**Proceedings of DETC'02**
**ASME 2002 Design Engineering Technical Conferences**
**and Computer and Information in Engineering Conference**
**Montreal, Canada, September 29-October 2, 2002**

# DETC2002/CIE-34507

# ARTIFICIAL INTELLIGENCE BASED INFERENCE TECHNIQUES FOR AUTOMATED PROCESS PLANNING FOR MACHINED PARTS

**Sankha Deb**
Dept. of Mathematics and Industrial Engineering
École Polytechnique
PO Box 6079, Station Centre-ville
Montreal (Quebec) H3C 3A7 Canada
sankha.deb@lycos.com

**Kalyan Ghosh**
Dept. of Mathematics and Industrial Engineering
École Polytechnique
PO Box 6079, Station Centre-ville
Montreal (Quebec) H3C 3A7 Canada
kalyan.ghosh@polymtl.ca

## ABSTRACT

Many areas of research in manufacturing are increasingly turning to applications of Artificial Intelligence (AI). The problem of developing inference strategies for automated process planning in machining is one such area of successful application of AI based approaches. Given the high complexity of the process planning expertise, development of inference techniques for automated process planning is a big challenge to researchers. The traditional inference methods based on variant and generative approaches using decision trees and decision tables suffer from a number of shortcomings, which have prompted researchers to seek alternative approaches and turn to AI for developing intelligent inference techniques. In this article, we have reviewed, categorized and summarized the research on applications of AI for developing inference methods for automated process planning systems. We have described our ongoing research work on developing an intelligent inference strategy based on artificial neural networks for implementing machining process selection for rotationally symmetric parts.

**Keywords:** *Computer-Aided Process Planning, artificial intelligence, neural networks, machining process selection, machined parts.*

## INTRODUCTION AND BACKGROUND

In recent years, there has been a surge in application of Artificial Intelligence (AI) based techniques (Pham et al [1]), impacting many areas of the decision-making and reasoning process in the manufacturing engineering domain, in particular those that require human intelligence and are hard to formalize completely. They include process modeling, monitoring and control of machining processes, inspection, diagnosis and quality management, process planning and scheduling, etc. In this article, we shall focus on application of AI for developing inference techniques for automated process planning for machined parts. This has been established as a problematic area for manufacturing companies, who invariably end up with process planning systems that do not fully meet their needs.

The process planning in the machined parts domain is a task that interprets the design information of the part and prescribes appropriate machining operations to manufacture the part, consistent with the requirements set forth in the design. To fully or even partially automate this task would certainly provide very tangible benefits like reduced dependence on qualified process planners, reduced lead-time between design and manufacturing, greater uniformity in process planning, increased productivity, to mention a few. Furthermore, an automated process planning interface can provide a smooth transition from Computer-Aided Design (CAD) to Computer-Aided Manufacturing (CAM) and in the process help achieve CAD / CAM integration. As a result, there has been an explosion of interest in automating the task of process planning by using various Computer-Aided Process Planning (CAPP) approaches.

Traditionally in manual process planning, the human planner performs inference tasks with regard to various process planning decisions based on intuition and rules of thumb gained from his experience, his expertise such as, ability to understand and analyze the requirements for parts, ability to understand the interactions between the part, manufacturing, quality, cost and his knowledge of machine tools, cutting tools and their capabilities and so on. So naturally, development of inference techniques for automated process planning constitute a very difficult problem domain, where decisions are a complex network of reasoning and relationships. Therefore, development of inference techniques for automated process planning is a big challenge to researchers. Over the years, there have been considerable efforts in developing inference techniques based on variant approaches and generative approaches using decision trees and decision tables. The variant approach is based on retrieval of plans for similar parts from preexisting databases, followed by editing the plan with intervention of a human process planner to create a variant to suit the specific requirements of the part being planned. The generative approach, on the other hand, is based on generating process plan for each part from scratch without referring to existing plans and with minimal human intervention. However, the traditional inference methods as mentioned above suffer from a number of shortcomings. Only similar plan results can be generated, in particular, those results generated from the variant approach based inference technique. The traditional generative approach using decision trees and decision tables work effectively for relatively simple decision making processes; moreover, they are relatively static in terms of representing process knowledge. Any modification of the current knowledge would require rewriting of atleast a small portion of the original program. Furthermore, they lack ability to automatically acquire knowledge (knowledge acquisition bottleneck) and adaptability to any major changes in product design, which is a big drawback especially in today's manufacturing environment, where enterprises are required to constantly redesign their products and reconfigure their manufacturing systems. These have prompted researchers to seek alternative approaches to traditional inference techniques for implementing CAPP and turn to AI based approaches with a view to overcome the limitations that we observed with the traditional variant and generative based approaches. So far, various AI based approaches such as expert systems (Chang [2]), fuzzy reasoning methods and neural networks (Dagli [3]) have been explored to develop inference techniques for generative CAPP systems. The survey of research on application of AI shows that it holds a lot of potential and it can have a powerful impact on manufacturing productivity, quality of the generated plans, manufacturing lead time and cost, resulting in improved performance of CAPP systems. In this article, we have briefly reviewed, categorized and summarized the research on some applications of AI for developing inference methods for CAPP systems, and we have described our ongoing research work on developing an intelligent Artificial Neural Network based inference strategy for automated selection of machining operation sequences for rotationally symmetric parts.

