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Ant colony optimization approach based on precedence constraint matrix for flexible process planning

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INTRODUCTION

In contemporary integrated manufacturing system, the CAPP (Computer Aided Process Planning) is for the PPS (Production Planning and Scheduling); meanwhile, it also needs the support of PPS system. The concurrent integration of CAPP and PPS, which formed the IPPS (Integrated Process Planning and Scheduling) system, is of great importance to improve equipment utilization, eliminate manufacturing resource conflicts, and reduce workpiece circulation time (Seker *et al*., 2013; Li *et al*., 2015; Zhang *et al*., 2015). However, the traditional CAPP is static, which may lead to the failure of the process plan (Usher *et al*., 1996). The process decisions are made under the assumption that the manufacturing resources are free at any time, without considering the plant dynamic events or equipment bottlenecks and other issues. Therefore, the process planning should be based on the specific manufacturing resources and generate a flexible process planning program, which can be dynamically integrated with the PPS system.

Flexible process planning implies the ability of a system to follow change requirements and thereby provide alternative ways of performing manufacturing operations on a part. In order to adapt to the dynamic environment of manufacturing resources and integrate with PPS system, process planning system should generate a large number of flexible process plans for each part, which is optimized and selected according to the manufacturing demands (Li *et al*., 2008). The flexible process planning, which is affected by process precedence constraints, involves many aspects, as the determination of sequence of operations, selection of machine tools, selection of cutting tools, selection of fixtures and so on, and it is also affected by process precedence constraints. As a result, the optimization and selection of flexible process planning are an NP-Complete problem (Petrović *et al*., 2015). The conventional non- heuristic methods cannot provide an optimal solution for this combinatorial problem. Thus, many researchers employed computational intelligence-based algorithms, such as genetic algorithm (GA), simulated annealing (SA), tabu search (TS), particle swarm optimization (PSO), ant colony optimization (ACO), and hybrid algorithms, to solve this problem.

Yiphoi et al. (1996) discussed various aspects of parallel machining that influence the generation of process plans and proposed a process planner by a genetic algorithm for sequencing operations. Qiao et al. (2010) proposed four types of process planning rules including precedence rules, clustering rules, adjacent order rules, and optimization rules in the fitness calculations for alternative operation sequences. They investigated the impact of various rules on the result of operation sequencing and that of genetic algorithms parameters on the solution efficiency, as well as the influence of manufacturing resource environment on the process planning. Huang et al. (2011) developed a solution framework for complex parts based on genetic algorithms approach combined with operation precedence graph (OPG). With modified initial population, crossover operator and mutation operator, this approach is able to optimize the process planning by simultaneously considering the assignment of machining resources, determining sequencing operation and setup plans.

Brown et al. (1997) proposed an alternative approach to accomplish the process planning of a part by decomposing the part into several features and determining the process method according to the feature description, and then applying a stochastic search technique according to simulated annealing to obtain a process plan. Considering the processing costs, G. H. Ma et al. (2000) proposed a process planning model for generating a feasible plan for a given part based on variable machining resources, and an algorithm based on simulated annealing was developed to search for the optimal solution. Musharavati et al. (2012) applied three simulated annealing algorithms that exploit auxiliary knowledge in different ways to handle a manufacturing process planning problem for reconfigurable manufacturing. The computational analysis shows that the simulated annealing algorithms that are supported by auxiliary knowledge can obtain a better optimal solution than that without auxiliary knowledge support. Li et al. (2004) utilized the tabu search based approach to solve the process planning problem under the machining and cutting tools changes.

Wang et al. (2011) took advantage of particle swarm optimization (PSO) to solve the process planning problem. In this approach, a solution representation scheme is introduced for the application of PSO, and two kinds of local search algorithms are incorporated and interweaved with PSO evolution to find the best solution of operation-method selection and sequencing. Li et al. (2013) proposed a modified PSO algorithm, in which the efficient encoding, updating, and random search methods are improved, to optimize the process planning problem, and instance analysis shows that modified PSO algorithm can generate satisfactory solutions and outperform the genetic algorithm and simulated annealing algorithm. Milica et al. (2015) developed a new algorithm based on the utilization of PSO algorithm incorporated with chaos theory to optimize the flexible process plans, and experimental studies show that the new algorithm has a better performance than GA, SA, hybrid GA-SA, and generic PSO based approach. Considering the variety of alternative machines, alternative tools, as well as tool access direction (TAD), Zoran et al. (2016) established a multi-objective optimization model for flexible process planning and developed a modified PSO to solve the nondeterministic combinatorial optimization problem.

Krishna et al. (2006) applied the ant colony algorithm as heuristic search technique to optimize the operations sequence by considering the various feasibility constraints of processing. In view of the cost for machining process, Liu et al. (2013) applied an ant colony optimization algorithm to solve the process planning problem, which is involved with the selection of the available machining resources, the sequence of machining operations, and the manufacturing constraints. Wang et al. (2015) represented the process planning problem as a directed graph that consists of nodes, directed/undirected arcs, and OR relations and utilized a two-stage ant colony optimization approach to solve the process planning problem based on the graph.

In flexible process planning, there are complex constraint precedence relationships in the processing operations. The key point of algorithm designing to solve the operational sequencing problem is to deal with the constraint precedence relationship. Researchers have used many methods to describe the problem of the processing operation constraint, such as Petri-net (Kiritsis *et al*., 1996), operation precedence graph (Wang *et al*., 2015), process plan network (Sormaz *et al*., 2003), and AND/OR graphs (Li *et al*., 2008). However, these methods are unable to solve the problem of dynamic updating of the constraint relationship among the processing operations. In this paper, the precedence constraint relationship was described by precedence constraint matrix, and the dynamic updating of the operation constraints was represented by the updating of precedence constraint matrix. The dynamic updating algorithm of operation constraints was incorporated with ant colony algorithm, which was used to find the optimal solution to flexible process planning problem in limited search space.

FLEXIBLE PROCESS PLANNING PROBLEM AND PREFERENCE CONSTRAINT MATRIX

In part processing, manufacturing features can generally be used to describe the geometric structure of the parts that need to remove materials, the corresponding size tolerance, position tolerance, surface roughness, and other technical requirements.

The flexible process planning can quickly get the optimal process route by resetting the alternative manufacturing resources when the response manufacturing environment changed. The process flexibility of parts can be divided into three types: machining sequence flexibility, operation flexibility, and manufacturing resources flexibility (Li *et* *al*., 2008; Wen *et al*., 2012). Machining sequence flexibility means that some processing operations of parts can interchange, mainly because the processing parts have multiple manufacturing characteristics; each manufacturing characteristic may have n_{op} (n_{op}≥1) machining operations. Since precedence constraints exist in partially machining operations and do not exist in other machining operations, the same part has a variety of processing order (Lv *et al*., 2013). The flexibility of machining operation means that the same manufacturing feature can be finished by choosing the different machining operation, resulting in various processing schemes for each manufacturing feature; each machining scheme contains different machining operations. The flexibility of manufacturing resources suggests that the machining operation of parts can be done by making use of different manufacturing equipment.

OP is machining operation, and *AO* is the set composed by machine tool (*M*) and tool (*T*) and tool access direction (*TAD*). Thus, it can be seen that the sequencing orders of machining operation are the more important work of process planning for a certain part; the process route can be expressed by the following formula:

$$PP = \{OP_1, OP_2, \cdots, OP_i\} \tag{1}$$

OP_i is the *i*-th machining operation of parts and can be expressed by the following formula:

$$OP_i = \{AO_{i1}, AO_{i2}, \cdots, AO_{ij}, \cdots, AO_{in}\} \tag{2}$$

AO_{ij} is corresponding to the *j*-th alternative operation of the *i*-th machining operation of parts and can be expressed by the following formula:

$$AO_{ij} = \{M_{ij}, T_{ij}, TAD_{ij}\} \tag{3}$$

M_{ij}, T_{ij} and TAD_{ij} represent, respectively, machine tool, tool, and tool feed direction of the alternative machining operation AO_{ij}. All the above alternative machining operations can be consisting of machining operations set, which is recorded as 0. Table 1 states any O_i of the alternative machining operation set.

