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An Integrated and Intelligent Computer-Aided Process Planning Methodology for Machined Rotationally Symmetrical Parts

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Abstract: *The research work reported in this paper is aimed at developing an integrated and intelligent CAPP methodology for machined rotationally symmetrical parts. Two important aspects of process planning, namely the machining operations selection and the set-up planning have been automated by this methodology. In addition, a methodology has been developed to efficiently extract the required data from the CAD model of the part and then feed it to the two process planning g modules. For machining operations selection, a novel back-propagation ANN methodology has been developed by prestructuring it with prior domain knowledge in the form of thumb rules. Further, an expert system based set-up planning methodology has been developed for automating the tasks of set-up formation, operation sequencing and datum selection for rotationally symmetrical parts. It has been implemented using the CLIPS rule-based expert system shell. The two process planning modules have been prefaced with a means for automatic feature recognition and extraction of CAD data from a commercial CAD software system, CATIA V5. The example of a rotationally symmetrical work piece has been analyzed using the proposed methodology to demonstrate their potential for application in a real manufacturing environment.*

Keywords: *Computer-Aided Process Planning, feature extraction, machining process selection, set-up planning, Artificial Intelligence.*

1. INTRODUCTION

The global competition and increasing demand for higher quality products at lower prices with shorter lead times have led to a growing focus on development of Computer Integrated Manufacturing (CIM) systems in manufacturing industries. In developing a CIM system, an automated process planning interface can play a key role especially in integrating Computer-Aided Design (CAD) and Computer-Aided Manufacturing (CAM). Consequently, a great deal of research has been devoted for developing Computer-Aided Process Planning (CAPP) systems that can automatically perform the task of process planning. A CAPP system, depending on the level of sophistication of its capability, may involve automating the interface between design and process planning as well as various process planning tasks such as process selection, machine tool and cutting tool selection, set-up planning, fixture selection, machining parameter selection and so on. In the research work presented in this paper, the authors have developed an integrated and intelligent CAPP methodology for machined rotationally symmetrical parts. The work presented here on process planning consists of automating the machining operations selection using a neural network approach, followed by an automated method of doing the various set-up planning tasks. Research contributions have been made in both these areas of process planning and they have been described in this paper. An interface between design and process planning has been created for automatic feature recognition from a commercial CAD software, CATIA. Using this interface, the two process planning modules get their necessary data in the desired format from the CAD database in a rapid manner and the whole integrated methodology becomes very efficient. In the next section, the pertinent research literature on machining operations selection and on set-up planning has been briefly reviewed.

1.1. Literature review of generative CAPP approaches for machining operations selection

The machining operations selection has been automated by various researchers using approaches such as mathematical models, decision trees, expert systems and artificial neural network (ANN). Qiao et al [1] presented another mathematical model based approach for generating different machining routes for producing a part. Shirur et al [2] developed an approach for operation selection by using a mathematical model for mapping the machinable volumes to feasible machining operations. Yongtao et al [3] proposed a mathematical model for selection of hole machining operations that is capable of generating an optimal sequence of operations by minimizing the number of tool changes. Wang et al [4] used a decision tree for machining operations selection. It is, however, inflexible and incapable of automatically acquiring knowledge. Khoshnevis et al [5] used a rule based expert system for hole making process selection. Wong et al [6] developed an algorithm using rule based process capability knowledge to generate an operations precedence tree, which is refined further using rules. Dana et al [7], Eskicioglu [8], Sabourin et al [9] and Jiang et al [10] each employed a rule based approach for operation selection and sequencing for various rotational and prismatic parts. Waiyagan et al [11] used a set of knowledge based rules and heuristics to solve the problem of operation selection and sequencing for mill-turn parts. Radwan [12] proposed a process selection approach for prismatic parts based on relational models between surface characteristics and manufacturing process capabilities. The expert systems are, however, only capable of solving problems with explicit rules. If the number of rules is large, their encoding and modification can become tedious and time consuming, the execution times are longer and conflicts between rules arise. They lack ability to automatically acquire knowledge. Knapp et al [13] used a back-propagation ANN that proposes machining alternatives, and another ANN that selects one alternative. Devireddy et al [14] used a back-propagation ANN to identify basic manufacturing operations for each feature in rotational components, and another ANN for refinement of operations. Devireddy et al [15] also proposed a back-propagation ANN for machining operations selection of all the features considering global operations sequencing. The ANNs are capable of automatically acquiring knowledge in the form of examples and then generalize. Modification of knowledge can be accomplished easily through retraining. It leads to faster inference compared to decision trees and expert systems. However, in spite of the above advantages of ANN, choosing training examples is tedious and time-consuming. Also an issue not adequately addressed is whether any prior domain knowledge, known to reduce the complexity of learning, could be taken advantage of. Further, the previous models tend to recommend a single operation sequence. Keeping in mind the above facts, the authors have developed a back-propagation ANN methodology for machining operations selection in rotationally symmetrical parts, which provides many solutions and the best one can then be chosen.

1.2 Literature review of generative CAPP approaches for set-up planning

The set-up planning tasks have been automated by approaches such as algorithms and graph theory based methods, expert system, fuzzy logic and neural networks. Huang et al [16], Zhang et al [17] and Lee et al [18] each used a graph theory based approach for set-up formation and datum selection for rotational parts. Lee et al [19] proposed an approach based on breadth-first search of graphs that is capable of generating the set-up plan for prismatic parts based on the precedence relations among machining features and their Tool Approach Directions (TAD) that were extracted from the CAD database by feature recognition algorithms. Huang [20], Gologlu [21] and Ramshbabu et al [22] each used an algorithmic approach for set-up planning. The above approaches are, however, inflexible, and the program must contain all possible input-output combinations and may need large computing resources. Joshi et al [23] used a rule based expert system for set-up formation based on commonality of Tool Approach Directions (TAD), resting face, machines, etc. and establishing operation precedences for sequencing in prismatic parts. Sabourin et al [9] used a rule based expert system combined with constraint programming for set-up generation and operations sequencing in prismatic parts. Kim et al [24] used rules to generate precedence constraints and cluster operations, and a mathematical model for set-up formation and operations sequencing subject to precedence constraints. Liu et al [25] developed a rule based approach for determining machining feature precedence constraints, an algorithmic approach for grouping the features into setups based on TADs, and a rule based approach for generating the sequence of machining the features. The expert system offers a structured knowledge representation in rule form, a modular architecture, an explanation facility and ability to acquire new knowledge through introduction of new rules. It, however, is unable to automatically acquire the rules and its execution time increases with increase in number of rules. Ong et al [26] used a fuzzy logic based set-up planning approach for prismatic parts. It is able to handle uncertainty. However, like expert systems it is unable to automatically acquire the rules. Chen et al [27] used an unsupervised ANN for set-up formation. Mei et al [28] used a back propagation ANN for datum selection. Chen et al [29] used a Hopfield ANN for feature sequencing in prismatic parts and simulated annealing to find the optimum sequence. Ming et al [30] used a self-organising ANN for set-up formation and a Hopfield ANN for operation sequencing in prismatic parts. The ANN offers the capability to automatically acquire knowledge, adapt to changing environments through re-training, and generalise. However, its lack of explicit rules and vagueness in knowledge representation leads to a black box nature.

The literature review indicates that in most of the previous research efforts for expert systems applications in set-up planning, a mixture of an expert system and some algorithmic approach was adopted that is inflexible and requires considerable human intervention in rewriting of original program when it becomes necessary to modify and update the knowledge base. Keeping the above in mind, the authors in this paper have presented a modular and flexible expert system methodology that they have developed for set-up planning of rotationally symmetrical parts for automating the different set-up planning tasks like set-up formation, operations sequencing and datum selection.

