An AI approach to process sequencing

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Process sequencing is one of the most difficult phases of process planning and it is influenced by many factors including part geometry, available manufacturing resources, and generated cutting forces. Computationally, this problem has been shown to be NP-hard, but in this paper, we describe a new AI based approach to optimizing this function using heuristic search techniques which shows a significant improvement over previous attempts.

Keywords: AI, CAPP, expert systems, process sequencing, process planning

Introduction

Process planning is one of the basic tasks to be performed in manufacturing systems. It is a detailed and difficult task traditionally done by highly skilled workers who have an intimate knowledge of a wide range of manufacturing processes and are themselves experienced machine operators. A major problem is that many of the people with these skills are now past middle age and fast approaching retirement while there are few adequate replacements among the younger generation. Another difficulty is that owing to the tedious and time-consuming nature of the tasks involved, process planners often do not make an exhaustive analysis of the requirements of a particular process, and instead they tend to rely heavily on experience. The inevitable result is that there is generally a lack of consistency among process plans prepared by different individuals with varying manufacturing backgrounds and levels of skill.

For reasons such as these, there has been increasing interest in ways to automate the process planning function. By using a computer, the tedious and repetitive aspects of process planning can be speeded up and this helps to optimize the total manufacturing function by releasing the experienced planners and enabling them to concentrate on those aspects outside the scope of a computer[1]. At the same time, more consistent process plans can be obtained by applying a standard set of rules which increases confidence in the system and helps in the rationalization of production. To automate process planning, the logic, judgement, and experience required for process planning must be captured and incorporated into a computer program.

AI techniques can aid in automating several of the reasoning activities required for process planning. To date, several different systems have been developed that use AI techniques for this purpose. This paper discusses how AI techniques can be used in the optimization of process sequences. Based on the nature of the problems involved in process sequencing, we analyse the computational complexity of process sequence optimization, and describe some algorithms for optimization of process sequences based on heuristic search techniques.

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Background

Process planning can be defined as that function that determines the sequence of individual manufacturing operations needed to produce a given part or product, the necessary resources, as well as associated machining conditions (feed, speed, etc.). In effect it is the subsystem responsible for the conversion of design data into work instructions[2]. The quality of the process plan generated is dependent on the experience and judgement of the planner. It is his responsibility to determine optimum process plans. The functions involved in process planning include the following:

- selection of operations
- sequencing the operations
- selection of the machine tools
- selection of the workpiece holding devices and datum surfaces
- selection of cutting tools
- determination of proper cutting conditions
- determination of cutting times and non-machining times

It can be appreciated that, if done manually, this is indeed a laborious task, and it is an ideal candidate for automation. Various approaches to automating this task have been proposed. Variant process planning techniques use part classification and coding along with the concepts of group technology. The parts are classified and coded according to their similarities in geometry, and manufacturing characteristics. Standard plans for each part family are stored in a part family matrix. To obtain a process plan for a new component, the code for the part is entered and the plan is retrieved if a similar part is found in the part family matrix. The user can examine and edit the plan. The

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new plan can be put into the part family matrix for future reference. Some examples of variant process planning systems are MIPLAN[3], CAPP[4] and TOJICAPP[5]. The main criticism to be made of variant process planning systems is that they do not fundamentally solve the problem. They rely on expert process planners to develop standard process plans and therefore lock in many of the difficulties and problems associated with manual systems[6]. Variant systems do not generate new process plans.

Another approach uses generative process planning systems. In a generative system, an individual plan is created from scratch for each part. Based on an analysis of the part geometry, material and other factors that would influence manufacturing decisions, the system generates a new process plan for each part. The manufacturing logic, formulae to determine machining conditions and standard times will be used by the system to produce the process plan. Some examples of generative systems are AUTAP[7], ICAPP[8,9] and TIPPS[10].

It is the generative process planning system that can link CAD and CAM together, but the lack of a good interface with a CAD system is the greatest handicap the researchers are facing. Though there are many systems that determine required operations, cutting parameters and production times, very few systems attempt to sequence the operations optimally or select jigs and fixtures. Another reason for this is the lack of universally accepted manufacturing logic for process sequencing and selection of jigs and fixtures. Most of the process planners use their experience for these phases of process planning. Nowadays, AI based systems using application-specific problem-solving knowledge to achieve a high level of performance in the field, which we would think of as requiring a human expert, are being used to automate some phases of process planning. There are several AI based process planning systems that have automated some phases of process planning. Examples of such systems include SIPS[11], GARI[12], TOM[13] and EXCAP[14].

