure 1 shows the proposed QPA structure for a general machining operation. The history of the part is the complete cutting routine, while the various episodes are composed of the different tools used to make the cutting history. Examples here would be end milling, face milling, boring and drilling operations. Under each episode are the events that are desired (achieve) and those to be avoided(prevent). Since end milling is the operation that is being evaluated, only one episode is considered, along with its associated events of maximum feedrate,shank failure, tooth failure, tool wear failure, tool deflection and chatter. The desired goal during this episode is to complete the end milling cut in the shortest amount of time while avoiding the undesired events. While a very fast cut is desired, both a good finish and part tolerance are also desired. Since neither of these quantities can be measured directly by sensor, they are inferred by the various prevent events. For example, to insure part tolerance, excessive deflection of the tool is prevented by monitoring the cutting force perpendicular to the feed path, and reducing the feedrate if the force and hence the deflection becomes excessive. Likewise, the surface finish can somewhat be inferred from the spindle speed, feedrate, tool deflection and chatter state.

Utilization of these described events for control requires event detection, an influence diagram, see Figure 2, and conflict ranking. Unfortunately, the event detection is not straightforward because of indirect sensing and the lack of sensor availability. Indirect sensing refers to the prediction of an event such as tooth failure or chatter through sensory data not directly associated with the event. For example, tooth failure cannot be predicted by a tooth failure sensor, it has to be inferred from the cutting force or acoustic emissions. In a similar fashion, the onset of all the other prevent events must be determined by indirect sensory data and detection algorithms. These algorithms can be quite complex and involved and often times are limited in their application to fairly simple cuts. None-the-less, one can develop a set of tools to predict the onset of various events through use of the cutting force, spindle speed, feedrate and acoustic emissions, etc. References [2-8] discuss various detection schemes.

The influences of the end milling process are shown in Figure 2. All of the controller variables are encapsulated by rectangular boxes. Cutter runout, i.e.tool eccentricity, is typically unwanted, but can only be minimized during set-up of the cutter in its tool holder. The achieve events are parallelograms and the prevent events are double ellipses. All other parameters influence these goals in a positive or negative manner. For instance, if the feed per tooth is increased, then the surface finish is degregaded and the cutting force is increased. The QPA control structure wants to achieve or prevent events during machining, thus it uses the influence diagram to trace from an event to a controller that can influence that particular event in the desired positive or negative fashion. When conflicts arise, it is up to the expert to rank the events in order of importance. For end milling, the following rank is suggested:

1. Shank failure
2. Tooth failure
3. Tool wear failure
4. Chatter
5. Tool deflection
6. Surface finish
7. Maximum feed rate

Control action is initiated when an event is occurring or when the desired event is not being achieved. Typically, this action consists of increasing, decreasing or holding constant the feedrate, spindle speed or depth of cut during each QPA sampling interval. Data from the sensors, examples being cutting force, spindle speed, feedrate and acoustic emission, is collected by the QPA system during each time interval and is used to determine the state of each of the events. If unwanted events are detected, then a planned control action is taken to eliminate that event. Action is also taken to make sure the desired events such as maximum feedrate occurs.

SIMULATION OF QPA CONTROL OF END MILLING QPA

Control of the end milling process was tested by simulation, using an experimentally validated end milling model [1] (see Figure 3) that is capable of simulating workpiece geometry changes, cutter deflection, and tooth and shank failure. In the simulations, the x feedrate input command signal was determined by the QPA controller, based on the x and y cutting force, the feedrates, and the spindle speed. QPA used this "sensed" information to determine if any prevent events were occurring, then through the experts encoded knowledge, executed the appropriate control to lower the feedrate. Once prevented, the QPA increased the feedrate or held it constant, depending on the band limit around the particular event in question.

A simplified QPA control system is tested here to validate the concept of QPA being applied to the end milling process. The only events that are considered are tooth and shank failure, and tool deflection. Tool wear, chatter and surface finish events are ignored because of the complexity in detection and because of the added QPA complexity.

One simulation trial result is presented here. Table I lists the trial, the geometry change associated with it, and the controller action. Figure 4 shows the workpiece geometry for the cut. The simulation is run assuming the cutter is starting in an existing cut. For this simulation, the QPA controller is trying to achieve maximum feedrate while preventing tool shank failure, tooth failure and part out-of-tolerance. The tool shank failure is associated with the total force on the end of the cutter. If this force exceeds a certain limit,then the cutter is in danger of failure through bending. The QPA response to this is to reduce the feedrate when the total force reaches a set limit. The tooth failure occurs as a result of overloading an individual tooth edge on the end mill. This overload condition can be detected by measuring the feedrate and the spindle speed and calculating the feed per tooth in millimeters. If this value is above a set limit, then the QPA reduces the feedrate so damage will not occur. Tolerance conditions are determined from the cutting force perpendicular to the path of the end mill. For this simulation run the cutter is moving in the x direction, so the tolerance is determined solely by the y force. The limit for the y force is determined by the length, diameter and material of the cutter,and the accepted deflection.

All of these prevent events have two process instances associated with them. The maximum level indicates to the QPA that the feedrate needs to be reduced, while the region between the minimum level and maximum level indicates that the feedrate should be held. The hold region is necessary to keep the feedrate command signal from oscillating from the on/off nature of the controller.

The results of the simulation trial are shown in Figure 5. In this run the axial depth is doubled from 6.35 to 12.7 mm at approximately one second, and the radial depth of cut is held constant at 6.35 mm. Before the axial depth change, the tooth failure prevent mode is in effect, see plot (c).

This limits the feed per tooth and reduces the possibility of tooth failure. After the axial depth change, the perpendicular force FFY, plot (b), is above its limit. This results in a lowering of the feedrate until FFY is inside the force band. The feedrate is now held constant until the force FFY is below the minimum value. Once this occurs, none of the prevent events are active and the feedrate is increased until FFY is once again within the given limits. The feed per tooth, plot (c), is very similar in shape to the command signal sent from the PC to the end milling system.

EXPERIMENTATION OF QPA ON A CNC MACHINING CENTER

The overall hardware configuration for QPA implementation and evaluation on a CNC machine is shown in Figure 6. The CNC 3-axis machining center is a Fadal VMC40,with a l5 HP AC spindle drive, a DC servo feed drive, and an automatic tool changer. The slide tachometer signals (x and y slide velocity) and the x and y force signals, are filtered by 10 Hz third-order butterworth filters to remove unwanted noise and force oscillations, and to prevent aliasing. Once filtered,the signals are converted to digital signals by the 386 PC computer using a 12 bit A/D and D/A data acquisition board. The QPA software then uses this data to determine the controller outputs necessary to maintain optimum cutting conditions. Final control of the CNC machine is achieved by down loading the controller outputs, through the D/A board on the PC, to the feed drive and spindle override circuits on the CNC.

The CNC tach signal is available from the electronics cabinet along with the feedrate and spindle speed override potentiometers. This pot allows the operators to adjust the rates in order to eliminate chatter and forced vibrations. Since the pots allow on-line control, they can be used as the input path for the QPA controller output. Using the pot as the override command is fairly safe for testing because it can only override the command signal 0-l50%of the programmed value.

Thus, if the programmed value has an upper limit that won't result in catastrophic failure, and an upper limit is placed on the output voltage from the QPA controller via the D/A board, then safe feed rates should result at all times. The x and y cutting forces are obtained with a Kistler model 9257A force dynamometer and charge amplifier.

The QPA system described earlier in the paper is implemented on a 386 PC. The code is written in Fortran and is based on the original QPA code developed at the Air Force Materials Lab. Data is stored by the PC for future processing while the QPA controller is active. The code allows for data sampling intervals down to 1 msec and for controller outputs down to 2 msec. However, as more event detection algorithms are added, the controller output interval time will increase. For the experimental run discussed below, an interval of 0.01 sec. was used, with a 1 percent change in feedrate per controller step. The results of one experimental run is discussed below. For this run the QPA system is controlling the Fadal CNC machining center during an end milling cut. The conditions of the cut are the same as in the simulation run, Table 1, except the deflection hold value is set to 280 N and the max value is set to 342 N.

The results of the experimental run are shown in Figure 7. Initially, the feedrate is increased until one of the prevent events occurs. As in the simulation run, the first limiting event is the tooth failure prevent mode, i.e.feed per tooth, plot (c). After the axial depth change, the perpendicular force Fy, plot (b), is above its maximum limit of

342 N. The feedrate is then reduced until Fy is within its acceptable band. The experimental results are very similar to the simulation results and hence validate the accuracy of the simulation models, and also show that QPA can effectively control the cutting conditions during a simple end milling cut on CNC machining center.

CONCLUSIONS

Simulation and experimental work show that QPA can be effective in adaptively controlling the feedrate of the end milling process to produce the fastest possible cut while preventing shank and tooth overloads, and maintaining part tolerance. Shank failure is detected by the total cutting force, tooth overload by the feed per tooth, and past out-of-tolerance by the cutting force perpendicular to the tool path. QPA maintained the highest feedrate possible while preventing the undesired events mentioned above.

QPA control cannot handle high feedrate, low spindle speed impacts of the cutter into the workpiece. The feed drive dynamics of the system itself are not fast enough to avoid tool or workpiece damage. The intent of QPA control is to manage the system during cutting operations such that catastrophic conditions do not occur, and such that an acceptable part is manufactured as quickly as possible.

Future work will include more sophisticated detection algorithms and more complicated cutter operations.

ACKNOWLEDGEMENTS

This work was supported by the Air Force Systems Command through the Air Force Office of Scientific Research and the Materials Lab (AFWAL/MLTC) at Wright Patterson Air Force Base.

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Trial Conditions

Radial Cut with Axial Depth Increase

AD: 6.35 to 12.7 mm RD: 6.35 mm

Cutter and Workpiece Data

4 Flute 38 deg. Helix, HHS, 12.7 mm Dia.,44.5 mm Length, Dry Cutting at 2000 rpm with a stiffness of 90,200 N/cm, workpiece is 2024-T8 Aluminum

Cutting Control Limits

	Hold Value	Max Value	Event
y force (N)	445	578	deflection
Total force (N)	667	890	tool breakage
Feed per tooth (mm)	.076	0.089	Tooth breakage

Table I. Geometry Workpiece and Model Details

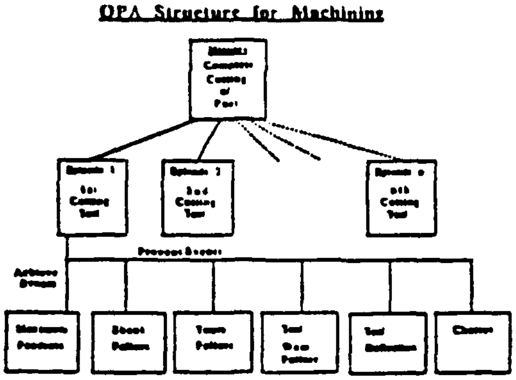


Figure 1. QPA Control Structure for End Milling

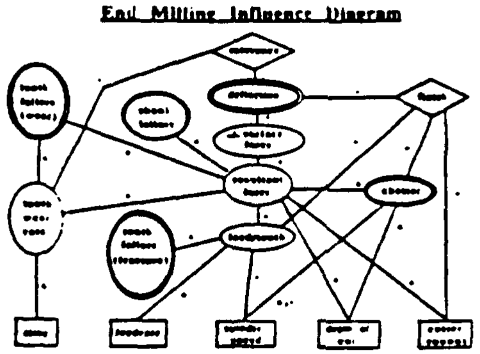


Figure 2. End Milling Influence Diagram

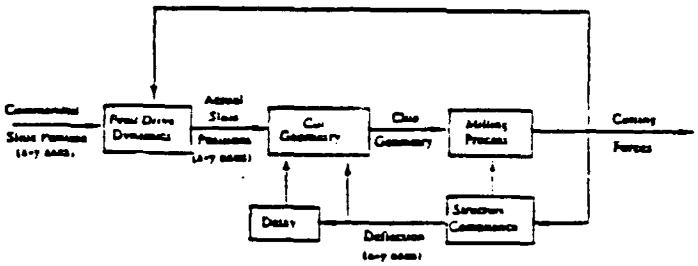


Figure 3. End Milling Block Diagram

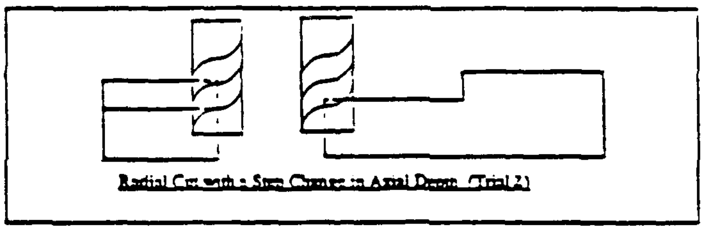
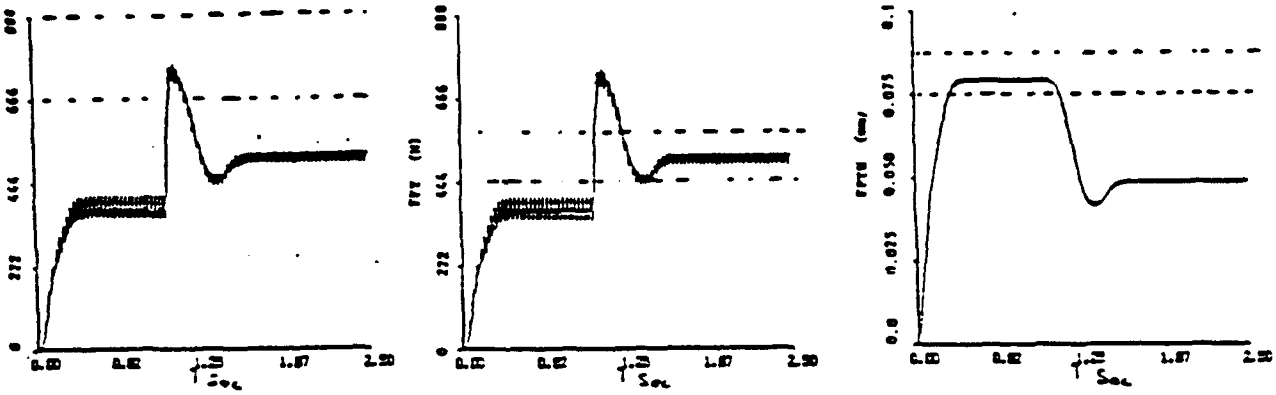


Figure 4. Simulated Cuts



(b) (c) (d)

Figure 5. Results for Simulation Trial

Experimental Testing Set Up

- Signal Processing and Computers
- Control of Only Cutting Force

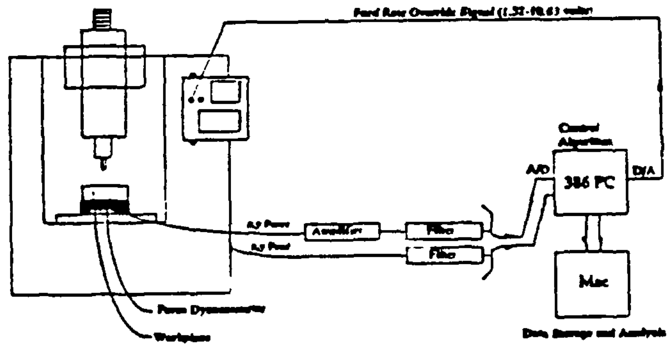


Figure 6. Controller Hardware

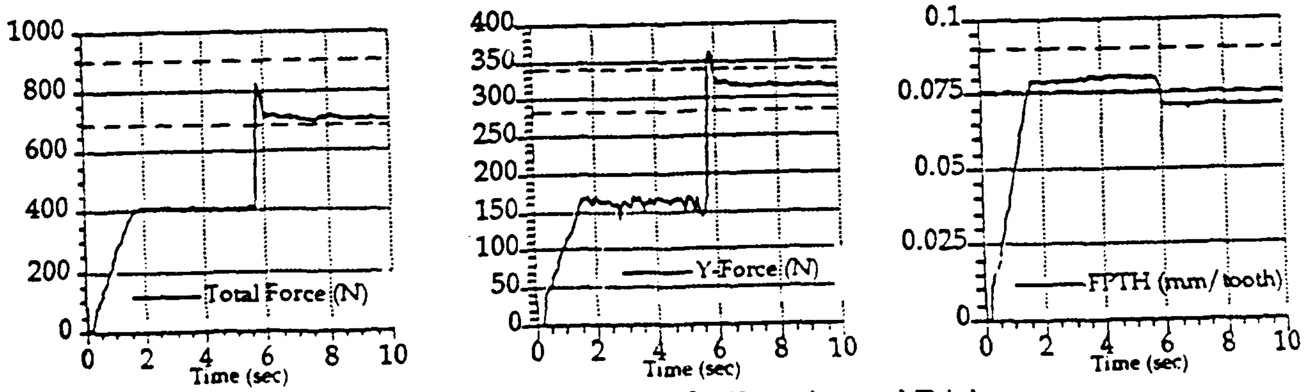


Figure 7. Results for Experimental Trial

QUALITATIVE CONTROL OF MOLECULAR BEAM EPITAXY

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INTRODUCTION

Manufacturing capability throughout the 20th century has continuously improved. Improvements have come both in the product and process. In the last forty years the development of the computer has very successfully been applied to both these areas of manufacturing.

One application of the computer has been to control manufacturing processes. The task of controlling a process is both demanding and tedious for a human and therefore more suitable for the computer. The use of open loop, time based supervisory control was established early in the computer era. Operators remained to supervise the computer but intervened only in extraordinary circumstances. The computer offered consistency by performing exactly the same each time.

In the past ten years methods for storing expert knowledge in a computer have been developed, particularly through research in the area of expert systems. This new technology has made possible a more advanced type of computer control. In this new method of control, labelled qualitative real time control, the computer generates a process path on the fly using knowledge about the process, and information provided by sensors. This new method of control enables specific information on the events of the current run to be factored into the process plan. The advantage of qualitative real time control comes from delaying decisions that are best made after certain information is available, until after that information becomes available.

The In-house Manufacturing Research Group of the Air Force Materials Laboratory has undertaken a program, entitled Qualitative Process Automation (QPA), to develop qualitative real time process control for application to materials processing.[5,6] Development of QPA systems for a number of manufacturing processes is underway. Success of any particular application is dependent on two factors:

1. Sufficient sensor input is available to monitor qualities,

2. Based on this input, the knowledge exists to determine how to influence these qualities.

This paper discusses the application of QPA to the semiconductor growth process, Molecular Beam Epitaxy, (MBE)which has been undertaken jointly with the Surface Interactions Branch of Materials Laboratory. Progress so far demonstrates that the knowledge base for QPA does not need to be complicated in order to be successful. In the next section, MBE will be described. The Approach Section will introduce the strategy for applying QPA to MBE and discuss the experimental results. The status of the project is reviewed in the Current Work Section.

THE APPLICATION

Molecular Beam Epitaxy is a high-precision technique for growing thin-film semiconductor crystals which was developed in the late 1960s at Bell Laboratories by Al Cho and John Arthur.[1] In MBE, a substrate of up to 3 inch diameter is suspended in the center of a vacuum chamber, called the Growth Chamber, which is maintained in a state of vacuum between 10^{-9} and 10^{-11} Torr. The top view of an MBE system is shown in Figure 1. Up to eight smaller ovens called Knudsen or Effusion Cells, adjoin the Growth Chamber. Each Knudsen Cell consists of a crucible loaded with a particular element such as Gallium (Ga), Arsenic (As), or Aluminum (Al) and a furnace which is used to heat the element to a vaporization temperature. The crucibles are screened off from the Growth Chamber by shutters. When a shutter is opened, a beam of atoms or molecules from that Knudsen Cell is emitted toward the wafer. The magnitude of the beam of atoms/molecules is called the flux and depends on the temperature of the material in the crucible. Generally, multiple beams are on concurrently. A proportion of the atoms/molecules bond epitaxially (coming from the Latin word "epi" which means on and "taxi" which means of the same structure) thus a crystal is grown.

MBE provides a great deal of control over the semiconductor material being grown and therefore produces devices of superior quality to all other semiconductor growth techniques. Very thin films down to a single monolayer (one layer of GaAs) can be deposited. Growth occurs at a relatively low temperature (580^{o}C to 620^{o}C for GaAs) so bulk diffusion is minimal and doping profiles are not disturbed. In addition the dislocation densities, interface abruptness, mobilities and minority carrier lifetimes of MBE grown films are generally equal or superior to those grown by other state-of-the-art epitaxial techniques.[9]

Conventional control of MBE is through the use of a process plan such as shown in Figure 2a. The length of time to grow each material layer is predetermined based on previous runs and calibration experiments run prior to the process run. Using this method of process control, MBE produces good results. Using Qualitative Process Control, we believe however, will produce even better results. A variety of factors can contribute to the quality of the material grown by the MBE process depending on the material being grown. A target type of material has been selected and for this material the following factors are considered important:

1) Material Layer Thicknesses
2) Alloy Concentration
3) Dopant Concentration
4) Impurity Levels
5) Smoothness of Material Layer Interfaces
6) Ga_{As} or As_{Ga} Antisites (Ga occupies As location or vice versa)
7) Vacancies (Missing atom)
8) Dislocations (Missing line of atoms)
9) Oval Defects

Improving Factors #1, Material Layer Thicknesses, and #5, Smoothness of Material Layer Interfaces, is the current focus of research. The impact of improving these factors is hard to predict because the level of achievement for these factors using current techniques is hard to measure. One MBE researcher reported thickness variations of up to 10%. A 10% thicker doped AlGaAs layer in a GaAs/AlGaAs depletion mode HEMT results in significantly altered behavior from that desired, beginning with a threshold voltage almost one volt lower.

In addition to improving the quality of material grown in MBE, time is also saved because the recipe no longer required and calibration for preparing the recipe is no longer necessary.

APPROACH

A 1st generation QPA controller, called the Alpha Controller, has been developed to control the MBE process and positively affect qualities #1, Material Layer Thicknesses, and #5, Smoothness of Material Layer Interfaces.[8] This controller was written in FORTH and runs on an IBM AT clone. The Alpha Controller uses one sensor and one type of actuator. The sensor in use, the Reflective High Energy Electron Diffraction (RHEED) sensor, provides excellent information about the state of the wafer surface, but unfortunately produces a side effect: heavy carbon contamination of the material. A controller using RHEED has no commercial value; the Alpha Controller was developed for the purpose of establishing Qualitative Control of MBE, with the intention of replacing RHEED with another sensor when it became available. A method using Ellipsometry is currently under investigation and will be discussed in the Current Work Section.

In the Alpha Controller, a portion of the RHEED sensor signal, called the Specular Spot Intensity, is refined using software to provide two additional pieces of information:

"Count" - The number of monolayers grown

"Amplitude" - A measure of the roughness of the wafer surface.

"Count" corresponds to the number of oscillations of the Specular Spot Intensity, and "Amplitude" corresponds to the amplitude of the Specular Spot Intensity. These signals are evaluated by the knowledge base, which then determines the state of growth. Based on the state and a description of the desired end product entered by the user before the beginning of the growth run, the knowledge base decides on the next setpoint of the Knudsen Cell shutters.

The Alpha Controller accomplishes real time control of the MBE machine with a small knowledge base. The first principle is that shutter changes to grow the next material layer are triggered when the previous material layer has been completed (ie. when "Count" = desired number of monolayers). This principal of using RHEED to count the material layers has previously been demonstrated by Sakamoto.[10] Sakamoto's implementation was in hardware and therefore could not be expanded easily to incorporate other real time feedback.