The organization of the article is as follows. First of all, a survey of research is given on applications of AI for developing inference methods for CAPP systems. Then the methodology for developing the proposed neural network based inference strategy for generation of machining operation sequences is explained. Finally, an illustrative example showing application of the approach developed in the article and the results are presented.

## SURVEY OF RESEARCH ON APPLICATIONS OF AI FOR DEVELOPING INFERENCE METHODS FOR CAPP

To date, different AI based approaches have been explored to develop inference techniques for implementing various sub functions of CAPP. In the following section, the potentials of each approach and their role in realization of intelligent CAPP have been highlighted. The relative advantages and disadvantages of different AI based techniques have been identified and results of the survey have been presented.

### Expert system based inference methods

A number of expert systems based inference methods have been reported in literature. A knowledge-based approach for hole machining process selection has been reported by Khoshnevis et al [4]. It takes in manufacturing features as input and generates possible sequences of machining operations and their subdivisions. Wong et al [5] have proposed an expert system based module for automatic process selection and sequencing for machining of prismatic parts. First of all, it automatically selects the operation sequences for machining each surface of the part from the given input part description, while respecting the precedence relationships. The operation sequences are subsequently refined to include further all the secondary machining operations while maintaining the precedence relationships and then linearized to obtain the final feasible process sequence by grouping machining operations using the same machine tools and/or cutting tools together. The entire knowledge base required for selection of operation sequences, refinement knowledge and linearizing strategy was implemented by using a rule-based expert system. Sabourin et al [6] have used an expert system based approach that generates a sequence of machining operations using production rules, taking into account technological attributes of features of the part, modelled using a feature-based modeller. Next it generates the machining set-ups using a constraint programming strategy by taking into account various constraints. An expert system architecture for CAPP for rotational components has been developed by Younis and Waheb [7]. It incorporates an interviewer module that enables the user to enter the design of the part using features and activate the problem solving module to generate a process plan. An algorithm is used to first assign to each feature as many alternative machining operations as possible and appropriate values of operation parameters and machine tools. The next phase of the algorithm generates dummy process plans by all possible combinations of available operations by the developed combination algorithm. Finally using the final selection rules, the best process plan is chosen. Jiang et al [8] have developed a CAPP system that extracts form features, represented by a GT coding and automatically generates detailed process plans for prismatic components using a rule based expert system. Radwan [9] has reported development of an expert system based CAPP approach for machining of different kinds of surfaces and holes. Process capability matrices were developed for each surface type and an expert system employed to generate process plans by matching the surface parametric data and required quality with respect to the capability matrices of each surface type.

The knowledge based expert systems offer a number of advantages over traditional inference methods such as structured knowledge representation in the form of rules, an explicit inference route, explanation facility and ability to adapt to dynamic manufacturing environment to a limited extent by introduction of new rules manually.

However, in spite of its widespread use due to the advantages it has to offer, the expert systems suffer from such weaknesses as for example, its inability to infer when information provided is incomplete and inability to automatically acquire knowledge in the form of example data and increase of execution times with increase in number of process plan rules.