2. PROPOSED METHODOLOGY FOR AUTOMATIC FEATURE RECOGNITION FROM CAD DATABASE

This section presents the proposed methodology (Parra-Castillo [31]) for automatic feature recognition from the CAD file in CATIA V5 R13 software and for extraction of data necessary as input to process planning modules of machining operations selection and set-up planning to be discussed in the subsequent sections. Other CAD modeling systems can be also used. The extracted input data comprise of types of features present in the part (such as holes, external steps, external tapers, external threads, grooves, faces, slots, keyways and so on), their dimensions (such as diameters, length of the cylindrical surfaces and so on), their dimensional and geometric tolerances, their surface finish and also information on the neighboring features. To accomplish seamless integration with the two process planning modules, the extracted data needs to be represented in a format directly usable by those modules. This has been realized by development of a graphical interface and making use of macro tool provided in the Visual Basic for Applications (VBA) module of CATIA. The following discussion treats the key issues in development of the methodology for automatic feature recognition.

2.1 Feature recognition and extraction of the data from the part model in CATIA

The developed feature recognition software is capable of displaying, in different windows, all the data contained in the part file, filename and location of the text files in which the data has been stored. CATIA stores the data of the part in different data collections, which can be accessed through the macro tool in the VBA module. Some of these data collections are briefly discussed below.

- In the Bodies collection, the names of all the parts contained in the file can be found, and thus any one of them can be extracted and displayed by accessing their contents.
- In Shapes collection, name of every single feature created in CATIA can be found.
- In the Sketches collection, all the basic designs done to create the part are contained. One can extract the X, Y, Z coordinates of the origin of the sketch from which the component has been created. The feature position in space can be extracted in order to place it with respect to others and extract their relations and connections. One can thus determine the neighboring features.
- In the Parameters collection, the name and the value of the different elements inside a feature can be extracted by navigating through the different levels of the feature tree. One can extract the parent of the feature in order to establish the connection between them and then extract the coordinates of the feature end points and thus determine its length.
- In the AnnotationSets collection, information about tolerances, surface finish and datums can be extracted, and thus path to the reference surface to which the datum is applied can be obtained. The connection between the datums and reference surfaces can be established through geometrical tolerances connected to the datum. This is possible because, in CATIA, the datum is related to one surface, and at the same time the geometrical tolerance is connected to another surface, and the third connection is

between the datum and geometrical tolerance. In the end, one can use these three links to establish the two surfaces that are associated.
The information on the tool approach directions is determined by formulating rules. For example, if an external cylindrical surface has the largest diameter, then it is assigned the left-right approach direction. Then for all the surfaces to the left of it, the tool approach direction left is assigned, and for all other surfaces to the right of it, the tool approach direction right is assigned. In a similar manner, the tool approach directions for internal features such as holes can be determined.

2.2 Storing the extracted data

After having extracted all the necessary data, their types are known and one can create variables of the same type to store their values. For example, all the names are of the type String and the values are of the type Double. Also there exists the data type ValueString, e.g. 50mm, that is composed of a number followed by a string of characters. In order to store this value, the string has to be separated from the number to be able to perform mathematical operations on them. Special variables to store the data and containing as many attributes as necessary have been created, e.g. feature.Name, feature.Diameter,feature.Length,feature.Internal,feature.StartPoint,feature.PerpendicularToPrincipalAxis and so on. The feature recognition software looks for data required by the CAPP system and stores them in the created variables, so that one can work on this data, do mathematical operations on them, and retrieve them when necessary.

2.3 Generation of the output data files

The developed feature recognition software module generates the output data as two data files in the format required by the process planning modules of machining operations selection and set-up planning. The first file includes, for each feature, the feature index, its name, its diameter or width, the dimensional tolerance and the surface finish. The second file includes, for each feature, the index, the name, the type (internal or external), the subtype (primary or secondary), the indices of the neighboring features and their names, the diameters of the feature and those of the neighboring features, the geometric tolerances and the approach direction of the cutting tool (Left, Right or both). Further, in order to introduce the feature names in the output file, proper translation of the features names from those automatically assigned by CATIA has to be done in order to conform to the names used by the CAPP system (e.g. External Step, External Taper, Hole, Face, Slot, etc). Further explanations of functioning of the data extraction module that has been developed are given in Section 5.

3. DEVELOPED NEURAL NETWORK BASED METHODOLOGY FOR SELECTION OF MACHINING OPERATIONS

The key issues of the proposed ANN based methodology (Deb [32]) for machining operations selection in rotationally symmetrical parts will be discussed below. It takes in as input the data file containing information on feature types and their attributes from the feature recognition module and is capable of selecting all possible machining operations.

3.1. Gathering of domain knowledge for formulating the thumb rules

A set of thumb rules has been developed to represent the prior domain knowledge available on machining operations selection. These rules have been employed to prestructure the input layer of the neural

network to take advantage of the fact that prior domain knowledge can help reduce the complexity of learning in ANN. Further, they have been used to serve as guidelines for choosing the input patterns of training examples for the ANN. Domain knowledge for formulating the above rules was collated from machining handbooks and textbooks ([33],[34],[35]) and expressed as:
IF (Feature is of the type Feat) AND… (Dimension of the Feature is Dim_i) AND… (Tolerance of the Feature is Tol_j) AND… (Surface finish of the Feature is SF_k), THEN (Operation sequence is $OpSeq_l$)

The different features and ranges of dimensions, tolerances and surface finish are given in Table 1 and the machining operations sequences are in Table 2. An extract from the thumb rules to be learnt by the neural network model is shown in Figure 1.

Feature type	Dimensions (Diameter or Width)	Tolerance	Surface finish
Hole	Up to 50mm (Length/Diameter ratio upto 10)	3-390μm	0.04-80μm
External step	Up to 50mm	4-390μm	0.08-80μm
Groove	Up to 50mm	40-250μm	2.5-20μm
Face	Up to 50mm	10-390μm	1.25-80μm
Slot	Up to 6mm	6-190μm	0.32-20μm
External taper	Up to 50mm	4-390μm	0.08-80μm
External thread	Up to 50mm	10-390μm	1.25-80μm

Table 1 Ranges of dimension, tolerance and surface finish considered for different features

Operation Sequence	Used for machining	Operation Sequence	Used for machining
Drill	Hole	Rough turn	Face
Drill-Counter Bore		Rough turn-Semi finish turn	
Drill-Counter Bore-Rough Ream-Semi finish Ream		Rough turn-Semi finish turn-Finish turn	
Drill-Rough Bore		Rough mill	Slot
Drill-Rough Bore-Semi finish bore		Rough mill-Semi finish mill	
Drill-Rough Bore-Semi finish Bore-Finish Bore		Rough mill-Semi finish mill-Finish mill	
Drill-Rough Bore-Semi finish Bore-Rough Grind-Semi finish Grind		Rough Turn	External taper
Drill-Rough Bore-Semi finish Bore-Rough Grind-Finish Grind		Rough Turn-Semi finish turn	
Drill-Rough Bore-Semi finish Bore-Grind-Hone		Rough Turn-Semi finish Turn-Finish Turn	
Deep hole drill		Rough Turn-Semi finish Turn-Rough Grind	
Rough Turn	External step	Rough Turn-Semi finish Turn-Rough Grind-Semi finish grind	
Rough Turn-Semi finish turn		Rough Turn-Semi finish Turn-Rough Grind-Finish Grind	
Rough Turn-Semi finish Turn-Finish Turn		Rough Turn-Threading	External thread
Rough Turn-Semi finish Turn-Rough Grind		Rough Turn-Semi finish turn-Threading	
Rough Turn-Semi finish Turn-Rough Grind-Finish Grind		Rough Turn-Semi finish Turn-Finish Turn-Threading	
Groove turning (one pass)	Groove		
Groove turning (two passes)			