The second principle is that a "healing" period is invoked, when "Amplitude" , which corresponds to the surface roughness, exceeds a threshold. During the "healing" period, all shutters are closed except the As shutter. As the name suggests, during "healing" the wafer surface is resmoothed. The "healing" process continues until the surface is sufficiently resmoothed.

The Alpha Controller was tested using a simulation of the MBE machine and RHEED sensor. The Alpha Controller was then connected to the MBE machine and a series of growth runs were performed. A number of modifications were made to the Controller during these experiments. A snapshot of asynchronously sampled data for a growth run in which the material specified in Figure 2b was grown is shown in Figure 3. The first material layer was grown during period 1. Upon opening of the Ga and As Shutters, the Spectral Spot Intensity began to oscillate. When "Count" reached five (5), it was reset to zero (0) and growth of the next material layer commenced. The time period over which the second material layer was grown is labelled Period 2. While on the fourth monolayer, a "Healing" period was triggered, which ended when the Spectral Spot Intensity exceeded a threshold value. The final monolayer of the second material layer was grown and then the Al shutter was again turned off and "Count" reset, signifying the beginning of growth of the third material layer.

CURRENT WORK

As MBE is a very new method of manufacturing, it is not surprising that knowledge about the behavior of materials when grown under various MBE conditions is very limited, or that sensor technology to monitor the growth is limited. These deficiencies are being addressed by current research.

A novel methodology for monitoring the growth at a high sample rate using Ellipsometry has been suggested by Poore which promises to provide the same information as RHEED while not producing the same harmful effects. Special high stiffness windows and custom-made mounting brackets for the ellipsometer have been installed. Experimentation is ready to proceed pending the availability of the MBE machine.

In the meantime, in order to integrate with some other research efforts in MBE, in particular, that of Heyob and Hunt[3], the alpha controller code is being transferred over to a new platform, LightSpeed C running on a Mac II. C on the Macintosh II is an easier to use and more powerful developing environment than Forth on the Z248.

Simultaneously with these two efforts, knowledge about the behavior of materials when grown under various MBE conditions is being gathered with the objective of learning about how to improve the seven other quality factors listed above through real time control. Currie is applying a neural model to the study of the MBE process whereas Kosel has developed a simulation of the MBE machine.[2,4] As new knowledge becomes available it will be incorporated into the Macintosh version of the Alpha Controller or perhaps a new controller based on the Qualitative Process Automation Language (QPAL).[7]

A QPAL knowledge base is under development as a cooperative effort with Universal Technology Corporation. The Manufacturing Research Group would very much like to control the MBE process using QPAL, as QPAL is a supported software product for real time process control that will facilitate transition of any technological improvement on MBE to industry. Additionally, QPAL is well thought out and coded, making development of the MBE knowledge base much easier. Inadequacies in the speed of QPAL need to be addressed.

In the process of developing a Qualitative Controller for MBE, other areas for improvement of MBE were discovered. Control of the fluxes is of tremendous importance to the growth of quality materials. Heyob, Hunt and Garrett have studied the response of the fluxes and have demonstrated that significant improvement can be realized in the flux response during set point and load changes. In addition, certain initialization and calibration operations must be performed prior to a growth run. This entire setup procedure is currently being automated.

SUMMARY

Qualitative Process Control is being applied to the semiconductor growth process, Molecular Beam Epitaxy. Two quality factors, #1, Material Layer Thicknesses, and #5, Smoothness of Material Layer Interfaces, are targeted for improvement. Real time control of these two factors has been demonstrated using RHEED. Use of RHEED has harmful side effects and so development of an alternative real time sensor, Ellipsometry, is on-going. Concurrently, the MBE process is being studied through a simulator and a neural network with the objective of learning about how to improve other qualities of the MBE product. In the meantime, the Qualitative MBE Controller is being transferred to a new platform, Lightspeed C on the Mac II in order to integrate with other work sponsored by the Manufacturing Research Group, in particular, a state space based flux control system.

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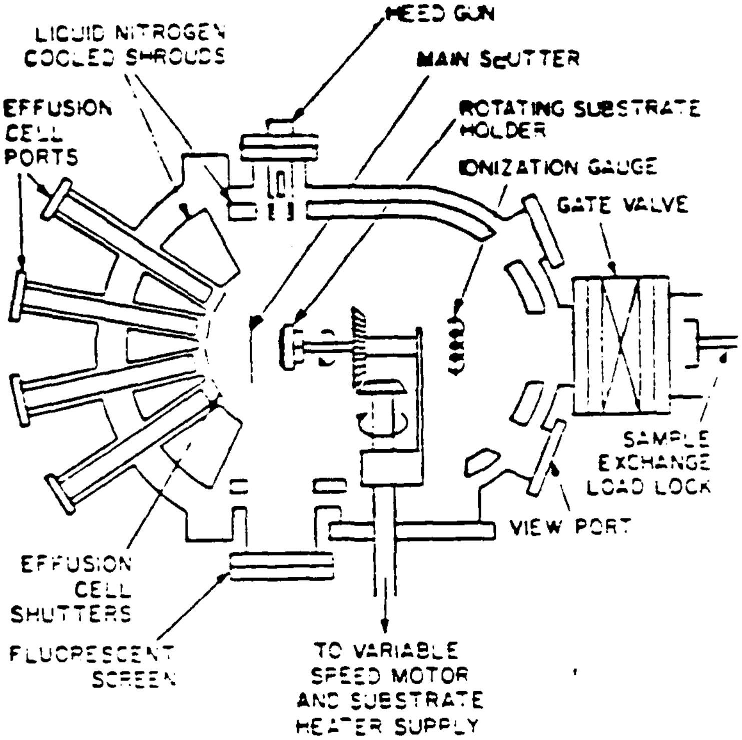

Figure 1: Schematic diagram of the MBE system viewed from the top. (Taken from Reference 1)

Material	Thickness(monolayers)	Shutters On Time(seconds)
GaAs	50	55
GaAlAs	100	70
GaAs	50	55

Figure 2a: A Growth Recipe for Conventional Control of MBE

Material	Thickness(monolayers)
GaAs	5
GaAlAs	5
GaAs	5

Figure 2b: A Growth Recipe for QPA Control of MBE

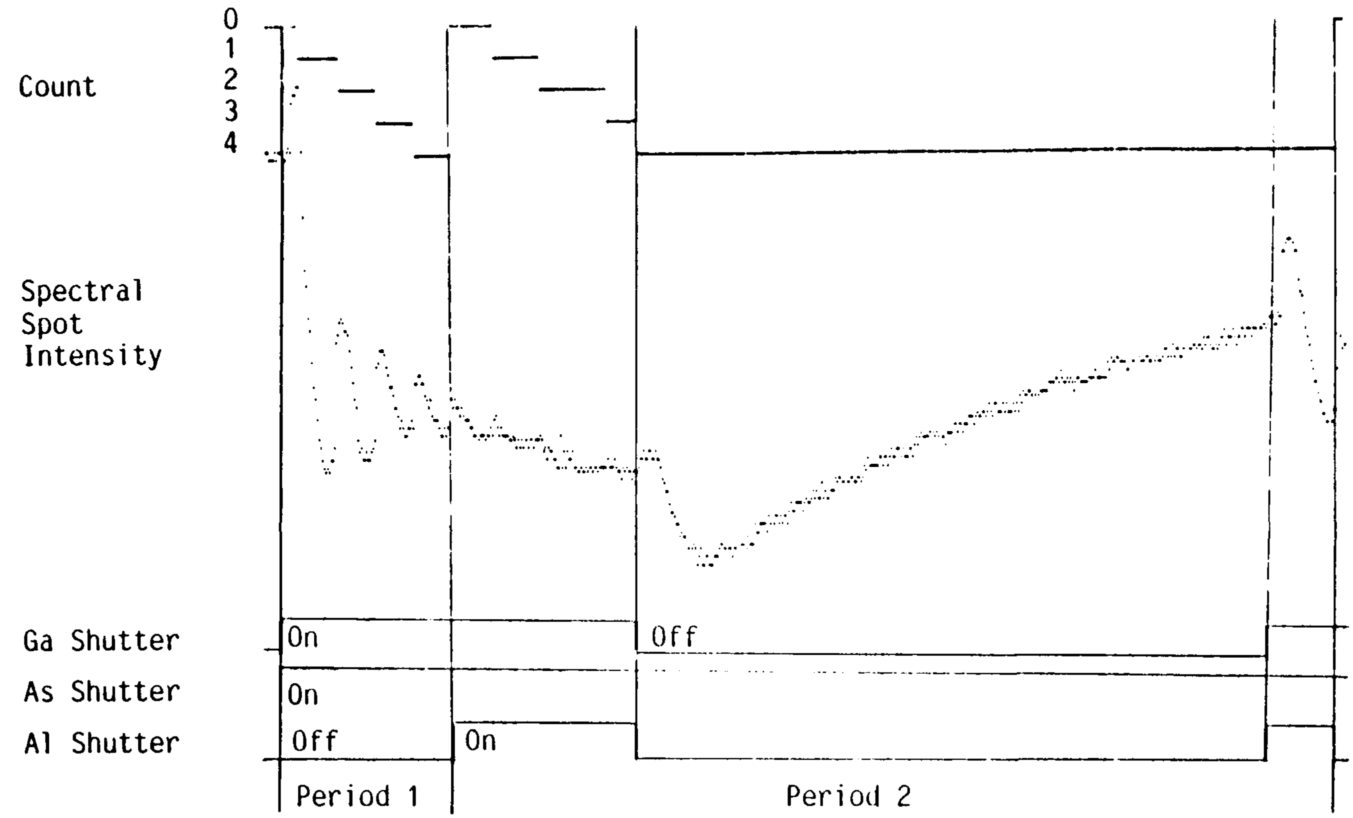

Figure 3: Asynchronously sampled data for growth of the material specified in Figure 2b using the Alpha Controller.

MBE SELF-DIRECTED FLUX CONTROL

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The growth of compound semiconductors by molecular beam epitaxy (MBE) can be facilitated by robust, self-directed control of the material fluxes. In the vacuum of the MBE machine, vaporized chemical elements contained in the Knudsen cells are diffused as fluxes to achieve focused crystalline growth on a substrate whose quality is largely dependent on the control of the flux. These primary controlled variables (i.e. the fluxes) are not directly observable; however, they are dependent and therefore controllable through the manipulated temperature variables of the Knudsen Cells. Effort is presently underway to implement outer loop flux control modules on the MBE machine (Figure 1) in order to provide automated growth of compound semiconductors with better performance (e.g. robustness, stability, repeatability, etc.) than is currently provided by the system. These flux control modules are based on Knudsen Cell temperature manipulation. An automated tuning of the Knudsen Cell temperature inner control loop is used to achieve a critically tuned process response that enables temperature setpoint changes with negligable error and quick settling time. A feedforward temperature setpoint control scheme is enacted to inversely cancel the transient flux disturbance which occurs upon shutter opening. The cascade flux control module makes temperature setpoint adjustments inferred from the delayed feedback of the RHEED (reflective high energy electron diffraction) scope and the ellipsometer. These control modules form an outer loop QPA control structure and provide a basis on which to build a self-directed control scheme. The efficiency of this outer loop control structure is dependent on the soundness and completeness of our system conceptualization.

Modern control theory conceptualizes a system by its *n-dimensional state space*, where n would equal the order of the system transfer function for a minimal realization. Self-directed control of a system allows autonomous generation of the processing path through this state space towards the desired end goal or product based on a number of planning and cost heuristics. This goal-driven nature of self-directed control is distinguished from the traditional state-driven philosophy in that path generation is not defined apriori as a function of time but must adapt insitu to events with respect to the expert knowledge base of the system. Since the processing path of the system is not known apriori, robust control of the system is very important because it provides for optimal performance over every reachable point (and, therefore, over every processing path) in the state space of the system. Robust control, based on a sound and complete conceptualization of the system state space, is a necessary foundation of self-directed control. A suitable compensation algorithm can then be determined for every reachable point in the state space. However, any sound conceptualization (e.g. semi-defined or qualitative) which is complete over the state space (as opposed to completely defining the state space) will allow robust control at reduced efficiency. Research is currently dedicated towards deriving a sound and complete conceptualization of the system state space. An empirical study of the MBE process and its component systems (e.g. flux control modules) and relationships (e.g. temperature to flux) is needed to further our knowledge of, and derive a modelling concept for, the state space of the system.

The MBE system utilizes Knudsen Cell furnaces to vaporize the various elemental materials for flux vapor deposition on a substrate. The growth of a particular device structure on a substrate requires precise control of the growth rate of each elemental material on the substrate, which is directly dependent on the duration of evaporant exposure to the substrate and the density of its flux impinging on the substrate. The time duration of flux exposure is controlled simply by mechanical manipulation of a shutter to obstruct the flux from impinging the substrate. The density of the flux is not as simple to control. The most direct means presently available to monitor the density of this beam is an ion gauge mounted in place of the substrate wafer. Replacing the substrate with an ion gauge to facilitate closed-loop process control represents an invasion to the process and thereby prevents insitu monitoring of the flux via an ion gauge. Other methods for inferring flux density employ RHEED scope and ellipsometer measurements. These methods are being explored for insitu growth measurements, but their indication of flux density are less precise than the ion gauge method and produce a composite measurement when multiple element fluxes are present. In evidence of the ion gauge utility for monitoring flux density, current MBE processes utilize a beam equivalent pressure (BEP) curve for each Knudsen Cell elemental material. These BEP curves provide a mapping of ion gauge pressure measurements of flux density to their corresponding Knudsen Cell temperatures for each cell over its prescribed operating temperature range. Insitu use of these BEP curves allows the MBE operator to prescribe a flux density by adjusting the setpoint temperature of the Knudsen Cell. By generating the BEP curves for each Knudsen Cell prior to the growth process, and then adjusting the flux density based on the BEP curves, a feed-forward control may be implemented. The actual flux density produced by this feed-forward scheme is dependent on the accuracy and repeatability of the BEP curves and on the accuracy and repeatability (i.e. soundness and completeness) of the Knudsen Cell temperature control that generates the flux.

To further the study of MBE flux control, the Knudsen Cells in the MBE system presently employ Eurotherm 825 PID temperature controllers. The MBE system manufacturer also provided a set of general purpose PID values to use over the operating range of each Knudsen Cell. These PID values, however, were broadly prescribed for PID control of a Knudsen Cell over its entire operating range. A topic of continuing interest in PID controllers is the automatic tuning of the PID parameters that results in a closed-loop system response with specified time-domain characteristics such as overshoot and settling time. With broadly prescribed PID parameters, the system performance (i.e. overshoot and settling time) varies widely with step changes of the process setpoint over different portions of its total operating range. This variation prevents any apriori assumptions about the system performance and the target variable, Knudsen Cell flux density. In addition, the performance of each Knudsen Cell temperature control loop was also observed to vary as the elemental material mass was depleted. To compensate for detuning of the temperature control loop as the material mass within each cell is consumed and to improve each control loop's performance within a specific domain of each Knudsen Cell temperature range, automatic tuning of the control loops was explored.

Initial set-up of each Knudsen Cell at its target temperature is done apriori to the growth process thereby allowing for the time consuming PID tuning period of its temperature controller. However, not all devices grown with the MBE process require only one static temperature for each Knudsen Cell involved. Some structures require flux density gradients over time for one or more Knudsen Cells simultaneously. Acquiring optimum flux density control and therefore optimum temperature control would require additional control loop PID tuning as the process approaches the boundaries of its tuning domain. The tuning domain is the specific temperature range for which the control loop is tuned; operation beyond this range would be degraded. To maintain specified performance as the process approaches a tuning domain boundary, retuning would be required. The severity of this retuning regime would increase as the size of each tuning domain decreased. However, the decreased size of a tuning domain from the full range of the controlled process would improve the tuning optimization and therefore improve the Knudsen Cell response within a narrow tuning domain. Therefore higher tuning optimization necessitates narrow tuning domains and therefore more occurrences of retuning.

A concept of apriori mapping of PID tuning parameters was devised to provide optimized temperature control in narrow domains over the entire operating range of each Knudsen Cell because traditional tuning techniques could not be applied insitu to the MBE process. The disturbances necessarily applied to the control loop process for traditional tuning techniques would degrade the MBE growth process; also, insitu tuning would introduce these disturbances frequently. The PID mapping would isolate the time consuming and process disturbing tuning routines for each Knudsen Cell from the MBE growth process. Two methods of building the PID map were explored to reduce the granularity of the tuning parameters. The first method involved the generation of many narrow tuning domains of PID parameters. This basic and practical implementation suggests (and the continuity and smoothness assumptions of conventional system analysis allow) the sectioning of the state space into a discrete table look-up method. Each axis of the state space can be broken into discrete intervals or tuning domains (i.e. scaled to a unit vector) whose length is based on the control scheme's sensitivity to that process variable. The assumption is that all points within that interval can be adequately represented by one point. The MBE process supervision would simply determine a Knudsen Cell setpoint and load in a new set of PID parameters for the appropriate domain in a table look-up format. The resolution of the tuning optimization would be limited to the granularity of the look-up table using this method. Therefore, a large number of PID domains would be needed in the table, necessitating automatic generation of these tuning parameters. Generation of the PID map for the Knudsen Cells was explored using commercial automatic tuning PID controllers and software based tuning algorithms. For a complete state space conceptualization, the generation of the PID parameters was laboriously slow. The second method involved the generation of a few narrow domains of PID parameters equally spaced across the range of each Knudsen Cell. The MBE process supervision would then determine a Knudsen Cell setpoint and load in a new set of PID parameters by interpolating between two adjacent PID domains in the look-up table. The resolution of the tuning optimization was maintained because of the continuity of the tuning parameters and the apriori PID mapping time was reduced significantly. In conclusion, empirical tuning of our self-directed control scheme over a complete, discrete experiment set (obtained from either of the above methods) will allow robust, automated control over the entire state space. As noted before, this tabular form of our state space is less efficient than a complete conceptualization (e.g. a set of differential equations) but it might be arrived at more readily.

Some limitations to Knudsen Cell control system response were still apparent using the PID mapping concept. In the PID control scheme, the proportional, integral, and derivative terms are defined to compensate a closed-loop system response to achieve specified time-domain characteristics such as overshoot and settling time. The proportional term, by its design, is a gain term that is proportional to the error in the control loop. This term changes the control loop gain as a function of error from setpoint, such as for different sizes of temperature setpoint step changes. The integral term integrates the control loop error to achieve zero steady-state error by resetting the controller's output. The derivative term provides an anticipation to the amount of energy applied to a control loop to minimize overshoot. These PID parameters are able to achieve specified time-domain characteristics by their combined interaction to control the amount and rate of energy applied to the control system. In the context of reaction curve tuning techniques (Figure 2), a set of tuning constants can be experimentally determined to produce desired system response for a given set of system conditions. If the system conditions change, the tuning constants will need adjustment to maintain the desired system response. The MBE process was found to produce widely varying system conditions and require the same system response. These varying system conditions include not only the desired setpoint temperature for each Knudsen Cell, but also the size and direction of the temperature step change to achieve the desired setpoint. As an example, the step size of the reaction curve should equal the actual step size required in the running process to insure optimum PID tuning. The conditions may also include the rate in which to achieve the target setpoint. Since the MBE process can consist of any number of possible flux conditions, a mapping of PID parameters for the associated Knudsen Cell would need to be exhaustively complex. Thus the table look-up process must be multi-dimensional to accommodate these additional flux conditions.

To meet the complex control tuning possibilities of each Knudsen Cell and to achieve a more complete state space conceptualization, a more extensive mapping of the Knudsen Cell process would be needed. This apriori mapping would actually be a profile of the Knudsen Cell characteristics in terms of conventional tuning parameters such as lag-time, maximum rate, critical gain and steady-state error mapped over the cell's entire operating range (Figures 3 & 4). The behavior of each of these mapped parameters would then be described by a set of differential equations, and these equations form a subspace of the n-dimensional state space to describe suitable PID parameters for all reachable conditions or states. The control algorithm would then accept the initial and final Knudsen Cell setpoints of a MBE process demand and generate the necessary PID parameters insitu for optimum execution of the process change. This state space concept can be taken to the next level of self-directed flux control to include the dynamic characteristics of the flux in the MBE growth chamber. Flux research in the MBE process has been concentrated upon controlling an initial flux density transient observed during Knudsen Cell shutter opening. The magnitude of this flux transient is affected by Knudsen Cell temperature, elemental mass within the cell, surface area of the elemental mass, and the shutter opening duty cycle. Current BEP curves are generated by manually recording flux pressure as a function of Knudsen Cell temperature. By the very nature of manually recorded data, these

BEP curves are based on steady-state flux pressure. To be useful to self-directed control, definition of the dynamic behavior of the flux upon initial shutter opening is needed. This dynamic flux behavior would be extracted apriori to the MBE growth process in the same manner as Knudsen Cell tuning parameters. Forming this flux behavior into a differential equation as a function of time, cell temperature and shutter state would describe yet another subspace of the system state space. A combination of the Knudsen Cell state space and the BEP state space would yield an n-dimensional flux state space suitable for self-directed MBE flux control. Using such a state space concept would allow a MBE supervisory system to directly prescribe a flux density necessary for a growth process. Through this state space model of the MBE system, the prescribed flux would return the necessary PIDs and setpoint for the Knudsen Cell controllers and time delays to shutter opening cycles.

The current development of these methods has produced significant improvement in Knudsen Cell temperature stability and therefore flux stability. Improving the inner control-loop performance of each Knudsen Cell in terms of overshoot and settling time has afforded the MBE system the ability to prescribe more demanding temperature versus flux relationships. Meeting these demands is a result of improved Eurotherm 818 controllers and noise reduction shielding which reduced system errors within the inner control loops and improved the accuracy of measured parameters (Figure 5). Combining accurate data efficiently in a n-dimensional state space is the next level of improvement in the MBE system to yield performance that is reliable and repeatable.

