Plan Based Automated Generation of Redesign Suggestion

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***Abstract*—This paper presents a plan-based manufacturability analysis and redesign approach. The first step of the presented approach is to generate alternative process plans. After that redesign suggestions are generated based on one of the best and feasible plan. Plan-based approach can provide more detailed and accurate analysis and redesign suggestions; but require large amount of computing time. The key element of the presented approach is a process planning system that can generate alternative process plans. In this paper, process planning is modeled from an optimization perspective and the model contains all the possible combination of operations to manufacture the part. Optimization algorithms such as Genetic algorithm (GA)/Simulate annealing (SA) are then used to overcome the computing complexity introduced by alternative process planning. Manufacturing cost is computed from the process plan as the measure of manufacturability. The computed manufacturing cost is analyzed to generate redesign suggestions. The modified design is then evaluated again by the process planner to make sure the manufacturing cost is decreased and manufacturability is increased. A case study generated by this approach is also given in this paper.**

***Index Terms*—Manufacturability Analysis, Optimization, Genetic Algorithms, Automated Process Planning.**

I. INTRODUCTION

The life cycle of a part begins from the design stage. At the beginning, the designer produces the initial design, mainly concerning on realizing the function of the part. At this stage, the results of the design exist in terms of geometric forms. Traditionally, the manufacturing capabilities and cost of the production process are seldom considered. After the part entering into the production stage, the manufacturing engineer may find that the part is quite difficult to be machined, while maybe a slight change in the part will be greatly beneficial. Then, advices on how to change the part is fed back to the part designer. Without the help of software tools, this could be time consuming iterations. This situation is best to be described as “over-the-wall” communication between design and manufacturing. To be highly competitive in the future marketplace, the design engineer must consider the whole manufacturing procedure, or the design engineer should communicate with the manufacturing engineer from the initial stage to acquire some manufacturing suggestions. Based on this requirement, software tools of manufacturability analysis and automatic redesign are to be developed.

Generally, there are two ways for analyzing the manufacturability. The first is called rule-based approach, which uses rules to identify infeasible design attributes from direct inspection of the design description. This approach typically utilizes simple local relationship between sections of the design and manufacturing cost. However, it is less suitable for complex designs and with no instruction as to how to remedy the problem [7].

Another approach is called plan-based approach. The first step of this approach is to generate alternative process plans and then evaluate the process plans and generate redesign suggestions based on one of the best plan. Plan-based approach can provide more detailed and accurate analysis and redesign suggestion, but require large amount of computing time.

This paper provides a plan-based redesign generation approach. Process planning is modeled from an optimization perspective and the model contains all the possible combination of operations to manufacture the part. Optimization algorithms such as Genetic algorithm (GA)/Simulate annealing (SA) are then used to overcome the computing complexity introduced by alternative process planning. An operation model instead of feature based model is used to get process plan which is more accurate and practical. Manufacturing cost is estimated from the detailed process plan as the measure of manufacturability. By generating a near-optimal process plan and evaluate it, we give redesign suggestions to the part in order to reduce manufacturing cost. Suggestions are in term of feature candidates that some modifications to them may reduce manufacturing cost.

The reminder of this paper is organized as follows. Section 2 is literature review. Section 3 is the overview of proposed approach. Section 4 discussed modeling process planning from an optimization perspective. Section 5 describes the detail implementation of the manufacturability analysis and redesign approach. Section 6 is a case study and section 7 draws the conclusion.

II. LITERATURE REVIEW

Great benefits can be acquired by applying manufacturability analysis and redesign. A complete literature review of this topic can be found from [2] and [17]. Applying manufacturability analysis in early design stage to

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reduce manufacturing cost is discussed in [14]. How manufacturability analysis can be integrated with the CAD/CAPP systems can be found in [15] and [21]. It could be a part of decision support systems [18]. Manufacturability analysis is also applied to improve a particular process such as micro milling/drilling [13].

There are many ways to do manufacturability analysis. In this section we focus on plan based manufacturability analysis. Generally, Research works in this area can be divided into three categories:

1) *Alternative process plan generation*

Generating of alternative process is usually the first step towards automatic manufacturability analysis and redesign. Hayes [7] used feature interactions (mainly due to fixturing consideration) to guide the search of set-ups and their sequences. Chu and Gadh [6] used a rule-based approach to generate process plan with minimum number of set-ups based on feature's tool access direction. Zhang et al. [8] discussed various constraints of set-up planning and developed a hybrid approach for set-up generation. Sarma and Wright [9] developed some algorithms to find near-optimal process plans which minimize set-ups and tool changes for milling "simply fixturable" part. Irani et al. [10] used the Latin multinomial method (LMM) to enumerate each feasible Hamilton path which represents a process plan. Generally, most of the researchers used features based model as their input.