### Fuzzy reasoning based inference methods

There have been reports of applications of fuzzy reasoning in developing inference methods for CAPP. Hashmi et al [10] have developed a fuzzy reasoning method for selection of machining speed for a depth of cut and material hardness. Fuzzy sets were constructed for input variable, hardness and output variable, speed. The necessary production rules were constructed based on knowledge extracted from data handbook. The results of the fuzzy reasoning method showed a good correlation between the machining data handbook's recommended cutting speed values and those predicted speed values using the fuzzy logic model. Ong et al [11] have reported the development of a fuzzy reasoning based inference method for computer-automated set-up planning for machining prismatic parts and castings. They used fuzzy sets and fuzzy relations in the representation of various relations between features composing the part being planned and then they used production rules and expert system techniques to represent the essential knowledge and model the set-up planning process. The use of fuzzy set theory has allowed them to model the uncertainties and complexities involved in human reasoning for set-up planning.

The application of fuzzy reasoning methods offer a structured and rule based knowledge representation similar to that of expert systems using IF-THEN rules with linguistic labels. It enjoys a significant advantage over the expert systems in that it is characterized by inability to handle uncertainty and reason with imprecise information.

The main weaknesses of fuzzy reasoning methods are, however, its inability to automatically acquire the inference rules and problem of finding appropriate membership functions for the fuzzy variables. It is further restricted to the fields where expert knowledge is available and the number of input variables is small.

### Neural networks based inference methods

Knapp et al [12] demonstrated the ability of neural network in the process selection and within feature process sequencing. In this work, two co-operating neural networks were utilized: the first one, a three layer back propagation neural network, takes in as input the attributes of a feature and proposes a set of machining alternatives; another fixed weight neural network selects exactly one of the alternatives. Parameters of the features are modified by the results of the operation until the final state of the feature has been reached. Chen et al [13] presented a neural network based approach to machine setup generation in process planning. In this reference, the authors discussed the use of an unsupervised neural network for clustering the features, comprising a part into setups based on commonality of cutting tools and tool approach directions of the features so as to minimize the number of tool changes. A neural network approach for automated selection of technological parameters of turning tools is reported by Santochi et al [14]. For each parameter of the tool, a neural network was designed and trained using the back propagation learning algorithm. Park et al [15] have applied a fuzzy ARTMAP neural network to develop the inference technique for automated selection of cutting conditions. The proposed neural network is capable of incremental supervised learning, which enables the model to be reinforced continually with information on new optimal cutting conditions by deleting the old information learned when new cutting conditions that are more effective for a certain circumstance are obtained. Eid [16] has developed a CAPP methodology that uses a back propagation neural network for selection and sequencing of machining operations for components with rotational symmetry. The features are assumed to be present in a certain order from the left face of the part. The process plan selection is done for all the features at a time taking into consideration the global sequencing of machining operations across all the features of the part. A back propagation neural network based CAPP approach for rotational components has been reported by Devireddy et al [17]. Two stages of decision making were implemented in the process plan generation approach. The first stage identifies the basic machining operations needed to generate the machining features and their sequences by a neural network by taking in as input feature types and their technological attributes. The second stage deals with further refinement of the manufacturing operations by another neural network taking in as input the feature attributes and basic machining operations selected in the first stage. The process plan selection is done one feature at a time including within feature process sequencing. Ming et al [18] have proposed a Hopfield neural network to select optimal sets of manufacturing operations for machining different features comprising a part. The detailed energy function of the Hopfield neural network specially constructed for solving such a problem was established. They first used a decision tree to generate a number of alternative sets of manufacturing operations for machining a given feature according to precision requirements specified for the feature. A genetic algorithm was subsequently used to solve the problem of allocation of optimal tolerance for each operation of set of sequenced manufacturing operations required to machine a feature, so that the total manufacturing cost is minimized. Next, the optimal set of manufacturing operations for machining each feature is selected by adopting a Hopfield neural network approach based on minimization of the sum of the selected sets of manufacturing operations and the dissimilarities in their manufacturing resource requirements for machining all the given features in a part.