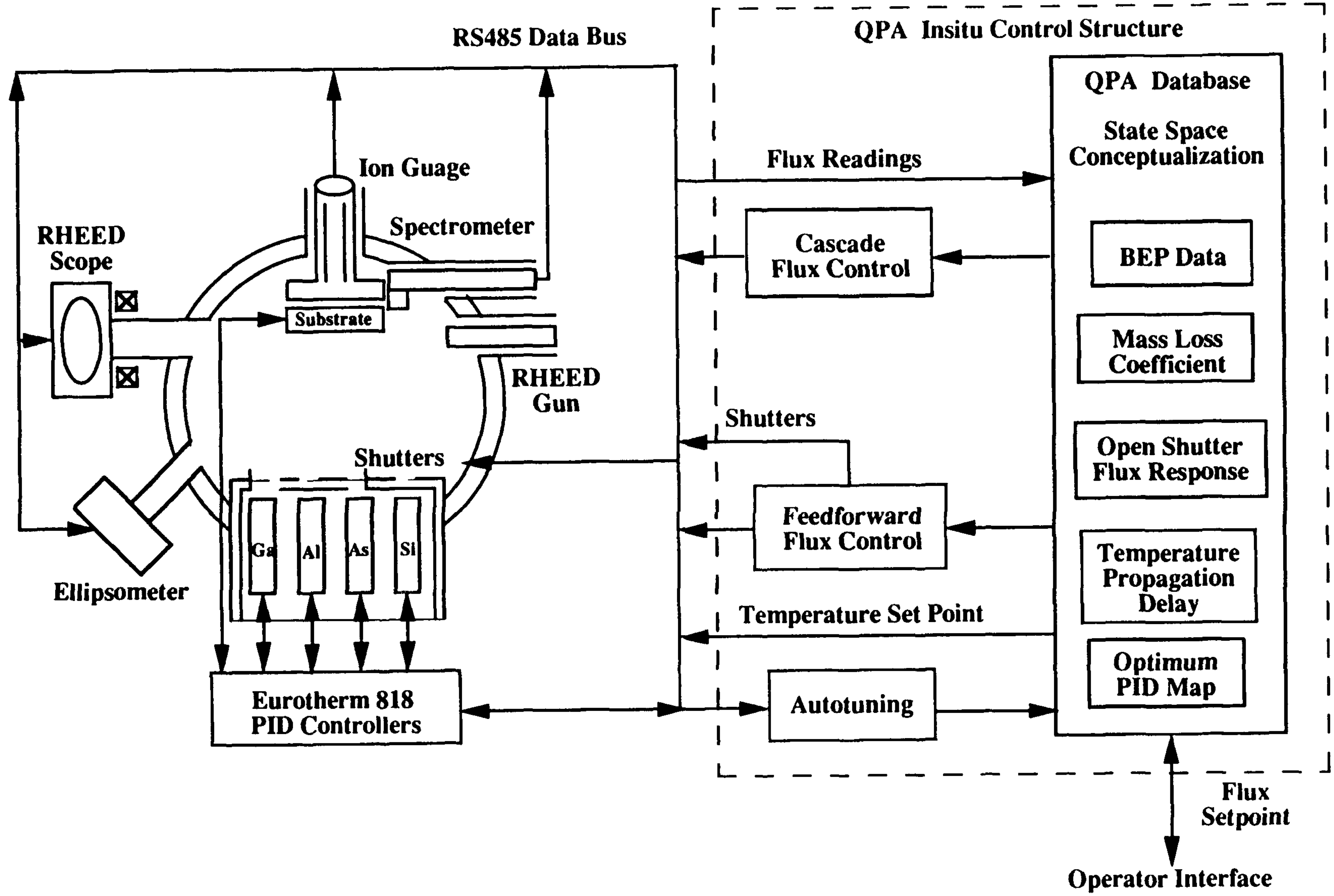


Figure 1. MBE Self-Directed Flux Beam Control

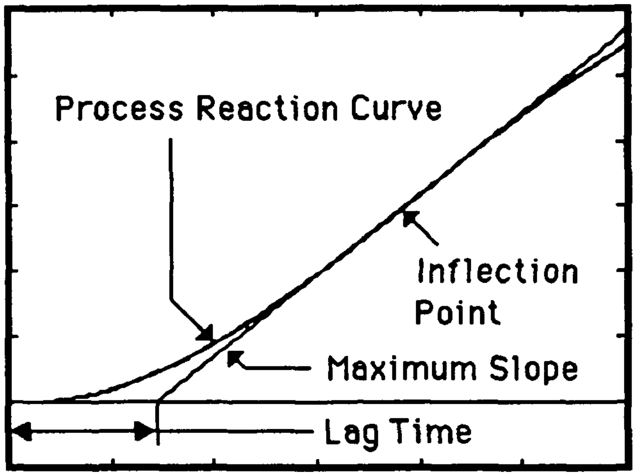


Figure 2. Process Reaction Curve

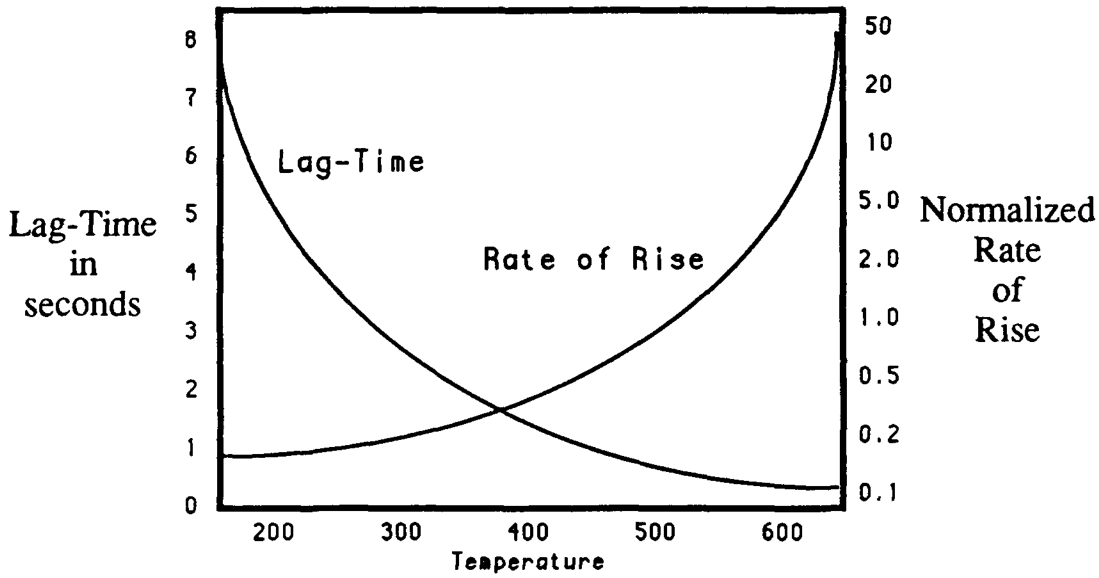


Figure 3. Lag Time/Rate of Rise versus Temperature

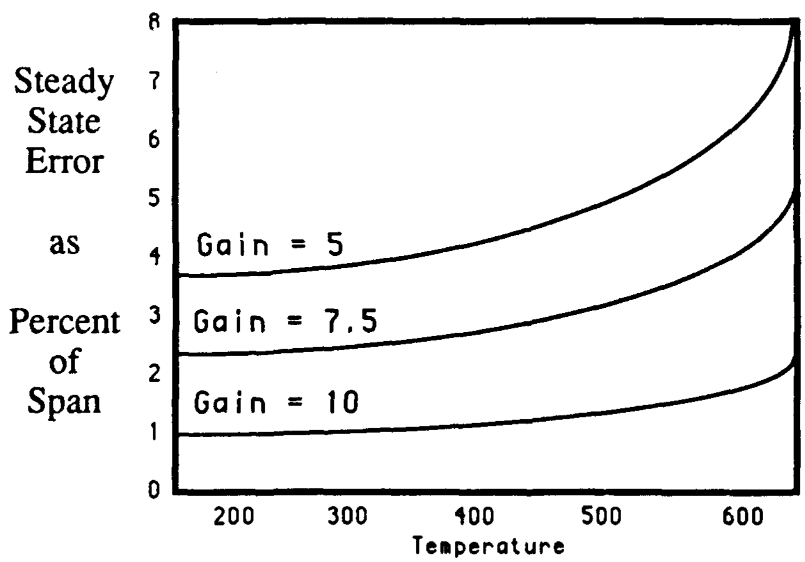
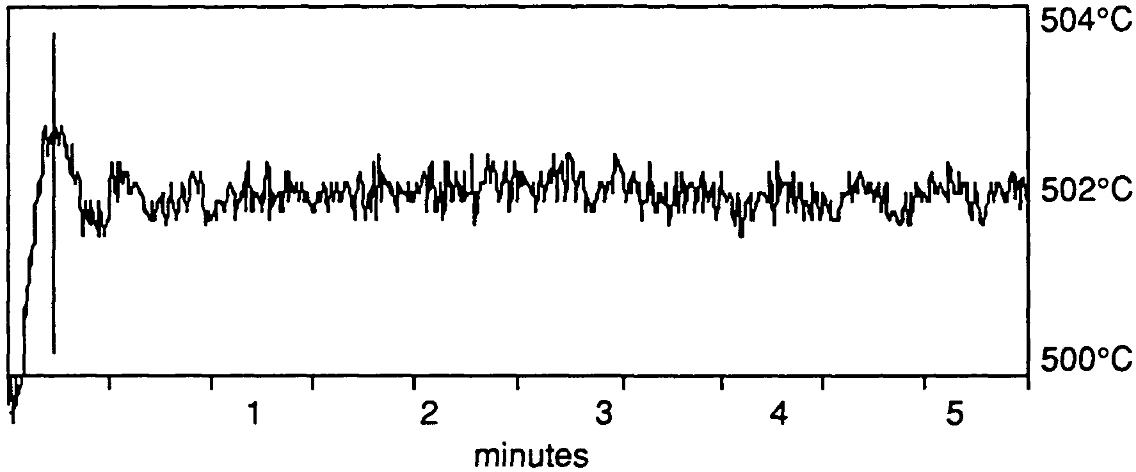
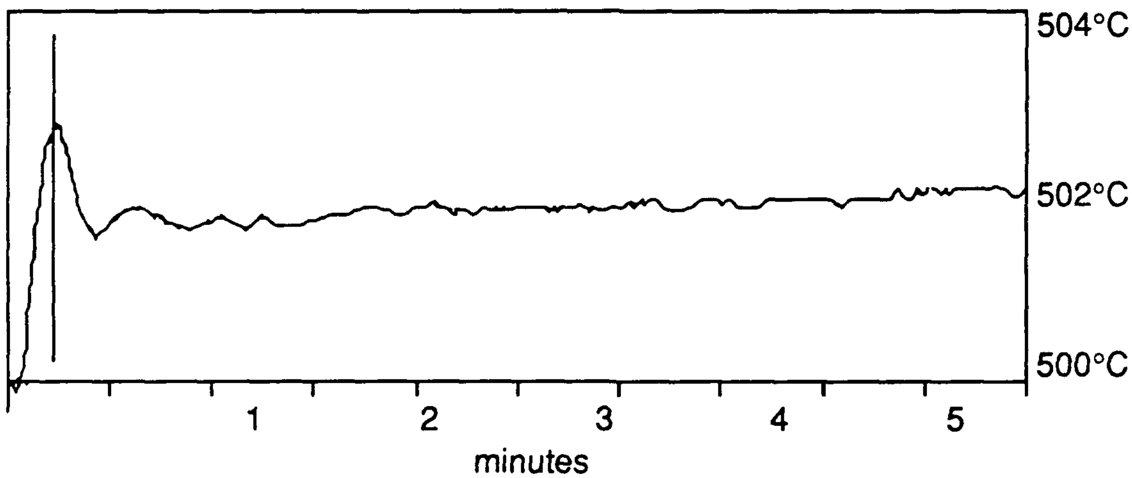


Figure 4. Gain/Steady-State Error versus Temperature



Two Degree Step Response Using Eurotherm 825 Controller
Proportional Band = 4.3, Integral time = 32, Derivative Time = 12.3
Maximum peak = 502.8°C at 13.12 seconds.



Two Degree Step Response Using Eurotherm 818 Controller
Proportional Band = 6.4, Integral time = 62, Derivative Time = 18.3
Maximum peak = 502.7°C at 13.78 seconds.

Figure 5. Eurotherm 818 versus 825, Noise and Stability

SELF-IMPROVING CONTROL FOR MBE USING A NEURAL MODEL

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INTRODUCTION

Research is currently being conducted at Tennessee Technological University to develop "intelligent", self-improving models to aid in the discovery of new knowledge for self-directed control of a Molecular Beam Epitaxy (MBE) system. This will enable in-situ (real-time) control path generation based on both product (material behavior) and processing (control agent) feedback. A 'product-process' control philosophy which emphasizes product quality is described together with a generic architecture for discovery of product and process knowledge.

SELF-DIRECTED, SELF-IMPROVING PROCESS CONTROL

The emphasis of this paper is the added dimension of self-improving material processing. If a process is self-directed, then the added feature of self-improvement is both inherent in and limited to the flexibility of the knowledge representation used. Inherent, because a self-directed control philosophy relates the process to the product (i.e., by emphasizing product quality) and generates the relationship in-situ or in real-time. Therefore, a self-improving process control system is simply the act of tuning the relationship between the product and process. Limited, because self-directed control is fundamentally rule (condition-action) based and, therefore, process self-improvement is dependent on selecting a technique and a strategy which is both effective and efficient in modifying rules. There are two important reasons for coupling self-improving with self-directed process control. First, self improving will aid in the creation of the knowledge base when the knowledge representation is unknown or difficult to acquire. Secondly, self improving can help in detecting changes within the process (aposteriori) that affect the knowledge base and the control of quality without the need for human intervention.

Without an accurate knowledge representation of the manufacturing system self-directed control achieves very little in terms of process control. Through the use of expert knowledge, analytical models of the physical system, and trial and error experimentation the knowledge base for self-directed control can be encoded for most manufacturing processes. However, some processes, particularly processes utilizing emerging technologies, there is a very limited understanding of the interaction between controlled variables and product quality. In this latter case the knowledge of an expert is often more of a "gut feel" rather than expressed in terms of precise, quantifiable process limits. Analytical models may exist in part but rarely do they encompass the broad spectrum of simulating an entire process from start to finish. Experimentation is the primary mode of knowledge acquisition, but even this form of knowledge is questionable at times due to a lack of time to isolate the variables and their interactions affecting the process. A self improving model will build the strengths of the relationship between controlled variables and desired material properties so that the time necessary for knowledge characterization of new materials and new processes is minimized.

In existing processes where the knowledge base is well established, new equipment or new materials may require changes to the knowledge base. As experimentation is conducted a self improving algorithm would quickly establish processing limitations and goals with respect to the changes made to the system. In addition, a self improving system would allow for quick responses to changes in the process variability due to increases in either equipment or raw material fluctuations. Whereas self-directed control has demonstrated a proficiency in handling in-process variability, a self improving model would aid in adjusting the knowledge base for shifts in the process parameters.

The task of this research is to develop an **efficient** methodology for synthesizing the relationship between process parameters and ex-situ product characteristics. An artificial neural model is being used to develop the recognition of patterns between process and product characteristics.

SELF-IMPROVING NEURAL INTERFACE FOR MBE

The problem of pattern recognition as applied to MBE knowledge acquisition is one of recognizing trends and response surfaces of multivariate input data, and predicting an estimate of an output pattern of variables. In his book on adaptive pattern recognition, Pao [1] classifies the subject into two basic methods. The first method is to classify multivariate patterns as a member of a specific class of patterns. The second method is to estimate output attribute values given a particular mapping of an input pattern. The neural network interface for MBE will utilize both types of pattern recognition *methodologies, classifying pattern membership and attribute estimation*, as illustrated in Figures 1(a), (b), and (c). Figure 1(a) shows the input pattern as represented by a multivariate vector of features which are passed through a filter. The function of the filter will be to cluster or discriminate among a historical database of MBE runs with processing parameters similar to the input pattern. The resultant output of the filter is a class of patterns relatively similar to the new input pattern which is used to create a transparent mapping for pattern recognition and estimation of the feature attribute values (Figure 1(b)), or in this case an MBE recipe. By using a class of similar patterns as the training set the construction of the transparent mapping and the accuracy of the estimation of attribute values is significantly improved due to the reduced variability of the input features. The final step (Figure 1(c)) is to use the transparent mapping formed in Figure 1(b) to estimate the appropriate attribute values given a specific input pattern vector.

CURRENT RESEARCH ISSUES

To filter the historical database of process parameters according to a template pattern of the current process involved, the use of an auto-associative neural network is being tested. Neural models under consideration are an adaptive Bidirectional Associative Memory (BAM) and a competitive learning network. The performance of these networks will be compared against a benchmark of a multivariate k-means cluster algorithm using the Euclidean distance between existing MBE runs and the proposed pattern.

Using the filtered data as a training set, the target values for creating new knowledge and rules to be used in the self-directed, in-situ process control architecture are generated using a hetero-associative neural model. The two most common neural models for this type of pattern recognition, where attribute values are returned as opposed to a classification membership, are back propagation and functional link networks. From previous research by Pao (2) and Currie(3) the functional link network responds much faster than the corresponding, back propagation. The research issue to be addressed is the construction of the functional link network in a dynamic sense. The enhanced attributes of the functional link network must be stated in advance, without knowing the impact on performance and reliability of results.

FUTURE RESEARCH DIRECTIONS

As the availability of MBE data allows for a detailed analysis of it is anticipated that additional problems will arise. In the future, the issue of predicting product feedback given a particular processing recipe will be addressed. Optimization of one or more processing variables given constraints on the recipe, the product requirements, or both. It is also planned to include a variety of different materials and device types. Finally, the application of a self-improving architecture should have the ability to be transferred to other material processes.

CONCLUSIONS

As intelligent material processing research begins to mature it is becoming clear that the power of such systems lies in their ability to: first, self-direct a process in terms of autonomous closed-loop control and second, self-improve in terms of "discovering" new knowledge. The use of neural models to facilitate self-improving an existing knowledge base may soon transform self-directed process control from a static, rule-based control architecture into a dynamic, autonomous material processing system.

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[3] Currie, K. R., "An Intelligent Neural Model for Recognition of Input/Output Patterns for a Molecular Beam Epitaxy Process", USAF-UES Summer Faculty Research Program Final Report, Contract No. F49620-88-C-0053, August, 1989.

(This research is supported by a grant from the Air Force Office of Scientific Research and their Research Initiation Program.)

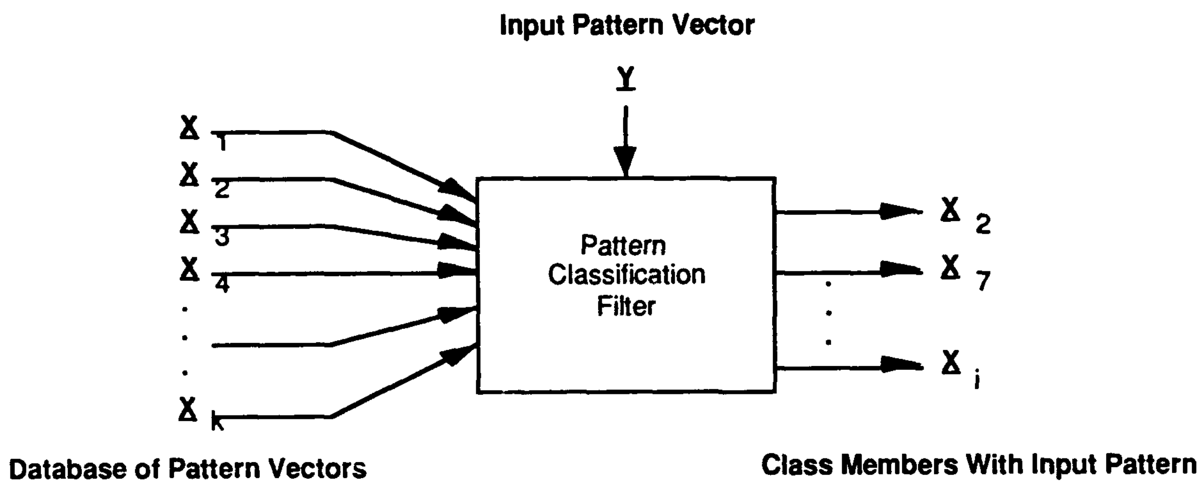

Figure 1 (a). Classification for Training Pattern Set

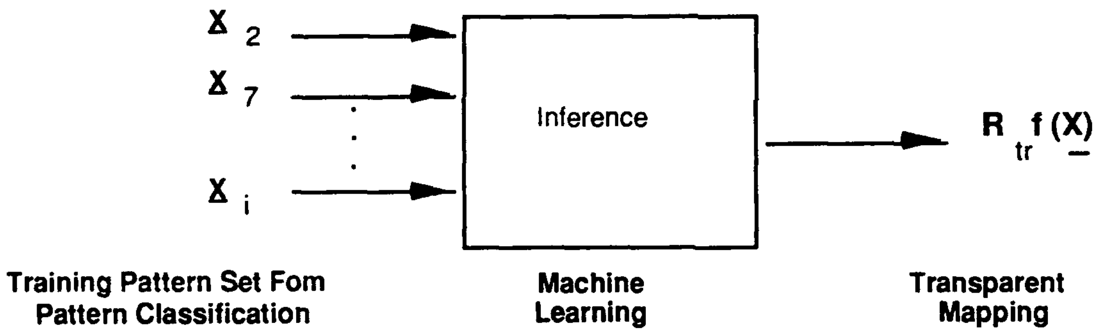

Figure 1(b). Creation of Transparent Mapping [1]

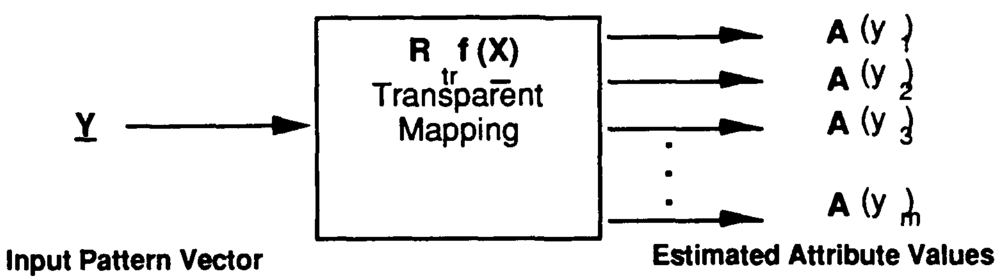

Figure 1(c). Estimation of Attribute Values [1]

QPA AND MODELS FOR COMPOSITE CURE AT MCDONNELL AIRCRAFT

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For many years the chemical industry has used process controllers to adjust operating conditions for changes in raw materials to achieve consistently high quality products. Most of these controllers maintained state variables, temperature and pressure, at predetermined values at critical stages of the process. Others control production rate, assure the correct ratio of ingredients for product quality and protect operating equipment. We are now applying that technology to autoclave curing of composites. One major difference between the normal continuous process control systems and the batch process control required of an autoclave is that the state variable set points for the process control systems are often constant for long periods of time, whereas state variable set points for an autoclave cure vary continually with time to meet the ever changing needs of the curing system. Both systems use feedback control.

The trick to achieving autoclave cure control is sensing the state of the curing laminate without jeopardizing laminate quality and then relating that measurement to the state variable changes. The first part of the Air Force sponsored Advanced Composite Processing Technology Development program (Contract No. F33615-88-C-5455) is that of selecting sensor systems which unobtrusively ascertain the laminate state. The second part is to relate sensor measurements to autoclave state variable path in a manner which assures high quality laminates. These two parts combined meet the objective of the program, i.e. to generate a real time cure cycle from sensor measurement of laminate physical parameters.

Six sensor systems have been chosen to monitor the laminates as they cure. Thermocouples measure temperature at the laminate surface. Fiber optic devices are embedded in the laminate to measure temperature and pressure. A microdielectrometer measures dielectric properties at the surface. A fluorescence optrode measures resin fluorescence of the curing resin at the laminate surface. An ultrasonic device measures laminate response to pressure waves and the effect on the pressure wave by the laminate. An eddy current sensor measures laminate thickness as it changes with time. The sensors tell us directly laminate temperature, resin pressure, that the resin is flowing, that the resin is solidifying, laminate thickness, and that voids may be present at their respective locations. These devices were selected such that there are at least two measurements of each property establishing automatic backup values if some sensor fails to operate.

A second set of sensors measures the state of the autoclave. Thermocouples measure autoclave temperature, and pressure transducers measure autoclave and vacuum pressures. There is a sensor to measure the pressure difference between the autoclave and a vacuum bag. Other sensors note the position of control actuators and the mechanical state of the autoclave system. Over a hundred sensor measurements are available to the cure control system.