2) *Plan evaluation*

Process plan evaluation has a very close relation to the measure of manufacturability. It is treated as a multiple attribute decision making problem since each process plan possesses multiple attribute (e.g., cost, time, and quality). In [5], a fuzzy approach for the evaluation of process plan, concentrating on the contribution of each process plan to the shop floor is presented. Zhang and Lu [20] presented an approach for the evaluation of economic aspects in an operation plan. Through cost analysis, the variable, fixed, and total costs associated with the machining operation are quantitatively determined.

3) *Manufacturability analysis based on process plans.*

Das et al. [4] provided a four steps approach to reduce set-up cost: a) processing, b) analyze the current design, c) Generate possible feature modifications, and 4) generate and present design alternatives. C.C Hayes [7] gave an approach which generating cost-reducing design which also reduced set-up times.

Other than plan based manufacturability analysis and redesign, other methods such as knowledge based manufacturability analysis systems are also reported [16] [19].

III. OVERVIEW OF PROPOSED APPROACH

Design and manufacturing process are flexible in nature. Usually features can be designed with a wide range of dimensions and still can serve the design functions. Same as features, operations or manufacturing process also are highly flexible in nature. Generally, there are three kinds of flexibilities of operations. They are: 1) operation selection flexibility, 2) machine selection flexibility, and 3) route flexibility. Flexibilities of design provide the possibility of redesign while flexibility of manufacturing process provides the possibility of manufacturability analysis. From the above analysis, we also can draw a conclusion that redesign should be provided in terms of design features which directly match the idea of designer while manufacturability analysis should choose operation as the basic element because it is the basic concept of a manufacture engineer. Thus we introduce feature variation and operation based model in our approach.

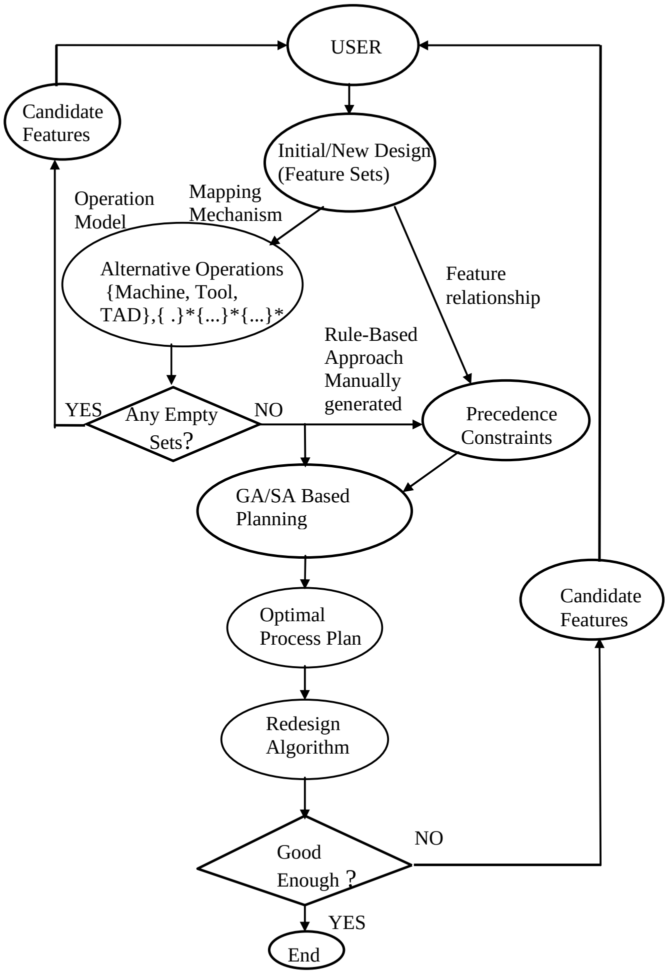

Fig. 1 Overview of the redesign cycle.

Fig. 1 is the overview of the proposed redesign cycle. The system starts from mapping a feature based model (design) to an operation based model. The detail of how this mapping is done is presented in the next section. The operation model will be the input of the process planning module.

Then genetic algorithm and/or simulated annealing are used to search the whole operation based model and get the near optimal process plan.

This plan is then analyzed by a redesign algorithm to find features that lead additional manufacturing cost. These features are selected as the candidate features for redesign consideration. If the user confirms the redesign suggestion, new designs are re-evaluated. If the result is good enough, the whole processes stop, otherwise possible alternative redesign suggestions are generated to provide more choice.