Process sequencing

Process sequencing is that task within process planning responsible for arranging the processes chosen to produce a part in a proper order or sequence, so as to obtain a reasonable process sequence (if possible, the optimum sequence) that can be used to manufacture the component. This is one of the most problematic parts of process planning and various surveys have shown that process sequencing does not lend itself to a perfect methodology[15]. This is not surprising because process sequencing is strictly a human oriented activity, highly dependent on individual skills, human memory and mood, and a mass of reference manuals. Though it is human oriented, there are certain factors that must be considered while selecting a particular process sequence. Some of the important factors that need to be considered were found to include part geometry, workpiece material, batch size, as well as available resources (e.g. machine tools, cutting tools, labour) and their capabilities[16].

The ultimate objective of process sequencing is to minimize the cost of production without sacrificing the quality of the product. The total production cost is given by[17]

$$C_{pc} = C_o(T_m + T_h) + T_m(C_t + C_o T_{tc})/T \qquad (1)$$

where C_{pc} is the cost per workpiece ($/piece); C_o, the cost to operate the machine tool ($/min); T_m, the machining time (min); T_h, the handling time (min); C_t, the cost of tooling ($ per cutting edge); T, the tool life (min); T_{tc}, the tool change time (min). In this equation, C_{pc} can be decreased by decreasing C_o, C_t, T_m, T_h and T_{tc}, or by increasing T. The value of C_o is dependent on the labour cost, the machine cost and the applicable overheads. Although the estimated value of C_o varies from one company to another, it will be constant within a particular firm. C_t, T and T_{tc} are also constants in a given situation and should not affect the optimization problem. Thus T_m and T_h are the most important process sequencing variables to consider in trying to optimize the production cost C_{pc}. The values of T_m and T_h are fairly similar for a given combination of machine tools, cutting tools and workpiece material across industries. Therefore, for a general application program, it is possible to minimize C_{pc} by minimizing T_m and T_h. Thus, the objective is to minimize T_m and T_h to minimize the production cost. Elsewhere, we have discussed the applicability of this to the problem of process sequence optimization[18].

Process sequence optimization

In this discussion we assume that the workpiece is described as a collection of machinable features, each of which either already exists in the original piece of stock, or else must be created by a sequence of one or more machining operations. We assume that for each feature F, we have already determined the following information:

- ☐ the identity of the surface in which F is to be machined
- ☐ one or more possible sequences of machining operations to use in creating F
- ☐ for each machining operation, the machines, cutting tools, and the tool trajectory (or trajectories, if more than one is possible) that must be used for that operation.

Some of this information may be changed by the process sequence optimization procedure.

When the total time a component spends on a machine is analysed, it can be seen that the total handling time is about 70% of the total time and the total machining time is 30%[19]. Since handling time is usually more than machining time, reduction of handling time is generally more important than reduction of machining time, and for this reason, the ensuing discussion will concentrate on this aspect. Handling time consists of work handling time and tool handling time; each is briefly discussed below.

Work handling time

Reduction of work handling time means that the number of times the component is reset on the machine must be minimized. This can be achieved by ensuring that all possible operations that can be performed during a particular setup must be completed before resetting the workpiece. Thus, the goal here is to minimize the number of setups. This can be done by grouping together all the operations to be performed on the same face using the same machine. Once the operations are arranged as such, the work handling time will be minimized. This assumes that each feature on which machining operations are to be made is associated with a particular face.

Tool handling time

Different operations to be performed within a setup may require using different tools, which involves tool handling time. Tool handing time is the time required for all tool changes that take place during the use of a particular machine. We distinguish between two types of tool changing time; one being inter-facial tool handling time, and the other being intra-facial tool handling time. We define intra-facial tool handling time as the time required for those tool changes that occur during a particular setup. We define inter-facial tool handling time as the time required to change tools when the setup of the part on the machine has been changed (i.e. the face to be accessed by the new tool is different). The number of tool changes can be reduced by the use of three strategies.

(1) Group together (as much as possible) all operations requiring the same tool. For example, if two holes of the same diameter are to be created using spade drilling, then doing the two spade drilling operations sequentially will avoid a tool change.