Even with all of these measurements, everything needed for cure control is not available. Models may be needed to supply properties which defy direct measurement such as resin saturation temperature and pressure. Models can compute resin viscosity and degree of cure from thermocouple measured temperatures and time. These serve as backup in case of sensor failure, but they are available only for resin systems which have been thoroughly studied in the laboratory. Figure 1, Cure Monitor Models, shows a list of property models included in our control system. Sensors and models based on these sensors have one disadvantage. The information is valid only at the point of measurement. Experience shows that different portions of the same laminate may undergo vastly different cycles as determined by tooling response to the autoclave environment. It is not always possible to locate sensors at critical positions within the part layup space because they cannot be embedded within the laminate space without adversely affecting mechanical properties.

A second kind of model predicts temperature and resin state throughout the laminate space from autoclave temperature and pressure and time. It provides backup for laminate thermocouples and a basis for predicting temperature in places inaccessible to sensors. The means of predicting the temperature of any point is the laminate is illustrated in Figure 2, Part Temperature Field in Thickness Direction. First the simulated temperature field (solid curve) is computed and compared to a sensor measured temperature at a give location. Second, the simulated temperature field is adjusted for the difference between the computed and measured temperature at the laminate thermocouple location creating the adjusted temperature field (dashed curve). And third, laminate properties are calculated for the adjusted temperature field for use by the cure cycle generator.

This simulation is run in real time using autoclave conditions as boundary values for the solution of finite element laminate models in real time. An autoclave clock time of 30 seconds may be simulated in less than 15 seconds. The computer waits the remainder of the 30 second interval before starting the next iteration keeping the model in synchronization with real time. Detailed layup information necessary for these models resides in a data base so that the autoclave operator can specify the load in terms of part name and then assign sensors to actual part locations.

There is a third model in this system. A simulation model of the autoclave response to control directions predicts the expected autoclave state change in time. If this expected state is different from the sensor measured state, then there is a malfunction which must be considered by the cure path generator and perhaps called to the attention of the operator. The second use of the autoclave simulator is to develop and test the cure cycle control software thoroughly off-line to minimize autoclave testing time.

The autoclave control system has three software components in addition to the sensors and control actuators as shown in Figure 3, Intelligent Autoclave Control System. They are the central autoclave system (GENISIS), the cure cycle monitor (CURMON), and the cure path generator (CURGEN). GENISIS is the central coordinator of the system calling upon CURMON to compute indirect measurements from sensor input and select information for evaluation by the cure path generator and calling upon CURGEN to determine new actuator set points from information provided by CURMON and its cycle generation knowledge base. These components run on three separate personal computer systems. GENISIS runs on an industrially hardened system; CURMON on an IBM PS/2 M80; and, CURGEN on an APPLE MACINTOSH.

Stand alone autoclave control is effected through GENISIS which is used in day to day operations. GENISIS receives signals from autoclave and part sensors,screens this raw data for validity, logs it for future reference, presents it on a display tube for operator edification, and issues instructions to the autoclave control system actuators. The operator controls cure cycles through the GENISIS system.

In the qualitative process automation (QPA) scheme, the cure monitor and cure path generator replace much of the operator intervention. In order for GENISIS to communicate with the cure monitor and cure path generator, a subcomputer board was added to the GENISIS hardware configuration. This electronics board formats sensor measured values for the cure monitor, cure monitor generated values for the cure path generator, and cure path generator output (autoclave set points) for GENISIS. The communicator board handles the serial port protocols for the individual computer systems allowing intelligent conversation between them.

The purpose of the cure monitor is two fold. First it reduces the hundred plus autoclave sensor values to a few important ones for consideration by the cure generator. Second it orchestrates the application of models to incoming data thereby relieving the cure path generator of arithmetic computations leaving it to efficiently apply the knowledge base in determining what to do next. Figure 4, Cure Monitor Time Step Process, illustrates the activities of the cure monitor. Cure monitor begins each iteration by reading the sensor and control system set points from GENISIS and updating a history arrays which store the last several readings from each instrument. Next it updates the measured parameter arrays by screening of averaging the history array values. For example, if there are three thermocouples at a given location, they are averaged to give a single temperature in the measured parameter array. Level I models compute properties by location which may be compared with sensor measurements at the same location. The simulation model computes the temperature and property fields and stores them in the simulated parameter array and the autoclave simulation model computes the expected autoclave state. After adjusting the simulation property fields for the difference in measured and predicted temperatures, the control parameter selector scans the available information for the most important parameters which it passes back to GENISIS which in turn passes on to CURGEN.

The cure generator applies rules to the screened data supplied by the cure monitor. The basic premise of the cycle generation strategy is that higher temperatures reduce cure time to achieve desired mechanical properties. Hence the autoclave set point is as high as possible without sacrificing part quality at any given time. Autoclave temperature is limited by mechanical operating limits, bag material melting point, resin propensity to boil or exotherm, residual stress potential, etc. Autoclave pressure is maintained at sufficient level for laminate compaction and void prevention. Bag pressure is maintained a levels which assure that all non-condensable gases are removed from the system and that the resin remains below its bubble point. In accomplishing the goal of a fully cured part, the cure generator considers the mechanical state of the autoclave system to assure safe operation.

There is a philosophy behind this control system. The control system generates the best cycle it can from the information supplied by the operator on load initialization. If the operator only lists the parts in the load, the system bases the cycle generation solely on sensor measurements. This is a pure QPA system. However, if the operator adds the prepreg name from which the laminates were made, the system runs the simple models which predict viscosity and degree of cure as backup for sensor failure. In addition, if the operator specifies part simulations, the system runs 1) the simple models which backup individual sensors and 2) simulation models which predict the degree of cure, viscosity and exotherm potential at points within the laminate beyond sensor reach. These values are made available to the cycle generator. The additional information available from models together with the real time control knowledge base will provide a basis for further cure cycle optimization.

In summary the system described herein combines modeling and QPA techniques to provide a robust autoclave control system. It will relieve the operator form the need to watch every instrument every minute by calling his attention to important autoclave status changes. At the same time QPA protects the curing laminates from a detrimental autoclave environment. Using this system the autoclave should produce high quality parts the first time, every time.

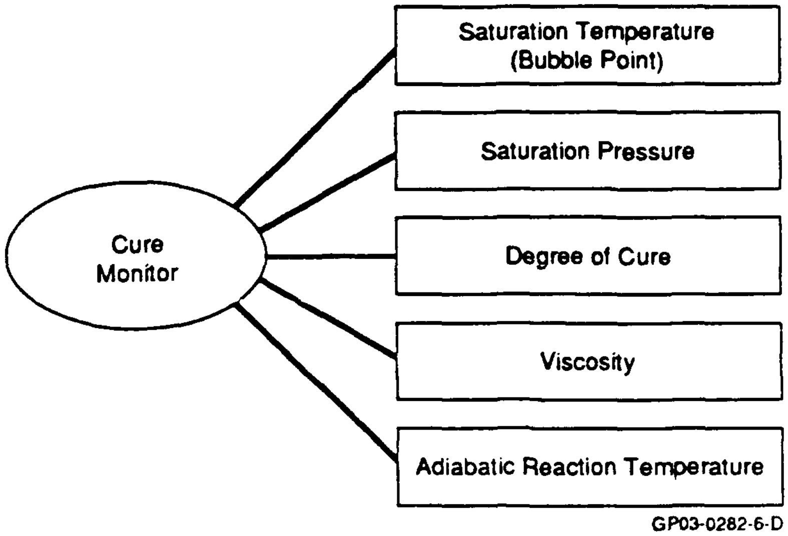

Figure I. Cure Monitor Models

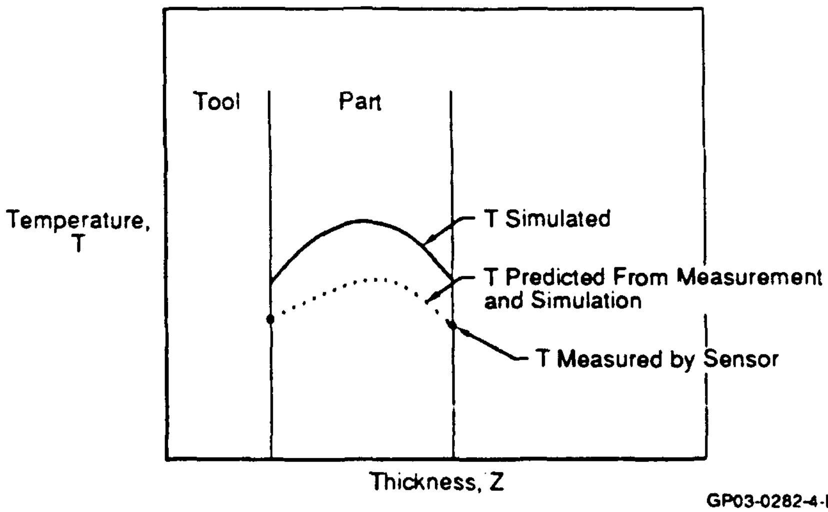

Figure II. Part Temperature Field in Thickness Direction

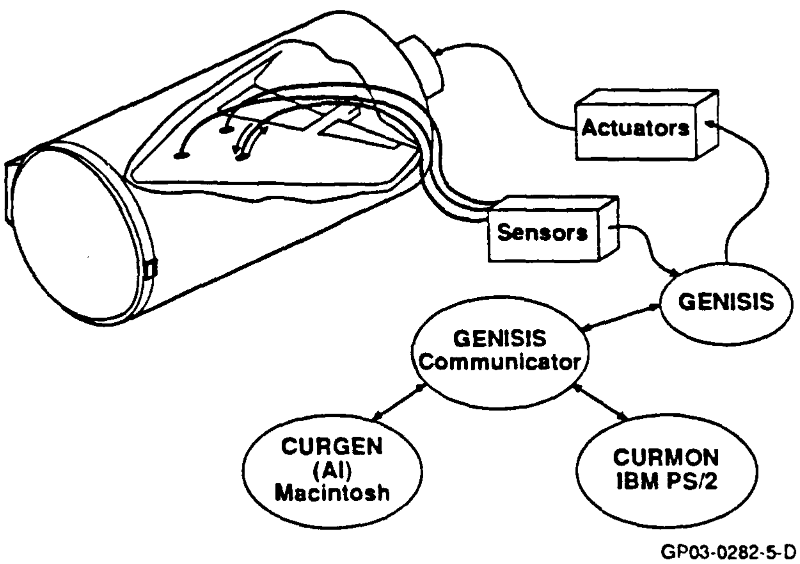

Figure III. Intelligent Autoclave Control System

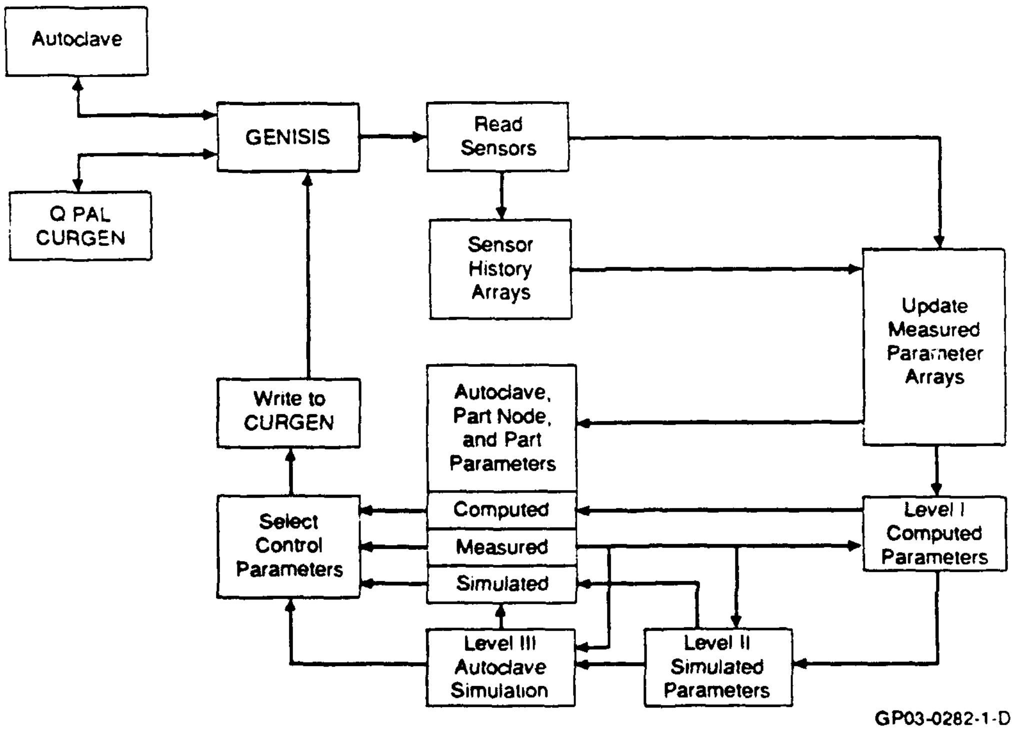

Figure IV. Cure Monitor Time Step Process

QPA FOR COMPOSITES CURING AT SACRAMENTO AIR LOGISTICS CENTERP

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INTRODUCTION

Sacramento Air Logistics Center (SM-ALC), located at McClellan AFB, CA, is one of five depot-level repair centers for the Air Force. Two of our major system program manager assignments include the F-111 and the A-10 Thunderbolt II aircraft. The Air Force Advanced Composites Program Office (ACPO) was assigned to SM-ALC in 1984. Our mission is to transition advanced composites technology from the Air Force laboratories and prime contractors into Air Force Logistics Command (AFLC) and the other major commands. One of the ways we are fulfilling this assignment is through technology insertions; i.e. we develop a piece of hardware or software and use it to increase the reliability and maintainability of a weapon system. Two of the hardware insertions of interest are the advanced composite

- F-111 forward ventral strake
- A-10 wing *leading edge.*

Both of these structures were designed and tested by the ACPO. They are now flight-certified and in production at SM-ALC.

Another major technology insertion effort is Qualitative Process Automation (QPA). QPA is an artificial intelligence-based process control system to control the cure of advanced composite structures. It was originally developed by a research team at Wright Research and Development Center (ref 1). SM-ALC, through the ACPO, became involved after a QPA industry review in June 1987. The ACPO, representing advanced composite engineering, and SM-ALC's Industrial Products Division (MAN), representing production, are committed to installing QPA on production autoclaves at SM-ALC and using it to process flight-certified advanced composite structures

CONVENTIONAL CURE PROFILES VS QPA KNOWLEDGE BASE

Conventional cure profiles are designed so that resins meeting certain initial requirements can be processed to meet or surpass the minimum cured laminate property specifications. Process 'windows' are set up, based on historical physical and mechanical data, through which materials of varying composition, B-staging, and viscosities can pass and still make acceptable laminates. This cure profile may be significantly different for structures containing the same resin but having different geometries. A typical profile will look something like this:

a. Apply 22" Hg vacuum minimum.
b. Ramp at 1 - 5^{o}F to 250 +/- 5^{o}F.
c. Hold at 250 +/- 5^{o}F for 45 minutes.
d. Apply 85 psig pressure 15 minutes into the hold. Vent vacuum when pressure reaches 20 psig.
e. Ramp at 1 - 5^{o}F to 350 +/-5^{o}F.
f. Hold for 120 minutes.
g. Cool laminate to 140^{o}F before releasing pressure.

One important fact to notice is that these profiles are firmly rooted in the time/temperature domain. QPA does not work explicitly in the time domain. QPA looks for states to occur that have been determined are important to the process (such as the onset of flow or gelation). These states are defined based on real-time sensor data. Since the state of the resin in real time is known, QPA does not have to rely on historical data or models to predict what the state of the resin is at a given time and temperature. It then uses these states to trigger events such as pressurization or the end of cure.

FACILITIES

The Industrial Products Division (MAN) at SM-ALC has two autoclaves currently in use and two that are in the process of being installed. The vessels possess the following characteristics:

		Baron	Tenney	Melco #1	Melco#2
Size	8' x 20'	10' x 24'	4' x 8'	8' x 30'	
Temperature (^{o}F)		650	450	800	800
Pressure (psi)	205	110	300	300	
No. TCs	20	12	48	24	
Bag Pressure (psia)		0 -140	0 -15	0 - 300	0 - 300
Dielectric Sensors		6	-	-	-
Ultrasonic Sensors		-	-	3	6

QPA has been installed on the Baron autoclave. However, persistent problems with the heaters have resulted in considerable down-time over the last year. This has led to very frustrating delays in the QPA program. The two new autoclaves (Melco #1 and #2) are scheduled to be operational by June 1990. If the Baron has not become operational by that time we may switch QPA over to one of the new Melco autoclaves.

QPA/CAPS ARCHITECTURE

The autoclaves at SM-ALC are presently controlled by the CAPS 310 system from Applied Polymer Technology Inc (APT). This system represents the state-of-the-art for conventional computer cure control. Data analysis and control decisions are made by a Hewlett-Packard HP 1000 computer. The HP 1000 sends its control signals to Barber-Colman PID controllers. We took advantage of the fact that this system was in place to ease the data acquisition requirements of QPA.

QPA runs a program called QPAL, developed by Universal Technology Corporation (UTC). The QPA Macintosh IIx is connected via its serial port through a multiplexer (mux) to the CAPS 310's HP 1000 (see Figure 1). During a QPA-controlled autoclave run CAPS is actually running a conventional cure profile in the background. QPA simply accesses the data the CAPS normally collects (autoclave temperature and pressure, and part temperature(s) and bag pressure). The control signals are sent to the PID controllers via command-override messages passed back through CAPS.

The architecture is flexible enough to handle different sensor systems at the same time. The autoclave at WRDC has a Micromet dielectric system connected through the mux to the Mac. There are two different sensor systems at SM-ALC: the Baron uses an HP 4274A Multi-Frequency LCR meter to collect dielectric data, while the new Melco autoclaves have the APT ACM 106 ultrasonic sensors. APT and UTC have devised a protocol to handle the passage of the diverse data that comes from these instruments. This protocol will allow additional sensor systems to be connected in the future without going through a major customized reprogramming effort that must be contracted out.

SYSTEM SAFETY/EXCEPTIONS

A section of the knowledge base has been developed to deal with the safety aspects of running an industrial autoclave. Based on my experience and that of the operators at SM-ALC, we have tried to think of all the possible failures that could occur and what, if any, action could be taken by the control system. This turns out to be a non-trivial exercise. A human operator can see an event occur (such as the vessel pressurizing above its setpoint) and take appropriate action (open the manual relief valve). The knowledge base has to take into consideration the event that is occurring, how it relates to the state of the cure at that time, and decide on proper control action. There are some events that elicit three different responses depending on when the event occurs during cure. One factor that is vitally important is that the QPA provide <u>consistent responses</u> to <u>unexpected events</u>. Human operators may provide different responses, depending on which operator is on duty, what day of the week it is, etc.

Some of the events that we detect and respond to are:

TC failure	dielectric sensor failure
heater failure	cooling failure
initial pressurization failure	over pressurization
under pressurization	exotherm

These responses may be simple messages posted to make the operator aware of the event, they may be a control response, or they may abort the run in a controlled manner.

IMPLEMENTATION PLANS

QPA has been installed on the Baron autoclave and established communications between QPA and the CAPS 310. The next order of business will be to test the safety, alarm, and exception features of the knowledge base on an empty autoclave. Situations will be created to emulate the desired event (or undesired event, as the case may be) and check to see that QPA fires the correct control response.

A series of test laminates will be cured to test the adequacy of the cure portion of the knowledge base. Much of this work has already been done by Ms Frances Abrams in her lab at WRDC. A series of standard laminates will then be cured to establish that QPA is giving us the desired mechanical properties. This testing will be used to certify QPA for use on production advanced composite structures.

Two other challenges face us in the coming year. One is to devise a knowledge base to handle multiple parts. The second challenge is to use a different sensor, namely the ultrasonic sensors found on the new Melco autoclaves. Both of these challenges will require much thought and hard work, but I expect that we shall soon be producing multiple parts with multiple sensors in the production environment.

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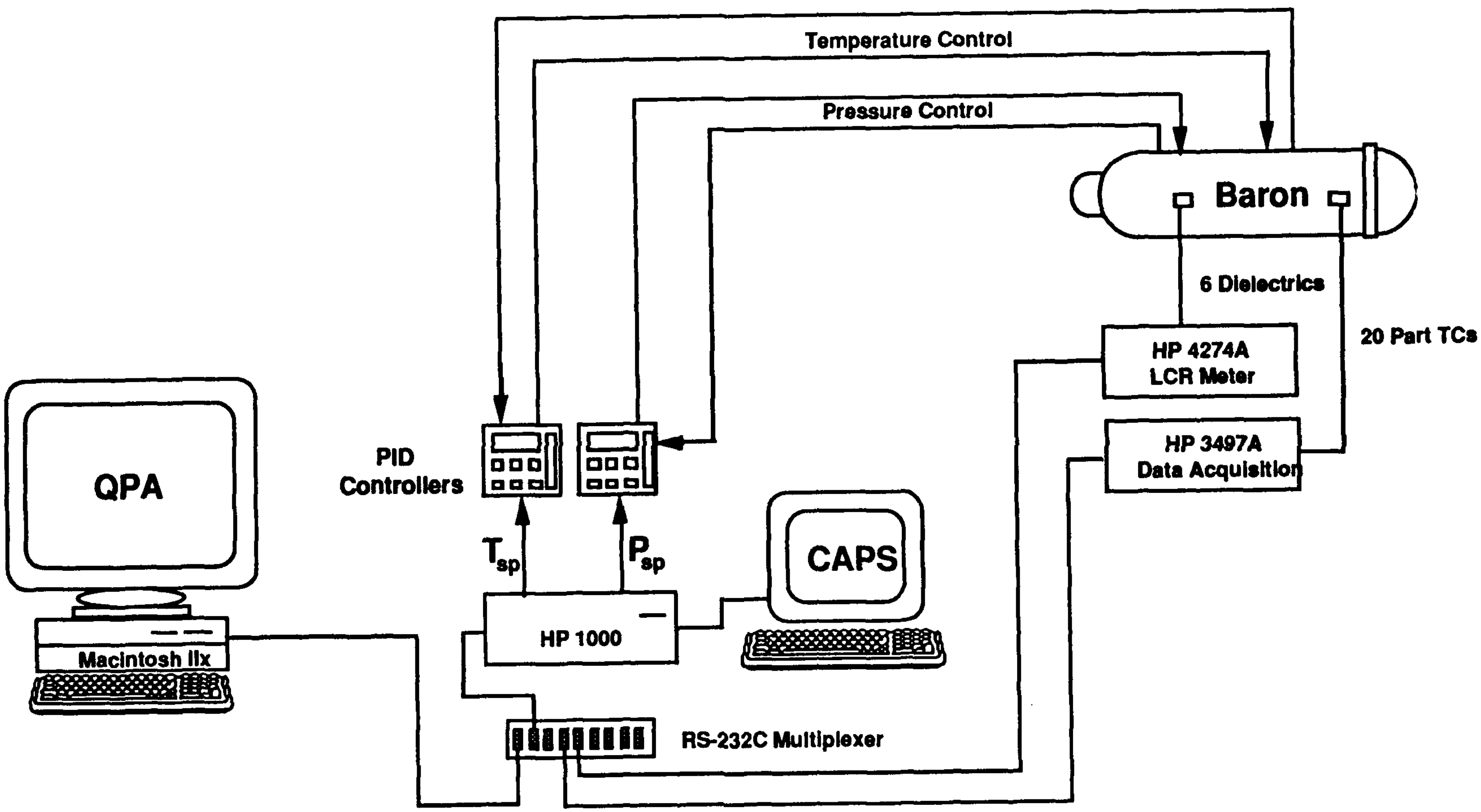

FIGURE 1 CAPS / QPA Architecture

'NEAR-OPTIMAL' CONTROL OF FORGING PROCESSES

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INTRODUCTION

In designing material-forming processes for components made of complex materials, the most important task is the selection of the controlling process parameters that will ensure part quality as well as specific mechanical and physical characteristics. The controlling process parameters are the sequence and number of material flow operations, the heat-treating conditions, and the associated quality-assurance tests. When designing forging processes, special features such as nonlinear irreversible finite-deformation flow must be considered. Simultaneously, the complex interdependence of forging process parameters and their effect on the quality of the finished part, the reliability, and the ability to inspect must be considered.