Table 2 Operation sequences considered for machining different features

IF (Feature is a Hole) AND (Diameter of the Hole is 10-18 mm) AND (Tolerance of the Hole is 5-18 μm) AND (Surface finish of the Hole is 0.04-1.25 μm), THEN (Operation sequence is Drilling-Rough Boring-Semi finish Boring-Grinding-Honing).
IF (Feature is a Hole) AND (Diameter of the Hole is 10-18 mm) AND (Tolerance of the Hole is 8-11 μm) AND (Surface finish of the Hole is 0.08-0.16 μm), THEN (Operation sequence is Drilling-Rough Boring-Semi finish Boring-Rough Grinding-Finish Grinding).
IF (Feature is a Hole) AND (Diameter of the Hole is 10-18 mm) AND (Tolerance of the Hole is 11-18 μm) AND (Surface finish of the Hole is 0.16-0.63 μm), THEN (Operation sequence is Drilling-Rough Boring-Semi finish Boring-Rough Grinding-Semi Finish Grinding).

Figure 1. Extract from the set of the thumb rules on selection of machining operations sequences for holes

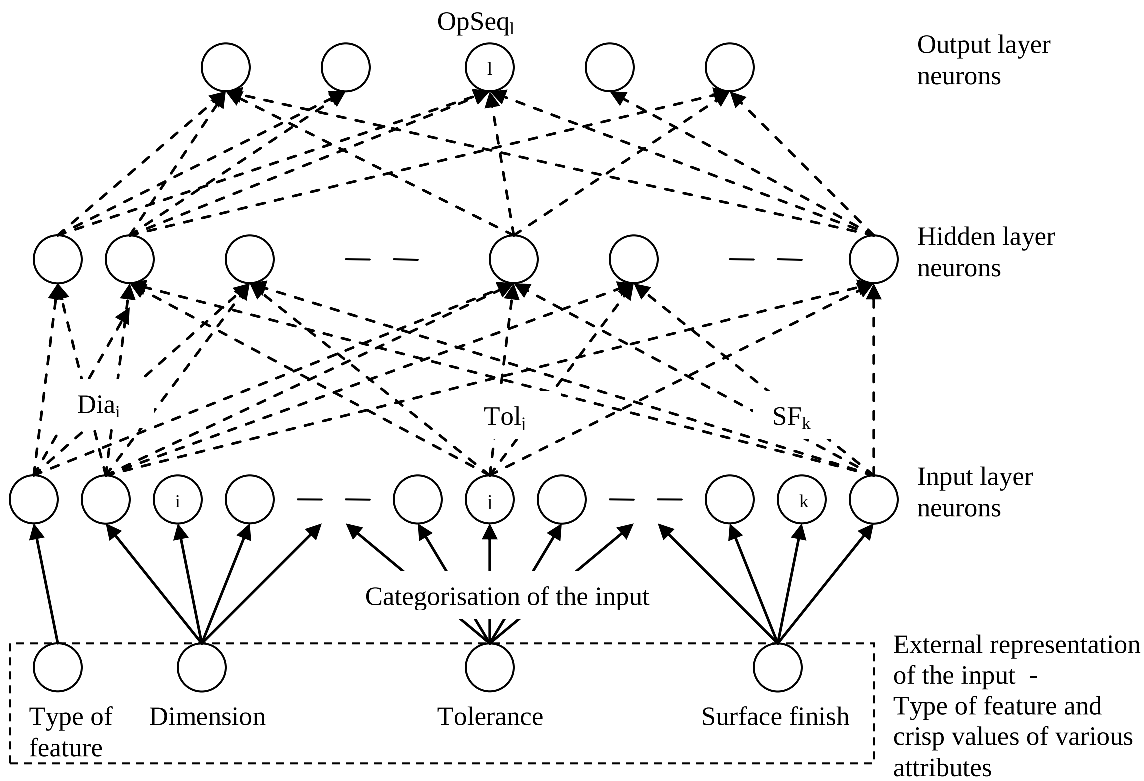


Figure 2. Topology of the proposed neural network model

3.2. Topology of the ANN model and the format of representation of the input and output variables

The topology of the proposed ANN model is shown in the Figure 2. The input variables consist of the feature type and its attributes obtained from the feature recognition module. The feature type is represented by integer values from 1 to 7 and their attributes represented by numerical values. The crisp values of these four variables constitute the external representation of input to the ANN. For example, for a hole of diameter 15 mm, tolerance 15 µm and surface finish 0.04 µm, it is the following input vector.

Column number	1	2	3	4
Value	1	15	15	0.04

Next it is translated into the format of internal representation of input before presenting it to the ANN. In other words, the crisp values of feature attributes are categorised into sets corresponding to all possible different ranges of dimension, tolerance and surface finish, encountered in the 'IF' part of the thumb rules. This is accomplished by simple classification rules. For example, let the diameter range encountered in the antecedent 'IF' part of the rule be 10 to 18 mm, then the rule like the one shown below may be used for assigning diameter values to the corresponding diameter set:

IF (feature is a hole) AND (its diameter lies between 10 and 18 mm), THEN (it is assigned to the diameter set for hole, 10-18 mm with a membership value of 1 or otherwise 0).

In a similar manner, rules may be used for assigning tolerance and surface finish values to the corresponding tolerance and surface finish sets.

The ANN input layer is designed such that one node is allocated for each of the feature types and the above sets of feature attributes. The number of nodes in the input layer is equal to one plus the number of all the possible different ranges of feature attributes encountered in the antecedent 'IF' part of the rules. In the 'IF' parts of the thumb rules, there are 38 diameter ranges, 168 tolerance ranges and 33 surface finish ranges. Therefore, the number of input layer nodes is 240 (=1+38+168+33). So the machining features and their attributes are represented as a vector of 240 elements forming the input pattern to the ANN. For example, the input pattern for a hole of diameter 15 mm, tolerance 15 µm and surface finish 0.04 µm is represented by the following.

Column number	1	2	3	4	5	6	7	..	64	65
Value	1	0	0	0	1	0	0	0	1	0

Column number	66	67	..	208	..	..	240
Value	0	0	0	1	0	..	0

In the above vector, the column number 1 stands for the feature type, column numbers [2-7], [8-14], [15-19], [20-25], [26-27], [28-34], [35-39] stand for the sets corresponding to the different ranges of diameter of the hole, external step, groove, face, slot, external taper and external thread respectively. Column numbers [40-93], [94-123], [124-135], [136-153], [154-159], [160-189], [190-207] stand for the sets corresponding to the different ranges of tolerance of the above seven features respectively. Column numbers [208-217], [218-223], [224-225], [226-228], [229-231], [232-237], [238-240] stand for the sets corresponding to the different ranges of surface finish of the above seven features respectively.

