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Expert, Neural and Fuzzy Systems in Process Planning

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Abstract Computer aided process planning (CAPP) aims at improving efficiency, quality, and productivity in a manufacturing concern through reducing lead-times and costs by utilizing better manufacturing practices thus improving competitiveness in the market. CAPP attempts to capture the thoughts and methods of the experienced process planner. Variant systems are understandable, generative systems can plan new parts. Expert systems increase flexibility, fuzzy logic captures vague knowledge while neural networks learn. The combination of fuzzy, neural and expert system technologies is necessary to capture and utilize the process planning logic. A system that maintains the dependability and clarity of variant systems, is capable of planning new parts, and improves itself through learning is needed by industry.

Key words computer aided process planning (CAPP); variant system; expert system; fuzzy-neural system; industry

Introduction

Computer aided process planning (CAPP) research has been underway now for about three decades, yet its adoption by industry has been painfully slow. Process planning serves as a vital link between design and manufacturing functions by planning the strategy for manufacturing a component. A process plan includes information about the component route, manufacturing processes, machines and tooling, process parameters, and time and cost estimates. It thus determines the cost, quality and production rate for a product. This paper traces some of the significant achievements in CAPP research and suggests what is still missing and needs to be done to meet the needs of industry as we move towards the 21st century.

With rapid developments in communications, worldwide trade is now a reality and competitiveness is the only way to survive in the market place. This has forced industries to computerize so as to tap into the high processing speeds and storage capacities of the computer. Computer integrated manufacturing system (CIMS) is recognized as an effective platform for increasing manufacturing competitiveness. CAPP is an essential key for achieving CIMS. Automating process planning increases production efficiency enabling more economical production of parts.

The initial development in CAPP research was the optimization of machining conditions[1]. For repetitive, relatively simple operations like determining machining conditions and times, the computer is certainly very helpful. The main programming language used was FORTRAN since extensive mathematical calculations were needed to determine operating data[2]. However, the feeling was that when more intelligent decisions involving a balanced judgment based on many criteria were needed, man still has an advantage over the computer. Much of the process planner's time is devoted to maintaining the process planning database. Because much of the maintenance is routine and can be improved in both speed and accuracy with computer automation, it was one of the first beneficiaries. The functions of paper, pencil, and file cabinet were delegated to the computer.

Process planning has traditionally been experience based and performed manually. A problem facing modern industry is the length of time required by a process planner to gain the necessary experience. The average age for a process planner has been

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estimated to be 51-55 years[3]. As the senior process planners reach retirement age, their replacements, often many years younger than them, have not acquired sufficient depth of experience and knowledge to replace that which will be lost through retirement. CAPP systems may provide the vehicle that simultaneously captures the expertise of these senior personnel in the form of "best practice" procedures or standardized process plans and acts as the training vehicle that disseminates this accumulated knowledge to the junior personnel who use the CAPP system for their daily work. The literature reveals that two typical approaches have been taken for CAPP. These are the variant approach[4] and the generative approach[5]. Table 1 summarizes the main strengths and weaknesses of these methods as well as artificial intelligence (AI), CIMS and concurrent engineering (CE) technologies. The following section looks at AI in CAPP.

Table 1 CAPP approaches

	CAPP system	main strengths	main weaknesses
method	variant	useful for similar parts understandable human planner has final control simple to develop and install	restricted to similar parts experienced planner still needed to edit process plans prepartation stage laborious
	generative	used for new and existing components consistent plans can be automated	narrow part domain not understandable by user significant programming effort needed
technology	AI	capable of solving unforeseen and unprecedented problems can work with incomplete and imprecise information preserves expert knowledge capable of learning and adapting to change	knowledge acquisition difficult lengthy development time slow and expensive in execution speed no general purpose intelligence exists
	CIMS	lower direct labor requirements low in-process inventories greater machine utilization shorter lead times improved quality scheduling flexibility	requires large initial capital investments requires more intensive use of facilities requires training in new labor skills organizational changes needed requires use of new planning and control methods
	CE	reduced lead time reduced costs improved quality	limits creativity of designer manufacturing decisions passed to the designer teamwork training needed

1 Expert, Neural Network and Fuzzy Systems in CAPP

1.1 Expert system

Expert system is following (see Fig. 1).