The working process of our system is similar to methods provided by Gupta [1], [3]. The differences are as followings: we use an operation-based model instead of a feature based model to do process planning and manufacturability analysis. An operation model is more complicated than a feature based model. It contains more manufacturing information and is more close to real manufacturing practices, therefore, we can consider the manufacturing capacity and get more accurate evaluations of production cost or production time. However, the operation based model also enlarges the search space, hence need more computation effort. GA/SA is used to overcome this. By using GA/SA, we can consider the machine, tool, and tool access direction (TAD) at the same time to acquire near optimal process plan.

The advantage of our approach is that our approach can give a redesign based on a near optimal process plan that consider all the possible feasible ways to manufacture the part.

IV. PROCESS PLANNING FROM AN OPTIMIZATION PERSPECTIVE

From Fig. 1, it can be easily seen that the core of a plan-based manufacturability analysis system is the process planning module that generates alternative process plans. The generation of alternative process plans can be treated as a constrained optimization problem. An operation based model can provide more information than a feature based model for planning. The consequence of introducing operation based model is the high computational complexity of process planning. Hence, we must find more efficiency search approach.

In process planning, several decisions must be made. They are operation selection, tool selection, machine selection, operation sequencing, etc. To treat process planning as an optimization problem, we define process planning as: *searching the plan solution space by considering the alternatives in operations selection and precedence constraints in operations sequencing simultaneously*. The major constraint is operation precedence relationships (PR's). A valid sequence must satisfy the precedence relationships between operations caused by geometrical and technological consideration. Reference [12] gives detail information of how to generate precedence relationships. With the plan solution space defined, the next step is to find a plan from all the alternatives that is the optimal according to a specified criterion.

The process planning task can be converted into allocate each operation to a unique set of machine tool (M), cutting tool (T), and tool access direction (TAD) with a unique position in the whole operation sequence subject to the precedence constraints and object criteria. Based on this, a CAPP model can be created for prismatic part in a job shop. Given a part of *m* features, each feature can then be mapped to a set of operations defined different combination of Machine (M), tool (T), and TAD, as shown in Fig. 2a.

With the precedence relationships between operations, a directed operation graph shown in Fig. 2b can be formed and it is called the operation model for process planning. Each parent node represents an operation set that contains many feasible operations (M, T, TAD). A directed edge between two operations represents the precedence relations between them, i.e., the one that the arrow points to must be performed after the other.

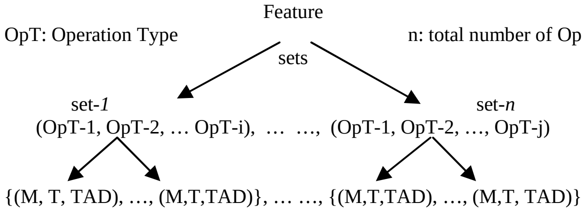

Fig. 2 (a) Mapping from feature to operations.

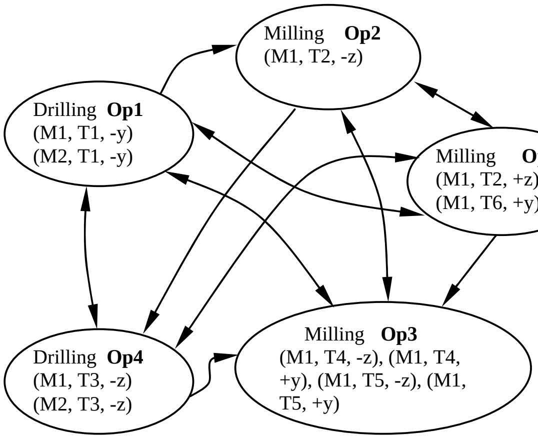

Fig. 2 (b) An example of an operation model.

With the graph representation of the operation model, the five cost factors for a process plan can be calculated as follows:

1) *Machine cost (MC)* is used to measure the machine cost in a process plan:

$$MC = \sum_{i=1}^{n} MCI_i \tag{1}$$

where *n* is the total number of Op's and MCI_i is the machine cost index for using machine-*i*, a constant for a particular machine.

2) *Tool cost (TC)* is used to measure the tool cost in a process plan:

$$TC = \sum_{i=1}^{n} TCI_i \tag{2}$$

where TCI_i is the tool cost index for using tool-*i*, a constant for a particular tool.