Table 1. Class definition of an alternative machining operation.

Variable *i*	Description
Alternative Operation_id	The alternative machining operation ID
Machine_id	The machine ID to execute the alternative machining operation
Machine_list	The candidate machine list for executing the alternative machining operation
Tool_id	The tool ID to execute the alternative machining operation
Tool_list	The candidate tool list for executing the alternative machining operation
TAD_id	The TAD ID to apply the alternative machining operation
TAD_list	The candidate TAD list for executing the alternative machining operation

There are precedence constraints in the machining operations because of the geometrical shape of manufacture feature and the constraint of manufacture process. This will be mainly embodied in the intersection occlusion of the manufacturing feature in the process of machining and the technological requirements. The usual processing precedence constraints mainly have the following situation:

(1) When the manufacture characteristics are machined on the same surface, they should strictly abide by the order of the roughing, semi-finishing, and finish machining.

(2) For the parts with surface and hole, if the plane is the datum of the hole, then abide by the surface after the hole.

(3) The reference surface should be machined prior to the machining feature associated with it.

(4) Main surface should be machined first, and then the minor surface is machined.

(5) If the two features intersect, along the feed direction, the obscured machining features should be machined later.

The problem of processing priority was expressed by using the operation precedence graph in more literatures (Huang *et al*., 2011; Lee *et al*., 2004); after processing priorities were expressed by making use of operator precedence graph, the operator precedence graph is used to ensure the feasibility of the processing sequence. In the actual machining process, operator precedence graph cannot express complicated processing priority constraint relation, especially the multi-level nested preference constraint relationship. In the choice process of machining operations, there will be dynamic change situation. The precedence constraint matrix can conveniently express preference constraint relationship in the alternative machining operations (Huang *et al*., 2016). Suppose there is N alternative operations in set 0; Nth-order matrix is defined to store the preference constraint relationship in alternative operations, as shown in formula (4):

$$C = \begin{bmatrix} C_{11} & C_{12} & \cdots & C_{1N} \\ C_{21} & C_{22} & \cdots & C_{2N} \\ \vdots & \vdots & & \vdots \\ C_{N1} & C_{N2} & \cdots & C_{NN} \end{bmatrix} \tag{4}$$

where O_{ij} represents the preference constraint relationship between O_i and O_j, $i,\ j = 1,2,\cdots,N$, the value is defined by the following rules: when the i-th alternative operation is prior to the j-th alternative operation, then $C_{ij} = 1$, $C_{ij} = 0$. When O_i and O_j belong to the same operation OP_k, then $C_{ij} = C_{ij} = -1$, under other cases, $C_{ij} = C_{ij} = 0$. Obviously, there is $C_{ij} = \{-1,0,1\}$.

Precedence constraints determined by the processing technology are in the layer of machining operation OP_i, then all alternative machining operations of OP_i have the same precedence constraints. It is related to the tool access direction whether intersection features possess obscured precedence constraints, As a consequence, the precedence constraints are in the layer of alternative machining operations AO_{ij}; then the alternative machining operations in the same machining operation OP_i have the different precedence constraints. The different machines and tools in the alternative operation set AO_{ij} of machining operation OP_i do not influence the preference constraint relations; therefore, the alternative machining operation OP_i will be redefined that it is only related with the direction of TAD_{ij} and is as follows:

$$AO_{ij} = \{M, T, TAD_{ij}\} \tag{5}$$

Suppose there is processing part as shown in figure 1 (Wang *et al*., 2015); part blank is the square envelope body, and processing operations of features are shown in table 2:

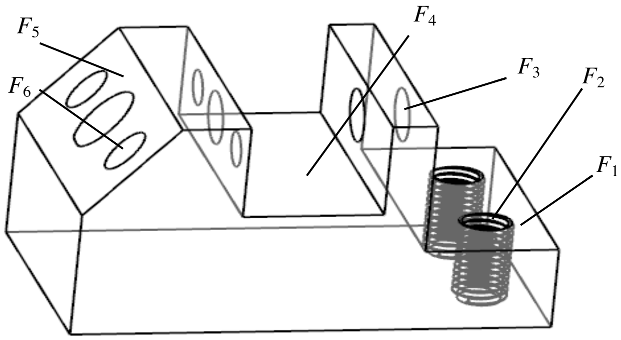

Fig. 1. An example part.

Table 2. Operation selection for the example part.

Features	Operations	Machines	Tools	TADs
F_1	Milling(OP_1)	M_1	$\mathcal{T}_1$	$-\mathcal{Z}$, $-\mathcal{X}$
F_2	Drilling(OP_2)	M_1, M_2	$\mathcal{T}_2$	$-\mathcal{Z}$
	Tapping(OP_3)	M_1, M_2	$\mathcal{T}_3$	$-\mathcal{Z}$
F_3	Drilling(OP_4)	M_1, M_2	$\mathcal{T}_4$	$-\mathcal{X}$
	Reaming(OP_5)	M_1, M_2	$\mathcal{T}_5$	$-\mathcal{X}$
F_4	Milling(OP_6)	M_1	$\mathcal{T}_1$, $\mathcal{T}_6$	$-\mathcal{Z}$
F_5	Milling(OP_7)	M_1	$\mathcal{T}_1$, $\mathcal{T}_6$	$-\mathcal{Z}$, $+\mathcal{Y}$
F_6	Drilling(OP_8)	M_1, M_2	$\mathcal{T}_7$	$+\mathcal{X}$
	Reaming(OP_9)	M_1, M_2	$\mathcal{T}_8$	$+\mathcal{X}$

In the above table, M_1 means vertical milling machine, M_2 means drilling machine, T_1 means mill cutter 1, T_2 means drill 1, T_3 means tapping tool, T_4 means drill 2, T_5 means reamer 1, T_6 means mill cutter 2, T_7 means drill 3, and T_8 means reamer 2. The alternative operation is as shown in table 3 according to the description of the formula (5):

Table 3. Description of the alternative operations.

Numbers	Operation	Alternative Operation	Machines	Tools	TADs
O_1	OP_1	AO_{11}	M_1	$\mathcal{T}_1$	$-\mathcal{Z}$
O_2	OP_1	AO_{12}	M_1	$\mathcal{T}_1$	$-\mathcal{X}$
O_3	OP_2	AO_{21}	M_1, M_2	$\mathcal{T}_2$	$-\mathcal{Z}$
O_4	OP_3	AO_{31}	M_1, M_2	$\mathcal{T}_3$	$-\mathcal{Z}$
O_5	OP_4	AO_{41}	M_1, M_2	$\mathcal{T}_4$	$-\mathcal{X}$
O_6	OP_5	AO_{51}	M_1, M_2	$\mathcal{T}_5$	$-\mathcal{X}$
O_7	OP_6	AO_{61}	M_1	$\mathcal{T}_1$, $\mathcal{T}_6$	$-\mathcal{Z}$
O_8	OP_7	AO_{71}	M_1	$\mathcal{T}_1$, $\mathcal{T}_6$	$-\mathcal{Z}$
O_9	OP_7	AO_{72}	M_1	$\mathcal{T}_1$, $\mathcal{T}_6$	$+\mathcal{Y}$
O_{10}	OP_8	AO_{81}	M_1, M_2	$\mathcal{T}_7$	$+\mathcal{X}$
O_{11}	OP_9	AO_{91}	M_1, M_2	$\mathcal{T}_7$	$+\mathcal{X}$