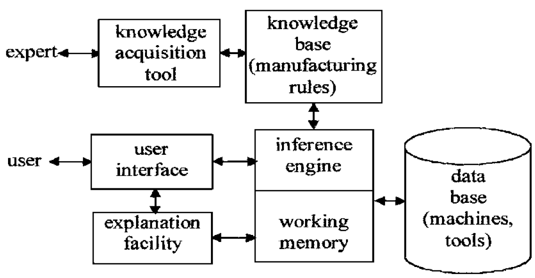

Fig. 1 Expert system structure

The knowledge based expert system approach was an acknowledgment that process planning is traditionally experience based and relies on much heuristic knowledge from the process planner which may only be applicable in a particular manufacturing environment. The knowledge base consists of these heuristics in form of rules. Figure 1 shows the basic structure of an expert system. Separation of the control or inference engine from the knowledge base and data base gives added flexibility. When new equipment or tools are installed or changed, only the database needs to be altered. For a different factory the knowledge base and data base can be changed while using the same inference engine. As all the partial results are stored in the workspace, the system is capable of retracing its path and the logic behind any particular decision can be found by the user. This facility is referred to as an explanation facility, giving added confidence to the system. Learning is also possible by addition of new rules to the knowledge base. TB-logic[6] is an expert system based process planning system which has been commercialized.

The biggest shortcoming of expert system approaches is in knowledge acquisition. It is difficult to extract the knowledge of planning from experienced machinists in the form of rules as required by the expert systems. Some knowledge is based on hunches and cannot be expressed in rule form. It is also difficult to ensure consistency of the rules in the knowledge base as its size grows. Thus very few expert systems based process planning systems have been used in industry despite the many promises. As the system grows in size, the speed of execution also suffers. A new tool for knowledge acquistion and even knowledge generation is needed[7]. Table 2 summarizes the main differences in the expert, neural and fuzzy AI systems.

Table 2 Expert, neural network and fuzzy systems

expert system	neural network	fuzzy system
symbolic	numeric	numeric
logical	associative	associative
sequential	parallel	parallel
no self-learning	self-learning	no self-learning
structured	unstructured	structured
comprehensible	black-box nature	comprehensible

1.2 Neural network

The use of artificial neural networks in process planning is an attempt to solve the knowledge acquisition "bottleneck" of expert systems. Learning in neural networks occurs internally within the network. Most neural networks learn by example; the network is provided with training data showing characteristics of a particular case and the desired output. The network then learns the relationships between the characteristics and the desired responses. The knowledge of neural networks is found in the internal weight structures of the connecting neurons. Feedback from executions of previous plans can be collected as training data and used to generated new planning knowledge thus gradually improving the system's performance. While this process can also be time consuming, this inductive approach to knowledge acquistion does not require the specification of IF-THEN rules.

It is very likely that portions of the planning knowledge represented in the present systems may become inappropriate once the manufacturing environment which the plans are designed for changes. Therefore, expert systems do have some limitations in terms of their ability to generalize or adapt to changing environments. Neural networks on the other hand specifically adapt to changing information through re-training and by their nature are designed to be able to generalize above and beyond the training cases presented in their construction phase. Deductions can be made when only partial information is available and neural networks are tolerant of noise and error in the data. They also exhibit graceful degradation of performance. Neural networks have been applied for process selection[8], feature sequencing[9] and datum selection[10] phases of process planning. The architecutre of a feedforward neural network is shown in Fig. 2.

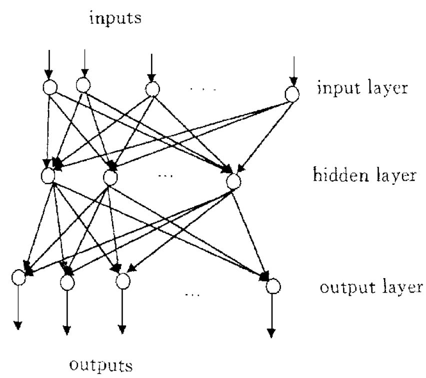

Fig. 2 Feed forward neural network architecture

However, neural networks have some shortcomings as compared to expert systems. The lack of explicitly stated rules and, additionally, the inability to generate a reasoning path due to the unique knowledge representation scheme leads to a blackbox nature. We do not know what the neural network encoded during the training period or what it will encode or forget in further training. A representative sample of training sets may not be available. The training time can be lengthy and depends on the choice of the initial parameters. The network topology is usually chosen in a trial by error method with "cross-talk" as a further complication in neural networks. It thus seems necessary to structure neural networks to overcome these limitations[11].

1.3 Fuzzy system

Fuzzy systems lie between expert systems which use structured knowledge representation in a symbolic manner and neural networks which cannot directly encode structured knowledge. The fuzzy approach combines the pure numerical approaches of neural networks with the structure rich approaches of expert systems. Neural and fuzzy systems encode sampled information in a parallel-distributed framework. Both frameworks are numerical. Fuzzy associative memory (FAM) systems as shown in Fig. 3 require separate storage of the associations as if each association in the FAM bank represented a separate feedforward neural network[12]. The system maps input fuzzy sets X to output fuzzy sets Y. Separate storage of FAM associations consumes space but provides an "audit" trail of FAM reasoning procedure and avoids cross-talk. The user can directly determine which FAM rules contributed how much membership activation to a concluded output. Separate storage also provides knowledge base modularity. The user can add or delete FAM-structured knowledge without disturbing stored knowledge. Both of these benefits are advantages over a pure neural-network architecture for encoding the same associations.

