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An Integrated Application of Neural Network, Fuzzy and Expert Systems for Machining Operation Sequencing

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Abstract A part is described using features. A neuro-fuzzy system then determines the machining sequence for each feature. Previous process plans were utilized to build, test, and validate the Neuro-Fuzzy Network (NFN). Parts having similar manufacturing sequences are grouped into families, also using an NFN. A standard manufacturing sequence is obtained for each family comprising all the operations applicable to the features of the parts in the family. An expert system then adapts this standard sequence for the particular part being planned. The optimal operation sequence is inherited by the new part. The procedure is demonstrated by an example industrial part.

Key words machining sequence; neuro-fuzzy; expert system; semi-generative; group technology

Introduction

Operation sequencing is an important subtask of process planning; its goal is to specify the sequence in which features are to be machined. This task is usually performed after the operation selection for each feature has been done. To remain competitive in today's manufacturing arena has become a difficult task. Customers continue to demand higher quality, lower prices, and more individual options. Therefore, the process plan must be right the first time. Manual process planning is highly time consuming and involves too many subjective decisions by a process planner. The lack of standardization and lack of skilled process planners have led researchers and industry to develop Computer Aided Process Planning (CAPP) systems. CAPP increases the accuracy and productivity of the total manufacturing planning effort. Improved operation selection and sequencing increases quality and reduces scrap.

Artificial Intelligence (AI) and more specifically expert systems have been applied to design generative process planning systems. Some of the process planning knowledge, however, relies on much heuristic knowledge from the process planner which may only be applicable in a particular manufacturing environment and cannot be expressed in explicit rule form as required by the expert system. Fuzzy logic enables approximate human reasoning in the face of uncertainty, ambiguity and vagueness to be captured. Most real life situations include manufacturing process planning fall into this category of decision making. Fuzzy systems are considered to be a natural link between symbolic and sub-symbolic approaches in AI. On the one hand they can handle uncertainties as neural networks, on the other hand they can manage both symbolic and numerical information. However, fuzzy systems usually do not incorporate automatic learning abilities and adaptive features. It seems that a very high performance can prospectively be obtained by combining neural network and fuzzy logic approaches and integrating their benefits. The resulting neuro-fuzzy system is a hybrid system, where the architecture remains fuzzy, but using neural techniques it can be trained automatically. Thus the neuro-fuzzy system exhibits uncertainty handling and learning ability, and moreover expert knowledge can be easily incorporated into the system and transparency of the rule based expert system is preserved. Hence, fuzzy logic reasoning and hybrid approaches combining expert systems, neural network and fuzzy logic appear to be the preferred AI

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approaches in process planning[1].

Variant process planning relies on the existence of previously used plans. The use of existing plans can be very cost effective. However, the pattern matching necessary to find appropriate plans to retrieve can get complicated. Also, plan modifications in response to changes in materials or manufacturing capabilities are not easily incorporated. The biggest disadvantage of this approach is that an experienced process planner is needed to consistently edit the process plans.

The best way to reduce manufacturing costs is to use standard parts. Years of process planning will teach the engineer that certain processing sequences or patterns tend to show up time and time again. This means that other preparatory processes often precede most known production processes. Once the process of manufacturing a standard part is optimized, all parts using it will reap the cost benefits. It has been estimated that eight percent of all parts are exact duplicates of existing designs. The duplicate effort could be better invested elsewhere.

The generative approach involves the generation of process plans automatically without referring to existing plans. Developing a generative system, however, results in heavy investment of manufacturing and software expertise in order to prepare the rule base used to select and sequence the operations. As a result there is a shift of emphasis from pure generative planning toward a combined use of variant and generative methods in a full-fledged CAPP system. Here, process plans can be assigned to both part families and characteristic features. By using such a means for representing manufacturing knowledge, the overall performance of the planning system is increased, and what is more important is the methods used by engineers to do process planning can be explored within the CAPP framework itself. Such semi-generative approach is generally more effective and allows quicker usability and payback without compromising long-term benefits.

1 Feature Based Modeling

A feature is a geometric shape defined by a parameter set, which has special meaning to a design or manufacturing engineer. A feature carries the notion of both the resultant part geometry and also a variety of non-geometric or geometrically related information. Feature based modeling is a process in which mechanical parts are specified in terms of their constituent parameterized features. This technique allows the product shape to be defined through form features and provides for communication of critical information to all applications through a shared database. Manufacturing operations can then be assigned to the feature types and the information contained in the features used to assist in process plan generation.