Another important goal in forging is to determine the optimum means for producing defect-free parts on a repeatable basis. The optimization criteria depend on the manufacturing goals and the product specifications; establishing the appropriate criteria requires in-depth views - both global and local - of manufacturing processes and material behavior. From an optimization viewpoint, manufacturing processes require the determination of material flow mechanics to achieve proper process design and to develop a rational strategy for process control.

Modeling of the forging process involves both mechanics and thermo-dynamics. The process, as a rule, is inhomogeneous and transient over a large volume of workpiece material, and the material flow process can be characterized as highly irreversible and stochastic in nature. The mechanics of the forging process are well established, and different analytical tools are available for analyzing most of the important steps of a total forging process.

OPTIMIZATION TECHNIQUE

The material behavior of the workpiece will be the focus for optimizing an ALPID (ref. 3) finite-element simulation for a typical hot-forging process. ALPID is a rigid-thermoviscoplastic finite-element program which is presently being used by many U.S. forging companies to design near-net-shape forgings for the aerospace industry. The importance of being able to characterize workpiece material properties under processing conditions is shown in Figure 1. In this figure the inelastic constitutive equation is the link between the equipment characteristics and the material system being modeled. The mathematical device converts the power supplied by the forging press to power dissipated by the workpiece material in the form of heat due to plastic working and microstructure evolution. The connection between the material system and the control system is made through a dynamic material model which describes the metallurgical response of the workpiece material to thermomechanical conditions of the forging process. Through process simulation a control algorithm can be developed for feedforward control of the equipment.

The behavior of the workpiece during nonlinear forced dissipative plastic flow determines how the forging process should be controlled and whether defects can be avoided while producing the required geometries, micro-structures, and properties in the finished product. As the workpiece material undergoes irreversible flow, it selects a special trajectory, which is defined by the input (rate of application of external stimuli) and the initial state of the material (prior thermomechanical history). The rate of application of external variables determines the state of the system during hot working.

The stability of the system is defined by maps connecting a set of inputs and outputs that describes the intrinsic workability of the workpiece in terms of its mechanical and microstructural stability. Material-stability-preserving-maps are developed from inelastic constitutive equations. The deforming body is said to be stable if a stable power input results in an output (microstructure, geometry, and heat) having stable characteristics in a Liapunov sense. (ref. 5)

By incorporating the stability information as nonholonomic constraints in ALPID, a designer can create a process control strategy based upon a near-optimal intrinsic-workability criterion. This approach to simulation optimization leads to realistic numerical predictions of nonlinear, irreversible deformation processes

EXAMPLE: TITANIUM ALLOY DISK FORGING PROCESS

The approach of optimizing deformation processes by using *material-stability-preserving maps* is demonstrated in the design of a Ti-6Al-2Sn-4Zr-2Mo disk forging process (ref. 2). The closed-die isothermal forging of this disk was previously analyzed using ALPID, with emphasis on the prediction of metal flow near the flash (ref. 1). Because of symmetry, it is sufficient to analyze only one quarter of the cross section of the forging. The predicted nodal-point velocity plots for 48, 68, and 72.1% reductions in height are shown in Figure 2. The plots clearly show the transition in metal flow from primarily upsetting deformation to die cavity filling to the final stage of forming flash.

In the current study, the process design goal was to fill the die cavity completely and to avoid the possibility of creating defects that are produced by critical states of stress in the forging process. The state of stress is defined by the stress rate path, which is the ratio of the mean hydrostatic stress to the effective stress. This stress ratio is a fundamental quantity in plasticity theory because materials change shape according to the applied effective stress-rate path. When this ratio is positive, a tensile state of stress exists; when it is negative, a compressive state of stress exists. The magnitude of the stress ratio represents the resultant loading condition of the deforming material. The distributions of the stress rate path ratio for the disk simulation at 48, 68, and 72.1% reductions in height are shown in Figure 3. At 48% reduction (Figure 3a), the center bore region of the disk has an approximate value of -1.0, and the outer rim region has positive values that reach a maximum of +0.37.

The transition from compression to tension (neutral surface) is controlled by the die radii. As the workpiece touches the outside die wall and continues to fill the die cavity, the tensile state of stress reduces to a small region that is filling the inside die corner. This situation presents a potential problem, namely, that of producing defects such as cracks in the finished forging. Therefore, enhanced metal flow and good intrinsic workability of the workpiece are needed in this location at the final stages of die filling in order to relax the stresses and thus avoid the possibility of defect formation.

The material-stability-preserving-map for Ti-6Al-2Sn-4Zr-2Mo with an initial Widmanstatten microstructure is shown in Figure 4. From this processing map, the optimum conditions for this material and application were determined to be a strain rate of 0.003 per second and a temperature of 926 C (ref. 4). In optimizing the ALPID simulation of the isothermal disk-forging process, the die velocity was changed to maintain the desired effective strain rate with a 0.1% tolerance limit in Element No. 47, which is positioned near the inside die corner (Figure 5) where final die filling is critical.

The optimal die velocity as a function of stroke is shown in Figure 6, and a total deformation time of 413.4 seconds would be required for this type of process control. The time-varying die velocity results of this simulation would provide the enhanced workability and metal flow required for the workpiece to flow around the die corner radii, to fill the inside die corner, and to fill the die cavity completely.

It is currently feasible to preprogram large hydraulic forging presses for constant or variable die velocity over a given load range. Feedback control systems can also be installed for regulating the ram speed with respect to forging pressure or workpiece temperature. Continuous ram speed control requires a combination of direct pumping and accumulator drive systems in order to achieve the required real-time changes in applied power during the forging process. The accumulator drive system provides a higher penetration speed, but toward the end of the stroke, as the force required for forging increases, the ram speed and load available at the ram decrease. The direct-drive system delivers the maximum available load during the entire ram stroke and thus provides the very high pressures required for final die filling. Therefore, the two drive systems are complementary, with the result being improved controllability of the forging process.

FUTURE RESEARCH

The future direction of this research will be in the development of robust, self directed process control methods. Advanced control design techniques must be developed for synthesizing desirable microstructures of difficult-to-process materials in a reproducible way. Quantitative and qualitative methods need to be coupled together for capturing both the physics of the process and the practical aspects of the process. Quantitative process models are currently capable of accurately describing the mechanics of the process and the particular flow and fracture phenomena of specific materials. Qualitative Process Automation (QPA) techniques are currently capable of supporting real-time control of material processes by coupling material-specific knowledge with expert heuristics about the process. Robust, self directed process control methods will have a significant impact on the producibility of advanced material systems which are typically very difficult to process. Some important research issues for further study are:

- the stochastic, nonlinear, nonhomogeneous nature associated with manufacturing processes;
- the development of qualitative and quantitative relationships among workpiece/die geometry, material flow field during processing, and the control system design; and
- the development of scientific methodologies for analyzing, optimizing, and controlling sequences of manufacturing processes.

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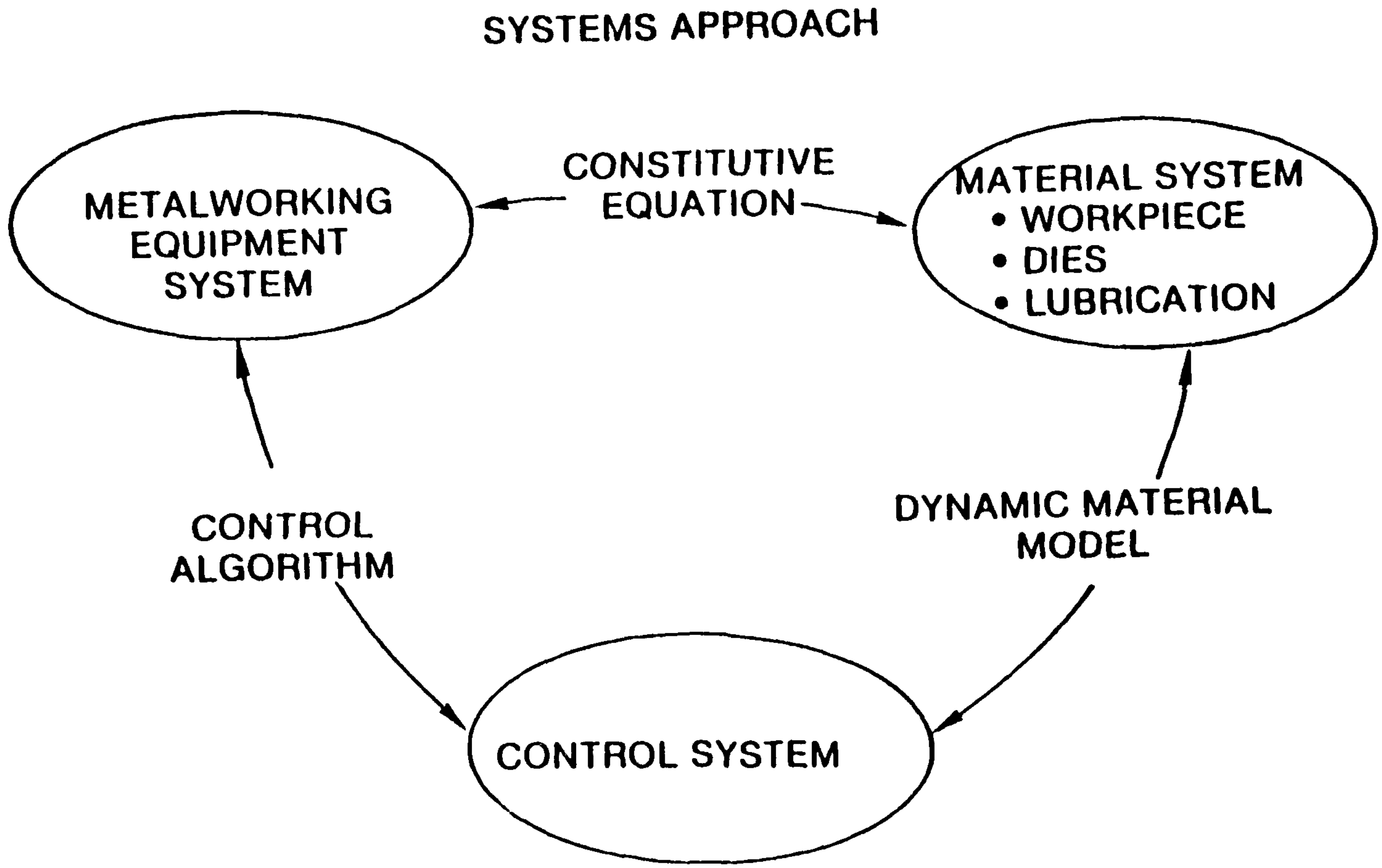

Figure 1. Systems Approach for modeling forging processes.

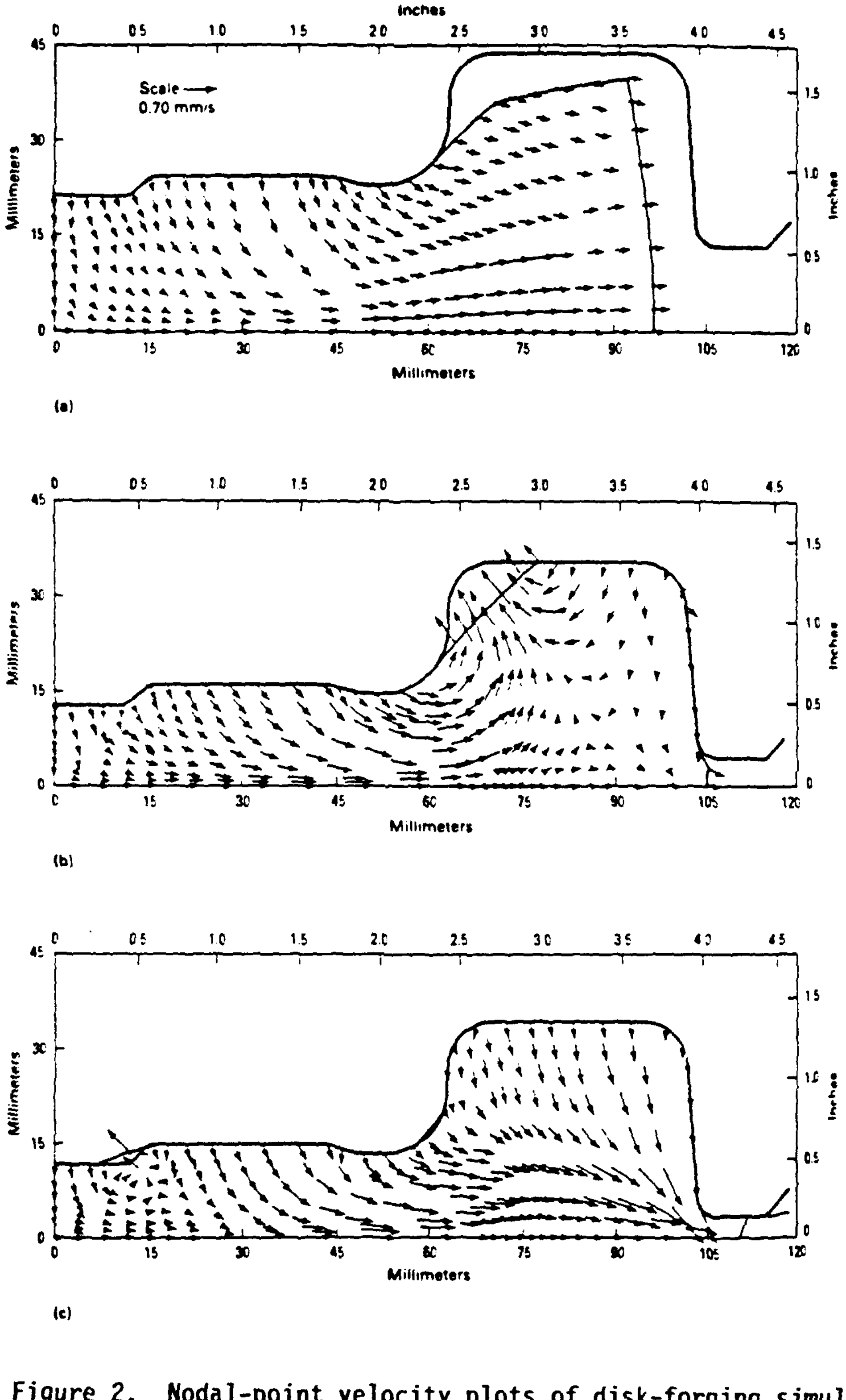

Figure 2. Nodal-point velocity plots of disk-forging simulation with constant die velocity at 48% (a), 68% (b), and 72.1% (c) reductions in height.

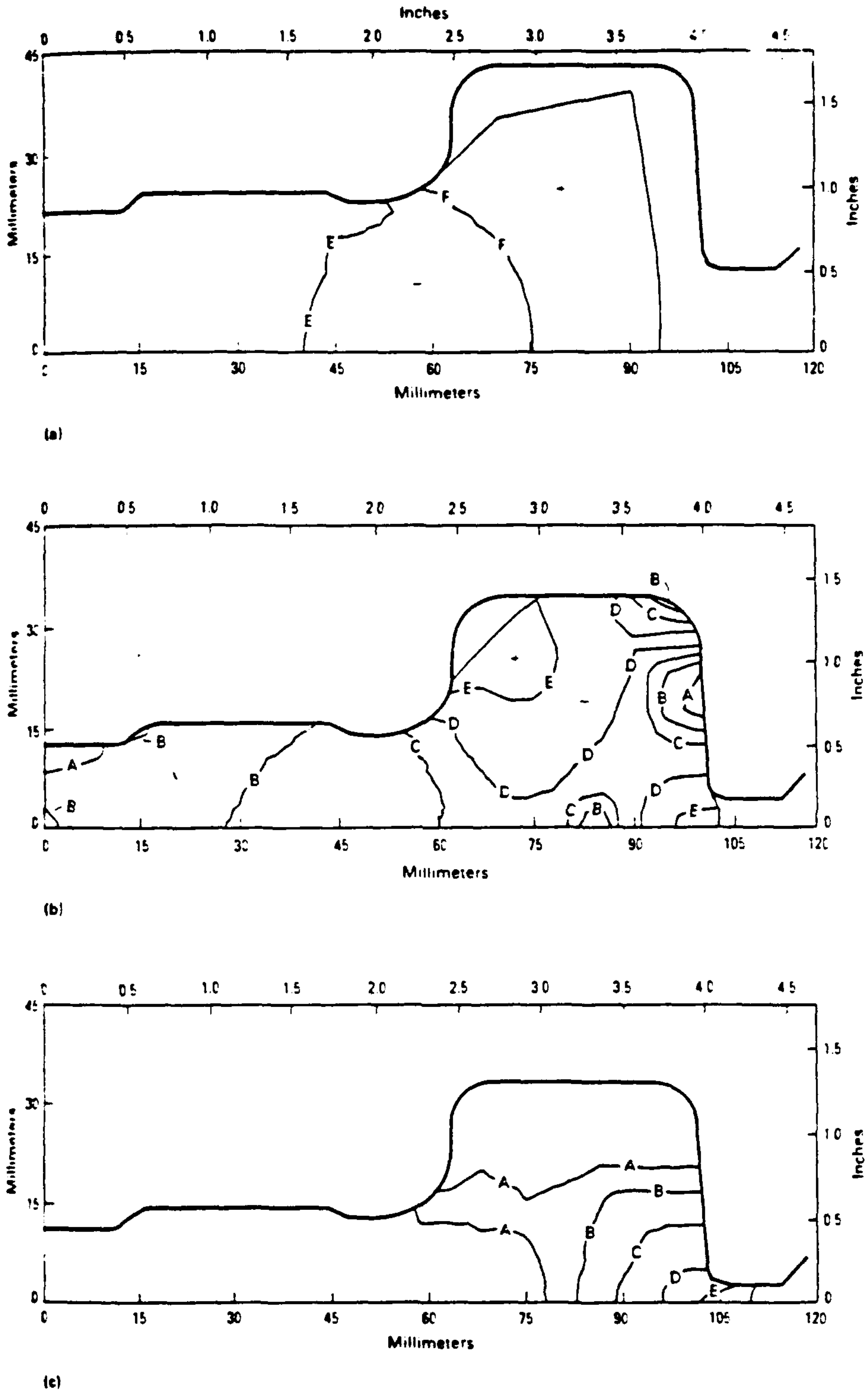

Figure 3. Effective stress rate-path contour plots of disk-forging simulation at 48% (a), 68% (b), and 72.1% (c) reductions in height.

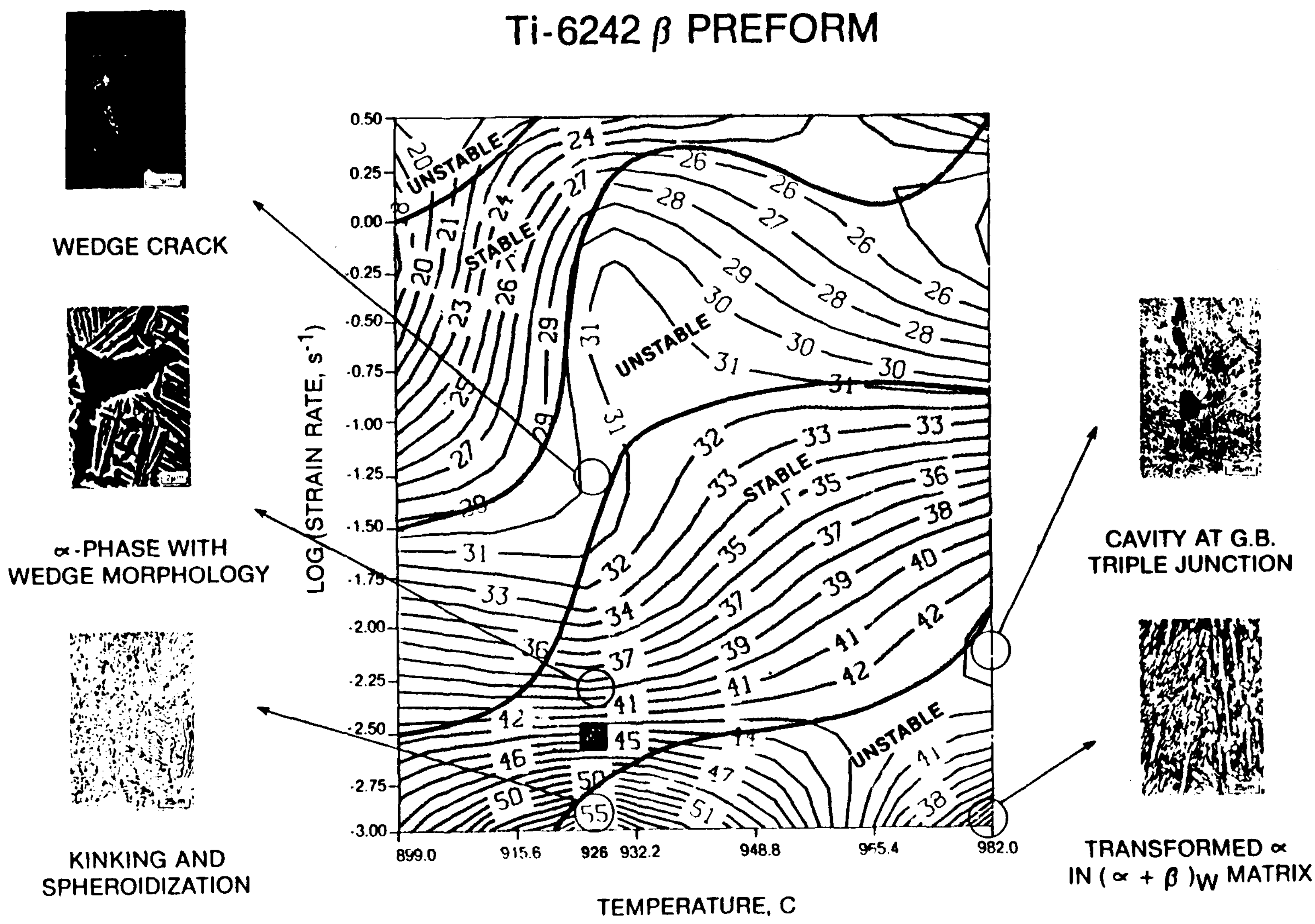

Figure 4. Material-stability-preserving-map for Ti-6242 Alloy.