The use of neural networks based inference techniques overcomes the deficiencies of expert systems and fuzzy reasoning methods to a certain extent. In situations where the process planning knowledge cannot be easily expressed in explicit rule form, neural network approach can be used to administer the implicit form of knowledge. The neural network is capable of performing pattern classification tasks by learning arbitrary mappings between the input and desired output patterns from a limited set of examples provided to the network during training. The possible inferences are stored implicitly and compactly in the weights of the network. They are characterized by their high processing speed once the network is trained, capable of adapting to changing environments through re-training and able to generalize beyond the original set of examples presented in their construction phase and produce meaningful solutions to the problems where input data contain errors or is incomplete.

 

However, inspite of the advantages as mentioned above, the neural networks based inference methods have some shortcomings over expert systems and fuzzy reasoning methods in that they provide no explanation of the rationale behind their inference procedure. They cannot directly encode structured knowledge unlike expert systems and fuzzy reasoning methods. Their lack of explicitly stated rules and vagueness in knowledge representation leads to a black box nature. The configuration of the neural network including training can be time consuming and the network topology is usually chosen by a trial and error method.

From the above, it is clear that the introduction of various AI approaches has significantly impacted the research and development of generative CAPP systems. They have enhanced the diversity of the knowledge representation and inference approaches in generative process planning resulting in improved performance. The above discussion on use of different emerging AI based approaches for implementing various CAPP sub functions has also stressed the need for adopting the right approach according to the nature of the problem domain as each AI approach has particular computational properties that make it suited for particular problems and not for others.

## PROPOSED INFERENCE STRATEGY FOR GENERATION OF MACHINING OPERATION SEQUENCES

A significant part of the reasoning process involved during the early stage of process planning in machining has to do with the choice of appropriate machining operations for manufacturing the part. It is made difficult by the large number of available machining operations and the planner has to come up with the optimum choice commensurate with the requirements of the part design. A process planner, who traditionally performs this task manually, routinely applies the knowledge acquired by learning the mappings between input patterns namely, the features and attributes of the part given in the part design database and output patterns consisting of machining operations to apply to these parts. Thus, the general problem setting in machining operation selection appears to be a pattern classification task, which is ideally suited for application of neural networks. Accordingly, we decided to explore the use of neural network for developing the inference technique to automatically perform this task. The survey of literature indicates that most of the neural network models developed for machining process selection tries to recommend a single machining operation sequence for a given part design. But, in practice, the process planning system needs to know the alternative ways of machining a part for use in developing process planning alternatives, so that the most appropriate plan can be selected depending upon machine tool availability and/or other technological constraints. Keeping this in mind, we have developed a neural network based inference strategy for generating all feasible operations sequences for machining a given feature of the part. One major assumption that we have made is that the product database is organized in the form of features. This helps in making the machining operation identification an easier task. Even if the original product is in other forms, a feature recognition module may be added in between to make use of our model. The focus of our proposed CAPP approach is on machining features commonly encountered in rotationally symmetric parts such as holes, external steps and the selection of machining operations is done for machining each feature of the part independently. In the following section, the detailed methodology for development of the neural network architecture is explained.

### Methodology for development of the neural network

A crucial step in development of the neural network is deciding on the input and output process planning decision variables. For our problem at hand, which is to generate operation sequences for machining the part, the main factors to be considered are the type of the feature and its characterizing attributes such as dimensions, tolerance and surface finish specifications, which therefore constitute the process planning input variables. The sequence of machining operations constitutes the process planning output variables. The input and output variables are organized into the input layer and output layer nodes of the neural network as shown in figure 1. Each input attribute of the feature is associated with a node in the input layer. The node takes on the values of the attribute, normalized to lie between 0 and 1. The network, whose aim is to generate all possible machining operation sequences, has a number of output nodes equal to the machining operation sequences feasible. Each operation sequence is associated with a node in the output layer. Each output node can assume a value lying between 0 and 1.

After having decided on the input and output variables of the neural network, the next step is to prepare the set of example input – output patterns to be learned by the neural network during its training. The above set of training examples is generated using thumb rules on machining process selection. Examples of some thumb rules for generation of operation sequences for machining holes is shown in figure 2. These rules were derived using the machining knowledge acquired from various sources such as machining handbooks (Bralla [19]), metal cutting and other textbooks (Wang et al [20]). An extract of the training example dataset is given in figure 3. For the training examples developed, the input patterns developed for this study are chosen in such a way that they cover the entire range of operating factors influencing the selection of machining operations for our problem at hand.