Part drawings from industry were studied in order to gather external and internal form features commonly occurring in the rotationally symmetric components. The generic features are incorporated into a library that ideally can be customized by the user. Combining different pre-defined generic form features from the feature library and specifying their parameter values, all the external and internal characteristics of the part are specified. The part as depicted in Fig. 1 is synthesized to consist of various external and internal features. The external features are divided into primary external features such as cylinder and thread, and secondary features such as spline, groove, and chamfer. Some features such as groove have subtypes rectangular groove and functional groove; chamfer has left chamfer and right chamfer. Center hole is an example of an internal feature.

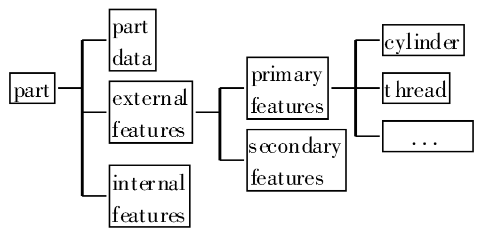

Fig. 1 Part model

An object-oriented framework has been adopted, hence features can easily be added or deleted from the system. A feature is an instance of a class. Examples of nongeometrical information are various types of tolerances (of size, form, position, etc.) and surface roughness. The user interacts with the system through a "Window" based graphical interface comprising menu selections, tool bars, and dialog boxes. Graphical displays provide a constant "feel" to the user in various phases of part modeling.

2 Machining Operation Selection

As the investigations of manufacturing documents for a company shows, it is possible to assign to each feature alternative operations and sometimes operation sequences too. A study of 24 process plans for rotational components comprising shafts, gear wheels, and disks from Guangzhou Machine Tool Factory was made to determine the sequences of machining operations for the features. This is shown in Table 1.

Table 1 Used process plan study

Feature	Number studied	Operation sequences
spline	10	4
cylinder	57	4
chamfer	36	1
centerhole	22	1
groove	27	1
thread	5	1

An NFN system was used for the operation selection. The system consists of the inputs, fuzzification, rule base, and outputs. A separate network is used for each feature. This reduces the size of the respective networks making it easier to train. It also gives knowledge base modularity. The inputs are the feature types and their attributes such as surface finish and tolerances. The operation sequences are the outputs. For the features which had several outputs, a further study was made on the feature specifications to determine the factors leading to these choices. The surface finish and whether it is a datum, were indentified for the cylinder feature. These are the inputs, which are then fuzzified into linguistic terms such as small, medium and large. Figure 2 shows the membership functions for surface finish.

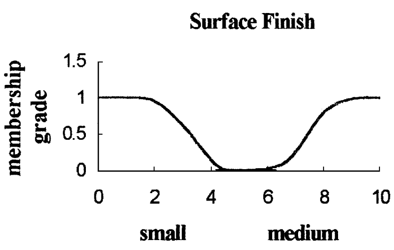

Fig. 2 Membership function of surface finish

Previous plans are used to generate the fuzzy rules by examining the plans to determine the manufacturing methods for the features and the factors that determine them. For cylinder features in parts with length to diameter ratio greater than 2 (shafts) and requiring finishes higher than 3.2 μm, a grinding operation was needed. For parts with lower length to diameter ratio and a surface roughness of 1.6 μm, a finish turning operation was sufficient. Figure 3 illustrates the resulting network of the cylinder feature for shaft parts.

The network has five layers. The first layer 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 third layer 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 is 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

$$f = w_{ij}^2 u_i^2 - \theta_j^2,$$

$$a_j^2 = \frac{1}{1 + e^{-f}}.$$

The weights and thresholds are tuned during learning. The BP algorithm[2] is used for this supervised learning.

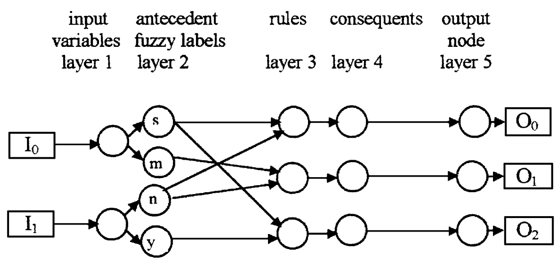

Fig. 3 Cylinder machining method selection for shafts

I_0, Surface finish; O_0: (i) Rough turn, (ii) Semi-finish turn, (iii) Finish grind;

I_1, Datum; O_1: (i) Rough turn, (ii) Semi-finish turn, (iii) Finish turn;

O_2: (i) Rough turn, (ii) Semi-finish turn, (iii) Rough grind (iv) Finish grind.