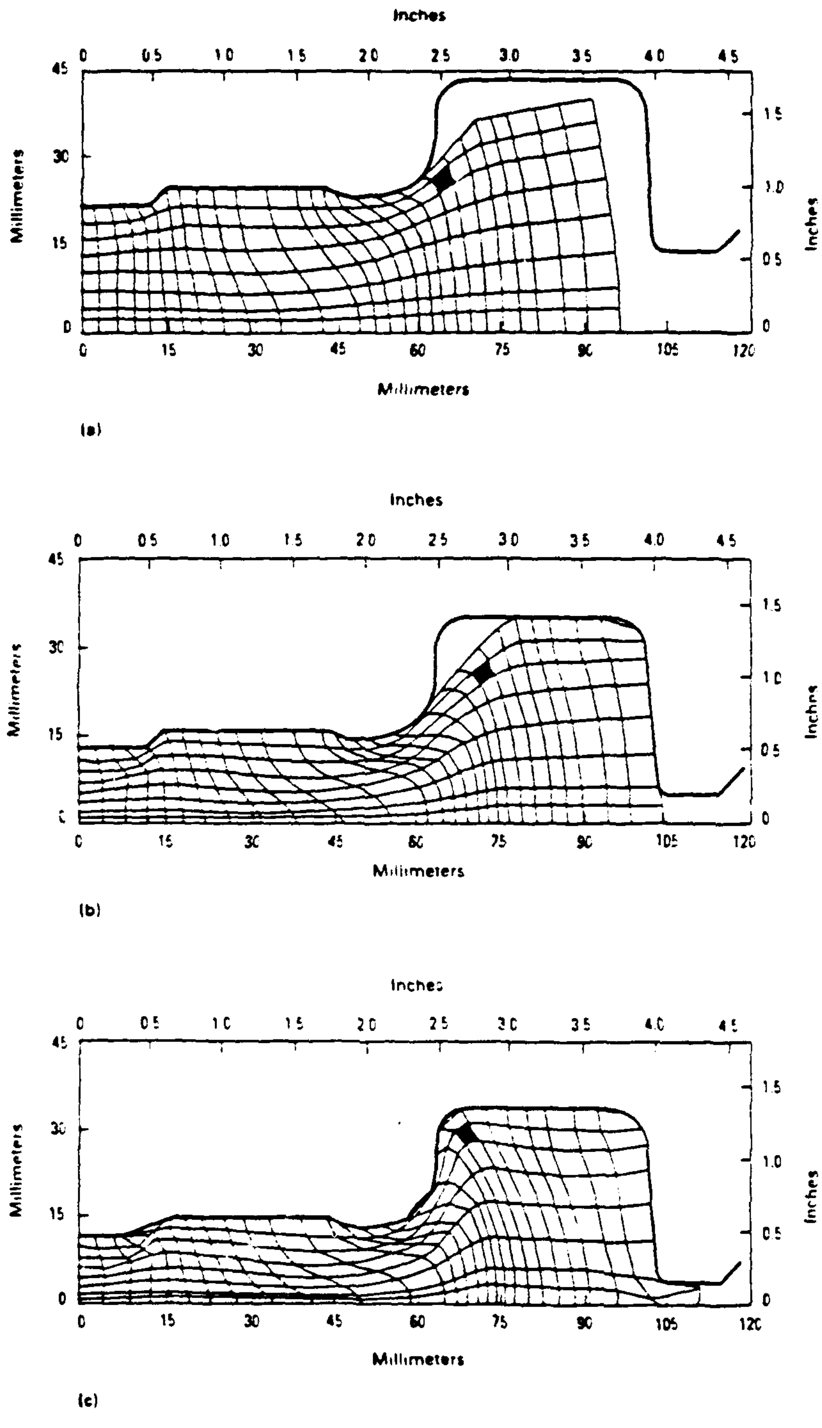

Figure 5. Grid distortion of disk-forging simulation with constant die velocity at 48% (a), 68% (b), and 72.1% (c) reductions in height. The black grid is Element No. 47.

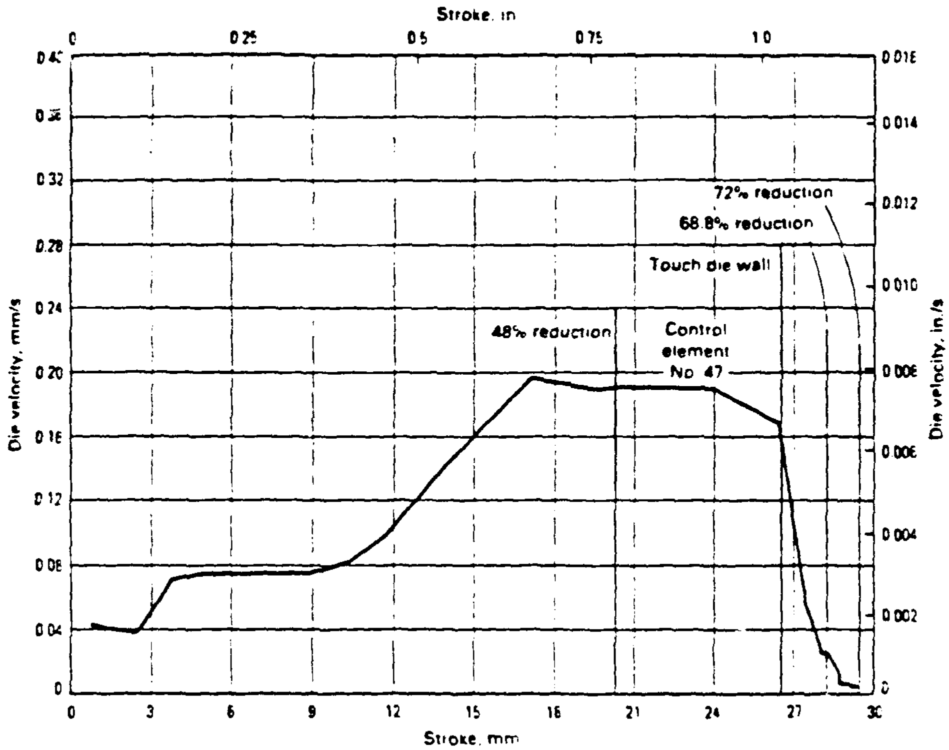

Figure 6. Die velocity versus stroke curve for disk-forging simulation.

PROCESS ENTROPY CONTROL FOR REDUCED QUALITY LOSS

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A mathematical basis for the guidance of advanced process control systems operating in uncertain environments has been developed. The resulting structure involves two levels ordered according to the principal of decreasing precision with increasing intelligence. Within this structure entropy functions are derived to provide a unified performance metric for both high accuracy inner feedback loops and the information uncertainty of outer qualitative loops. With this method the goal of optimum process automation is realizable as the mathematical programming solution that minimizes total entropy. Progress in the realization of this approach is described in the following narrative.

Control engineering benefits from a heritage of creative development by contributors from both academic and industrial communities. Early mathematical solution of the stability of closed-loop systems prompted widespread control implementations that were expedited by insightful frequency-domain design methods. System-theoretic modeling provided additional perspectives with electrical network interpretations that facilitated the transformation from continuous-time analog to discrete-time digital systems. State-space modern control methods then extended these analytical capabilities to enable optimal control design by defining inner system states and their transitions in an n-dimensional process space. Adaptive control advanced these preceding stages by automating system identification and optimization procedures online to achieve reduced uncertainty through additional control complexity. Present initiatives in self-organizing intelligent control seek decision and disambiguation capabilities for goal-oriented control purposes that subsume all of the previous stages of control advancement.

The unifying purpose of all of the stages of control advancement is the disorder reduction of processes of interest through identification and subsequent minimization of the variability of their controlled variables, where advancement is characterized by the accommodation of increasingly complex process representations with correspondingly complex control structures. Progress necessary to meet recent interest in advancing control system quality, however, requires comprehensive new accountability and understanding of the variability of control parameters. This development addresses that need first by the definition of quantitative error analysis methods for digital control systems, and interprets these results in terms of statistical quality identities to achieve a linkage between control system design and the new quality technologies.

Advancement in digital control system quality is demonstrated by linking the apriori accountability of example sensor-to-actuator inner control loop errors of Table 1 with statistical quality identities which traditionally have been only aposteriori accessible. Device and system elements are specified for a control loop that has been mathematically modeled to determine the total error e_c associated with the controlled variable. This error is interpreted in terms of statistical quality identities including the quality loss function L and process performance index Cpk shown in Figure 1, and defined by equations (1) and (2). For purposes of this illustration a 1% steady-state error is assumed between the setpoint r and controlled-variable c. Principal findings disclose an increasing controlled-variable quality loss for setpoints less than full scale because of the relative increase in e_c with decreasing process measurement values. Tolerance design has been demonstrated to achieve a consistent improvement in this ratio with a corresponding reduction in quality loss to that available at full scale for all setpoint values. This analysis assumes inner-loop controller tuning optimization that minimizes steady-state error and contributes to total error minimization, where major error excursions constitute control instability.

Figure 2 illustrates an advanced qualitative process automation (QPA) outer control loop description developed for insitu control decomposed into process episodes, instances, and indicies. Episodes describe a linear sequence of events that occur during a processing cycle divisible into process instances that are necessary to accomplish events in terms of achieve and prevent goals. Process instances have a sequential existence with defined start and end conditions, and provide closed-loop control through process indices which link sensors and actuators to achieve event-driven control. An insitu process representation enables better control by overcoming the limitation of conventional control which has access only to process boundaries. However, the data and knowledge bases which contain this information also possess information exchange uncertainties which influence control performance. The magnitude of the information exchange uncertainties may be defined by 0=E P logP <1 of equation (3) in terms of stochastic elements P evaluated from evidence theory, fuzzy sets, or probability. Entropy defies disciplinary boundaries in its application, including manufacturing processes, within which entropy offers a representation of uncertainty whose minimization is axiomatic.

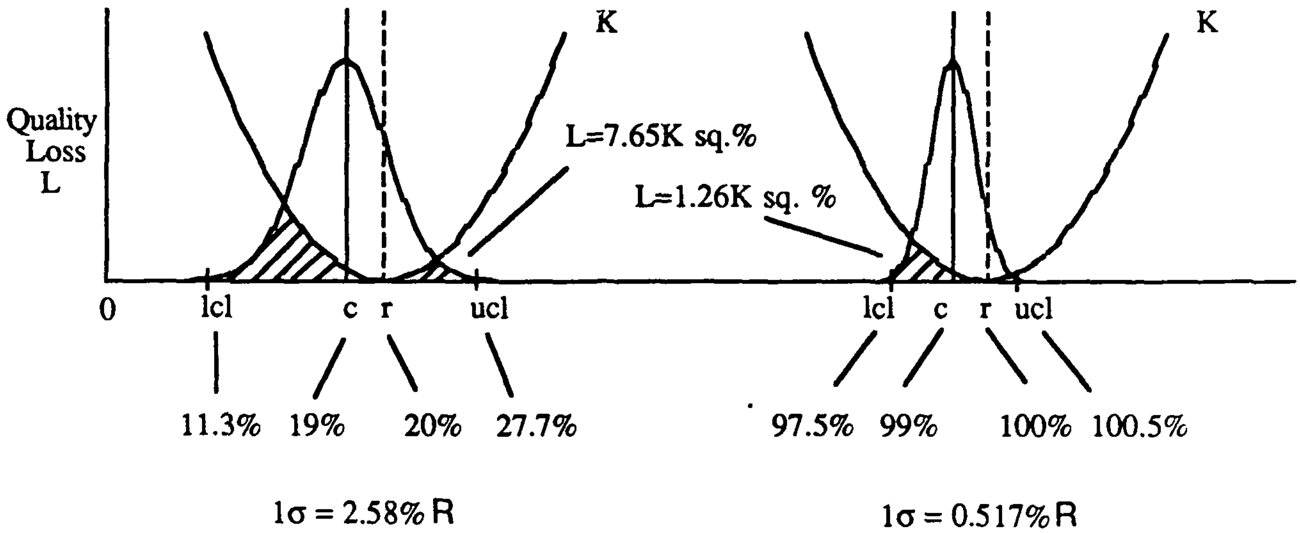
The reliability of control systems is concerned with the prediction of device failures from mean time between failure (MTBF) data and the operating period of interest by equation (4). Equation (5) then defines the unreliability for a single control channel, where unreliability equals 1-reliability. The combination of control system error and reliability on a mean-square error basis to form a parametric entropy metric provides a means for reasoning about uncertainties and relating decisions to the physical constraints of a process. This is provided by equation (6), and equation (7) describes combined information and parametric entropies as an argument to enable such reasoning. Utilizing the example sensor-to-actuator parameter uncertainty e_c of 0.517% and an unreliability Q of 1% provides a channel parametric entropy Hp of 0.012 (1.12%). Beneficially, this additive property of entropy provides a quantitative criterion for combining disparate uncertainties into a unified metric for insitu control guidance. This also articulates a means for evaluating process constraints including failures, transient uncertainties, and ambiguities with application of the dual-difference fault-tolerant structure, shown in Figure 3, which utilizes these uncertainties for validation and fault isolation purposes.

With respect to information exchange, entropy provides a measure of the information exchange uncertainty for sources including computer data and knowledge bases. The pooling and organization of information is an important practical problem in the design of intelligent systems. An important result of applying the entropy metric to probabilistically defined information processing is that entropy minimization corresponds to the focusing of information. For example, at a primitive level of definition the conflict between two equiprobable alternative actions in a qualitative control system yield an entropy value of 0.301 by equation (3), whereas four equiprobable alternatives yield a value of 0.602. A single information source has a limiting entropy value of zero because its exchange is certain. Figure 4 postulates the structure of an entropy integrated manufacturing process that benefits from these measures.

$L = K[(r-c)^2 + (e_c)^2\}$	quality loss function	(1)
$Cpk = \| c\text{-lcl,ucl}/3e_c > 1$	process performance index	(2)
$H_I = -E\ Pj \log Pj$	information entropy	(3)
$l_i = t / MTBF_i$	failure rate	(4)
$Q = [1-\exp(-\overset{M}{E}\ l_i)]\ 100\%$	channel unreliability	(5)
$H_p = [ec^2 + Q^2]^{0.5}$	parametric entropy	(6)
$H = H_I + H_p$	additive entropy	(7)

Sensor	0.318%	
Filter	0.250%	
Amplifier	0.143%	
Multiplexer	0.010%	
Sample Hold	0.020%	
A/D	0.071%	
Sinc	0.083%	
D/A	0.033%	
Intersample	0.173%	
e_c RSS	0.517%	1s confidence

Table 1. Sensor-to-Actuator Error Budget



$$\varepsilon_{c100\%} = 0.517\%\ FS \bullet \frac{100\%}{100\%} = 0.517\%\ R$$

$$\varepsilon_{c20\%} = 0.517\%\ FS \bullet \frac{100\%}{20\%} = 2.58\%\ R$$

$$L_{100\%} = K \bullet \left[1\%^2 + 0.517\%^2\right] = K \bullet 1.26\ sq.\ \%$$

$$L_{20\%} = K \bullet \left[1\%^2 + 2.58\%^2\right] = K \bullet 7.65\ sq.\ \%$$

$$C_{PK100\%} = \frac{|99\% - 97.5\%|}{(3)\ (0.517\%)} = 1$$

$$C_{PK20\%} = \frac{|19\% - 11.3\%|}{(3)\ (2.58\%)} = 1$$

Figure 1. Controlled-Variable Uncertainty Interpreted by Statistical Quality Identities Before Tolerance Design (setpoint r, controlled variable c, limits lcl-ucl)

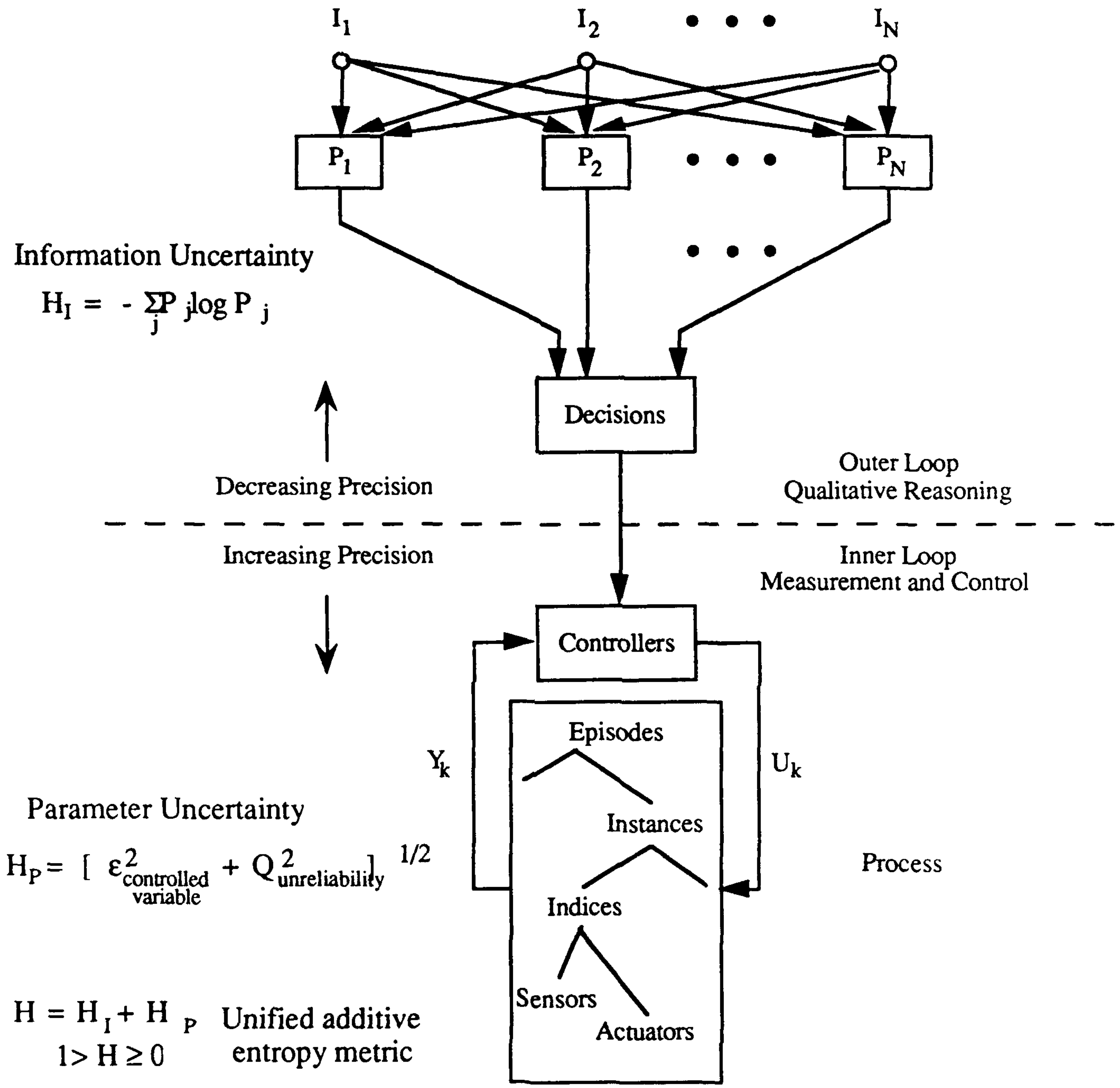
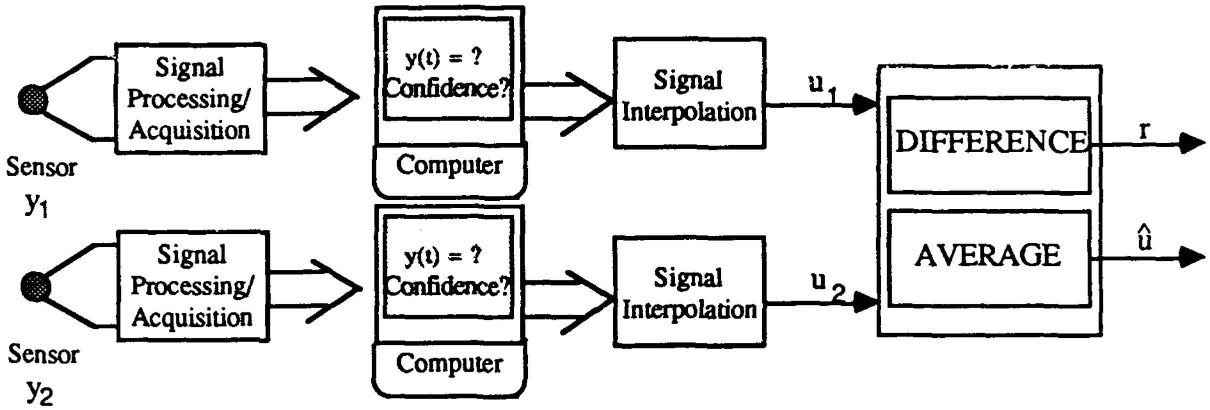