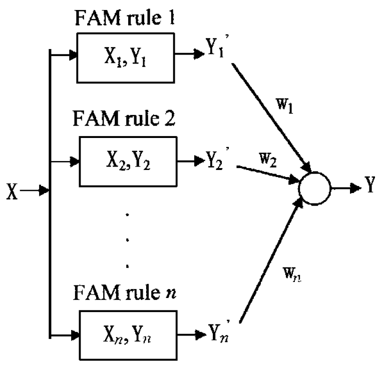

Fig. 3 FAM based fuzzy system

An input vector activates all the FAM rules but to different degrees. If none of the FAM rules is satisfied then there will be no output. A neural network will tend to have a nonnull output in this case. We may desire this for classification problems but not for inferential problems. When we ask an expert a question outside his field of knowledge, it may be more prudent if he gives no response than if he gives an educated guess. Gu et al.[13] applied neural network modeling to feature recognition and FAM to operation selection. The FAM approach can also be used in other aspects of process planning such as machine tool and tool selection. In process planning some knowledge associated with the manufacturing environment, planning standards, and good machining practice is ambiguous. A fuzzy approach allows this knowledge to be captured. However, the fuzzy rules and membership functions need to be determined to use an FAM system.

1.4 Composite system

The generation of fuzzy rules and determination of the membership functions in FAMS can be done through expert experience, statistical analysis, or neural network approaches[14]. An expert can articulate known rules. Where training examples are available, they are used to statistically determine the applied fuzzy rules. Figure 4 shows the two dimensional case where an input X is mapped to output Y. The ten sampled input-output cases are placed in the corresponding cells. Each cell with an entry represents a fuzzy rule such as "IF X is medium THEN Y is medium". The frequency of each cell represents the weighting of the rules. A cell with more entries represents a more important rule than one containing only a single entry. When the number of inputs and outputs increases then the dimensionality of the matrix increases.

X \ Y	VS	S	M	L	VL
VS					.
S				..	
M			....		
L			..		
VL	.				

VS is very small; S, small; M, medium; L, large; VL, very large

Fig 4 Fuzzy rule estimation

Neural network approaches further use the samples to tune the membership functions of the inputs and the weights of the various rules. By using fuzzy neural networks the learning ability of neural networks is incorporated into rule based knowledge systems without sacrificing the merits of inexact reasoning and fast decision making. Figure 5 illustrates such a scheme.

It is thus clear that to more effectively solve the process planning problem a composite approach[15] involving neural, expert and fuzzy systems is needed to better model the decision making process of the human process planner. The neural structure allows learning by tuning the system parameters. The structured or rule-based nature allows high level reasoning and an understandable system. The use of fuzzy sets allows the thoughts of the process planner to be captured. An expert system is needed to provide an easy way of inputting data, providing consistency checks and interpreting the numerical output of the neural network.

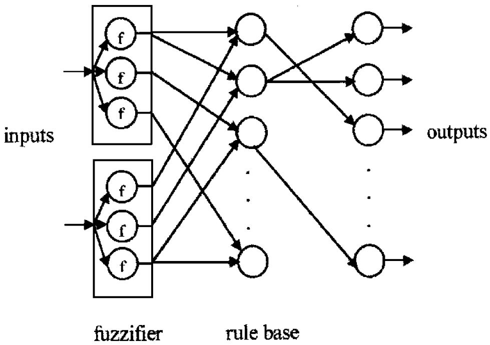

Fig. 5 A fuzzy neural network

1.5 Spline machining example

Spline is a feature that commonly occurs on machine parts such as shafts. A study on 7 process plans containing 10 spline features was made to determine the sequence of machining operations and the characteristics determining these selections. Figure 6 illustrates the resulting network structure. The inputs are the surface finish of the splines (I_0), the surface finish of the sides of the splines(I_1), and the straightness accuracy requirement (I_2). Surface finish is fuzzified into small (s) and medium (m) while straightness accuracy is fuzzified into small, medium and large (l). The outputs are the 4 manufacturing sequences O_0 – O_3.

The fuzzy-neural network has five layers. The layer 1 is the input layer. Layer 2 is the fuzzification layer. The outputs of this layer are the fuzzy functions of the inputs. Each neuron of the layer 3 represents a fuzzy rule. Layer 3 links define the preconditions of the rule nodes, while layer 4 links incorporate the rule's consequences. Layer 5 is the output layer.