Along the same tool access direction of adjacency features, alternative machining operations AO_{11} and AO_{21} have the preference constraint relationship. Preference constraint relations in the machining operations are as follows: OP_1 is prior to OP_2 and OP_3, OP_2 is prior to OP_3, OP_4 is prior to OP_5, OP_4 and OP_5 are prior to OP_6, OP_8 is prior to OP_9, and OP_8 and OP_9 are prior to OP_7. When there are preference constraint relations between machining operations, then the alternative machining operation also has the corresponding preference constraint relation; according to formula (4), preference constraint matrix is as shown in figure 2.

$$
\begin{array}{c}
\\ O_1 \\ O_2 \\ O_3 \\ O_4 \\ O_5 \\ O_6 \\ O_7 \\ O_8 \\ O_9 \\ O_{10} \\ O_{11}
\end{array}
\begin{array}{c}
\begin{array}{ccccccccccc} O_1 & O_2 & O_3 & O_4 & O_5 & O_6 & O_7 & O_8 & O_9 & O_{10} & O_{11} \end{array} \\
\begin{bmatrix}
0 & -1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
-1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0
\end{bmatrix}
\end{array}
$$

Fig. 2. The precedence constraint matrix.

According to the definition of the above alternative machining operator precedence constraint matrix C, if there is $C_{ij} = C_{ji} = -1$, then $C_{ij} = C_{ji} = 0$; get the matrix C'. Alternative machining operations O are divided into three types on the basis of C': independent alternative machining operations, priority alternative machining operations, and subsequent alternative machining operations; they are, respectively, defined as follows.

Definition 1 Independent alternative machining operations set O_I. If alternative machining operations O_i is in precedence constraint matrix, then there is a relation $\sum_{i=1}^{N} C_{ij} = \sum_{j=1}^{N} C_{ji} = 0$, indicating that the alternative machining operation has no precedence constraint relationship with other alternative operations, which is the independent alternative machining operations.

Definition 2 Precedence alternative machining operations set O_P. If alternative machining operation O_i is in precedence constraint matrix, then there is a relation $\sum_{i=1}^{N} C_{ij} = 0$ and $\sum_{j=1}^{N} C_{ji} \neq 0$, revealing that O_i is precedence alternative machining operation of one or more alternative machining operations.

Definition 3 Subsequent alternative machining operations set O_S. If alternative processing operation O_i is in precedence constraint matrix, then there is a relation $\sum_{i=1}^{N} C_{ij} \neq 0$, indicating that O_i begins to machine after one or more alternative machining operations have finished, which is the subsequent alternative processing operation.

According to the above definition, O_1, O_2, O_5 and O_{10} belong to precedence alternative machining operations set O_P, while the others belong to the subsequent alternative machining operations set O_S; there is no independent alternative machining operations set O_I. The precedence alternative machining operations set O_P and independent alternative machining operations set O_I belong to the current feasible alternative machining operations. So the definition of feasible alternative machining operation can be defined as follows.

Definition 4 feasible alternative machining operations set O_F. If alternative machining operation O_i is in precedence constraint matrix, then there is a relation $\sum_{i=1}^{N} C_{ij} = 0$, revealing that O_i is precedence alternative machining operation or independent alternative machining operations, which is the feasible alternative processing operation.

GENERATION OF DYNAMIC FEASIBLE ALTERNATIVE MACHINING OPERATIONS SET

When planning the flexible manufacturing route, the chosen alternative machining operations will not be chosen again, which belong to Tabu alternative machining operations set. And when a certain machining operation has more alternative machining operations, the other alternative machining operations will not be chosen again after one of the alternative machining operations is chosen, which also belongs to Tabu alternative machining operations set. Suppose Tabu alternative processing operation list is $\mathrm{Tab}_t(0)$, then the feasible alternative processing operation list is $\mathrm{Fea}_{t+1}(0_F) = (\mathrm{Fea}_t(0_F) - \mathrm{Tab}_t(0))$. Since Tabu alternative processing operation list $\mathrm{Tab}_t(0)$ is updated dynamically with the selection of each step, feasible alternative machining operation list $\mathrm{Fea}_{t+1}(0_F)$ is also dynamically updated.

The selected nodes are all machining operations selected from current feasible alternative processing operations list. It assumes the current selected alternative machining operation is O_i, and the alternative machining operations set of process route is 0_R. According to the preceding definition, there are two ways to achieve the dynamic update of 0_F; one is to update dynamically 0_S, and combine 0_S with 0_R, and generate $\mathrm{Tab}_t(0)$ to realize the dynamic update of $\mathrm{Fea}_{t+1}(0_F)$. The other method is that the diagonal values of the alternative machining operation choose to enter 0_R in each step. And other alternative machining operations belong to the same machining operations and are all set to constant according to the definition of 0_F, so that they do not meet the definition that each column sum is zero and realize the dynamic update of 0_F. The second method is employed in this paper, and then the generating process of current dynamic update feasible alternative processing operations set is as shown in figure 3.

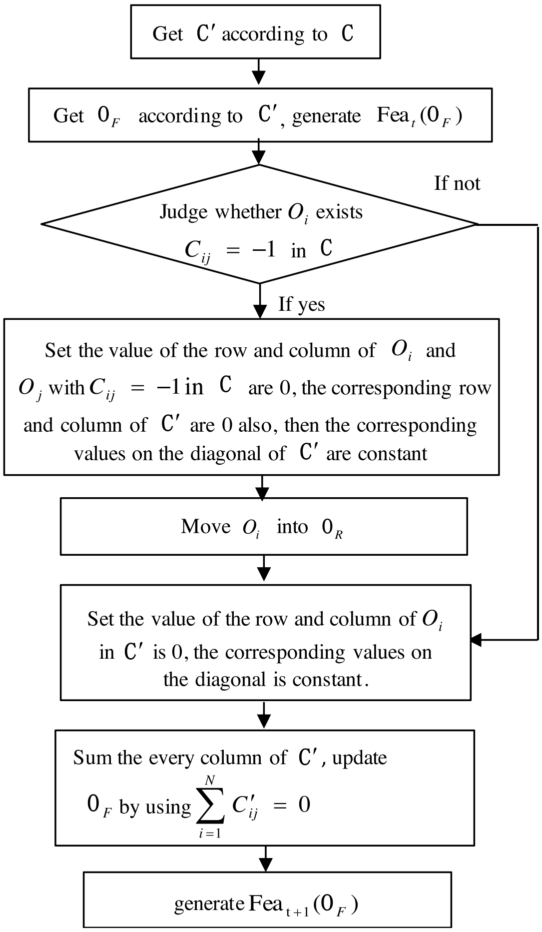

Fig. 3. Generating process of feasible alternative processing operation list.

The steps generated by the above feasible alternative machining operations list are explained as follows:

Step 1: If there is $C_{ij} = C_{ji} = -1$ in alternative processing operator precedence constraints matrix C, then set $C_{ij} = C_{ji} = 0$, and get matrix C'.

Step 2: Using definition 4, we can get feasible alternative machining operations set 0_F based on matrix C'; then feasible alternative machining operations list $\mathrm{Fea}_t(0_F)$ can be gotten in time t.

Step 3: Determine whether O_i exists $C_{ij} = -1$ in C; if no, go to Step 6.

Step 4: If yes, set the value of the row and column of O_i and O_j with $C_{ij} = -1$ in C and C' as 0; the corresponding values on the diagonal of C' are set to constant;

Step 5: Move O_i into process route set 0_R;

Step 6: Set the values of the row and column of O_i in C' as 0; the corresponding row and column of C' are 0 as well; then the corresponding values on the diagonal of C' are constant;

Step 7: Sum every column of C', and update feasible alternative processing operation set 0_F under the condition of $\sum_{i=1}^{N} C'_{ij} = 0$; then feasible alternative machining operations list $\mathrm{Fea}_{t+1}(0_F)$ can be gotten in time t+1.