Figure 2. Qualitative In situ Control Structure



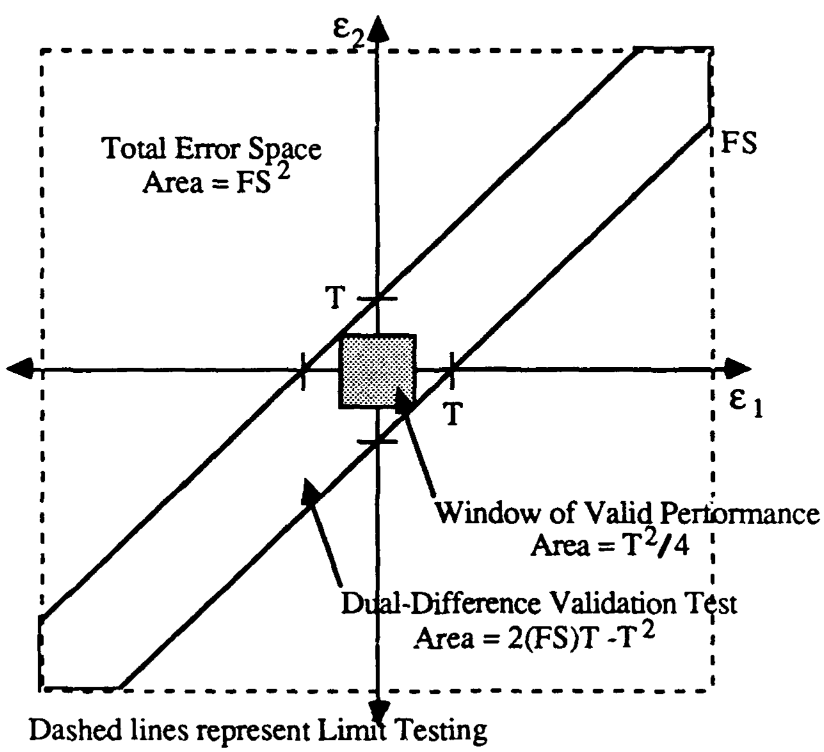


Figure 3. Dual-Difference Fault-Tolerant Structure

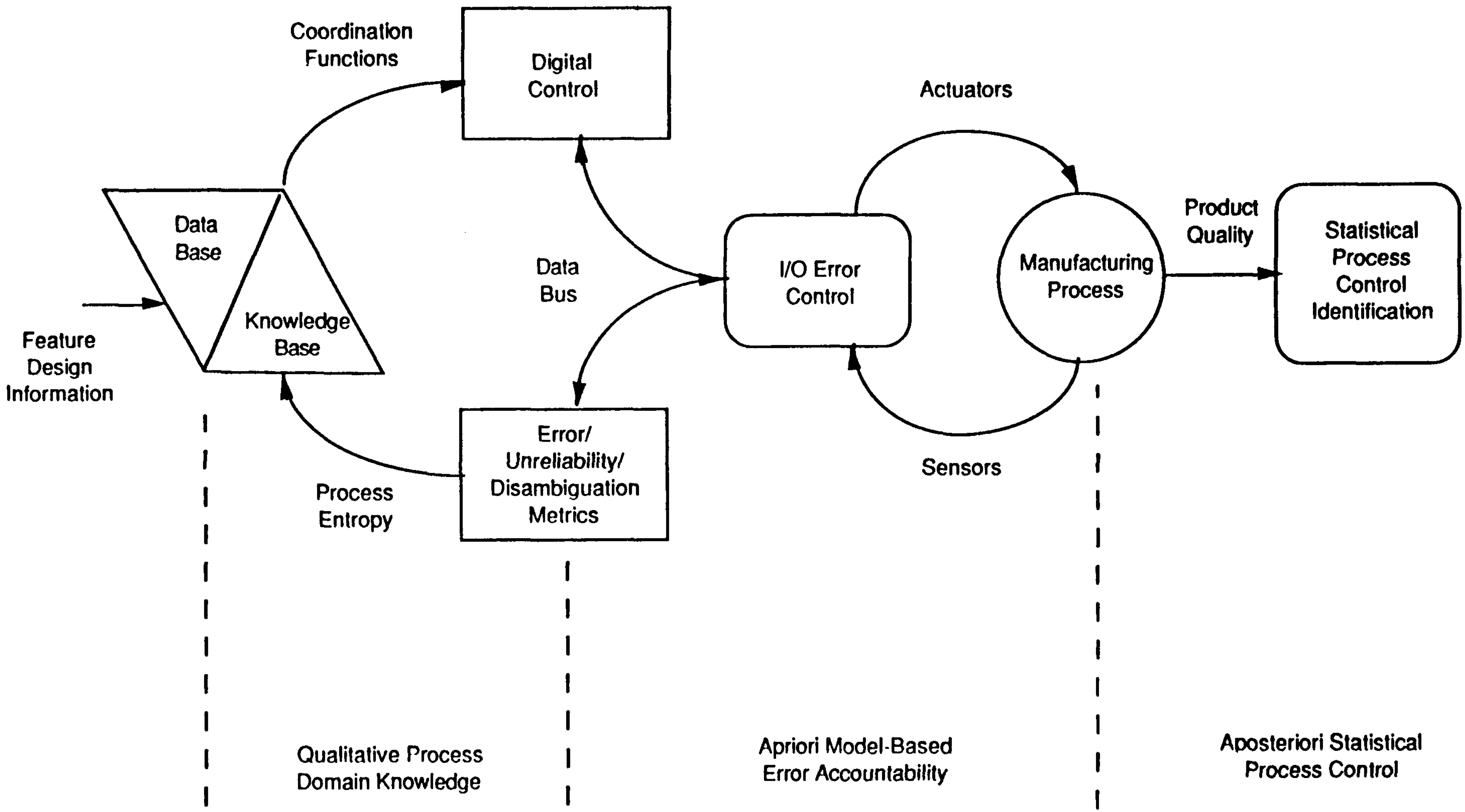


Figure 4. Entropy Guided Manufacturing Process

AN INTRODUCTION TO QUALITATIVE PROCESS DISCOVERY

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INTRODUCTION

A discovery system capable of assisting materials engineers with the development of process control protocols is under development at ThinkAlong Software. The system, called QPD—Qualitative Process Discovery—has demonstrated its ability to generate a control algorithm for polymer curing on an autoclave simulator. We briefly review progress on the discovery project. The current research is performed as a visiting scientist task by one of us (DJW) at Wright-Patterson Air Force Base, Ohio.

The progress supports the hypothesis that a discovery system which is endowed with a knowledge base of elements of process models gleaned from the physical sciences can be constructed and applied to an interesting task domain. The system, while operating in a real or simulated process environment, can learn to control the particular process it is tasked to control. At the same time, the discovery system learns how to explain the process it is observing and controlling. Finally, the system may discover something about the process (through its search and conjecture mechanisms) which is not directly explainable by the prior knowledge provided.

Current work derives from our earlier experience with a qualitative reasoning system called QPA—Qualitative Process Automation—for closed-loop process control in real-world, noisy environments. It also draws from our work with learning mechanisms for applied artificial intelligence in the field of discovery and theory formation. We all know that ovens and pressure cookers are utilized for curing—baking, if you like—chemical compounds. We also know that autoclaves—large pressure cookers—can cure chemical compounds such as polymers, with a control protocol derived solely from the cure in progress. What we may not know, or understand fully, are the details of some of the many processes involved in the cure and its proper protocol. A more complete understanding will contribute to improved polymer-based products.

We describe here a discovery system as it has been applied to the polymer cure domain. Thus, this paper begins with a brief review of that domain. We then follow with an overview of the discovery system architecture, and conclude with a discussion of early results.

CONDENSATION CURING POLYMERS

In a condensation polymerization (cure) process, pairs of individual, reactive monomers become involved. Such pairs join to form the polymer at their reactive sites. The term "condensation" derives from the by-products of this reaction, and such by-products, typically in the form of gas or vapors, form an interesting topic for theory formation. A second by-product of the reaction is heat.

We can summarize what we know about condensation curing in a "proto-history," coined here to mean *prototypical history*, statement:

- the polymer starts in an unreacted period—no chemical reaction yet
- the polymer enters a reactive period—the chemical reaction occurs
- the polymer reaction ends when all possible bonds have been formed

This proto-history—a prototype for a typical polymer cure history—is the basis for the cure protocol QPD built during the trials we discuss in below.

AN ARCHITECTURE FOR DISCOVERY

The Scholar's Companion (TSC), like KEE and other artificial intelligence products used by other consultants, is a proprietary, commercial artificial intelligence software/hardware product, currently under development at ThinkAlong Software. TSC combines principles from several fields, pulling inspiration and design from the fields of cognitive science, philosophy of science, artificial intelligence, computer science, and nonlinear systems. The system currently runs on an Apple Macintosh II platform.

The system consists of a toolbox of coded "subcognitive" routines, which each handle some fundamental aspect of the discovery process. Fundamental control of the routines, however, is provided by the knowledge base.

Figure 1 illustrates the basic data flow in the engine of The Scholar's Companion [Park and Wood, 1989]. The architecture supporting this data flow is a combined spreading activation neural network and rule-based symbolic system. The spreading activation neural network captures semantic relations while the symbolic system supports the behaviors of the system.

The knowledge base is arguably the most important aspect of a discovery system, given that the system requires an appropriate knowledge base upon which to base further useful discoveries. QPD is a part of the TSC knowledge base. As Figure 1 illustrates, the knowledge base is the center of the TSC computational universe. The system communicates with the outside "world" through sensors and "muscles."

In the research described here and reported in [Park and Wood, 1990], the primary sensor/muscle system is an autoclave cure simulator. The QPD system coupled a simple knowledge base on polymers with the simulator and conducted its own trials. The basic algorithm of the prototype QPD system is:

Find a proto-history
Try it
Tune as necessary
Loop to Try it

Exercising this algorithm, the trials resulted in a cure protocol in the form of a TSC knowledge base entry. It is the result of that cure algorithm development we present next.

RESULTS: A POLYMER CURE PROTOCOL

QPD started with a simple knowledge base entry similar to the polymer proto-history discussed above. This entry described the four primary states a polymer may visit during its cure cycle. With knowledge of these states as a form of *expectations* of what a polymer cure should look like, QPD exercised the simulator. As the cure progressed, *expectation failures* occurred when the next possible state is not the state the cure cycle actually visits. QPD then mutates the protocol to account for (we say: *explain*) the variation. The result is a cure cycle as illustrated in Figure 2, and a TSC knowledge base entry capable of controlling the autoclave.

The cure resulting from QPD trials indicates that the system was able to detect and deal with the exothermic reaction of the polymer. It is truncated with the polymer at cure temperature since that is the point at which the system determines the cure is complete. This fact serves to illustrate that the cure protocol, as built by the prototype QPD in its early trials, is by no means complete. Much work remains to be accomplished before the system is complete; that work is underway currently, and the QPD algorithm should be capable of achieving interesting results in many process control domains.

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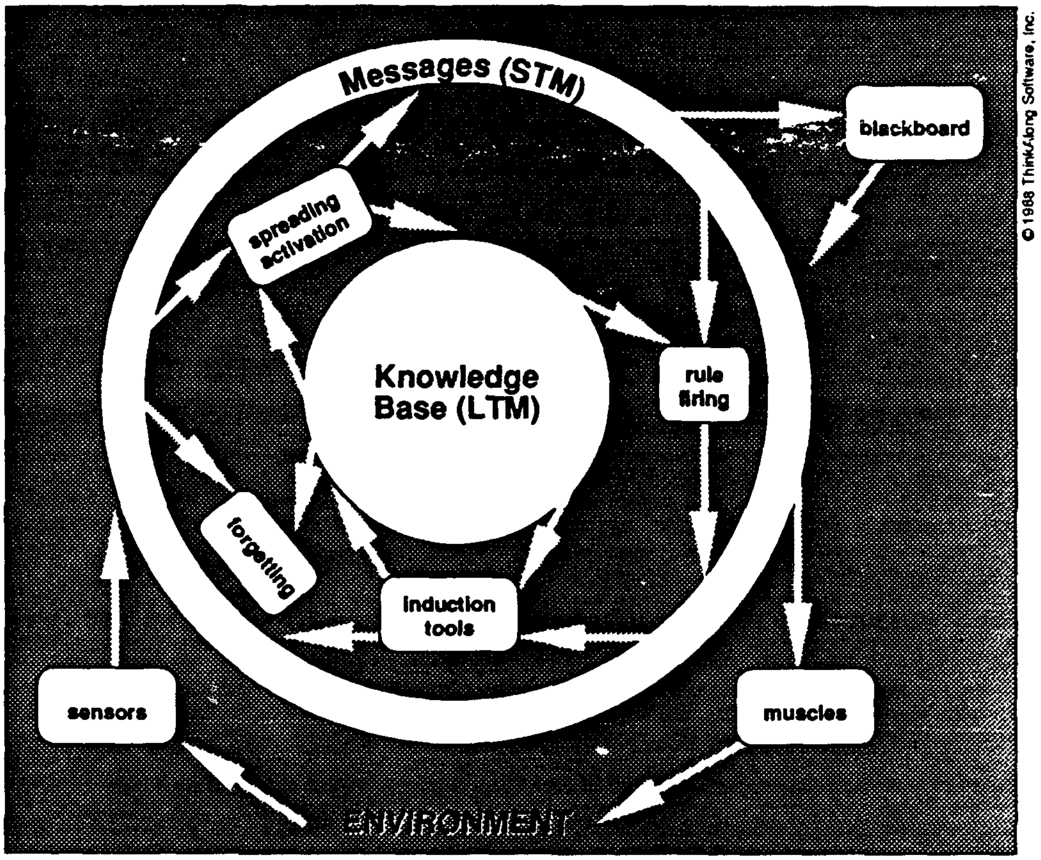

Figure 1 Architecture of The Scholar's Companion

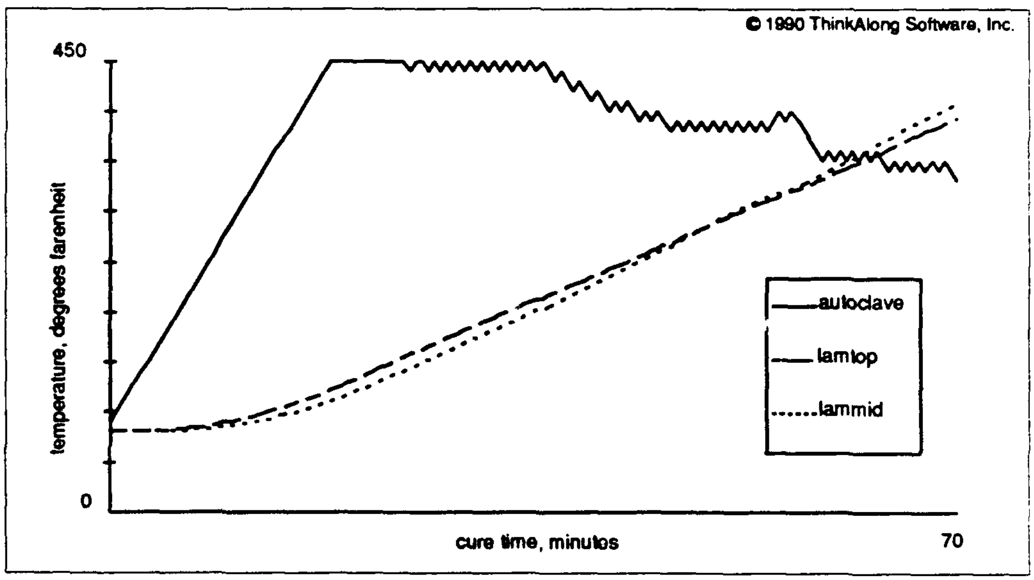

Figure 2 QPD Cure Results

Possible Roles for Neural-Nets in QPA Systems

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POSSIBLE ROLES FOR NEURAL-NETS IN QPA SYSTEMS

We suggest that there are at least three ways in which Neural-Net technology might be used to advantage in Qualitative Process Automation (QPA) systems.

Such technology can be used

- for relating quantitative and qualitative entities in QPA,
- for monitoring the nature of the control process through exercise of predictive estimation, or
- for management of experiential information.

With regards to the first role, we note that the QPA relies on qualitative use of accurate quantitative from appropriately placed in-situ sensors. In the exercise of QPA, transition is made from one control plan to another when certain conditions are observed. These conditions are often expressed rather arbitrarily in terms of quantized intervals in the range of sensor data, for example we might say that if 125 < temperature < 250 and P_1 < pressure < P_2, then a certain state in "episode " x is considered to have been attained and appropriate control rules are activated.

However experience indicates that it is difficult to specify and maintain such quantization ranges correctly and consistently for a number of sensors simultaneously. Nor is it easy to adjust those range quantization values adaptively.

It is not difficult to understand why this should be so. In Figure 1(a), we illustrate circumstances where it is feasible to quantize sensor data ranges independently, even though the antecedent of the control rule might take the form of a conjunctive statement of the sensor data conditions. This is a form of sensor data fusion which suffices in some cases, but is not generally useful. For example, for circumstances shown in Figure 1(b), if the rule is to turn an activator to ON if the system state is within the irregularly shaped figures, it might be difficult to describe the appropriate conditions adequately in terms of independently specified quantized intervals. If the intervals are taken sufficiently coarse, many errors will occur. On the other hand, if the quantization is made sufficiently fine, then a confusingly large number of rules will have to be developed, a rather unpleasant prospect.

Neural-net computing can be used to deal with the situation in the following way. Instead of quantizing the ranges of sensor output values, we can proceed in a more gestalt manner, by considering the state of the process as a point in sensor output space. As shown in Figure 2, when using such a representation, many states might be different and yet be sufficiently similar so that any of those states would be sufficient reason for activation of a qualitative control action, such as START-CURE (in the curing of a composite in an autoclave) or END-CURE or START-COOL DOWN.

In such a representation, we have a more comprehensive view of the relationship between the various sensor outputs and we can visualize the progress of the process as the system traverses sensor space. Not only are sensor data truly "fused" to provide a useful and economical description of the system, but many such descriptions are organized into clusters each with a prototype and a label. Any system state is rapidly recognized as belonging to one of the clusters and it is therefore easy to think of it as being in one of the states of QPA and appropriate control actions can be activated.

In addition, such prototypes can be manipulated adaptively with the use of the Learning Vector Quantization algorithm [1], so that inappropriate sensor data patterns which would otherwise be included into a cluster can be avoided by moving the prototype pattern away from those patterns which should be excluded.
The second role is that of using a supervised learning net for learning a network representation of the process. As shown in Figure 3, this is achieved by training a net which when presented with the sensor output vectors x(n-k), x..., x(n-1), x(n) is able to predictively estimate the value of the vector x(n+1). This estimated value $\hat{x}(n+1)$ is very important and very valuable because it can be used to monitor the nature of the process, or to detect sensor failure, or to detect the onset of a great deal of noise.

We have shown that accurate predictive estimation is possible even for highly nonlinear processes and even for conditions of deterministic chaotic nonlinear dynamics [2]. It is known that the nonlinear dynamic system discussed by Feigenbaum [3] and others can develop a variety of temporal behaviours depending on the value of a system parameter l. As l increases in value, going from 0 to 1, the behaviour pattern becomes increasingly more complex becoming chaotic (in a deterministic manner) as l Æ 1. Examples of such behaviour are exhibited in Figure 4 for different values of l.

Both the backpropagation net and the Functional-Link net [4] algorithms can be used for prediction purposes. It is interesting that both nets do equally well for nonchaotic motion, but in the chaotic region only the Functional-Link net is capable of predicting several time intervals ahead. This is shown in Figure 5.

The third role is in the management of experience information. We advocate organization of process control experience information into Episodal Associative Memory.

Process control then becomes a matter of memory. Have we done such a thing before? What did we do? How did it turn out? Should we do similar things in the present case? What can we expect? What should we avoid?

The architecture of such a memory is illustrated in Figure 6. The idea is to represent the experience of each process action as an episode. Episodes are self-organized into clusters called Memory Organization Packages (MOPS). Themes associated with each episode are learned with a supervised learning net. This is to say that every episode in a certain MOP would activate a theme pattern more or less similar to that one engendered by the prototype of that MOP.

Theme patterns are also self organized into Thematic Organization Packages (TOPS) which in turn are associated with TOPS.

This structure allows us to store a large number of process control situations in terms of a smaller number of groups of MOPS with means for easy reminding, but with no loss of detail. As discussed elsewhere, a member of interesting functionalities including cross-context reminding can be provided by this type of memory [5].

In summary, we believe that QPA is a useful a useful and powerful approach and neural net computing can be used in the implementation of QPA.

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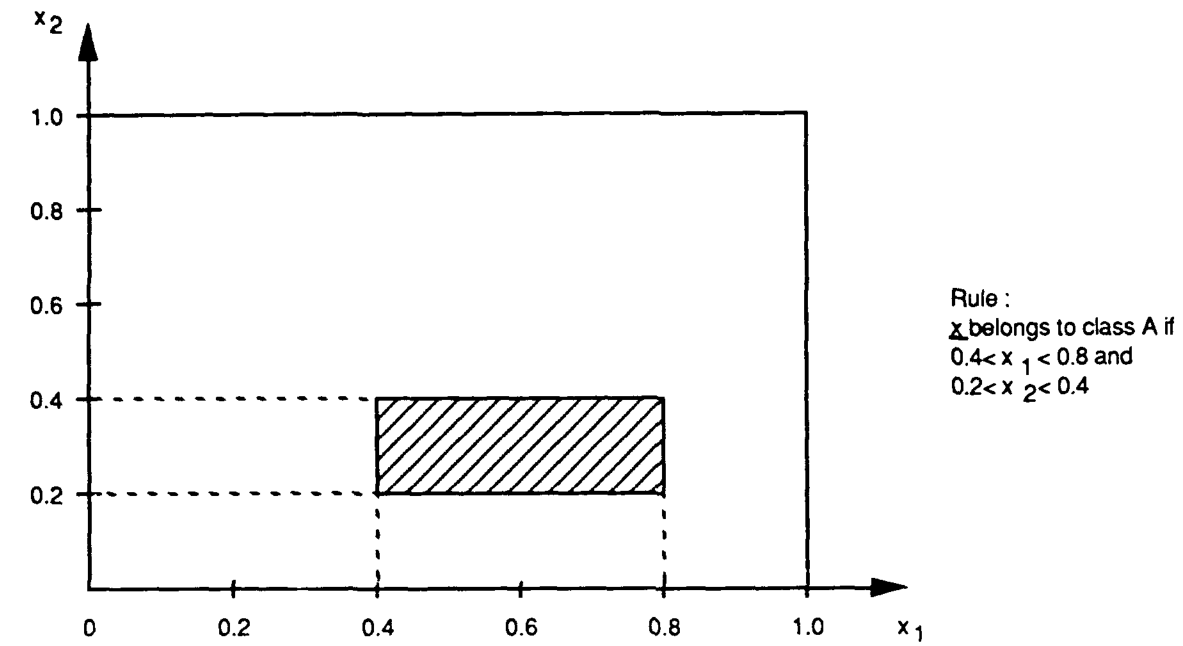


Figure 1(a). Pattern Recognition Circumstances.
Circumstance where sensor data can be fused readily with use of conjunctive statements.

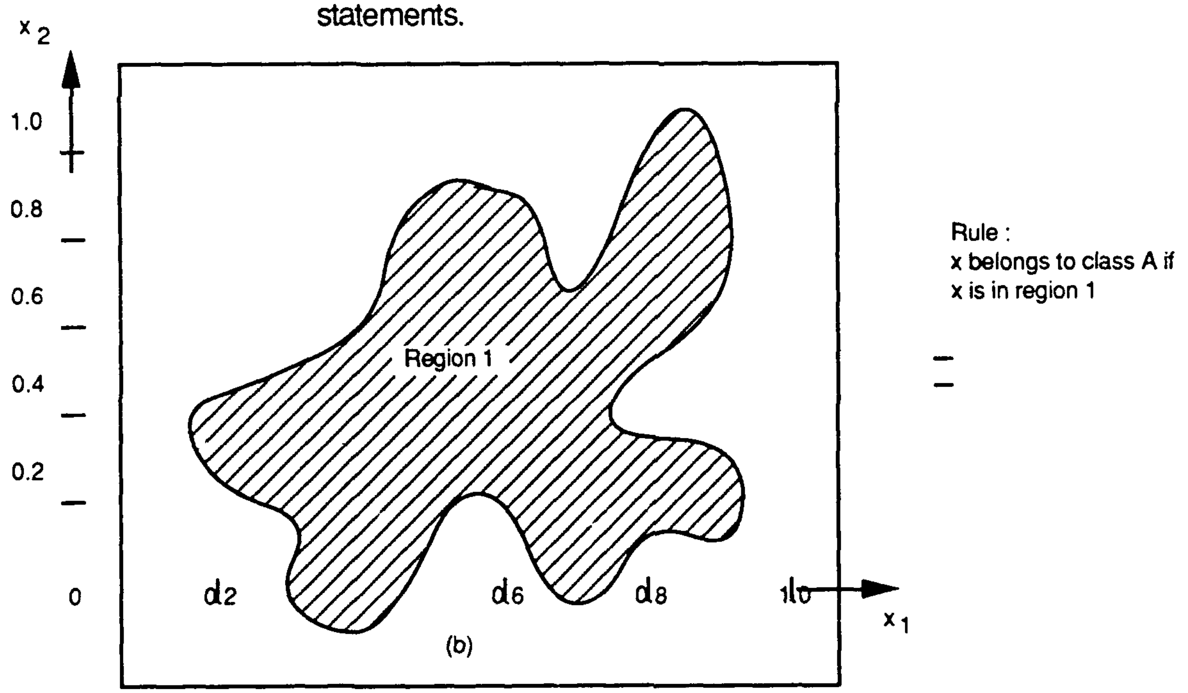


Figure 1(b). Pattern Recognition Circumstances.
More general conditions.