The output variables comprise of the feasible operation sequences. The output layer of the ANN is designed such that one node is allocated to each feasible operation sequence found in the 'THEN' part of the rules. Each output layer node either assumes a nonzero value to indicate suitability of an operation sequence or zero otherwise. The number of nodes in the output layer is equal to the number of all the feasible machining operation sequences found in the consequent part of the rules. In the thumb rules developed, 33 different operation sequences have been found in the consequent part of the rules. So the number of nodes in the output layer is 33. With those 33 neuron values, the feasible alternative machining operation sequences are represented as an output pattern vector. For machining the hole of diameter 15 mm, tolerance 15 µm and surface finish 0.04, the operation sequence is Drilling - Rough Boring - Semi finish Boring – Grinding - Honing, which is represented in the above format by the following vector:

Column number	1	2	3	4	5	6
Value	0	0	0	0	0	0

Column number		7	8	9	..	33
Value		0	0	1	0	0

In the above vector, each of the column numbers [1-10], [11-16], [17-18], [19-21], [22-24], [25-30] and [31-33] stand for a feasible operations sequence for machining the different features namely hole, external step, groove, face, slot, external taper and external thread respectively.

3.3 Training and validation of the ANN

The standard back-propagation algorithm is used as the learning mechanism for the ANN. The training examples are prepared using the thumb rules. Table 3 shows a training dataset prepared using the rules of Figure 1. The input pattern of each training example, in its external representation format, has 4 columns representing the type of feature and its attributes, and the output pattern has 33 columns representing the various feasible machining operation sequences. The input patterns for the training examples have been chosen in such a way that they cover the entire range of the feature type, diameter, tolerance and surface finish found in the antecedent part ‘IF’ of the rules given in Fig. 1. From Table 3, it can be found that for all the training examples, a dimension of 15 mm has been chosen as the whole diameter. By doing so, it is automatically assigned to the node for the set corresponding to diameter range 10-18 mm by using the classification rule; it is sufficient to represent all the possibilities in the range of 10 to 18 mm. In a similar manner, the representative values for tolerance and surface finish have been chosen. Then by different combinations of these values of feature type, diameter, tolerance and surface finish, the training examples of Table 3 have been arrived at. A total of 318 training examples have been developed using all the thumb rules.

Table 3 Examples of input and output patterns for machining operations selection

No	**Input pattern**				**Output pattern (feasible machining operation sequences)**								
	Feat type	**Dia**	**Tol**	**Surf finish**									
	1	**2**	**3**	**4**	**1**	**..**	**6**	**7**	**8**	**9**	**10**	**..**	**33**
1	1	15	5	0.04	0	0	0	0	0	1	0	0	0
2	1	15	5	0.063	0	0	0	0	0	1	0	0	0
3	1	15	5	0.08	0	0	0	0	0	1	0	0	0
4	1	15	5	0.16	0	0	0	0	0	1	0	0	0
5	1	15	5	0.63	0	0	0	0	0	1	0	0	0
6	1	15	8	0.04	0	0	0	0	0	1	0	0	0
7	1	15	8	0.063	0	0	0	0	0	1	0	0	0
8	1	15	8	0.08	0	0	0	0	1	1	0	0	0
9	1	15	8	0.16	0	0	0	0	0	1	0	0	0
10	1	15	8	0.63	0	0	0	0	0	1	0	0	0
11	1	15	11	0.04	0	0	0	0	0	1	0	0	0
12	1	15	11	0.063	0	0	0	0	0	1	0	0	0
13	1	15	11	0.08	0	0	0	0	0	1	0	0	0
14	1	15	11	0.16	0	0	0	1	0	1	0	0	0
15	1	15	11	0.63	0	0	0	0	0	1	0	0	0

The commercial software package *Neuframe V4* [36] is used to simulate the ANN. After a number of trials, the following optimum architecture and parameters of the ANN have been chosen:

Number of hidden layers	1
Number of hidden layer nodes	9
Mode of training	Pattern
Learning rate	0.4
Momentum rate	0.9

The training has been performed until the error reached 0.5%. The number of iterations needed was 18471 and the time taken was about 16 minutes on a Pentium 4, 1.7 GHz Personal Computer with 1 GB RAM. The performance of ANN has been tested on several input feature attributes, which have not been used as part of the training dataset. They indicated a good correlation with the Machining Data Handbook's recommendations.

4. PROPOSED EXPERT SYSTEM BASED METHODOLOGY FOR SET-UP PLANNING

The key issues of the proposed expert system based methodology (Deb [32]) for set-up planning will be discussed below. It is capable of generating set-up plans automatically by taking in as input the data files containing information about the features present in the part from the feature recognition module developed in Section 2, and the selected machining operations from the machining operations selection module developed in Section 3. It has been implemented by using CLIPS rule-based expert system shell [37].

4.1 Development of the overall structure of the expert system

The expert system is shown in Figure 3. It mainly consists of a database, a knowledge base and an inference engine, the details of which are given below.

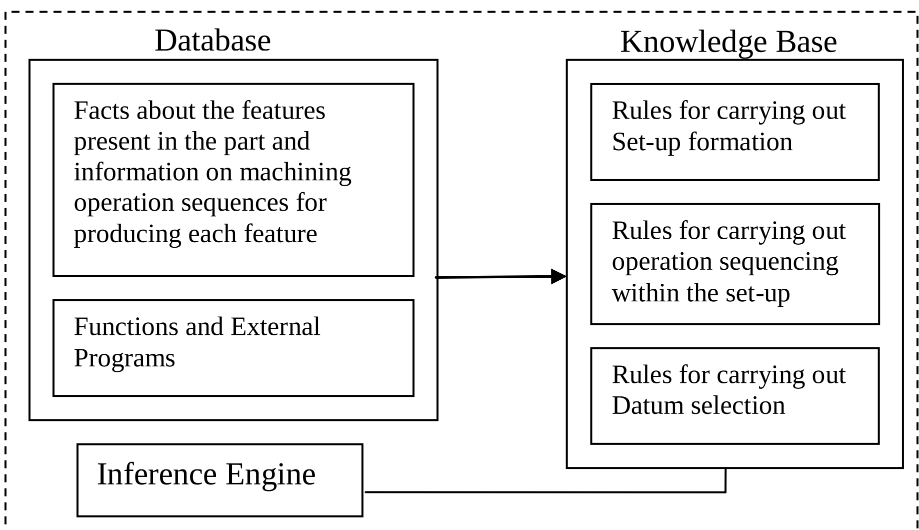


Figure 3. Overall structure of the set-up planning module which is based on expert system

4.2 Database

The database comprises of data files containing information about features present in the part and machining operations as well as functions and external programs for performing calculations. The input information includes feature types, dimensions, geometric tolerance relationships between features, and TADs for each feature, obtained from the feature recognition module developed in Section 2. It also includes machining operations obtained from the process selection module developed in Section 3. A format for representation of input data has been developed as shown in Figure 4(a), using a template which is a list of named fields called slots used to store values. For example, the input data on a feature may be entered as follows:

```
(feature (number 4)
(name EXTERNAL_STEP)
(type EXTERNAL)(subtype PRIMARY)
(adjacent_features 3 5)
(adjacent_features_names FACE
EXTERNAL_TAPER)
(step_diameter 49)(TAD right-left))
```

A format for representation of input data for machining operations has been developed using the template as shown in Fig. 4(b). For example, the input data for a machining operation may be entered as follows:

```
(operation (number 401)(type turn)
(machining_stage rough)(on-feature 4)
(TAD right-left)
(relation-with-feature 2 13)(tolerance 0.1 0.2))
```