3) *Machine change cost (MCC)* is used to measure the total machine change cost in a process plan.

$$MCC = MCCI \times \sum_{i=1}^{n-1} \Omega(M_{i+1} - M_i) \tag{3}$$

where *MCCI* is the machine change cost index, a constant and M_i is the ID of the machine used for operation-*i*.

$$\Omega(M_i - M_j) = \begin{cases} 1 & if \;\; M_i \neq M_j \\ 0 & if \;\; M_i = M_j \end{cases} \tag{4}$$

4) *Set-up change cost (SCC)* is to measure the total set-up change cost in a process plan. A set-up change is needed when two adjacent Ops performed on the same machine with different TADs.

$$SCC = SCCI \times \sum_{i=1}^{n-1}((1-\Omega(M_{i+1}-M_i))\times\Omega(TAD_{i+1}-TAD_i)) \qquad (5)$$

where *SCCI* is the set-up change cost index, a constant.

5) *Tool change cost (TCC):* is used to measure the total cutting tool change cost in a process plan. A tool change is needed when two adjacent Ops performed on the same machine with different tools.

$$TCC = TCCI \times \sum_{i=1}^{n-1}((1-\Omega(M_{i+1}-M_i))\times\Omega(T_{i+1}-T_i)) \qquad (6)$$

where *TCCI* is the tool change cost index, a constant.

These cost factors can be used either individually or collectively as a cost compound based on the requirement and the data availability of the job shop.

As such, the process planning problem can be rephrased as to identify a child node from every parent node and put them into an order which does not violate any precedence relationship between two parent nodes while achieving the least cost compound (CC).

It can be found that solving the above optimization problem will be time consuming. To overcome the computing complexity and take full advantage of operation-based model, GA and SA are used and proved to be effective by our previous research [11], [12].

The first step in formulating a GA/SA for process planning is to map the problem solutions (process plans) to string representations. Illuminated by the works of Bruns [21], we use a knowledge-dependent string to represent all solution space. For an *n*-operation problem, a string representing a process plan is composed of *n* gene segments. Each gene segment contains a child node Op (M-ID, T-ID, TAD) from an unique parent node and its order number in the string. This representation is illustrated in Fig. 3. It is clear that this string representation can cover all the solution space due to the selection of machines, cutting tools, TADs, and the sequence among operations. The algorithms of genetic algorithm and simulated annealing are shown in Algorithm 1 and 2. Please refer our previous research [11], [12] for more detailed information about how to apply genetic algorithm and simulated annealing algorithms to process planning problems.

Gene Segment

Op1	Op2	Op4	Op5	Op3	Op6
Machine 1	Machine 1	Machine 7	Machine 7	Machine 5	Machine 6
Tool 1	Tool 1	Tool 7	Tool 4	Tool 5	Tool 5
TAD +x	TAD +x	TAD +x	TAD +y	TAD +y	TAD -z

Fig. 3 A string representing a process plan with six operations.

Algorithm 1: Genetic Algorithm for Process Planning Problem

```
Begin
    k = 0;
    Initialize population P(m): (n: no. of operations, m: no. of populations)
        Plan (1) {Opi: (M(1,i)/T(1,i)/TAD(1,i)), i=1, …, n}
        Plan (2) {Opi: (M(2,i)/T(2,i)/TAD(2,i)), i=1, …, n}
        ….
        Plan (m) {Opi: (M(m,i)/T(m,i)/TAD(m,i)), i=1, …, n}
    Evaluate initial population P(m): fitness(i)=CC(i), i=1,…,m
    While k < 8000 do
        Generate new generations $P_{new}(m)$:
            Reproduction;
            Crossover;
            Mutation for M, T, TAD, Operation sequence
        Evaluate solutions in the population $P_{new}(m)$;
        k=k+1;
    end
end
```

Algorithm 2: Simulated Annealing for Process Planning Problem

```
Begin
    Random generate a plan, called the current-plan:
        Plan {Opi: M(i)/T(i)/TAD(i), i=1,…, n}, n is the no. of operations
    Start from the initial temperature $T=T_0$;
    While not reaching the final temperature $T_{lowest}$ do
        a)  Make a random change to the current-plan, let temp-plan be
            the plan after the change;
        b)  Check to make sure that temp-plan is valid otherwise go back
            to a)
        c)  Calculate the costs of current-plan (E1) and temp-plan (E2).
            If E2 < E1
                Let temp-plan be current-plan;
            Else
                Randomly generate X (0<X<1);
                If $X<e^{(E1-E2)/T}$
                    Let temp-plan be current-plan;
                Else
                    Let current-plan remain unchanged.
                End if
            End if
        d)  Repeat a) to c) until a criterion is satisfied;
        e)  Reduce the temperature to a new T;
    end
end
```

V. DETAIL IMPLEMENTATION OF REDESIGN PROCESS

Manufacturability analysis is done is two stages. First, evaluate the part's manufacturability when constructing the operation model. Second, evaluate the part's manufacturability after an optimal process plan is generated.