Use of Neural-Nets in QPA

Role 1: Relating Quantitative and Qualitative

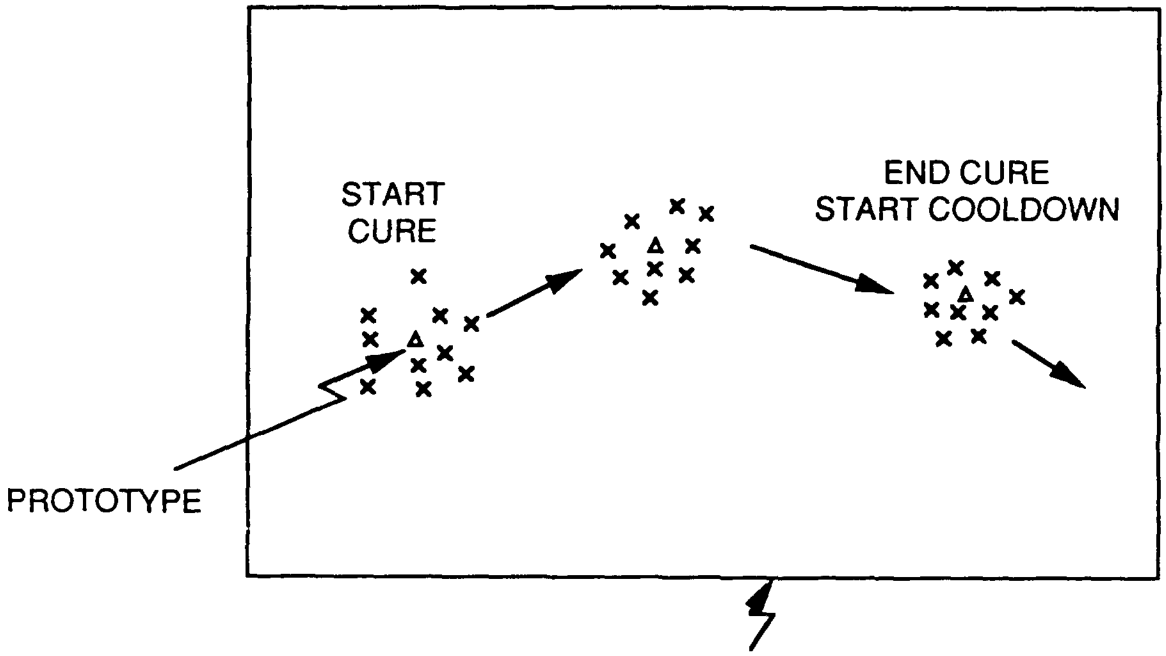
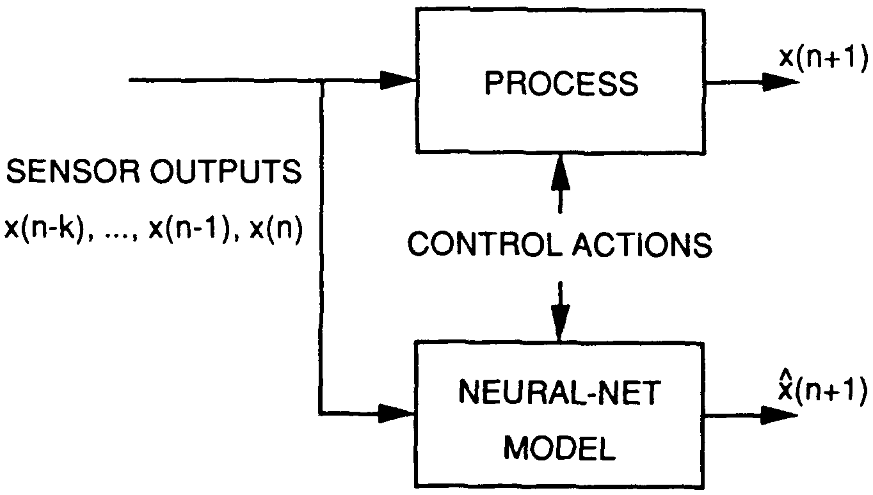


Figure 2. Sensor Data Fusion with Use of Self-Organized Clusters.

Use of Neural-Nets in QPA

Role 2: Monitoring the Nature of the Process Through Predictive Estimation



Comparison of $\hat{x}(n+1)$ with $x(n+1)$ provides information on whether nature of process is changing, also useful for detecting failure of sensors.

Figure 3. Learning a Model of a Process and Checking on the Adequacy of the Model.

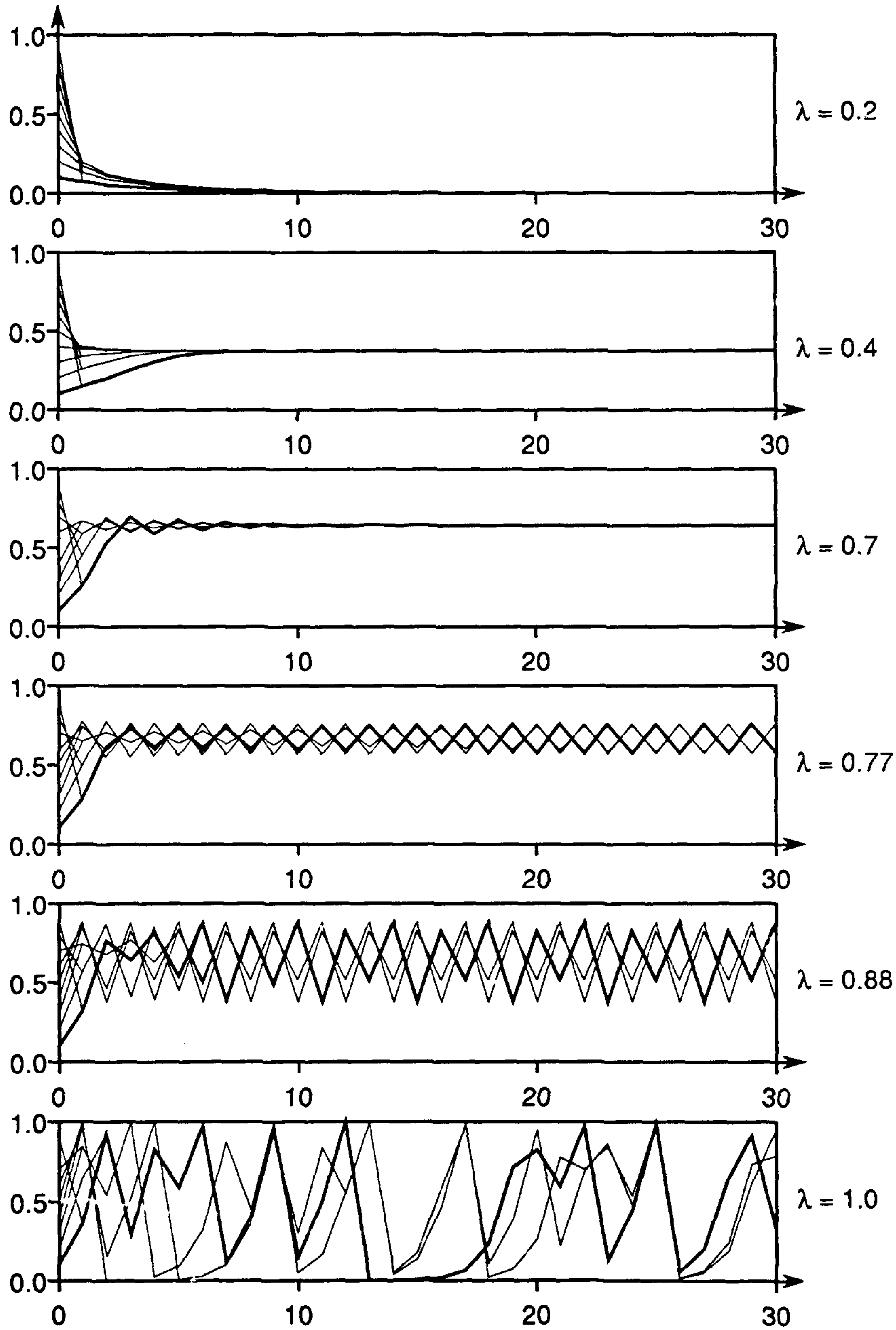
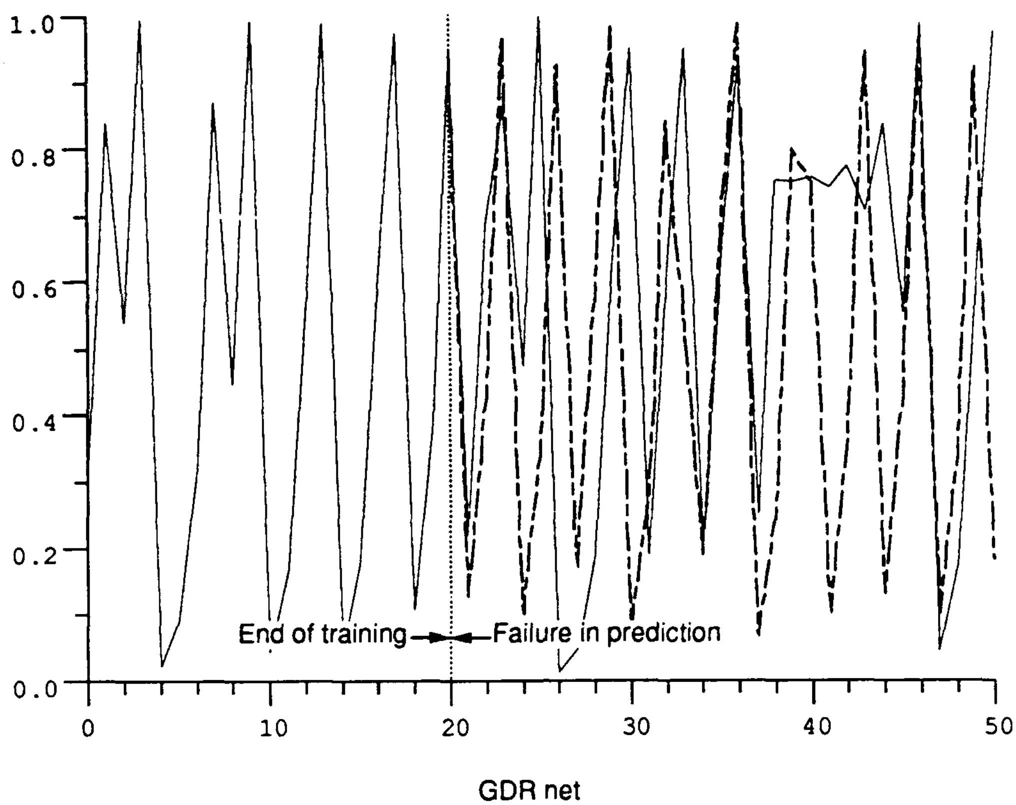


Figure 4. Qualitative Nature of Output Time Sequences for Different Values of External Parameter λ.



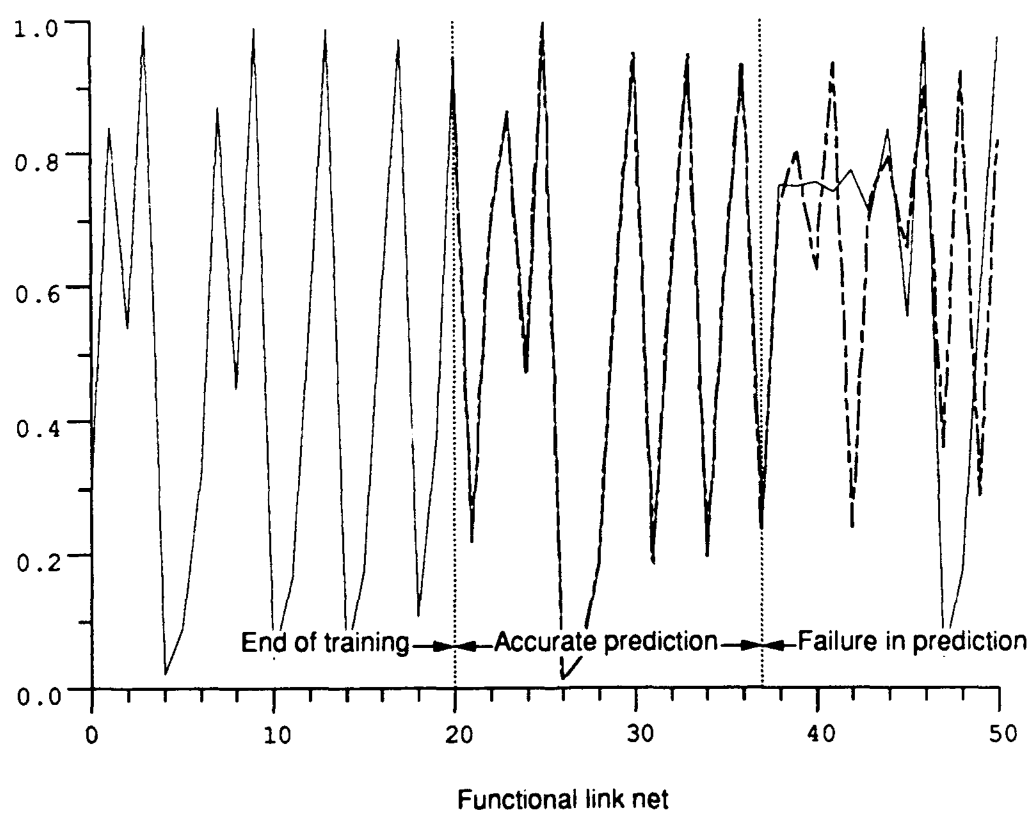


Figure 5. Prediction of Chaotic System Behavior Using GDR and Functional Link Nets.

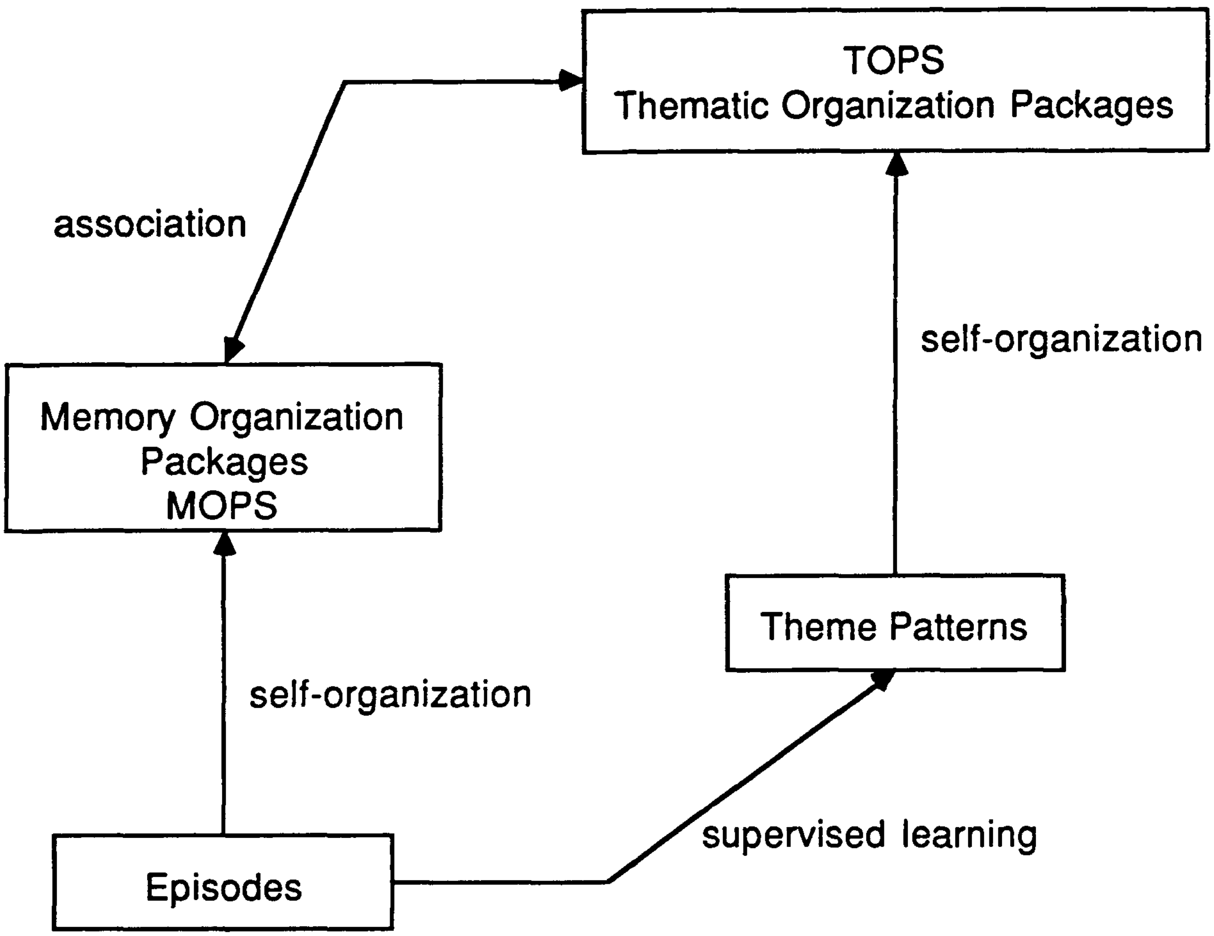


Figure 6 Schematic Illustration of a Basic Structure in the Episodal Associative Memory.

FUTURE DIRECTIONS: SELF-DIRECTED CONTROL TECHNOLOGY

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INTRODUCTION

As "intelligent" systems research begins to mature it is becoming clear that their future depends not only on their ability to self-direct a process, whether material processing, resource scheduling, product design or any type of productive activity, but as well their ability to self-improve in terms of "discovering" new knowledge. Current research efforts in self-directed and/or self-improving material processing systems suggest we may soon (perhaps less than a decade) be conducting material science by machine, i.e. a material processing system to augment the process of scientific discovery - conjecturing hypotheses, conducting experiments and discovering new knowledge about a material or process.

Beyond the purely scientific interests associated with intelligent systems research is a very 'economic' motivation - product quality. The pursuit of various product quality initiatives (i.e. improved: process repeatability, process yield, material properties, etc.) must remain central to intelligent systems research and therein embodied in the definition of self-directed control: a philosophy and architecture which, when manifested in a control system, enables on-line or in-situ generation of a "product-directed" control-cycle.

FUTURE DIRECTIONS

The concept of self-directed and/or self-improving control is an active topic of pursuit by researchers across government, industry and academia. Research directions are many and varied involving 1) different materials and/or processes, 2) automation of process knowledge development, 3) sensor technology, 4) sensed-data processing, 5) process data relationships and analysis, 6) coupling of material processing with design (simultaneous design of shape and material properties), 7) process optimization, 8) process entropy control, 9) process discovery, and 10) coupling of qualitative reasoning (heuristics) with neural networks and/or quantitative models.

Although most of the above directions are forward-looking in the sense of advanced computer technology, two of them address the context of self-directed control. The first is with regard to the relationship and integration of self-directed control with conventional philosophies such as statistical process control. The second considers the introduction of qualitative techniques to process control and therein the development of more comprehensive and representative measures of overall control system uncertainty. The system uncertainty is the sum of the system sensed-data processing error due to sensor A-D/D-A, filtering, amplification, bandwidth, and sampling which is combined with the uncertainty or error associated with heuristic inference (i.e. providing a good but not necessarily an optimal response to process conditions).

In the interest of refining QPA and integrating self-control technology with its environment, recent research has addressed the various input and output interfaces for process control applications. One example is the reduction of process noise (which all processes experience) through the use of neural network technology. In lieu of simply averaging data over a defined time period the sensed-data from the process is classified by a probability neural network which has proven through simulation (against stored data from prior process runs) to improve the accuracy of the measured data compared with the actual process data.

The man/machine interface is also being addressed in terms of developing a graphical means of representing the process so that the control system can self-generate the structure and in some cases the content (heuristics) of the knowledge base for enabling self-directed control. The remaining interface is the output, i.e., the data generated by each process run and the knowledge which is embedded regarding a better understanding of the process. The associated research is to facilitate qualitative and/or graphical analysis of the data and therein aid the process control engineer in developing a new knowledge base or refining an existing one. A complementary effort has been to develop a mapping of the output results, e.g., material properties of interest, and the input process parameters using an artificial neural network. Such a mapping would guide the process engineer in setting up the process to interpolate or extrapolate as required to achieve new properties or to reliably attain previously successful results.

Longer term the research objective of self-directed control technology is 'science by machine' where coupled to the control system is a discovery system which is designed to learn new knowledge. Such knowledge will not be attainable through conventional data analysis or mapping techniques and thus the coupling of neural networks to rule-based inferencing systems may effect a significant contribution. The use of neural networks appear most useful in the area of associative memories for the construction of newly discovered rules and inferencing techniques using a 'spreading-activation' concept wherein reasoning such as analogy, abduction and generalization are feasible.

Many new directions are being considered relative to material processing. The breadth of applications is beginning to expand particularly in the area of new processes where desired material shape and properties are a simultaneous result of the process, e.g., laminated composites and other plastics forming processes. Although a breakthrough is still uncertain, semiconductor growth processes appear to be yet another material processing domain which will benefit from self-directed control technology. Because the semiconductor device industry and the processes are both very new and unique, self-directed control technology has been a welcome pursuit and significant advances in quality are expected.

From a general or overall material processing perspective there is more acceptance of self-directed control technology for those material processes which do not have an existing and well established control technology. An example is material removal, i.e., machining, where many years and millions of dollars have been invested in existing machine tool controller architectures. Notwithstanding this history, a recent machine tool industry initiative sponsored by the Air Force Manufacturing Technology Directorate and in collaboration with the National Center for Manufacturing Sciences may improve acceptance. Together these organizations are attempting to establish a Next Generation Controller Architecture to enable a more rapid and organized transition to self-directed control technology for the machine tool industry.

In contrast to the material processing applications, an equally significant new direction is product design. Product design as a process is not new, yet it is an area soon to undergo tremendous change as computer technology begins to address the scope and depth of the process. The first step will be the coupling of product and process design via feature-based design systems. These systems will be controlled similar to the material processing applications via 'product-directed' feedback which will simulate the processing (fabrication, inspection, etc.) of the product. The designer will be guided much like the material processing agent (e.g., an autoclave) toward a design which satisfies <u>multiple</u> product objectives and goals. And much the same as material processing, the control path will be generated using heuristics to both satisfy near real-time performance and to capture that which can not be mathematically modeled and optimized.

In my opinion, the most important future direction for self-directed control technology is the coupling of <u>process control with product design</u>. Self-directed control technology will be a necessary enabling technology to achieve this integration. The research problem will be to develop a representation scheme which subsumes existing and projected hardware and software and a language (e.g. PDES, NGCA, etc.) which transcends industries, products, materials and processes.

The opportunities before the Manufacturing Research Group and its stable of university and industrial researchers is to provide <u>leadership</u> in demonstrating the feasibility of this coupling. The opportunities before us are our participation together with the Sacramento Air Logistic Center (SM-ALC) in the Next Generation Controller Architecture project and to expand our involvement with the 4950th Test Wing in their pursuits to become a showcase factory-of-the-future. Both of these efforts represent an opportunity to couple our process control research with our product design research.

Also of consideration is the work sponsored by the Manufacturing Technology Directorate to develop a Platform for the Automated Construction of Intelligent Systems (PACIS) - a language for building integrated intelligent systems. The question is what pieces of this work to employ in the short term which enable the demonstration of 'threaded-couplings' of process control and product design, i.e., at SM-ALC the coupling of QPAL to feature-based design for composites and at the 4950th the coupling of Rapid Design System (RDS) with self-directed control of end-mill machining.

These are some of the directions and opportunities before us today. The challenge is to adapt to what tomorrow may bring.

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