The input data is saved as a data file with extension .clp.

```
(deftemplate MAIN::feature
(slot number (type INTEGER) (default ?NONE))
(slot name (type SYMBOL) (allowed-symbols CHAMFER EXTERNAL_STEP FACE GROOVE HOLE KEYWAY
EXTERNAL_TAPER THREAD HOLE))
(slot type (type SYMBOL) (allowed-symbols EXTERNAL INTERNAL))
(slot subtype (type SYMBOL) (allowed-symbols PRIMARY SECONDARY))
(slot secondary_feature_to (type INTEGER) (default ?DERIVE))
(multislot adjacent_features (type INTEGER) (default ?DERIVE))
(multislot adjacent_features_names (type SYMBOL) (allowed-symbols CHAMFER EXTERNAL_STEP FACE
GROOVE HOLE KEYWAY EXTERNAL_TAPER THREAD HOLE))
(multislot reference_features (type INTEGER) (default 0))
(slot step_diameter (type NUMBER))
(multislot adjacent_step_diameters (type NUMBER))
(slot hole_diameter (type NUMBER)) (slot hole_depth (type NUMBER))
(multislot adjacent_hole_diameters (type NUMBER))
(multislot adjacent_hole_depths (type NUMBER))
(slot TAD (type SYMBOL) (allowed-symbols left right right-left) (default ?NONE)))
```

(a) **Feature template**

```
(deftemplate operation
(slot number (type INTEGER) (default ?NONE))
(slot type (type SYMBOL) (default ?NONE))
(slot machining_stage (type SYMBOL) (allowed-symbols rough semifinish finish) (default rough))
(slot on-feature (type INTEGER) (default ?NONE))
(slot TAD (type SYMBOL) (allowed-symbols left right right-left) (default ?NONE))
(multislot relation-with-feature (type NUMBER) (default 0))
(multislot tolerance (type NUMBER) (default ?DERIVE)))
```

(b) Operation template

Figure 4. Format of representation of the input data

```
(deftemplate MAIN::operation
(slot number (type INTEGER) (default ?NONE))
(slot type (type SYMBOL))
(slot machining_stage (type SYMBOL) (allowed-symbols rough semifinish finish) (default rough))
(slot setup-cluster (type SYMBOL) (allowed-symbols left right))
(multislot preceding_opn (type INTEGER) (default 0)))
```

(c) Modified Operation template

Figure 4. Format of representation of the input data (Contd.)

4.3 Knowledge base

The knowledge base consists of rules to solve the different set-up planning tasks. The inference engine is based on a forward chaining strategy.

4.3.1 Knowledge base for solving set-up formation

A set of rules are used for clustering the machining operations into two set-ups: right and left, after considering TADs of the features and the tolerance relationships between them. For example, if a machining operation on a feature is encountered having both TADs (left and right) and which has tolerance relationships with more than one feature each having a single TAD, then the operation is assigned to the same set-up as the operation on the other feature with which it has the tightest tolerance. The example of a rule is shown in Figure 5. It states that if there exists an "operation" about machining a feature A having both TADs and tolerance relationship with more than one feature with a single TAD, and if the feature B with which it has the tightest tolerance has the TAD "left", then operation on A is also assigned the TAD "left" and the same set-up as operation on B. The above rule calls three functions: "feature-with-tightest-tolerance" that returns the feature identifier having the tightest tolerance relationship with A, "update-relation-with-feature" and "update-tolerance" that are used to update the "relation-with-feature" and the "tolerance" slots respectively by removing the tolerance relationships between features that have been already satisfied.

4.3.2 Knowledge base for solving operation sequencing

The decision on determining sequences of operations is based on precedence constraints between features and manufacturing logic in ordering the operations. Rules have been developed based on heuristic and expert knowledge from machining textbooks and handbooks. For example, there may be a constraint requiring that subsequent features should not destroy the properties of features machined previously, e.g. machining of a groove prior to the adjacent thread (Figure 6). Figure 7 shows the rule for the above example. It states that, if there exists a feature A of the type thread having one of the adjacent features B of the type groove, then the precedence relationship between the machining operations on A and B will be first machining of B, followed by machining of A.

For sequencing of operations, two types of manufacturing logic for ordering the operations are used: machining of external surfaces, followed by internal surfaces, and rough machining, followed by semi-finish machining, followed by finish machining. Another priority for operations sequencing is that for a certain set-up, the machining of the features is done starting from one end, while respecting the precedence constraints. It helps to reduce the tool travel distances and idle tool motion. The information about set-up cluster and preceding operations are incorporated as new slots into the "operation" facts template, which is redefined as shown in Figure 4(c).

Next the operations sequencing is accomplished using a set of rules. First two multi-field variables are defined namely, the set-up clusters from the left and the right. Then all the "operation" facts are scanned and a set of rules is used for assigning each operation to one of the two set-up clusters in the sequential order in which they must be performed. For example, a machining operation can be assigned to a set-up cluster only if all of its preceding operations have been assigned. Figure 8 gives some examples of rules. First, two global variables have been defined, namely "sequence-left-cluster" indicating the set-up cluster from left and "opn-left-cluster" indicating an operation belonging to it. The sample rule 1 states that if an operation n1 meant for rough-machining of an external step and belonging to the left set-up cluster is encountered, and if it has one preceding operation n2 belonging to the left set-up cluster and has been already assigned to the "sequence-left-cluster" variable, then operation n1 may be assigned to the "sequence-left-cluster" variable. The sample rule 2 is similar to sample rule 1 except that it is meant for semi-finish machining of an external step. The salience or priority in execution of rule 1 is higher than that of rule 2, signifying that if conditions for firing both the rules are satisfied, then the actions of rule1 are executed first followed by that of rule 2, which causes the rough machining operation to be assigned to the operations sequence ahead of the semi-finish machining operation.

```
(defrule sample_rule_setup_formation
        ?f1 <- (operation (TAD right-left))
        (test (>= (length$ (fact-slot-value ?f1 tolerance)) 2))
        (operation (TAD left) (on-feature =(feature-with-tightest-tolerance ?f1)))
=>      (modify ?f1 (TAD left) (relation-with-feature =(update-relation-with-feature ?f1))
(tolerance =(update-tolerance ?f1))))
```

Figure 5. Typical rule for set-up formation

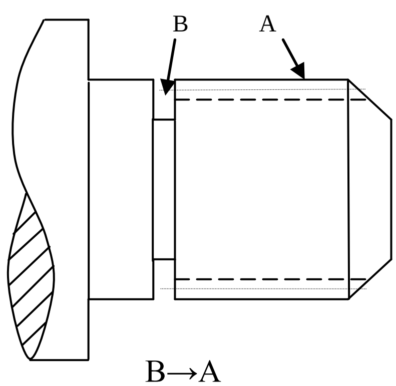


Figure 6. Example of a feature precedence relation

```
(defrule sample_rule1
        (feature (number ?A) (name THREAD) (adjacent_features $? ?B $?)
         (adjacent_features_names $? GROOVE $?))
⇨       (assert (precedence ?B ?A)))
```

Figure 7. Typical rules for deriving machining operation precedences

```
 (defglobal ?*sequence-left-cluster* = 0
              ?*opn-left-cluster* = 0 )
(defrule sample-rule-1
            (declare (salience 99))
            ?f1 <- (opn (number ?n1) (machining_stage rough) (setup-cluster left) (preceding_opn ?n2))
            (operation (number ?n1)  (on-feature ?N1)) (feature (number ?N1) (name EXTERNAL_STEP))
            (test (not (= ?n2 0)))
            (opn (number ?n2)  (machining_stage rough) (setup-cluster left))
=>          (bind ?*opn-left-cluster* (fact-slot-value ?f1 number))
            (if (subsetp (create$ ?n2) (create$ ?*sequence-left-cluster*))
               then  (bind ?*sequence-left-cluster* (create$ ?*sequence-left-cluster* ?*opn-left-cluster*))))
(defrule sample-rule-2
            (declare (salience 79))
            ?f1 <- (opn (number ?n1) (machining_stage semifinish) (setup-cluster left) (preceding_opn ?n2))
            (operation (number ?n1)  (on-feature ?N1)) (feature (number ?N1) (name EXTERNAL_STEP))
            (test (not (= ?n2 0)))
            (opn (number ?n2)  (machining_stage semifinish) (setup-cluster left))
=>          (bind ?*opn-left-cluster* (fact-slot-value ?f1 number))
            (if (subsetp (create$ ?n2) (create$ ?*sequence-left-cluster*))
               then  (bind ?*sequence-left-cluster* (create$ ?*sequence-left-cluster* ?*opn-left-cluster*))))
```

Figure 8. Typical rules for operation sequencing

4.3.3 Knowledge base for solving datum selection

The decision on selecting datum surfaces is based according to the following:
- select as datum the part surface, having orientation different from surfaces being machined and with tightest tolerance with one of the surfaces obtained in the set-up
- when no tolerance relationship exists, select as datum part surface having orientation different from surfaces being machined and largest diameter/longest cylindrical surface.