(2) If the tool diameter for an operation is not critical, change the tool diameter to allow the operation to be grouped together with other operations. For example, if there are different operations requiring centre drills of diameter 3.5 mm, 4 mm and 5 mm, then all three centre-drilling operations can be performed using the same centre drill. The tools can be changed for other types of operations also, but one must be careful while doing this. For example, if the required hole diameter is 25 mm, the diameter of the final drill cannot be changed to 24 mm or 26 mm. Also, if threading and reaming should be performed, the penultimate drill diameters must be selected carefully.

(3) Choose a different process plan for making a particular feature, if this will allow the processes in the plan to be grouped together with other operations for other features in a better way. For example, if two holes h_1 and h_2 of the same diameter are to be created using twist drilling and spade drilling, respectively, then a tool change can be avoided by creating h_1 using spade drilling instead of twist drilling. When such changes are made in the process plan for a feature, it is important to ensure that the new plan will still satisfy the required surface finish and machining tolerances.

Depending on the number of plans available for each machining feature, we have different ways for minimizing the number of tool changes. Below, we discuss the case of one plan for each feature and the case of more than one plan for each feature separately.

One plan for each feature

When there is one plan available for each feature, we can simply group all the operations requiring the same tool together, so that the number of tool changes can be minimized. This is possible because operations in the machining domain have a special property: there is a partial order over the set of operations required for a given feature; e.g. if O_1 is before O_2 in one plan, then O_2 cannot be before O_1 in any other plan for the same feature.

If the sequence of operations on each face is arranged such that the tool that was used for the last operation on face 'F_i' can be used for the first operation on face 'F_{i+1}', on the same machine tool, then there will be some reduction in the inter-facial tool handling time. This depends on the type of operation. For example, a twist drill cannot be used before using a centre drill unless a pre-drilled hole is present. Threading cannot be done before drilling a hole. Therefore, the 'precedence relationships' of the different operations are very important. It is very unlikely that all last operations on a given face 'F_i' use the same tool as the first operation on the next face 'F_{i+1}'. But it is possible that some of the faces might be arranged so that the inter-facial tool handling time between two consecutive faces is zero. Thus it is possible to obtain a combination of such faces which will be subsets of the complete sequence of operations. These combinations of faces can be appended to obtain the best possible sequence.

When there is one plan available for each feature, the results of inter-facial tool handling time minimization will be a set of partially ordered plans, one for each face. We can use P_i to represent the ith such plan. The relationship between the P_is can be represented by a directed acyclic graph, where vertex n_i represents the ith face, and there is an edge from vertex n_i to n_j if there is an operation which is both one of the last operations in P_i and also one of the first operations in P_j. We can use V for the set of vertices and E for the set of edges. Given $G = (V, E)$, algorithm 1 below will return the optimal sequence of faces that will minimize the inter-facial tool handling time.

Algorithm 1 Let v be a vertex in G. Also let *indegree* (v) be the number of edges pointing at v, *outdegree* (v) be the number of edges pointing away from v and $e(v)$ be the set of edges either pointing into or away from v. Let S be a set, initially empty.

While $V \neq \emptyset$ **do** (V is the remaining vertex set)
  If there exists a vertex v such that *indegree* (v) $= 1$ and *outdegree* (v) $= 0$ **then**
    $S := S \cup \{e(v)\}$
  else
    select a vertex v such that *outdegree* (v) $= 0$
    $S := S \cup \{any - edge - ine(v)\}$;
  End {*If*}
  $V := V - v$
  $E := E - e(v)$;
End {*While*}

This algorithm will terminate in time in the order of $(|E| + |V|)$. The algorithm has been implemented in our sequence optimization system called SEQUENCE. The operation of SEQUENCE will be described later.

More than one plan for each feature

Usually, we will have more than one way available to us for making a feature. Different choices of process plans will result in global plans of different tool handling times. For example, consider the hole-creation operations again. Several different kinds of hole-creation operations are available (twist drilling, spade drilling, gun drilling, etc.), as well as several different kinds of hole-improvement operations (reaming, boring, grinding, etc.). Similar operations can be merged, thus eliminating the task of changing the cutting tool.

For example, suppose hole h_1 can be made by the plan

P_1: spade-drill h_1, then bore h_1;

and hole h_2 can be made by either of the plans

P_2: twist-drill h_2, then bore h_2;

P'_2: spade-drill h_2, then bore h_2;

with $\mathrm{cost}(P_2) < \mathrm{cost}(P'_2)$. If h_1 and h_2 have different diameters, then the least costly global plan will be to combine P_1 and P_2. This plan will require four tool changes. However, if they have the same diameter, then a less costly global plan can be found by combining P_1 and P'_2, merging the two spade-drilling operations, and merging the two boring operations, and yielding the following global plan:

puton-spade-drill, spade-drill h_1,

spade-drill h_2, puton-bore, bore h_1, bore h_2

This process plan only requires two tool changes. Below, we will distinguish between the optimization of inter- and intra-facial tool handling cases.