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.

To train the network, the desired method is obtained from the used process plans. Since the boundaries for the input's fuzzy sets are known, the initial weights and threshold values for the membership functions can be determined. The membership functions were then tuned to reflect the desired outputs 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 activation. Outputs with activation values greater than 0.5 were taken to be alternative manufacturing methods. The level of activation reflects the confidence associated with a particular method. The work is coded in an object-oriented framework in C++. The NFN is represented as a class. The network for each feature is an instance of the class. Sparse matrix techniques are utilized and only the existing node connections need to be recorded and processed. The supervised learning tests and validates the initial network structure. The networks were trained with actual numerical input representing the parameters of the features and the optimum manufacturing operations as represented in the process plans. At least one input-output pair was used for each rule. The network correctly trained for all the cases. Since the network structure is already determined, the training is fast. The initial membership functions were found to be accurate and no further tuning was indeed necessary. As the system has correctly learned the manufacturing practices, it is ready for use to determine the operation sequences for the features. The obtained sequences for the example part are shown in Table 2.

Table 2 Feature operation sequences

Feature	Operation sequence
cylinders	(i) Rough turn; (ii) Semi-finish turn (iii) Finish grind
thread	(i) Rough turn; (ii) Finish turn (iii) Turn thread
chamfer	Chamfer
groove	Groove
spline	(i) Rough spline; (ii) Finish grind (iii) Shave and chamfer
centerhole	(i) Drill; (ii) De-burr

3 Operations Sequencing

Implementation of Group Technology (GT) in an enterprise makes the production more adaptive, flexible, and competitive. GT philosophy is used to group together those components having similar features and requiring similar sequences of machining operations. This allows manufacturing engineers to plan efficiently the layout of machines in the factory in order to reduce the handling and transfer of components as much as possible. It also assists the designer standardize components and avoid specifying machined features that the company is not equipped to handle.

By applying the part family concept, inferencing and expert knowledge can more easily and effectively be extracted and organized. Grouping parts into families introduces system modularity and makes it work faster by limiting the search space. Effective part family formation, is therefore the key to implementation of the GT concept. Parts should be grouped such that the resulting families have simple conceptual interpretations. This allows engineers and managers to make decisions that depend on part families efficiently and intelligently. Background knowledge about part attributes should be utilized.

The application for which families are formed should affect the choice of attributes by which the parts are classified. Traditional techniques by use of numerical codes cannot describe parts in enough detail to be useful for automatic generation of process plans. Any characteristics of a part corresponding to a certain family are fuzzy, and there does not exist absolute hard partition. Hence, a fuzzy approach should be utilized to classify the parts.

To deal with part families, a hybrid architecture combining generative and variant process plan generation is utilized. After having selected the best manufacturing operations for the features, the operations sequence are determined on the basis of the standard sequence for each family reflecting the proposal of the process planner and company specific structure. This structure consists of a comprehensive network of all operations. A standard processing sequence for a family comprises appropriate set-ups and operations. For a particular part, adapting the relevant family sequence according to the features and operations of the part creates the detailed processing sequence.

3.1 Part family formation

An NFN system is utilized to group the parts into families[3]. The structure of the system consists of the inputs, fuzzification, rule base, and outputs. The inputs are the attributes that determine the classification while the outputs are the families.

Different comparison parameters or attributes can be selected for different comparison objectives. It is expected that engineers frequently change their criteria according to real manufacturing requirements or personal preferences. A study was made on process plans for 12 shafts, 3 gear wheels, and 9 disks from Guangzhou Machine Tool Factory to determine the factors leading to similar processing sequence in each of the three families. The length to maximum diameter ratio (LD), presence of gears (GR), all the features found in shaft family (FS), in gearwheel family (FG), and in disk family (FD), were identified as the input comparison factors. Figure 4 shows the resulting network.

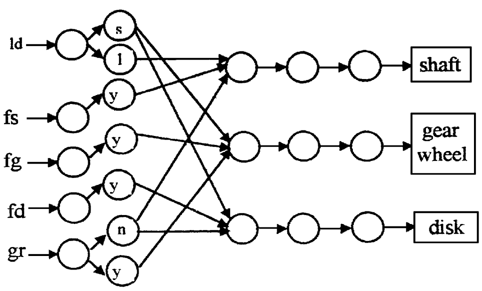

Fig 4 Neuro fuzzy network for part family selection

If the features for the part to be classified are contained in the family, then the input value is 1, otherwise it is − 1. If a gear feature is present, the input is 1, otherwise it is − 1. The length to maximum diameter ratio for gearwheels and disks were found to range 0.1 – 3.4 while for shafts, the range was 2.7 – 11.2. Using these boundary values, the weights and thresholds in the fuzzification functions are determined. Thus the variable was fuzzified into small and large with an overlap near a ratio of 3. The fuzzification functions are shown in Fig. 5.