The selection process of a process route of parts shown in figure 1 is shown in figure 4.

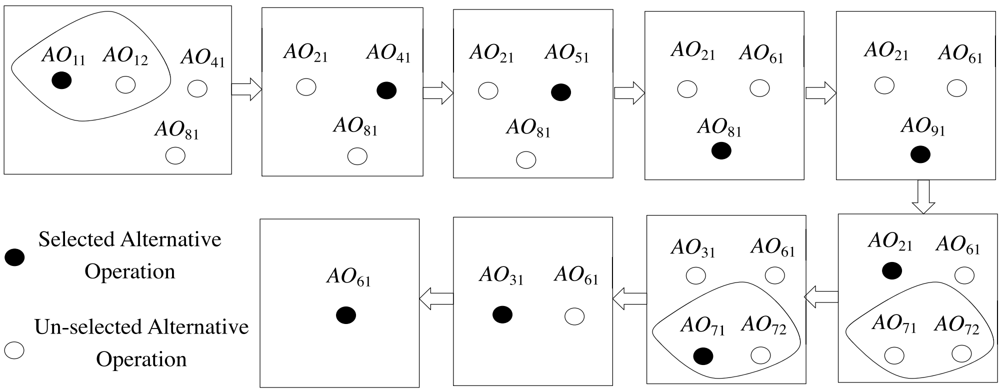

Fig. 4. Selected alternative operation for the example part.

Process route selection of the above parts is carried out in feasible alternative processing operation every time the alternative machining operations are updated dynamically. At the same time, it is clear that the scale of the solving problem is greatly shrunk after the search space limit of each step of the process planning.

OPTIMIZATION OBJECTIVE OF FLEXIBLE PROCESS PLANNING

The flexible process planning problem is generally described as follows: in view of the all feasible processing route of machined parts, choose from one of them, which optimizes some indicators. In the existing study, optimization goal based on machining time and cost are usually used (Liu *et al.*, 2013; Blanch *et al.*, 2011; Ciurana *et al.*, 2008). The optimization goal based on the manufacturing cost is mainly considered in this paper, which will include the following five aspects: cost of machine tools, tooling cost, cost of machine tool changing, cost of tools changing, and cost of the clamping changing; the specific calculation process are described as follows:

(1) Machine tools cost of the total parts processing (*TMC*)

$$TMC = \sum_{i=1}^{n} M_j C_i , \qquad j = OP[i].machine\_id \tag{6}$$

M_jC_i is the manufacturing cost of machine tool that the *j*-th machine tools in the *i*-th machining operations need, and *n* is the number of machining operations.

(2) The total tooling cost of parts processing (*TTC*)

$$TTC = \sum_{i=1}^{n} T_j C_i \ , \quad j = OP[i].tool\_id \tag{7}$$

T_jC_i is the tooling cost that the j-th tools in the i-th machining operation need.

(3) The total cost of machine tool changing (*TMCC*)

$$TMCC = MCC \times NMC \tag{8}$$

MCC is the cost that machine tools need; we can consider that every time the cost of the machine tool transformation is the same. *NMC* is the times of machine tool transformation, which can be calculated by formula (9) and formula (10).

$$NMC = \sum_{i=1}^{n-1} \Omega 1(M_j, M_k) \ , \quad j = OP[i].machine\_id \quad k = OP[i+1].machine\_id \tag{9}$$

$$\Omega 1(X, Y) = \begin{cases} 1, & X \neq Y \\ 0, & X = Y \end{cases} \tag{10}$$

(4) The total cost of tools changing (*TTCC*)

The machining operations of the two adjacent parts do not need to transform tool only when using the same tool and machine tool. Otherwise, the tools need to be changed.

$$TTCC = TCC \times NTC \tag{11}$$

TCC is the cost of tools changing once. *NTC* is the times of tools changing, which can be calculated by formulas (12) and (13).

$$\begin{aligned} &NTC = \sum_{i=1}^{n-1} \Omega 2(\Omega 1(M_j, M_k),\ \Omega 1(T_l, T_m)) \\ &j = OP[i].machine\_id,\ k = OP[i+1].machine\_id \\ &l = OP[i].tool\_id,\ m = OP[i+1].tool\_id \end{aligned} \tag{12}$$

$$\Omega 2(X, Y) = \begin{cases} 0, & X = Y = 0 \\ 1, & \text{ortherwise} \end{cases} \tag{13}$$

(5) The set-up changing cost of parts (*TSCC*)

The machining operations of the two adjacent parts can be thought as they do not need set-up changing only when they use the same tool and the same feed direction. Otherwise, set-up changing needs to be done once.

$$TSCC = (NSC + 1) \times SCC \tag{14}$$

SCC is the cost of set-up changing once. *NSC* is the times of production preparation, which can be calculated by formulas (15) and (16).

$$\begin{aligned} &NSC = \sum_{i=1}^{n} \Omega 2(\Omega 1(M_j, M_k),\ \Omega 1(TAD_l, TAD_m)) \\ &j = OP[i].machine\_id,\ k = OP[i+1].machine\_id \\ &l = OP[i].TAD\_id,\ m = OP[i+1].TAD\_id \end{aligned} \tag{15}$$

$$NS = NSC + 1 \tag{16}$$

(6) The total weighted cost of parts (*TWC*)

The optimization goal based on the machining cost can be set to minimum total weighted cost, which is shown as formula (17):

$$\mathrm{Min}\,TWC = w_1 \times TMC + w_2 \times TTC + w_3 \times TMCC + w_4 \times TTCC + w_5 \times TSCC \tag{17}$$

A NOVEL TWO-STAGE ACO ALGORITHM FOR FPP

The ACO algorithm is a population-based heuristic, which simulates the foraging behavior of ants and develops mechanisms of cooperation and learning to solve optimization problems (Dorigo *et al.*, 1996). In an ant colony, ants lay pheromone trails on the path while foraging to share information with other ants and direct them toward food sources. An isolated ant may move randomly and lay pheromone trail over traversed path. An ant encountering a previously laid trail can apply a probabilistic approach, which favors the path with the highest pheromone trail to decide where to go, thus reinforcing the trail with its own pheromone. This forms a positive feedback, enabling rapid discovery of food source. Eventually, with the cooperation among ants, the shortest route from the colony to food source can be established. ACO uses the similar cooperation mechanism to search for good solutions to optimization problems.

The flexible process planning problem is a non-deterministic polynomial complete (NP-Complete) problem (Liu *et al.*, 2013). Due to the existence of operation precedence constraints in the problem, infeasible solutions often occur when using heuristics (e.g., GA, ACO, etc.) to solve the problem. To ensure the feasibility of the process plans, additional adjustments need to be done. The adjustment methods that prevail in the literature include constraint adjustment method (Li *et al.*, 2002), penalty function method, and restricting the search space. Due to lack of prior information, when dealing with complex precedence constraints, constraint adjustment methods may lead to a very slow convergence of the algorithm, and penalty function method mainly applies when there is a clear boundary between feasible and infeasible regions. Hence, this paper utilizes the adjustment method of restricting the search space and develops a novel ACO algorithm integrated with a dynamic adjustment of the alternative machining operations set. The proposed algorithm consists of two stages: i) the first stage is for constraint-based operation selection and sequencing; ii) the second stage aims at allocating resources (i.e., machines and tools) for the selected and sequenced operations obtained from the first stage, taking each alternative machine-tool combination for an operation as a sub-node that subordinates to that operation node.