The next step involves performing training of the neural network. A fully connected multilayer feed forward perceptron is used for developing the neural network. The standard back propagation algorithm is used as the learning mechanism for the neural network. The neural network is presented with the set of training examples, from which the network implicitly derives the rules. Several experiments need to be carried out to identify the optimum configuration of the neural network that gives the minimum value of the network error. At the end of training of the network, the generalization capability of the network is verified by validation tests presenting pairs of inputs and outputs (validation set) describing intermediate situations with respect to those proposed during training. Whenever the network fails in the validation set, the training set needs to be modified by adding to the training set the situations of the validation set, which have generated greater errors.

 

## ILLUSTRATIVE EXAMPLE

Here, we have a developed a neural network model as shown in figure 4 to illustrate the application of the CAPP approach for generation of machining operation sequences in rotationally symmetric parts. The input layer of the neural network consists of 5 nodes to represent 5 input variables, namely type of the feature such as step, hole and characterizing attributes such as diameter, tolerance and surface finish. The output layer consists of 7 nodes, representing all the feasible machining operation sequences for our problem at hand. Then training examples were formulated carefully so as to cover the entire range of diameter, tolerance and surface finish requirements. Extract from the training examples has been earlier shown in figure 3. All the above training patterns were normalized to lie between 0 and 1 before presenting them to the network. The standard back propagation learning technique was used to train the neural network. The simulation of the neural network for the present study was carried out using the Neuframe 4 software [21]. After a number of experiments, an optimum structure of the neural network was obtained with 2 hidden layers, having 12 neurons in the 1st hidden layer and 9 neurons in the 2nd hidden layer. A total of 140 training patterns were used in training the network. The learning rate and momentum rates were chosen as 0.07 and 0.71 respectively. The number of iterations required for training the network to the error level of 4% is 27738. The example part shown in figure 5 is used to illustrate the application of the developed neural network architecture in generation of machining operation sequences for untrained parts. The operation sequences generated by the neural network for the example part are given in Fig. 6. The above results show a good correlation between the machining data handbook's recommended operation sequences and the operation sequences generated by the developed neural network.

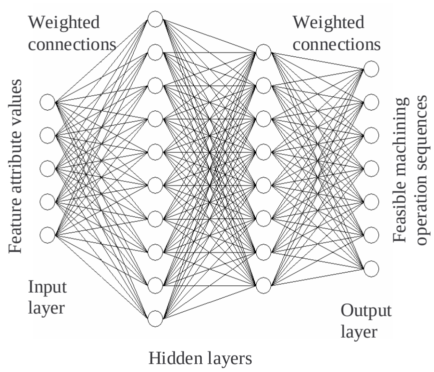


Figure 1 General architecture of the Neural Network

IF Diameter of Hole is 18-30 AND Tolerance is 0.013-0.052 mm AND Surface finish is 0.16-5 µm THEN Drilling-Reaming is recommended

IF Diameter of Hole is 18-30 AND Tolerance is 0.021-0.33 mm AND Surface finish is 0.63-20 µm THEN Drilling-Boring is recommended

IF Diameter of Hole is 18-30 AND Tolerance is 0.009-0.052 mm AND Surface finish is 0.08-2.5 µm THEN Drilling-Boring-Grinding is recommended

IF Diameter of Hole is 18-30 AND Tolerance is 0.006-0.021 mm AND Surface finish is 0.04-1.25 µm THEN Drilling-Boring-Honing is recommended

Figure 2 Example of some thumb rules used for generation of operation sequences for machining holes

| **Training Inputs** | | | | | **Training targets** | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Step | Hole | Diameter (mm) | Tolerance (µm) | Surface finish (µm) | Turn | Turn-Grind | Drill | Drill-Ream | Drill-Bore | Drill-Bore-Grind | Drill-Bore-Hone |
| 1 | 0 | 18 | 270 | 80 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 30 | 52 | 2.5 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| 0 | 1 | 18 | 43 | 2.5 | 0 | 0 | 0 | 1 | 1 | 1 | 0 |
| 0 | 1 | 30 | 21 | 1.25 | 0 | 0 | 0 | 1 | 1 | 1 | 1 |
| 0 | 1 | 50 | 62 | 2.5 | 0 | 0 | 0 | 1 | 1 | 1 | 0 |