The nodes in layer 1 just transmit input values to the next layer with unity link weights, $w_i^1 = 1$, where the superscript and subscript indicate the layer and node respectively. A layer 2 node performs a membership function. The sigmoid function can be used to perform this fuzzification. Let the node inputs be denoted as u, node outputs as a, net input to a node f, and the threshold value θ, then

$$f = w_{ij}^2 u_i^2 - \theta_j^2, \quad a_i^2 = \frac{1}{1 + e^{-f}}.$$

The weights and thresholds are tuned during learning.

Performing precondition matching of the fuzzy rules, layer 3 nodes fulfil the AND operation. Multiplication is used for this operation with $w_i^3 = 1$. The nodes in layer 4 integrate the fired rules having the same consequence by the OR operator. Summation is used for this operation with $w_i^4 = 1$. Layer 5 performs the weighting of the outputs. Hence the weights w_i^5 also need to be trained. Using the sigmoid function in the output layer constrains the output between 0 and 1 reflecting the confidence level for the method. The output of the system is the machining method and the degree of confidence associated with it.

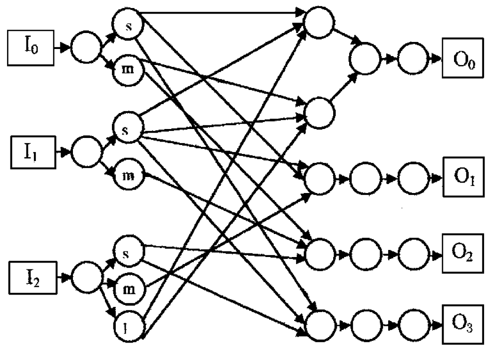

Fig 6 Spline machining method selection

I_0, splines side finish; I_1, splines top finish;

I_2, splines side straightness tolerance

O_0: 1, rough spline; 2, finish grind; 3, shave and chamfer

O_1: 1, rough spline; 2, finish grind; 3, grind sides; 4, shave and chamfer

O_2: 1, rough spline; 2, finish mill sides; 3, mill bottom; 4, finish grind; 5, shave and chamfer

O_3: 1, rough spline; 2, finish spline; 3, finish grind; 4, shave and chamfer

To train the network, the desired method is obtained from the process plans. Since the boundaries for the input's fuzzy sets are known, the weights and threshold values for the membership functions can be determined. The membership functions were tuned to reflect the desired output by adjusting the weights and thresholds in layer 2. A weighting value of unity was maintained in layer 5 for each rule. The desired output is the one with the highest value. Outputs with values greater than 0.5 were taken to be alternative manufacturing methods. The network correctly trained to determine the manufacturing sequence for the 10 spline features. Since the network structure is already determined, the training is fast. As the system has correctly learned the manufacturing practices, it is ready for use. Where an expert can give the confidence levels for the outputs, supervised learning methods such as the backward propagation (BP) algorithm can be used.

2 Industrial Requirements for CAPP Systems

Industry claims that currently available CAPP systems do not fulfill their needs. User friendliness is still a problem and data input costs are too high. The interfaces to surrounding software are not available or insufficient and many products prove to be "promiseware". Further complains are that the systems are black-boxes because their internal heuristics and algorithms are not known or cannot be changed by the user. They do not tolerate systems that take long to install and prefer systems that are flexible and can be adapted to their company's products. Also, tools which focus more on synthesis would be of more assistance during the process planning[16].

3 Discussion and Conclusions

A direct link with the CAD database and the use of an expert system to facilitate data input would ease the burden of inputting data. Fuzzy neural networks help in synthesizing the knowledge that is needed for process planning. Feature based design and concurrent engineering address the integration of CAPP and design functions. The object-oriented programming paradigm meshes with the way people naturally interpret the world. Human understanding largely rests on identification and generalization (objects and classes), finding relationships between groups (containment and inheritance), and interfacing through the normal interface of an entity (behaviors). With object-oriented programming, well-structured complex systems with high efficiency and convenience can more easily be constructed. The software components or even entire systems are more re-usable and the systems can also evolve over time and be modified when needed without completely abandoning or redesigning them.

To increase flexibility on the shop floor, alternative process plans ought to be given rather than selecting one too early to give only one optimum plan. Also, a new trend is that the programs ought to conform with the STEP standard as a means of facilitating interchange of product data and process plans between different systems[17]. It is noted that the systems which have been used in industry allow participation of the user in the decision making process. This perhaps is one of the reasons for the popularity of variant systems. Some systems support both variant and generative capabilities, which could be a new trend for CAPP systems.

A system using fuzzy neural networks in the individual modules of CAPP will lead to more understanding of the structure, behavior and outcome by the users. An object-oriented programming structure gives modularity which facilitates customization and expansion of the system. CAPP systems should include human input in the process.

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