ANT COLONY AND TRANSITION PROBABILITY

Assume that there are N operations. Take each operation as a particular node in the graph. An edge (O_i, O_j) represents that operation O_j be processed right after O_i. Let m be the total number of ants in the colony, $b_i(t)$ be the number of ants situated at operation node O_i at time t ($\sum_{i=1}^{N} b_i(t) = m$), and $\tau_{ij}(t)$ be the intensity of pheromone trail on edge (O_i, O_j) at time t. Take $\Gamma = \{\tau_{ij}(t) \mid 0_i, 0_j \subset 0\}$ as the set of pheromone trail intensity for all the alternative edges at time t. Assume that the initial intensities of pheromone trail on each edge are equal, and $\tau_{ij}(0) = \mathrm{const}$.

Individual ants lay pheromone trails on the traversed edges and choose their next operation node with respect to probabilities that depend on pheromone trails and the attractiveness of alternative options (i.e., next operation). The transition probability for ant k $(k = 1,2,\cdots,m)$ at operation node O_i to move to node O_j for the next step is defined as

$$P_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha}[\eta_{ik}(t)]^{\beta}}{\sum_{s \in \mathrm{Fea}_t(0)} [\tau_{is}(t)]^{\alpha}[\eta_{is}(t)]^{\beta}} & s \in \mathrm{Fea}_t(0) \\ 0 & \text{otherwise} \end{cases} \tag{18}$$

where $\mathrm{Fea}_t(0)$ represents the set of all the alternative operation nodes for the next step, and parameters α and β weigh the relative importance of trail versus attractiveness. $\eta_{ij}(t)$ is a heuristic function that evaluates the attractiveness of edge (O_i, O_j), which depends on the production cost of the edge, as shown in Eq. (19). The less an edge cost is, the more attractive it is; hence there is a higher probability for ants following it.

$$\eta_{ik}(t) = \frac{1}{C_{ij}} \tag{19}$$

PHEROMONE UPDATING

At each iteration, individual ants change pheromone trail intensity by laying their own pheromone trails on the traversed edges. Pheromones are updated by the following rule:

$$\tau_{ij}(t + N) = (1 - \rho) \cdot \tau_{ij}(t) + \Delta\tau_{ij}(t) \tag{20}$$

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t) \tag{21}$$

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} Q/TWC & \text{if ant k traverses edge } (O_i, O_j) \\ 0 & \text{otherwise} \end{cases} \tag{22}$$

where $\rho \in [0,1)$ is the pheromone evaporation rate, and $1-\rho$ stands for the pheromone persistence factor. $\Delta\tau_{ij}(t)$ is the pheromone increment of edge (O_i, O_j), and $\Delta\tau_{ij}^{k}(t)$ refers to the quantity of pheromone laid on edge (O_i, O_j) by ant k ($k = 1,2,\cdots,m$). Q is a constant and TWC is the total weighted cost defined in Eq. (17). Assume that $\Delta\tau_{ij}(0) = 0$.

To better explore the search space and prevent premature convergence, a lower bound $\tau_{\min}$ and an upper bound $\tau_{\max}$ are imposed on pheromone trails, preventing the relative differences between pheromone trails from becoming too extreme. Use Eq. (24) to adjust trails within $[\tau_{\min}, \tau_{\max}]$.

$$\tau_{ij}(t + N, k) = \begin{cases} \tau_{min} & if\ \tau_{ij}(t + N, k) \le \tau_{min} \\ \tau_{ij}(t + N, k) & if\ \tau_{min} < \tau_{ij}(t + N, k) \le \tau_{max} \\ \tau_{max} & if\ \tau_{ij}(t + N, k) > \tau_{max} \end{cases} \tag{24}$$

OVERALL PROCEDURE OF THE PROPOSED ALGORITHM FOR FPP

The main idea of the proposed algorithm is as follows: First randomly place each ant on an operation node from the feasible alternative machining operations list $\mathrm{Fea}_0(0_F)$; update the precedence constraint matrix and the feasible alternative machining operations set 0_F; select the next operation node from the updated feasible alternative machining operations list $\mathrm{Fea}_t(0_F)$. Synthesize the transition probability to alternative operations; repeat the previous two steps until a feasible complete process plan has been produced. Through iterations of ants searching, the process plan with the least cost can be obtained.

Step 0. Specify the parameters such as the total number of ants m, the pheromone evaporation rate ρ, weights α and β, and the maximal iteration number $N_{c_{\max}}$. Set $\tau_{ij}(0) = const$ and $\Delta\tau_{ij}(0) = 0$ $(i,\ j = 1,\ 2, \cdots, N)$. Set $t = 0$ and the iteration number $N_c = 1$.

Stage 1 Precedence constraint-based operation selection

Step 1.1 Set the index of ant $k = 1$.

Step 1.2 Obtain the feasible alternative machining operations set 0_F, and initial feasible alternative machining operations list $\mathrm{Fea}_0(0_F)$.

Step 1.3 Randomly place ant k on an operation node from $\mathrm{Fea}_0(0_F)$. Set $t = t+1$. Update $\mathrm{Fea}_t(0_F)$ according to the dynamic adjustment method of the alternative operations set.

Step 1.4 Compute $\eta_{ik}(t)$ and $P_{ij}^{k}(t)$ according to Eqs. (19)-(20). With the transition probability $P_{ij}^{k}(t)$, select the next operation node from $\mathrm{Fea}_t(0)$ for ant *k*.

Step 1.5 Set $t = t+1$. Update $\mathrm{Fea}_t(0)$.

Step 1.6 If there is no operation left in $\mathrm{Fea}_t(0)$, execute Stage 2. Otherwise, go to Step 1.4.

Stage 2 Machine and tool resource allocation

Step 2.1 Set the maximal cycle times $N_{m\text{-}max}$, $N_m = N_m + 1$.

Step 2.2 Randomly choose a machine from Machine_list and a tool from Tool_list for the first selected operation O_i in the process plan (i.e., the traversed route of ant *k*) generated in Stage 1. Record the machine ID and the tool ID.

Step 2.3 Choose the machine-tool combination for the next operation with the least changeover cost when switching from the previous operation. This step continues until all the operations in the process plan have been allocated with machine and tool resource.

Step 2.4 Compute the total weighted cost *TWC* for the process plan generated by ant *k*.

Step 2.5 Find the minimum *TWC* in all cycle times, and save the process route information of manufacturing resource selection.

Step 2.6 Set $k = k + 1$. If $k < m$, and return to Step 1.2. Otherwise, execute Step 2.7.

Step 2.7 Find the best process plan with the least *TWC* among all the *m* process plans generated by these *m* ants.

Step 2.8 Update the pheromones according to Eqs. (20)-(24). Set $N_c = N_c + 1$.

Step 3 If $N_c \geq N_{c_{\max}}$, terminate the algorithm and output the best process plan with the minimum *TWC*. Otherwise, empty the alternative operations set, and return to Stage 1.

CASE STUDY

The algorithm proposed in this paper is verified by the part shown in figure 5 (Li *et al.*, 2002); firstly, the conditions set are as follows: (a) all the machine tools and cutting tools are available; set the value of $w_1 \sim w_5$ in objective function (17) to be 1. (b) All the machine tools and cutting tools are available, in objective function (17), $w_2 = w_5 = 0$, $w_1 = w_3 = w_4 = 1$.

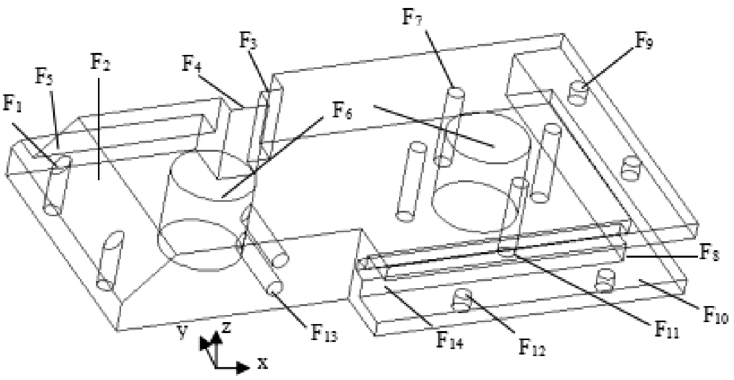

Fig. 5. Geometric figure of Instance parts.