Minimization of intra-facial tool handling time When there is more than one plan available, our optimization system has to choose one plan for each feature, such that after merging the operations of the same type, the global plan will have the minimum number of tool changes. It has been shown that such a problem is NP-hard[20]. However, we have found a good heuristic algorithm which will return the optimal set of plans.

Our heuristic algorithm is a version of a best-first branch-and-bound search algorithm, which searches through a state space. The state space is a tree in which each state is a set of plans, one plan for each of the first k goals for some k. The initial state is the empty set (i.e. $k = 0$). If S is a state containing plans for the goals $G_1, G_2, \ldots, G_k$, then the immediate successors of S are all of the sets $S \cup \{P\}$ such that P is a plan for G_{k+1}. A goal state is any state in which plans have been chosen for all of the goals.

We define the cost of a state S to be the cost of the plan obtained by combining the plans in S and then merging; i.e.

$$\mathrm{cost}(S) = \mathrm{cost}(\mathrm{merge}(S))$$

Clearly, $\mathrm{cost}(S)$ is a lower bound on the cost of any successor of S, but a better lower bound can be found as follows. Suppose S contains plans for $G_1, \ldots, G_k$. For each $t > k$, let $P^*(S, t)$ be the plan P for G_t which minimizes $\mathrm{cost}(\mathrm{merge}(S \cup \{P\}))$. Let

$$L(S) = \max_{t>k} \mathrm{cost}(\mathrm{merge}(S \cup \{P^*(S, t)\}))$$

Then $L(S)$ is a lower bound on the cost of any successor to S. We have developed a way to compute this cost efficiently[20].

In the search algorithm, pruning is done by computing an upper bound on the cost of the best global plan. For each G_i, let $\mathrm{best}(G_i)$ be the plan for G_i of least cost. The upper bound is

$$U = \mathrm{cost}(\mathrm{merge}\{\mathrm{best}(G_1), \mathrm{best}(G_2), \ldots, \mathrm{best}(G_n)\})$$

During the search, any state whose cost is greater than U can be discarded.

The search algorithm appears below. This algorithm is a best-first branch-and-bound search, and is guaranteed to return the optimal solution. Except for the use of U for pruning, this algorithm can also be thought of as a version of the A* search procedure, with $h(S) = L(S) - \mathrm{cost}(S)$ as the heuristic function.

Algorithm 2

```
A := (∅)        (A is the branch-and-bound active list)
U := upper bound, computed as described above
loop
   S := pop(A)       (remove the first element of the list)
   if S is a goal state then return S
   if L(S) ≤ U then begin
      B := the successors of S, in order of least
      L-value first
      put the members of B into A, and sort A
   end
repeat
```

In the worst case, algorithm 2 takes exponential time. Since the global plan optimization problem is NP-hard, this is not surprising. What would be more interesting is how well algorithm 2 does on the average. However, the structure of the global plan optimization problem is complicated enough that it is not clear how to characterize what an 'average case' should be; and there is evidence that the 'average case' will be different for each application area. Therefore, we have restricted ourselves to doing empirical studies of the performance of algorithm 2 on a class of problems that seemed to us to be 'reasonable'. For the plans that we examined, algorithm 2 examined only about 3% of the search space, but given the nature of our test, this should be considered solely as a preliminary result.

Minimization of inter-facial tool handling time When we consider the optimization of tool handling time with features on different faces, one way to obtain a 'good' solution is to first apply the algorithm 2 of the last section, then use algorithm 1 to get an ordering of the faces.

However, one may not be able to find the best solution in this way. An optimal solution will not only specify which plans are chosen for the features, but also specify an ordering of the faces so that the correct order of setup operations can be performed. In order to find the optimal answer, we may need to search through a much larger search space, which may consume much more computational effort than necessary. On the other hand, the method we presented above can be thought of as a good approximation algorithm, whose solution will not be too far from the optimal answers. We are currently working on an implementation of this approach for the SIPS process planning system, which is capable of generating multiple plans for each feature.