A. Manufacturability analysis when constructing the operation model

The objective of this stage is to evaluate if the part is manufacturable. When a part comes into manufacturing, the process planner first checks the manufacturability, analyzes the geometry and tolerance to evaluate whether the part can be machined in the current job shop. In our approach, this is done when mapping the feature to operations. For any feature F_i, if the mapping result is an empty set, the current design is not manufacturable and F_i will be the candidate for redesign consideration. The following two examples show how this step is done.

Example I: Some features cannot be produced in the current job shop.

As mentioned before, some of the parts can't be machined because the designer mainly considers the function instead of the manufacturability of the part during design. An example is shown in Fig. 4 to show this problem. The evaluation results are:

- F2:*Rect-Slot(blind)* cannot be machined because it has no valid TAD.
- F3:*Rect-Pocket* cannot be machined because the radius of the pocket is zero.

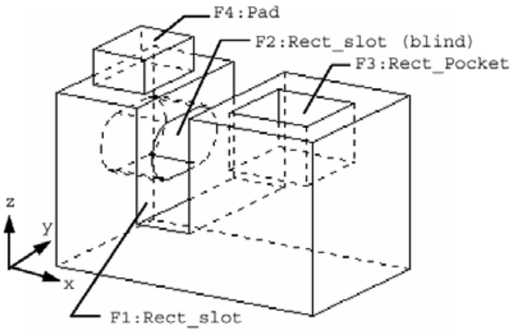

Fig. 4 Part 1 for manufacturability analysis.

The above evaluation results are fed back to the designer as the process planner does not have the right to change the part. The designer can modify feature F3 by two alternative methods: change it to round corner or make four holes at the corner. After the designer changes the *blind Rect-slot* into a *through Rect-slot* and adds radius to F3:*Rect-Pocket* (shown in Fig. 5) , all features can be machined now.

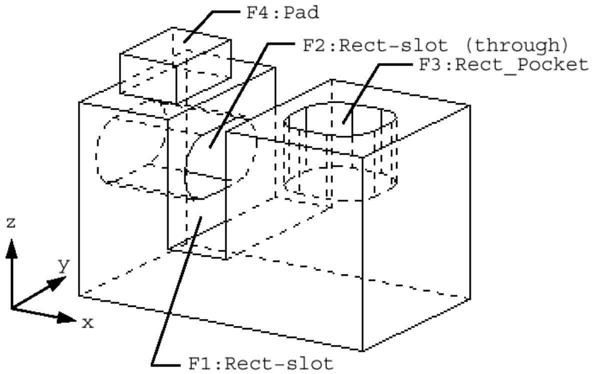

Fig. 5 Redesigned part based on feedback information.

Example II: An operation cannot be performed due to the lack of proper cutting tools or machines.

As shown in Fig. 6, the evaluation result suggests that *F5 (Slot)* cannot be machined because there is no proper T-slot cutters, *F7 (Simple-hole)* cannot be machined because there is no drills with sufficient length in the job shop. This suggests some new tools to be added in the database.

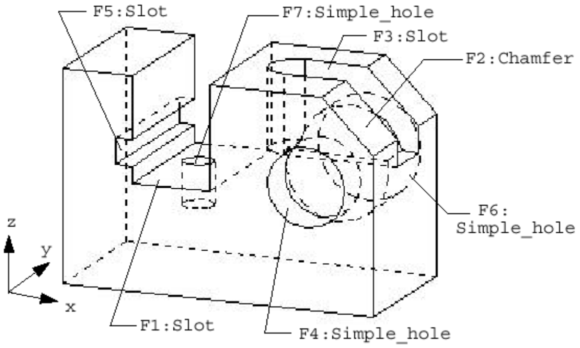

Fig. 6 Part 2 for manufacturability analysis.

B. Manufacturability analysis after generating optimal process plans

The objective of this stage is to further reduce the overall cost. When a part can be machined with current job shop capacity, the optimal/near optimal process plans will be generated by our GA/SA based algorithms. However, the overall cost might be too high. Then the operations will be analyzed to further reduce the cost.

Manufacturing cost can be divided into two types: 1) major cost; which includes machine cost, tool cost, 2) auxiliary cost or change cost which includes machine change cost, tool change cost, and set-up change cost. These two different type costs are introduced by different design factors and hence act as different roles in redesign. Major cost is always determined by local design information. For example, a grinding machine is needed when the finish requirement of a surface is very high.

On the contrary, auxiliary costs are always led by global relations. For example, a set-up change happens because two features have two different tool access directions. Reducing major cost and auxiliary cost usually are conflicting objectives. If you choose a powerful machine which cut down the auxiliary cost, (a CNC center instead of several conventional machines), you must increase machine cost and vice visa. Hence, good resign algorithms should be able to generate a global optimal design that considers as more possible redesign options as possible.