The above principles for datum selection have been implemented using a set of rules to determine the locating and clamping surfaces. Figure 9 gives an example of a rule. It states that if feature C encountered in the facts list is of type external step and if TAD for machining C is left and if C has tightest geometric tolerance relationship with feature X of type external step and if TAD for machining X is right, then external cylindrical surface of X may be chosen as clamping surface and vertical surface of X may be chosen as locating surface for the left set-up.

```
(defrule sample-rule-1
            (feature (number ?c) (name EXTERNAL_STEP))
            ?f1 <- (operation (on-feature ?c) (TAD left))
            (test (>= (length$ (fact-slot-value ?f1 tolerance)) 2))
            (operation (on-feature =(feature-with-tightest-tolerance ?f1)) (TAD right))
=>          (assert (datums_selected (setup left) (clamping_surface =(feature-with-tightest-tolerance ?f1)) (locating_surface
=(feature-with-tightest-tolerance ?f1)))))
(defrule MAIN::sample-rule-2
            (not (operation (TAD left) (relation-with-feature ~0)))
            (feature (number ?a) (type EXTERNAL) (name EXTERNAL_STEP))
            (feature-with-largest-dia (number ?a)) (operation (on-feature ?a) (TAD right))
    ⇨          (assert (datums_selected (setup left) (clamping_surface ?a) (locating_surface ?a))))
```

Figure 9. Typical rules for datum selection

5. ILLUSTRATIVE EXAMPLE

A shaft shown in Figure 10 is used to demonstrate the application of the proposed methodologies. The part contains the following 30 machining features: numbers 1, 3 and 14 are of the type face, features 2, 4, 6, 7, 8, 9 and 13 are of the type external step, feature 5 is of the type external taper, features 10 and 12 are of the type groove, feature 11 is of the type external thread, features 15, 16, 17 and 18 are of the type hole, feature 19 (8 in number) is of the type hole, and feature 20 (4 in number) is of the type slot. The TAD for machining features 1, 2, 3, 15 and 16 is left, the TAD for machining features 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 18 and 20 is right, and the TAD for machining features 4, 17 and 19 may be either left or right. Feature 4 has geometric tolerance relationships (shown in Figure 11) of 3μm, 5μm and 4μm respectively with features 2, 7 and 13. The part has been modeled using the commercial CAD software, CATIA, and Figure 11 shows the feature tree of the part in CATIA. The information about the different features present in the part has to be extracted from the CAD datafiles of the part. The results of the output when feature recognition program is executed show that all the elements have been recognized. For example, the sketch name and coordinates that are used to create the cylindrical feature Pad.1 in Figure 11, has been extracted by the feature recognizer and are shown in Figure 12(a). After comparing the results obtained from the feature recognizer with the feature tree of the part shown in Figure 11, it was found that the software was able to recognize all the sketches as well as all the data needed by the CAPP system. Figure 12(b) shows an extract of the output from the feature recognizer illustrating the features and the values of their attributes. The following explains how the feature recognition of a cylindrical surface has been done. By reading the contents of the shapes collection, the software detects the cylindrical surface and gets into the sublist of attributes to access them. The end points of the feature are obtained and thus its length. Next the parent of the feature is located and thus the sketch on which it is based. Once the name of the sketch is found, it is possible to get into the Sketches collection and to retrieve its coordinates in order to locate the feature in the space, thus the neighbouring features may be established. Also, it is possible to extract the constraints linked to the sketch profile so that the radius can be extracted. In Fig. 12(b), for the cylindrical surface 1 (Pad.1), the position of the starting point from the origin (2 mm) and that of the end point (0 mm) have been extracted, thus the length of the feature (2 mm) is obtained. The radius (15mm) is also extracted. An extract from the two output files for the feature 12 of the type groove is given below:

File 1:
(feature (number 12)
(name GROOVE) (feature_diameter 14)
(feature_max_toler 0,05)
(feature_min_toler 0))

File 2:
(feature (number 12) (name GROOVE)
(type EXTERNAL) (subtype PRIMARY)
(adjacent_features 13 11)
(adjacent_features_names EXTERNAL_STEP THREAD) (TAD Right))