Selection of the final sequence

Before selecting the best sequence, the database will have a number of possible sequences. In determining which of these is the best one, we take into account what we call the weighting factor. The weighting factor for a particular feature is defined as the ratio of the volume of material removed in making the feature to the total volume of material removed in making the component. It is good practice in manufacturing for features having a greater weighting factor to be machined first so that much of the heat is carried away by the chips and less material is left for further machining. The final sequence is selected by considering the weighting factor for each feature and where possible sequencing operations with larger weighting factors first.

Example

The ideas discussed above have been implemented in our sequence optimization system called SEQUENCE. The current implementation is only for the case of one plan available for each feature, although that of multiple plans is also being studied. SEQUENCE is currently integrated with the ICAPP process planning system[21]. It should be noted, however, that SEQUENCE is an independent module capable of accepting input from any CAPP system and operating on it to generate the best operations sequence, provided the input is in the correct format. SEQUENCE is only concerned with the sequencing problem, taking as input descriptive information about each operation consisting of the following data:

- an operation identification number
- the machine tool code
- code for face on which the operation is to be performed
- drawing code to identify the particular feature
- operation type
- tool type
- tool diameter
- weighting factor

Table 1 is a typical input to SEQUENCE, consisting of the above defined data for a simple test component.

This input is grouped by SEQUENCE such that all operations on the same face requiring the same machine will be processed in one setup, thus minimizing the work handling time. SEQUENCE then arranges the operations on a face in decreasing order of the weighting factors for features. That is, it processes the features with the highest weighting factor, and hence the feature requiring the bulk of material removal first. SEQUENCE has the capability to change tools if necessary, to help minimize the tool handling time as discussed above. SEQUENCE also considers the dependencies existing between any two faces of a component, arranging the faces in a descending order of weighting factors of the features. For 'through-hole' types of features, SEQUENCE also considers the feasibility of machining the feature from a face opposite to that specified in the input, if so doing would result in a feature grouping that reduces overall processing time. Further, SEQUENCE determines those operations that could be changed so as to reduce handling time, thereby attempting to get a more refined process sequence. SEQUENCE also prints messages to help the planner to take some precautions during machining. The final sequence so obtained is then returned to ICAPP for further processing. The final output of SEQUENCE for the above input data which would form the input to ICAPP is shown in Table 2. You will notice that the face numbers for operations 100 and 110 have been changed. This is because the associated features were through-holes and such change was found to be beneficial.
The total production time resulting from the final sequence of operations was 93 min which represents a 17% saving when compared to the production time of 112 min for the original sequence[16]. The level of savings to be expected will clearly vary with the complexity of the part concerned, but increasing complexity is also likely to lead to increased savings by using the techniques outlined above.

Table 1 Input operations sequence

opn-id	machine	face	optyp	drcd	tool	tldia	wtfct
10	20	1	1	F1	1	200.0	3.4
20	20	2	2	S2	2	32.0	22.5
30	20	2	2	S3	2	32.0	22.5
40	20	1	5	H0	4	5.0	30.2
50	20	1	5	H0	5	34.0	30.2
60	20	5	3	SL	2	32.0	6.7
70	20	1	4	P1	3	35.0	2.2
80	20	3	1	F3	1	125.0	2.5
90	20	4	1	F4	1	160.0	2.6
100	20	6	5	HT	4	3.5	7.4
110	20	6	5	HT	5	26.0	7.4

Table 2 Final operations sequence

opn-id	machine	face	optyp	drcd	tool	tldia	wtfct
10	20	1	1	F1	1	200.0	3.4
70	20	1	4	P1	3	35.0	2.2
40	20	1	5	H0	4	5.0	30.2
100	20	1	5	HT	4	5.0	7.4
110	20	1	5	HT	5	26.0	7.4
50	20	1	5	H0	5	34.0	30.2
90	20	4	1	F4	1	160.0	2.6
80	20	3	1	F3	1	125.0	2.5
60	20	5	3	SL	2	32.0	6.7
20	20	2	2	S2	2	32.0	22.5
30	20	2	2	S3	2	32.0	22.5

Conclusion

The importance of improved manufacturing technology has been outlined, and it has been demonstrated that CAPP was important for the integration of CAD and CAM. A review of several process planning systems (variant and generative) showed that very few systems were optimizing process sequences. It was shown that the important factors influencing a particular sequence are the part geometry, the available machines and cutting tools as well as required cutting forces. A methodology for process sequencing and the expert system developed by the authors for process sequence optimization were described and the pertinent algorithms presented. Significant improvements in the operations sequence generated by an actual CAPP system (as measured by the required processing time) have been shown to be obtainable by using our approach.

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