The above parts have 14 manufacturing features. The relevant resources and costs of machines and tools are shown in tables 4-5, and the related information of machining operations are shown in table 6. Suppose the *MCC* cost of machines changing once is 300, the *SCC* cost of tools changing once is 120, and the *SCC* cost of starting the transformation once is 15.

Table 4. Machine resources and costs.

Machines no.	Types	mc_i
1	Drill machine	10
2	Milling machine	35
3	Three-axis vertical milling machine	60

Table 5. Tool resources and costs.

Tools no.	Types	mc_i
1	Drill 1	3
2	Drill 2	3
3	Reamer	8
4	Boring tool	15
5	Milling cutter 1	10
6	Milling cutter 2	15
7	Slot cutter	10
8	Chamfer tool	10

Table 6. Description of the alternative operations.

Numbers	Features	Feature descriptions	Operations	Alternative Operations	Machines	Tools	TAD
O_1	F_1	Two holes	OP_1	AO_{11}	M_1, M_2, M_3	$\mathcal{T}_1$	$+\mathcal{Z}$
O_2	F_1		OP_1	AO_{12}	M_1, M_2, M_3	$\mathcal{T}_1$	$-\mathcal{Z}$
O_3	F_2	A chamfer	OP_2	AO_{21}	M_2, M_3	$\mathcal{T}_8$	$-\mathcal{X}$
O_4	F_2		OP_2	AO_{22}	M_2, M_3	$\mathcal{T}_8$	$+\mathcal{Y}$
O_5	F_2		OP_2	AO_{23}	M_2, M_3	$\mathcal{T}_8$	$-\mathcal{Y}$
O_6	F_2		OP_2	AO_{24}	M_2, M_3	$\mathcal{T}_8$	$-\mathcal{Z}$
O_7	F_3	A slot	OP_3	AO_{31}	M_2, M_3	$\mathcal{T}_5$, $\mathcal{T}_6$	$+\mathcal{Y}$
O_8	F_4	A slot	OP_4	AO_{41}	M_2	$\mathcal{T}_5$, $\mathcal{T}_6$	$+\mathcal{Y}$
O_9	F_5	A step	OP_5	AO_{51}	M_2, M_3	$\mathcal{T}_5$, $\mathcal{T}_6$	$+\mathcal{Y}$

O_{10}	F_5		OP_5	AO_{52}	M_2, M_3	$\mathcal{T}_5, \mathcal{T}_6$	$-\mathcal{Z}$
O_{11}	F_6	Two holes	OP_6	AO_{61}	M_1, M_2, M_3	$\mathcal{T}_2$	$+\mathcal{Z}$
O_{12}	F_6		OP_6	AO_{62}	M_1, M_2, M_3	$\mathcal{T}_2$	$-\mathcal{Z}$
O_{13}	F_7	Four holes	OP_7	AO_{71}	M_1, M_2, M_3	$\mathcal{T}_1$	$+\mathcal{Z}$
O_{14}	F_7		OP_7	AO_{72}	M_1, M_2, M_3	$\mathcal{T}_1$	$-\mathcal{Z}$
O_{15}	F_8	A slot	OP_8	AO_{81}	M_2, M_3	$\mathcal{T}_5, \mathcal{T}_6$	$+\mathcal{X}$
O_{16}	F_9	Two holes	OP_9	AO_{91}	M_1, M_2, M_3	$\mathcal{T}_1$	$-\mathcal{Z}$
O_{17}	F_{10}	A slot	OP_{10}	AO_{101}	M_2, M_3	$\mathcal{T}_5, \mathcal{T}_6$	$-\mathcal{Y}$
O_{18}	F_{11}	A slot	OP_{11}	AO_{111}	M_2, M_3	$\mathcal{T}_5, \mathcal{T}_6$	$-\mathcal{Y}$
O_{19}	F_{12}	Two holes	OP_{12}	AO_{121}	M_1, M_2, M_3	$\mathcal{T}_1$	$+\mathcal{Z}$
O_{20}	F_{12}		OP_{12}	AO_{122}	M_1, M_2, M_3	$\mathcal{T}_1$	$-\mathcal{Z}$
O_{21}	F_{13}	A step	OP_{13}	AO_{131}	M_2, M_3	$\mathcal{T}_5, \mathcal{T}_6$	$-\mathcal{X}$
O_{22}	F_{13}		OP_{13}	AO_{132}	M_2, M_3	$\mathcal{T}_5, \mathcal{T}_6$	$-\mathcal{Y}$
O_{23}	F_{14}	Two holes	OP_{14}	AO_{141}	M_1, M_2, M_3	$\mathcal{T}_1$	$-\mathcal{Y}$

In the literature (Li *et al*., 2004) and (Li *et al*., 2013), preference sequence constraints between each feature are shown in table 7.

Table 7. Machining constraints and interaction.

Constraints	Descriptions	Hard or soft
Tool interactions	F_1 should be prior to F_2	Hard
Datum interactions	F_6 should be prior to F_7	Hard
	F_{10} should be prior to F_{11}	
	F_{13} should be prior to F_{14}	
Thin-wall interactions	F_9 should be prior to F_8	Soft
	F_{12} should be prior to F_{10}	
Material removal interactions	F_8 should be prior to F_9	Soft
	F_{10} should be prior to F_{12}	
	F_{13} should be prior to F_{14}	

In the above machining precedence constraints, the feature F_1 has two alternative machining operations; when the feature F_1 uses AO_{11} to machine, then the relation F_1 should be prior to F_2 which may be not established. Mainly consider the above Hard constraints of machining precedence constraints; the precedence constraint matrix is gotten as shown in figure 6.

$$
\begin{array}{c}
\begin{array}{c} \\ O_1 \\ O_2 \\ O_3 \\ O_4 \\ O_5 \\ O_6 \\ O_7 \\ O_8 \\ O_9 \\ O_{10} \\ O_{11} \\ O_{12} \\ O_{13} \\ O_{14} \\ O_{15} \\ O_{16} \\ O_{17} \\ O_{18} \\ O_{19} \\ O_{20} \\ O_{21} \\ O_{22} \\ O_{23} \end{array}
\begin{array}{c}
\begin{array}{ccccccccccccccccccccccc} O_1 & O_2 & O_3 & O_4 & O_5 & O_6 & O_7 & O_8 & O_9 & O_{10} & O_{11} & O_{12} & O_{13} & O_{14} & O_{15} & O_{16} & O_{17} & O_{18} & O_{19} & O_{20} & O_{21} & O_{22} & O_{23} \end{array} \\
\begin{bmatrix}
0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
-1 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & -1 & -1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & -1 & 0 & -1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & -1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & -1 & -1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
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0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\end{array}
\end{array}
$$

Fig. 6. The precedence constraint matrix for the example part.

The setting parameters of ant colony algorithm are as follows: the number of ants m=15, $\alpha = 1$, $\beta = 2$, $\rho = 0.1$, $N_{c_{max}} = 50$, Q=3000, $\tau_{ij}(0) = 1$. The situations (a) and (b) of the instance parts, respectively, run 10 times; the optimum value of every generation is as shown in figures (6) and (7).