After the optimal process plan of the original design is generated, the system will analyze the plan and generate a pool of features as the candidates to be redesigned. The candidate features are features that cause either the highest major cost such as using an expensive machine or highest change cost, for example, there is a set-up change between two features.

Redesign in our approach at this stage is to enlarge the operation set pool of the candidate features. This can be done by varying the design specification of the feature such as dimensions or tolerance and re-mapping a feature to a larger operation set.

The following examples will show how to find candidate features by analyzing the process plan.

Example I: Major cost which includes machine cost and tool cost.

Major cost is hard to modify, it is determined by the surface finish of the features. However, if the surface finish of a feature can be loosen a little bit, it will significant reduce the manufacturing cost. For example, to produce a feature with less expensive machines and use general machines instead of specified machines. An example is shown in Fig. 7. The rectangle slot F1 has sharp corners, which cannot be made with a vertical mill machine. Feature F1 can be made through a wire electrical discharge machine. However, the cost is increased. Redesign suggestion is made for this case, if the rectangle slot can be changed by adding some fillets at the four corners, the feature then can be made through regular vertical milling machines. It also reduces the machine change costs.

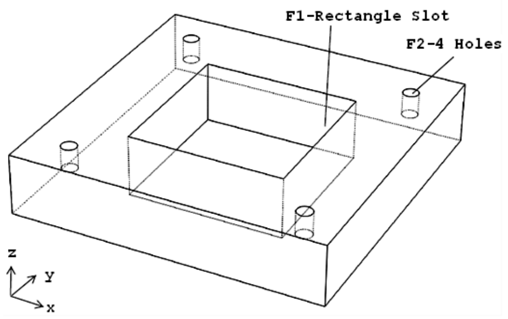

Fig. 7 Part 3 for manufacturing analysis.

Example II: Auxiliary cost which includes machine change cost, tool change cost and set-up change cost

- Set-up changes: A potential feature can be modified to increase the options of TAD so that a set-up change cost can be reduced. An example is given in Fig. 8. Due to the current job environment, the slot F2 cannot be made through the –z direction, because the depth of the slot. If feature F2 is not a critical feature, the redesign module will inform designer that if the depth of the slot changed to 2.5mm, we will have proper tool to machine the feature, so that the set-up changes will be reduced.
- Tool changes: When several consecutive operations can be made with same machines and same tool assess directions, but different cutting tool, it involves with tool change between operations. If one feature is not critical in dimension, the feature might be a potential feature to be modified to use same cutting tool with previous or consecutive operations, so that the tool change cost will be reduced.

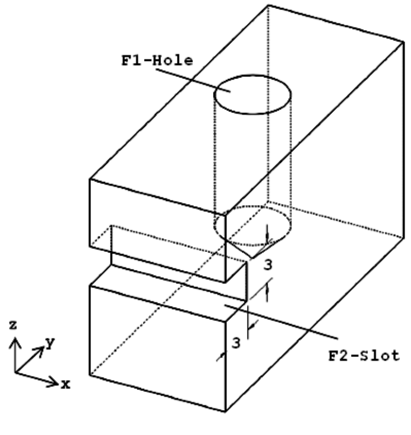

Fig. 8 Part 4 for manufacturing analysis.

- Machine changes: a potential feature can be modified to reduce the machine change cost. For example, in Fig. 7, if the fillet is added to F1: rectangle slot, the machine change is avoided.

When the features that can be redesigned are identified, information will be bed back to designers, so that designer can make the decision whether the dimension can be changed or not.

Up to this point, with loosed constraints in certain features, more tools and machines can be used. Therefore, the searching space is enlarged. The redesign process can be illustrated in Fig. 9.

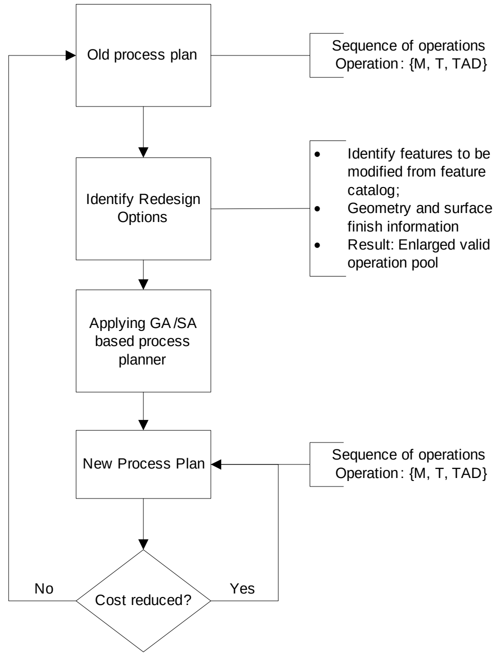

Fig. 9 Redesign algorithms.