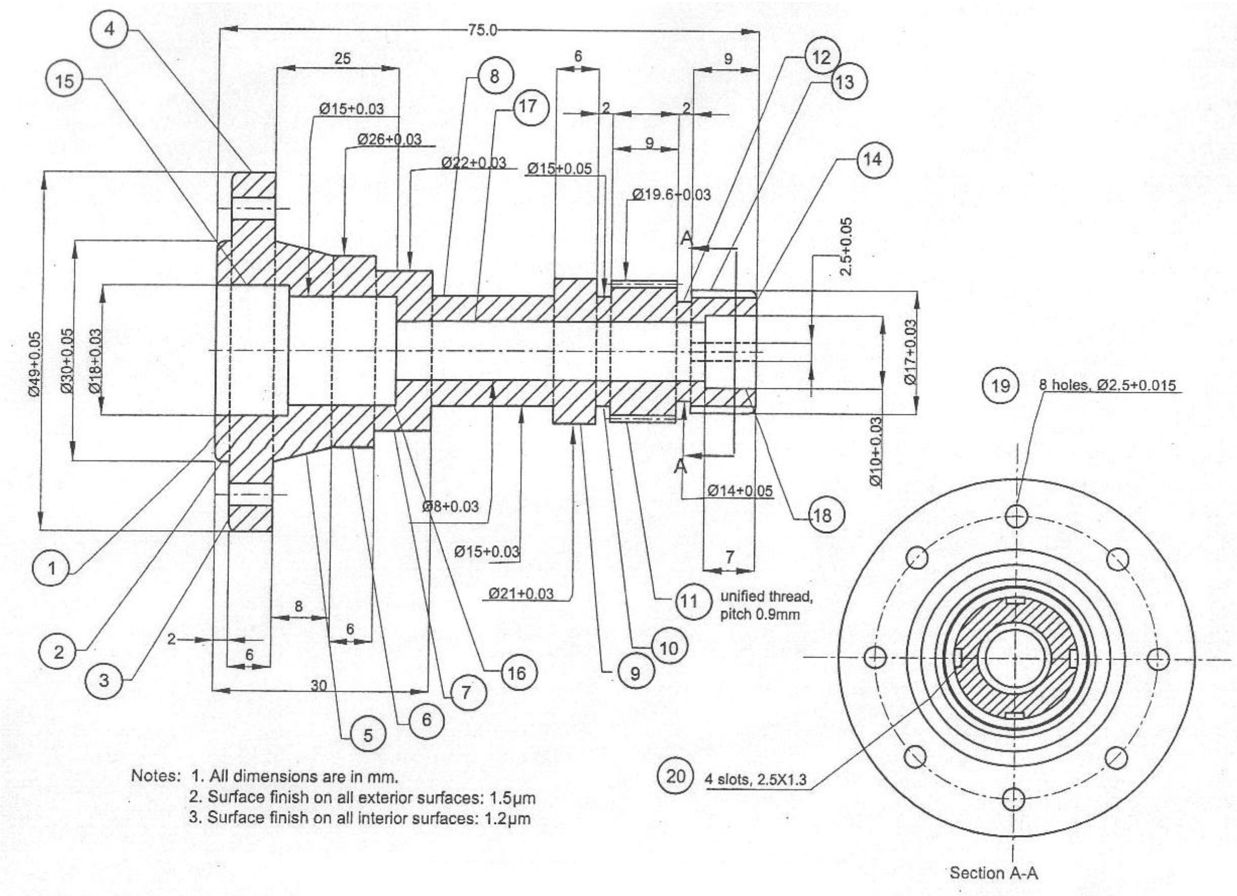


Figure 10. A Rotationally Symmetrical Part

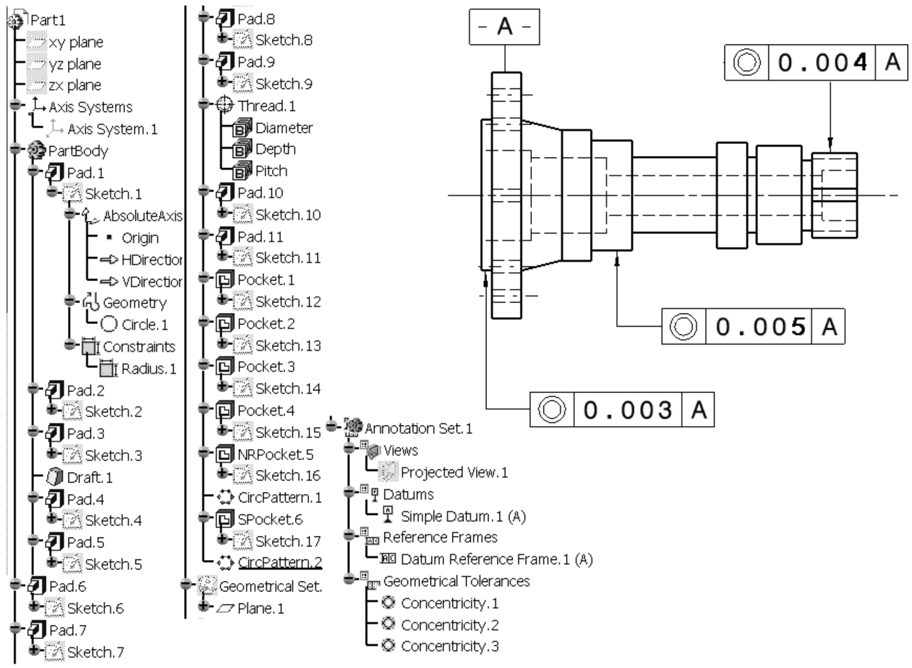
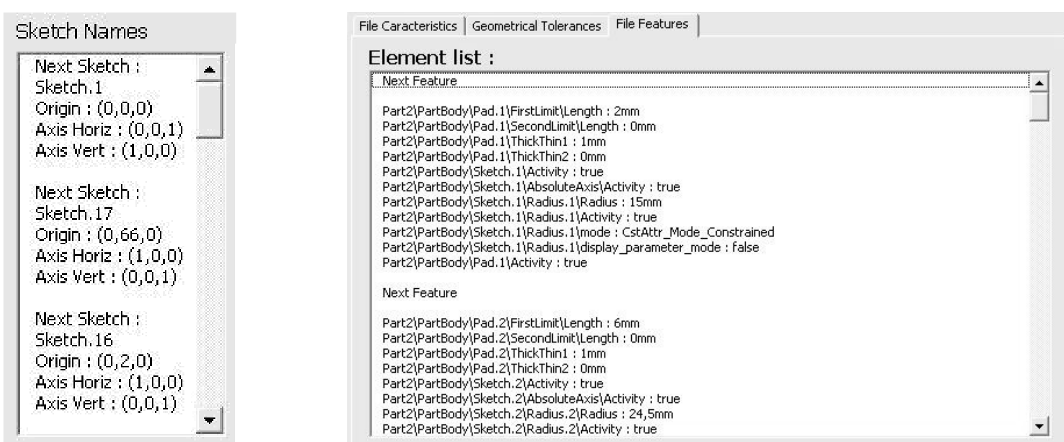


Figure 11. Feature Tree of the Part in CATIA with details of Pad.1



(a) (b)

Figure 12. Extract from Results of the Output from the Feature Recognizer

Next the machining operation sequences have to be determined. After presenting the type, dimension, tolerance and surface finish of each feature to the input layer of ANN, all the possible machining operations for producing each feature are generated automatically as shown in Table 4. The above results exhibit a good correlation with the Machining Data Handbook's recommendations. They will then form the input for the set-up planning module. It took less than 5 seconds on a Pentium 4, 1.7 GHz PC 1 GB RAM to generate the above.

Table 4 Machining operations generated by the neural network for producing different features of the part shown in Fig. 10 (Alt. stands for Alternative)

Feature identifier	Feature type	Operation sequences generated by the neural network
1,3,14	Face	Rough turn→ Semi finish turn→ Finish turn
2,4, 6,7,8,9,13	External step	Alt. 1: Rough Turn→ Semi finish Turn→ Finish Turn Alt. 2: Rough Turn→ Semi finish Turn→ Rough Grind
5	External taper	Alt. 1: Rough Turn→ Semi finish Turn→ Finish Turn Alt. 2: Rough Turn→ Semi finish Turn→ Rough Grind
10,12	Groove	Groove turning (two passes)
11	External thread	Rough Turn→ Semi finish Turn→ Finish Turn→ Threading
15,16,17,18	Hole	Alt. 1: Drill→ Counterbore→ Rough Ream→ Semi finish Ream; Alt. 2: Drill→ Rough Bore→ Semi finish Bore→ Finish Bore; Alt. 3: Deep hole drill
19	Holes X 8 nos.	Alt. 1: Drill-Rough Bore-Semi finish Bore-Finish Bore ; Alt. 2: Deep hole drill
20	Slot X 4 nos.	Rough mill-Semi finish mill

Next the set-up plan for machining the part shown in Figure 10 has to be determined. The machining operations selected are shown in Table 5. The above information is represented in the input data format of CLIPS following the syntax given in the template definition of "features" and "operations", and is stored in data files with the extension .clp. These data files are then loaded into the CLIPS environment and the expert system program is executed. Table 6 summarises the results of the output generated that includes the group of operations in each set-up, the operations sequence and the method of locating and clamping the part in each set-up. It took a little over 2 minutes on a Pentium 4, 1.7 GHz PC with 1GB RAM to generate the above output. The results indicate that the machining of rotationally symmetrical features of the part on CNC lathe has to be carried out in two set-ups. The machining operations on 1, 2, 3, 15 and 16 have been assigned to the left set-up since their TAD is left. Similarly the machining operations on 5, 6, 7, 8, 9, 10, 11, 12, 13, 14 and 18 have been assigned to the right set-up since their TAD is right. The machining operations on 4 have been assigned to the left set-up because 4 has a tighter geometric tolerance relationship with 2 as compared to that with 7 and 13. The machining of features 19 and 20 has to be carried out in two different set-ups on the CNC milling machine. Also in Table 6, the different machining operations have been listed in the sequence in which they are to be performed in each set-up after considering the various precedence constraints as well as the manufacturing logic in sequencing as discussed in Section 4.3.2. Further, the features to be used for locating and clamping the part for each set-up have been identified after considering the heuristic principles discussed in Section 4.3.3.