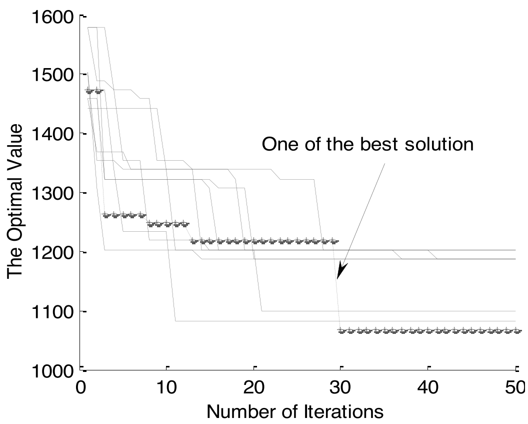

Fig. 6. Optimal value of each iteration in condition (a).

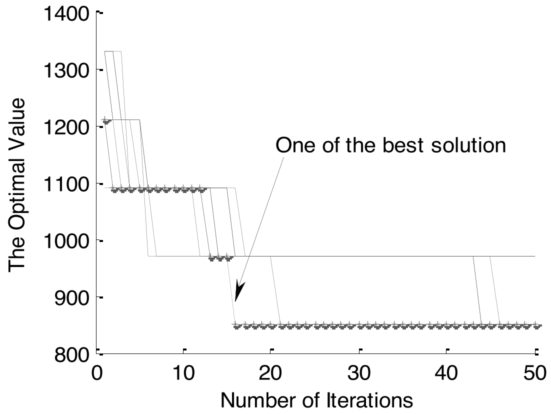

Fig. 7. Optimal value of each iteration in condition (b).

In the result of condition (a), TWC(1083) occurs 1 time, TWC(1098) occurs 1 time, TWC(1113) occurs 1 time, TWC(1188) occurs 4 times, and TWC(1203) occurs 3 times. In the result of condition (b), TWC(850) occurs 6 times, and TWC(970) occurs 4 times. The flexible precedence constraint problems are not considered in this paper, which will violate flexible constraint added to the total cost in the way of penalty cost. In this instance, there are two pairs of soft interactions shown in table 7: (1) F_9 should be prior to F_8 and F_8 should be prior to F_9. (2) F_{12} should be prior to F_{10} and F_{10} should be prior to F_{12}. Therefore, in order to facilitate comparison with other algorithms, for any feasible process plan, the penalty cost should be 200. The comparing results with other algorithms are shown in table 8. The optimal solution under the conditions of (a) and (b) is shown in table (9) and table (10).

Table 8. The results compared for the example part.

Condition	Proposed Algorithm	Two-stage ACO (Wang *et al.*, 2015)	ACO (Liu *et al.*, 2013)	Genetic Algorithm (Li *et al.*, 2002)	Simulated annealing (Li *et al.*, 2002)	Tabu search (Li *et al.*, 2014)
(a)						
Mean	1363.9	1329.0	1329.5	1611.0	1373.5	1342.0
Maximum	1403.0	1348.0	1343.0	1778.0	1518.0	1378.0
Minimum	1283.0	1328.0	1328.0	1478.0	1328.0	1328.0
(b)						
Mean	1098.0	1170.0	1170.0	1482.0	1217.0	1194.0
Maximum	1170.0	1170.0	1170.0	1650.0	1345.0	1290.0
Minimum	1050.0	1170.0	1170.0	1410.0	1170.0	1170.0

It is shown from table 8 that the minimum TWC(1083) is the best result among all of six algorithms under the condition of (a). The minimum TWC(1050) and the mean TWC(1098) are the best results among all of six algorithms under the condition of (b). In the literature [19], the number of iterations is 200; the number of ants is 25. If the number of iterations is increased, this can increase the occurrence number of relatively small optimization values such as TWC(1083) and TWC(1098) under the condition of (a) and further reduce the average optimized.

Table 9. One of the best flexible process planning under condition (a) for the example part.

No.	O_7	O_9	O_8	O_{17}	O_{18}	O_{22}	O_{15}	O_{23}	O_{16}	O_{14}	O_1	O_{19}	O_3	O_{12}
Feature	F_3	F_5	F_4	F_{10}	F_{11}	F_{13}	F_8	F_{14}	F_9	F_7	F_1	F_{12}	F_2	F_6
A-Op.	AO_{31}	AO_{51}	AO_{41}	AO_{101}	AO_{111}	AO_{132}	AO_{81}	AO_{141}	AO_{91}	AO_{72}	AO_1	AO_{121}	AO_{21}	AO_{62}
Machine	M_2	M_2	M_2	M_2	M_2	M_2	M_2	M_2	M_2	M_2	M_2	M_2	M_2	M_2
Tool	T_5	T_5	T_5	T_5	T_5	T_5	T_5	T_1	T_1	T_1	T_1	T_1	T_8	T_2
TAD	+*Y*	+*Y*	+*Y*	-*Y*	-*Y*	-*Y*	+*X*	-*Y*	-*Z*	-*Z*	+*Z*	+*Z*	-*X*	-*Z*

Get the value of parameters by calculation as follows: the value of *TMC* is 490, the value of *TTC* is 98, the value of *MCC* is 0, the value of *NMC* is 0, the value of *TMCC* is 0, the value of *TCC* is 120, the value of *NTC* is 3, the value of *TTCC* is 360, the value of *NS* is 9, the value of *SCC* is 15, the value of *TSCC* is 135, the value of *TWC* is 1083, and the penalty cost is 200.

Table 10. One of the best flexible process planning under condition (b) for the example part.

No.	O_{17}	O_{18}	O_{15}	O_9	O_{21}	O_8	O_7	O_1	O_{20}	O_{16}	O_{14}	O_{23}	O_{11}	O_5
Feature	F_{10}	F_{11}	F_8	F_5	F_{13}	F_4	F_3	F_1	F_{12}	F_9	F_7	F_{14}	F_6	F_2
A-Op.	AO_{101}	AO_{111}	AO_{81}	AO_{51}	AO_{131}	AO_{41}	AO_{31}	AO_1	AO_{122}	AO_{91}	AO_{72}	AO_{141}	AO_{61}	AO_{23}
Machine	M_2	M_2	M_2	M_2	M_2	M_2	M_2	M_2	M_2	M_2	M_2	M_2	M_2	M_2
Tool	T_5	T_5	T_5	T_5	T_5	T_5	T_5	T_1	T_1	T_1	T_1	T_1	T_2	T_8
TAD	-*Y*	-*Y*	+*X*	+*Y*	-*X*	+*Y*	+*Y*	+*Z*	-*Z*	-*Z*	-*Z*	-*Y*	-*Z*	-*Y*

Get the value of parameters by calculation as follows: the value of *TMC* is 490, the value of *TTC* is 98, the value of *TCC* is 120, the value of *NTC* is 3, the value of *TTCC* is 360, the value of *TWC* is 948, and the penalty cost is 200.

According to the above calculation example, the cost of machines changing once is higher than the cost of machining a feature, and the cost of tools changing once is higher than cost of machining a feature. Consequently, the solved optimal solution changes machine tools and cutting tools as little as possible under the premise of meeting the processing precedence constraints. The following two conditions are set in order to further test effectiveness of the algorithm: (c) all the machine tools and cutting tools are available, but the drilling operation must be finished by machine tool M_1; the value of $w_1 \sim w_5$ in objective function is set to 1. (d) all the machine tools and cutting tools are available, but the drilling operation must be finished by machine tool M_1; the values of parameters in objective function (17) are as follows: $w_2 = w_5 = 0$, $w_1 = w_3 = w_4 = 1$. The parameter settings of algorithm are described above; the number of iterations $N_{c_{max}} = 100$, similarly running 10 times. The optimum value of every generation is shown in figures 8 and 9. The optimum solution under the conditions of (c) and (d) is, respectively, shown in table 11 and table 12.