VI. CASE STUDY

Following is a case used to demonstrate the effectiveness of the algorithms presented in this paper. Fig. 10 and 11 show the original design of a prismatic part.

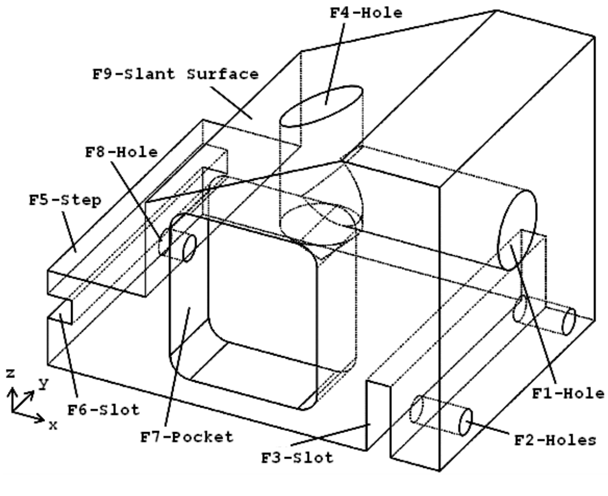

Fig. 10 A prismatic part.

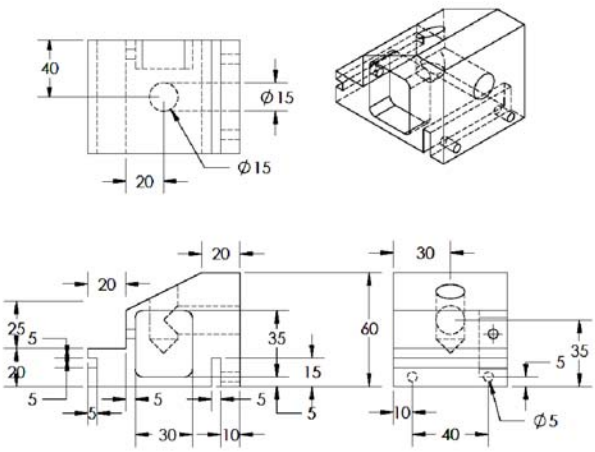

Fig. 11 Detailed dimensions of the machined prismatic part.

The precedence relationship is listed in Table I. The job shop machines and tools are listed in Table II and III. Table IV lists the available operations.

Table I Precedence relationships for the tested case.

Feature	Predecessors	Feature	Predecessors
F1	Nil	F6	F5
F2	Nil	F7	F5
F3	Nil	F8	F5
F4	F5	F9	F4, F5
F5	Nil		

Table II Machines in the job shop.

Machine code	Machine type	Table size	Travel size (dir-x, dir-y, dir-z)	Accuracy
M1	Vertical CNC	1400x650	1200x600x700	0.01
M2	Vertical Mill	1300x280	850x400x400	0.02
M3	Drill Press	1000x280	850x400x400	0.1
M4	Horizontal CNC	1300x550	930x750x1380	0.02
M5	Horizontal Mill	1800x1200	1400x1120x1000	0.01

Table III Cutting tools in the job shop.

Tool code	Tool type	diameter, flute length	TCI (tool cost)
T1	End_Mill	(20,30)	10
T2	End_Mill	(30, 50)	10
T3	End_Mill	(15, 20)	10
T4	End_Mill	(40, 60)	12
T5	Side_Mill	(50, 10)	8
T6	T_slot_cutter	(30, 15)	16
T7	Drill	(20, 55)	3
T8	Drill	(30, 50)	3
T9	Slot cutter	(80, 6)	6
T10	Center_drill	(20, 5)	2
T11	Angle_cutter	(40, 45)	10
T12	End_Mill	(10, 20)	10
T13	Drill	(8, 30)	6
T14	Drill	(10, 35)	3
T15	T_slot_cutter	(20, 6)	6
T16	Drill	(4, 30)	3
T17	End_Mill	(5, 12)	8

Table IV All available operations for the tested case.