The NFN trained and tested correctly for all 24 cases. No training was indeed needed as the initial fuzzification functions were found to be accurate. The cases test and validate the network, which can then be used to group new parts. The example part was found to belong to the shaft family. The standard process sequence for this family is then used to optimize the operations sequence for the part.

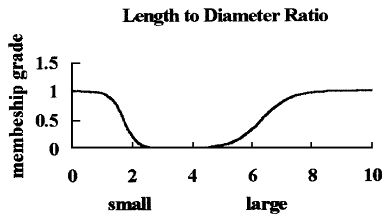

Fig. 5 Membership function of length to diameter ratio

3.2 Optimizing the sequence

An expert system is utilized to adapt the operation sequence for the chosen family to suit the part whose operation sequence is being determined[4]. An expert system comprises the knowledge base, the inference engine, and the user interface. The knowledge base is the standard operation sequence for the family consisting of all the operations appropriate for the features in the family. The inference mechanism allows the manipulation of this knowledge by retrieval and adaptation. The optimized sequence is inherited by the new part. This kind of learning, experience accumulated in the past, is reused in an indirect and more efficient way. The adaptation is as follows:

I. GO to head of standard sequence list.
II. Get next standard feature and operation from standard sequence.
III. GO to head of part feature list.
IV. Get next feature of part.
V. Compare standard feature with feature of part
  If same
    Get next operation for part feature
    Compare operations for part and standard features
      If same
        Output feature name and Operation
        Delete operation from part
VI. Last feature of part?
  No, Go to IV
  Yes, Go to VII
VII. Last standard feature?
  No, Go to II
  Yes, Go to VIII
VIII. Output complete operation sequence list for part.
IX. Stop.

The standard sequence indicates operations which have to be done in the same setup such as semi-finish turning, grooving and chamfering operations. These are also output as one set-up for the particular part.

4 Results and Discussion

The example shaft part is shown being modeled in Fig. 6.

Feature parameters are entered through dialog boxes as shown in Fig. 7 for cylinder feature.

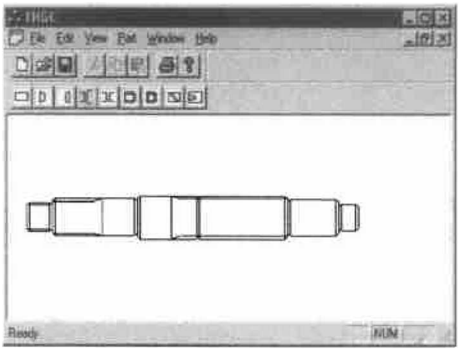

Fig 6 Feature based part modeling

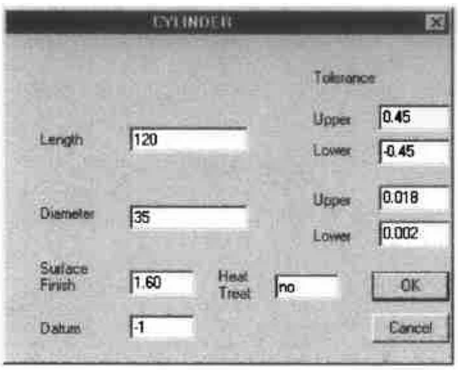

Fig. 7 Cylinder feature parameters input dialog box

The operations sequence output for the example part is in agreement with the operations sequence from the experienced process planner. The facing and center hole drilling has been put together with cylinder turning in step 2 of the optimized standard sequence. As given by the process planner in the process plans, these were done in two steps (2 and 5) requiring a change of sides twice. The combination of operations leads to more cost savings.

After selection of the machines to be used, some operations may also need to be put together if they are done on the same machine. An example is the thread turning and semi-finish turning of the cylinder features, if both operations are done on the same lathe machine.

5 Conclusions

Using optimized manufacturing sequences for part families utilizes the GT concept leading to cost savings, improved productivity and competitiveness. The neuro-fuzzy approach effectively represents process planning knowledge as used by the experienced process planner. The modularized nature of the whole system enables easy expansion to model different industrial applications.

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