Table 5 Machining operation sequences for producing different features of the part shown in Figure 10

Feature identifier	Feature type	Operation description	Operation identifier
1	Face	Rough turn	101
		Semi finish turn	102
		Finish turn	103
2	External step	Rough Turn	201
		Semi finish Turn	202
		Finish Turn	203
3	Face	Rough turn	301
		Semi finish turn	302
		Finish turn	303
4	External step	Rough Turn	401
		Semi finish Turn	402
		Finish Turn	403
5	External taper	Rough Turn	501
		Semi finish Turn	502
		Finish Turn	503
6	External step	Rough Turn	601
		Semi finish Turn	602
		Finish Turn	603
7	External step	Rough Turn	701
		Semi finish Turn	702
		Finish Turn	703
8	External step	Rough Turn	801
		Semi finish Turn	802
		Finish Turn	803
9	External step	Rough Turn	901
		Semi finish Turn	902
		Finish Turn	903
10	Groove	Groove turning (two passes)	10
11	External thread	Rough Turn	1101
		Semi finish Turn	1102
		Finish Turn	1103
		Threading	11
12	Groove	Groove turning (two passes)	12
13	External step	Rough Turn	1301
		Semi finish Turn	1302
		Finish Turn	1303

Feature identifier	Feature type	Operation description	Operation identifier
14	Face	Rough turn Semi finish turn Finish turn	1401 1402 1403
15	Hole	Drill Rough Bore Semi finish Bore Finish Bore	1501 15001 15002 15003
16	Hole	Drill Rough Bore Semi finish Bore Finish Bore	1601 16001 16002 16003
17	Hole	Drill Rough Bore Semi finish Bore Finish Bore	1701 17001 17002 17003
18	Hole	Drill Rough Bore Semi finish Bore Finish Bore	1801 18001 18002 18003
19	Hole	Drill Rough Bore Semi finish Bore Finish Bore	1901 19001 19002 19003
20	Slot	Rough mill Semi finish mill	2001 2002

Table 6 Set-up plan recommended by the expert system based set-up planner

Machine tool	Set-up	Sequential order of machining operations	Datum features	
			Clamping	Locating
CNC lathe	Left	101 201 401 301 102 202 402 302 103 203 403 303 17 1601 16001 1501 15001 16002 15002 16003 15003	13	14
	Right	1401 1301 11101 901 701 601 801 501 1402 1302 11102 902 702 602 802 502 1403 1303 11103 903 703 603 803 503 12 10 11 1801 18001 18002 18003	4	3
CNC milling machine	-	1901 19001 19002 19003	13	14
CNC milling machine	-	2001 2002	4	3

6. DISCUSSION

In this article, we have presented an efficient method of machining operations selection using ANNs, which is much easier to train and use than those which had been proposed earlier. The set-up planning is done exclusively by an expert system which is modular in nature and is convenient to modify and to use. Both these modules have been integrated with an automated data extraction system that obtains the necessary data from the CAD database and provides them to the process planning modules in a fully automated manner. These three topics are briefly discussed below.

In the approach proposed here, the machining operations selection is done by an ANN. Unlike the previous publications that have used neural networks, the ANN approach proposed in this paper recommends all possible alternative operation sequences for machining a certain feature. This provides an opportunity for choosing an optimal sequence; for example, to minimize the cost. The ANN model in this paper has been prestructured with prior domain knowledge in the form of thumb rules, with each input layer node representing a range of input variables found in the 'IF' part of the rules and each output layer node a possible machining operation sequence found in the 'THEN' part of the rules. In addition, a more systematic method of choosing training examples has been proposed here. In neural network approaches by previous researchers, training of the network could become an arduous task since there were no guidelines for choosing of input patterns of the training examples, and a lot of trial and error was involved. In the present approach, the thumb rules developed for selection of machining operations are used to serve as guidelines during the preparation of training examples. The input patterns have to be chosen in such a way that they activate one or more of those thumb rules. This approach results in a shorter training time of the neural network for a certain job and of course, this has a favorable effect on the practical utility of the method. Compared to the approaches such as decision trees, the method proposed here is more flexible because the modification of the knowledge base can be effectuated by merely retraining it.

As regards set-up planning, most of the previous expert system approaches had been developed for prismatic parts. Furthermore, in most of the previous approaches, a mixture of expert systems and some algorithmic approach had been adopted that is inflexible; to modify it, it might require rewriting of the original program, which could be tedious and time-consuming. In the present paper, a pure expert system approach is adopted to solve different set-up planning problems for rotationally symmetrical parts. Its modular nature gives added flexibility to the proposed approach. Any modification of the knowledge base can be done by modifying the rules that is less time consuming than modifying the original program with algorithmic approaches. However, care must be exercised to ensure that the new rules are consistent with the existing rules. Another of its important advantages is the fast computation time, which reduces the process planning time and hence the cost.

The data needed by the two process planning modules of machining operations selection and set-up planning is automatically extracted from the CAD database using the feature recognition module that has been presented in this paper. The necessary data are extracted and are stored in a common database and are subsequently used for process planning.

7. SCOPE FOR FURTHER WORK

The ANN methodology for machining operations selection may be expanded to include other features and it may be adapted to mill-turn and prismatic parts. The expert system based set-up planning methodology may be expanded by considering other constraints, e.g. fixturing. There is scope for optimization using AI approaches such as genetic algorithm. A direction for future research could be modification of the set-up planning methodology by considering normalized values of relative tolerances. Further work needs to be done on integration of the proposed modules with other modules of the CAPP system such as modules for machine tool and cutting tool selection, selection of cutting parameters, etc.

8. CONCLUSIONS

In this paper, a review of previous research has been given for automating the tasks of machining operations selection and set-up planning in generative CAPP systems. A methodology has been developed for automatic feature recognition and extraction of data from the CAD file of the part modeled by the commercial CAD software, CATIA. It is capable of extracting the data and storing them in datafiles in the format that is directly accessible by the process planning modules of machining operations selection and set-up planning. For machining operations selection of rotationally symmetrical parts, a novel back-propagation ANN methodology has been developed by prestructuring it with prior domain knowledge. It takes in attributes of each feature obtained from the feature recognition module and automatically selects all possible alternative machining operations. A comparison with approaches developed by previous researchers has been given. The advantages of the proposed approach over previously developed back-propagation ANN approaches are manifold. It simplifies the preparation of training examples and helps to better ensure that the entire problem domain is represented. It takes shorter time for preparation of the training examples and the computation time has been found to be reasonably fast. The modification of its knowledge base can be accomplished quickly by simply retraining it. Further, an expert system based set-up planning methodology has been developed for automating the tasks of set-up formation, operation sequencing and datum selection for rotationally symmetrical parts. It has been implemented by using the CLIPS rule-based expert system shell. It takes in information about different features present in the part obtained from the feature recognition module as well as information about machining operations obtained from the process selection module, and is capable of generating set-up plans automatically. The proposed approach is more flexible than the previously developed approaches based on combined expert system and algorithmic approaches particularly when it comes to modification of its knowledge bases. The example of a rotationally symmetrical workpiece has been analyzed using the proposed integrated methodology to demonstrate its potential for application in the real manufacturing environment. By this methodology, the feature recognition and extraction of data from the part model in CAD system and the process planning tasks of machining operations selection and the set-up planning of rotationally symmetrical machined parts can be accomplished automatically by investing a very limited amount of time, making them attractive and cost effective for industrial applications.

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