Operation	Feature	OpT	Ms	Ts	TADs	Cost index
OperE1	F1	Center_drilling	M1, M2, M3, M4, M5	T10	-x	MCI(M1) =70 MCI(M2) =30 MCI(M3) =10 MCI(M4) =40 MCI(M5) =85 MCCI =150 SCCI =90 TCCI =20
OperE2		Drilling	M1, M2, M4, M5	T14	-x	
OperE3		Milling	M1, M2	T3	-x	
OperE4	F2	Center_drilling	M1, M2, M3, M4, M5	T10	-x	
OperE5		Drilling	M1, M2, M4, M5	T16	-x	
OperE6		Milling	M1, M2	T17	-x	
OperE7	F3	Mill	M1, M2	T17	+z	
OperE8	F4	Center_drilling	M1, M2, M3, M4, M5	T10	-z	
OperE9		Drilling	M1, M2, M4, M5	T14	-z	
OperE10		Milling	M1, M2	T3	-z	
OperE11	F5	Milling	M1, M2	T1,T2, T3, T4	-z, +x	
			M4, M5	T5	-z, +x	
OperE12	F6	Milling	M1, M2, M4, M5	T17	+x	
OperE13	F7	Milling	M1, M2	T12	+y	
OperE14	F8	Center_drilling	M1, M2, M3, M4, M5	T10	+x	
OperE15		Drilling	M1, M2, M4, M5	T16	+x	
OperE16		Milling	M1, M2	T17	+x	
OperE17	F9	Milling	M1, M2,	T1, T2, T4	-y, +y	

Table V shows the generated optimal plan. It can be found that it will need 3 set-up changes to finish this part and this Auxiliary cost is considered to be too high and thus needs redesign.

Table V The optimal process plan of old design.

Operation	M	T	TAD	Summary
Op11	M2	T3	+x	Total Cost: 1122 No. of machine changes: 0 No. of set-up changes: 3 No. of tool changes: 12
Op14	M2	T10	+x	
Op15	M2	T16	+x	
Op16	M2	T17	+x	
Op12	M2	T17	-z	
Op8	M2	T10	-z	
Op9	M2	T14	-z	
Op10	M2	T3	-z	
Op13	M2	T3	-z	
Op17	M2	T1	-x	
Op4	M2	T10	-x	
Op1	M2	T10	-x	
Op2	M2	T14	-x	
Op3	M2	T3	-x	
Op5	M2	T16	-x	
Op6	M2	T17	-x	
Op7	M2	T17	+z	

To reduce the number of set-up changes, the redesign algorithms will find the set-up that contains the minimum number of operations and the corresponding features of these operations are treated as redesign candidates. In this example, set-up +z contains only one operation Op7 and it caused one set-up change. Thus F3 is the redesign candidate.

Table VI New optimal Process plan after redesign.

Operation	M	T	TAD	Summary
Op11	M2	T2	+x	
Op14	M2	T10	+x	Total Cost: 1050
Op5	M2	T16	+x	
Op16	M2	T17	+x	No. of machine changes: 0
Op12	M2	T17	-z	
Op8	M2	T10	-z	No. of set-up changes: 2
Op9	M2	T14	-z	
Op10	M2	T3	-z	
Op13	M2	T3	-z	No. of tool changes: 13
Op17	M2	T1	-x	
Op7	M2	T9		
Op1	M2	T10	-x	
Op4	M2	T10	-x	
Op2	M2	T14	-x	
Op3	M2	T3	-x	
Op5	M2	T16	-x	
Op6	M2	T17	-x	

The objective of the redesign is to reduce the set-up change caused by Op7 and in order to do so the TAD of operation 7 should be changed from +z to the TAD of its adjacent Op6 (-x). The potential tools from the job shop are a side mill with the width of 6mm, and a T_slot_cutter with 6 mm width. Currently the slot dimension of F3 is 5mm. If the dimension of the slot can be modified to a dimension larger than 6mm, so that the two cutting tools can be used to make the feature F3. With that change, two more cutting tools (T9 and T15) can be used. Table VI is the new plan generated based on the redesigned suggestion. The overall cost reduced to 1055, the set-up cost reduced to 2.

VII. CONCLUSION

This paper presents a plan-based manufacturability analysis and redesign approach by generating alternative process plans. After that redesign suggestions are generated based on one of the best and feasible plan. Plan-based approach can provide more detailed and accurate analysis and redesign suggestions; but require large amount of computing time. Optimization algorithms such as Genetic algorithm (GA)/Simulate annealing (SA) are then used to overcome the computing complexity introduced by alternative process planning. Manufacturing cost is computed from the process plan as the measure of manufacturability. The computed manufacturing cost is analyzed to generate redesign suggestions. The modified design is then evaluated again by the process planner to make sure the manufacturing cost is decreased and manufacturability is increased.

One important issue of proposed method is the plan evaluation criteria. In the proposed approach, manufacturing cost is used to measure manufacturability. Complicated evaluation criteria to measure manufacturability should be studied in the future. Further research direction is to fully automate the proposed approach.

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