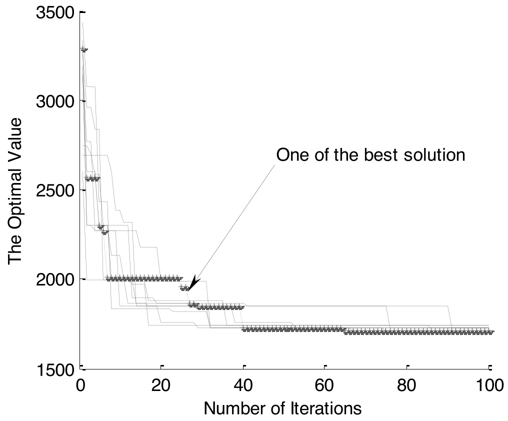

Fig. 8. Optimal value of each iteration in condition (c).

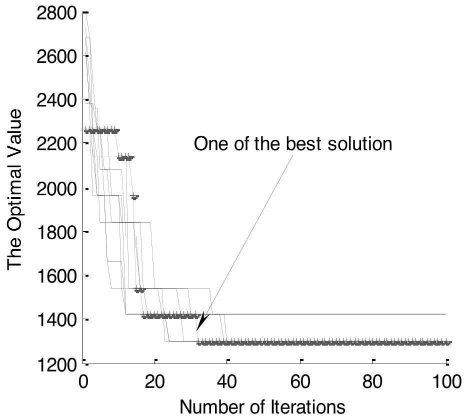

Fig. 9. Optimal value of each iteration in condition (d).

Table 10. One of the best flexible process planning under condition (c) for the example part.

No.	O_{17}	O_{18}	O_{22}	O_{8}	O_{7}	O_{10}	O_{15}	O_{11}	O_{16}	O_{14}	O_{20}	O_{23}	O_{2}	O_{6}
Feature	F_{10}	F_{11}	F_{13}	F_{4}	F_{3}	F_{5}	F_{8}	F_{6}	F_{9}	F_{7}	F_{12}	F_{14}	F_{1}	F_{6}
A-Op.	AO_{101}	AO_{111}	AO_{131}	AO_{41}	AO_{31}	AO_{51}	AO_{81}	AO_{61}	AO_{91}	AO_{72}	AO_{122}	AO_{141}	AO_{12}	AO_{62}
Machine	M_{2}	M_{2}	M_{2}	M_{2}	M_{2}	M_{2}	M_{2}	M_{1}	M_{1}	M_{1}	M_{1}	M_{1}	M_{1}	M_{2}
Tool	T_{5}	T_{5}	T_{5}	T_{5}	T_{5}	T_{5}	T_{5}	T_{2}	T_{1}	T_{1}	T_{1}	T_{1}	T_{1}	T_{8}
TAD	-Y	-Y	-Y	+Y	+Y	-Z	+X	+Z	-Z	-Z	-Z	-Y	-Z	-Z

Table 11. One of the best flexible process planning under condition (d) for the example part.

No.	O_{15}	O_{17}	O_{18}	O_{22}	O_8	O_9	O_7	O_{12}	O_{23}	O_{13}	O_{16}	O_{19}	O_2	O_4
Feature	F_8	F_{10}	F_{11}	F_{13}	F_4	F_5	F_3	F_6	F_{14}	F_7	F_9	F_{12}	F_1	F_2
A-Op.	AO_{81}	AO_{101}	AO_{111}	AO_{132}	AO_{41}	AO_{51}	AO_{31}	AO_{62}	AO_{141}	AO_{71}	AO_{91}	AO_{121}	AO_{12}	AO_{22}
Machine	M_2	M_2	M_2	M_2	M_2	M_2	M_2	M_1	M_1	M_1	M_1	M_1	M_1	M_2
Tool	T_5	T_5	T_5	T_5	T_5	T_5	T_5	T_2	T_1	T_1	T_1	T_1	T_1	T_8
TAD	$+X$	$-Y$	$-Y$	$-Y$	$+Y$	$+Y$	$+Y$	$-Z$	$-Y$	$+Z$	$+Z$	$-Z$	$-Z$	$+Y$

Because the drilling operation can only be done by machine M_1, there are precedence constraints in the alternative machining operations; so, the machining tools need to be changed twice at least. The optimum value is 1928 (with the value of penalty cost being 200) under the condition of (c), and the optimum value is 1500 (with the value of penalty cost being 200) under the condition of (d). The results running ten times independently also show that it can search the minimum value, which can be searched currently many times.

CONCLUSIONS

An ant colony optimization method is proposed to solve the flexible process planning problem based on the dynamic updating of feasible alternative machining operations. The solution process is to search the route of the feasible alternative machining operations firstly and then select the processing operation resource on the basis of the obtained process route. The approach presented here has several advantages in the following aspects:

(1) In the description of flexible process planning, the alternative machining operations were generated by the TAD. The solving of the process planning is divided into two stages: the first stage is to determine the sequence of the alternative machining operations, and the second is to configure the manufacturing resources for the alternative machining operation sequences.

(2) In the processing of precedence constraint, the alternative machining operations were classified based on the precedence constraint matrix. As a result, it is very convenient to obtain the set of the feasible alternative machining operations, which was dynamically updated by setting the values of the row and the column corresponding to the last selected alternative machining operations to 0 in the precedence constraint matrix and the values of the corresponding diagonal were set to constant. Through the processing above, the next search space of ACO can be effectively limited.

(3) In the processing of the alternative machining operations, only one feasible alternative machining operation can be selected for the same machining process. By searching for the presence of a value of -1 in the row and column corresponding to the selected alternative machining operations in the precedence constraint matrix, the row and column of the corresponding feasible alternative machining operations are set to 0 and diagonals are set to constant, if -1 presents. As a result, only one feasible alternative machining operation can be selected in the same machining operation according to the definition of the feasible alternative machining operation.

(4) In terms of the performance of algorithms proposed, the results show that the proposed algorithm is superior to one performance index at least compared with the existing algorithms through specific examples. Moreover, the robustness of the algorithm is better.

In further study, the method of precedence constraint dynamic updating proposed in this paper can be incorporated with other intelligent algorithms to solve the problems of process planning and production scheduling, which could be compared with the existing algorithms to enhance the performance of the algorithm even more.

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نهج لتحسين مستعمرة النمل استناداً إلى مصفوفة قيود الأسبقية لتخطيط العمليات المرن

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الخلاصة

يتم استخدام نهج مبتكر مدمج في البحث يعتمد على تحسين مستعمرة النمل (ACO) لتحسين تخطيط العمليات المرن بهدف تقليل تكاليف الوزن الإجمالية (TWC) مقابل قيود الأسبقية. أولاً، يوصف تخطيط العمليات المرن (FPP) على أنه ترتيب عمليات التشغيل البديلة عن طريق تحليل عملية المعالجة إلى عدة عمليات تشغيل اختيارية تستند إلى اتجاهات الوصول المختلفة للأداة، وتحديد قيود الأسبقية لعمليات التشغيل البديلة. نظراً لتحديد مجموعة عمليات التشغيل البديلة الممكنة لعملية المعالجة، واستخدام مصفوفة قيود الأسبقية لوصف علاقة قيد الأسبقية، يصبح تسلسل قيد الأسبقية هو الحد من مساحة البحث للحصول على الحل الأمثل. بعد ذلك، يتم استخدام خوارزمية مستعمرة النمل للبحث في التسلسل المُحدد لعمليات التشغيل البديلة بناءً على طريقة تحديد مساحة البحث. نظراً لأن كل نملة تحصل على توجيه عملية ممكن، يتم الحصول على مورد التصنيع الأمثل لكل عملية بديلة من مورد التصنيع المحدد عشوائياً بواسطة قاعدة التكلفة الدنيا، أخيراً بالمقارنة مع الخوارزمية الجينية الموجودة، والبحث في التبو، وخوارزمية التلدين الصلب والمستعمرة العامة، ثبت أن الخوارزمية المقترحة هي الجدوى والقدرة التنافسية على سبيل المثال.