Figure 3 Extract from training example dataset of the neural network

## SUMMARY AND CONCLUSIONS

In this article, we have reviewed, categorized and summarized the research on some applications of AI for developing inference methods for CAPP systems. We have described our ongoing research on developing a neural network based inference strategy for implementing machining process selection in CAPP systems for rotationally symmetric parts. It takes in as input the attributes of the features and automatically generates all the feasible alternative machining operation sequences. We explained the methodology followed in development of neural network architecture and discussed the key issues in connection with gathering of domain expertise necessary for preparation of training examples for the neural network and designing, training of the neural network. Finally an illustrative example is given to illustrate the application of approach developed in the article for generation of machining operation sequences. At this point, we have developed a neural network model for handling presence of two types of features namely, external steps and holes, most commonly encountered in rotational parts. We are currently working on extensions of our proposed approach to further include other types of features.

The neural network based inference strategy that we developed has the following benefits. It possesses the ability to automatically acquire the knowledge for machining process selection directly from training examples presented to it at the time of training and thus helps to ease the knowledge acquisition bottleneck to some extent. For the above reason, it is now easy to incorporate the knowledge about capability of any new machining process, which may be necessary in case of a major change in product design or possibly due to development of a new improved machining process. Thus it allows the CAPP system to perform effectively and efficiently, by enabling the system to adapt more readily to any major changes in the product design and in response to the rapidly changing manufacturing environment. Furthermore, the methodology presented here can substantially reduce the time taken to develop an automated process planning system.

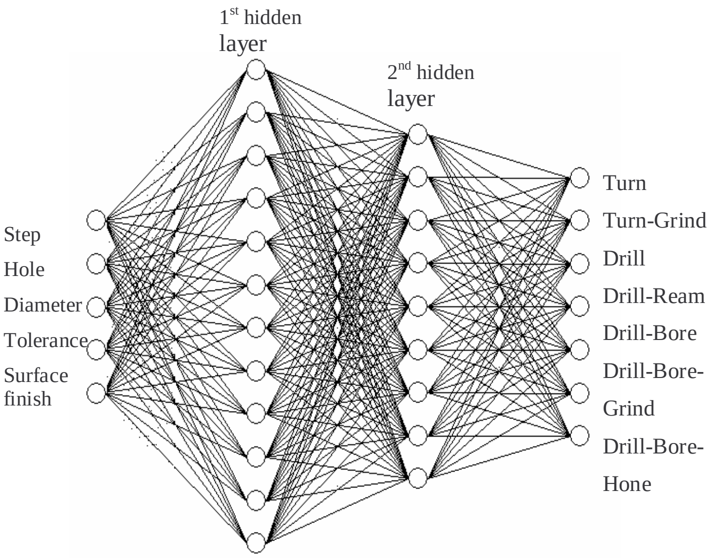


Figure 4 Neural network architecture for automated selection of machining operations

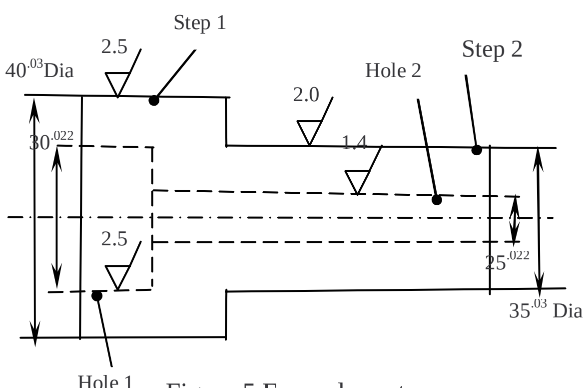


Figure 5 Example part

| Feature | Feasible machining operation sequences |
|---|---|
| Step 1 | Alt. 1: Turn<br>Alt. 2: Turn-Grind |
| Step 2 | Alt. 1: Turn<br>Alt. 2: Turn-Grind |
| Hole 1 | Alt. 1: Drill-Bore<br>Alt. 2: Drill-Ream<br>Alt. 3: Drill-Bore-Grind |
| Hole 2 | Alt. 1: Drill-Bore<br>Alt. 2: Drill-Ream<br>Alt. 3: Drill-Bore-Grind |

Figure 6 Selection of some machining operation sequences for the example part shown in Figure 5
Note: Alt. stands for "Alternative"

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