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ORIGINAL ARTICLE

A two-stage ant colony optimization approach based on a directed graph for process planning

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Abstract An innovative approach based on the two-stage ant colony optimization (ACO) approach is used to optimize the process plan with the objective of minimizing total production costs (TPC) against process constraints. First, the process planning (PP) problem is represented as a directed graph that consists of nodes, directed/undirected arcs, and *OR* relations. The ant colony finds the shortest path on the graph to achieve the optimal solution. Second, a two-stage ACO approach is introduced to deal with the PP problem based on the graph. In the first stage, the ant colony is guided by pheromones and heuristic information of the nodes on the graph, which will be reduced to a simple weighed graph consisting of the favorable nodes and the directed/undirected arcs linking those nodes. In the second stage, the ant colony is guided by heuristic information of nodes and pheromones of arcs on the simple graph to achieve the optimal solution. Third, the simulation experiments for two parts are conducted to illustrate the application of the two-stage ACO approach to the PP problem. The compared results with the results of other algorithms verify the feasibility and competitiveness of the proposed approach.

Keywords Process planning · Ant colony optimization · Directed graph · Two-stage

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1 Introduction

In a computer-aided process planning (CAPP) system, two activities must be performed: (1) recognizing features and (2) selecting and sequencing machining operations [1–3]. This paper focuses on the second activity, which is modeled as a PP problem. For producing a part, the process planning includes the determination of the machines, cutting tools, and set-ups for each feature; the selection of the machining operations; and sequencing of the machining operations against process constraints. Due to the complexity of the part structures and the variety of machine shop situations, the PP problem is difficult to solve. Many approaches have been proposed to achieve the optimal process plan in the past two decades. In this paper, an innovative approach based on the two-stage ACO approach is proposed to optimize the process plan. The contribution of this article is described as follows:

(1) The PP problem is represented as a directed graph. The graph consists of nodes, directed/undirected arcs, and *OR* relations. The nodes represent all of the alternative operations (*AO*s) of each feature. The directed arcs denote the precedence constraints among the operations. The undirected arcs denote the possible visited path for the ant colony. The *OR* relations denote the alternation of operations affiliated with the same manufacturing feature.
(2) An innovative approach based on the two-stage ACO approach is used to optimize the process plan based on the directed graph. In Stage 1, the nodes are the pheromone carriers. The ant colony is guided by the pheromones and heuristic information of the nodes to form a set of favorable nodes. The initial graph will be reduced to a simple weighted graph consisting of the favorable nodes and the directed/undirected arcs among those nodes after Stage 1. In stage 2, directed/undirected arcs

are the pheromone carriers. The ant colony is guided by heuristic information of the nodes and pheromones of the arcs to achieve the optimal process plan with the objective of minimizing the TPC.

2 Previous related works

The application of graph theory in the PP problem can be traced back to the research by Prabhu et al. r [4]. In their research, a hybrid unsupervised learning approach was proposed to solve the PP problem. Several graph-based algorithms are incorporated into the unsupervised learning approach to obtain the optimal tool sequence for the determined features sequence in a set-up that minimizes the number of tool changes. Lin et al. [5] proposed a graph-based search strategy to sequence the machining operations for a prismatic part with process constraints. The graph is constructed in reference with alternative machining operations for the features. According to the predefined precedence constraints, the high-quality process plan is generated using the graph-search strategy. Huang et al. [6] combined graph theory accompanied by constraints matrix into the traditional GA. In their approach, the precedence constraints among operations are formulated in an operation precedence graph (OPG). The population is initialized by an elaborately designed topologic sort approach based on the OPG.

The ACO approach, proposed by Dorigo et al. [7], is a new swarm intelligence approach to solve the NP-complete combinatorial optimization problem. The ACO approach has been applied to deal with many optimization problems, such as traveling salesman problem (TSP) [7], vehicle routing problem (VRP) [8, 9], hole-making process optimization [10, 11], assembly line balancing problem [12, 13], the jog shop scheduling problem [14, 15], etc.

The application of ACO to the PP problem was first introduced by Krishna and Mallikarjuna [16]. Krishna and Mallikarjuna proposed a novel approach to apply the ant colony algorithm as an efficient search technique for the PP problem by considering various feasibility constraints. In their approach, a relative cost matrix is generated, taking into consideration the change of machine tools, cutting tools, and machining parameters. This search considered the potential of ACO for use in the PP problem simply. Some deep discussion is lacking, for example, application of the ACO considering the complex machining environments, the analysis of the ACO in a large-scale PP problem, etc. Liu et al. [17] converted the PP problem into a constraint-based TSP using a weight graph and constructed a mathematical model for the PP problem against the process constraints. The simulation results for the complex part are satisfactory, but a detailed explanation for the adjusted strategy of the ACO parameters is expected to convince the simulation results.

In addition to the graph theory and ACO, many optimization approaches have been developed to solve the PP problem, such as the genetic algorithm (GA) [2, 18], the tabu search (TS) approach [3, 19], the simulated annealing (SA) algorithm [1, 20], particle swarm optimization (PSO) [21, 22], artificial neural networks [23], and artificial immune system (AIS) [24].

Zhang et al. [18] improved various GAs to solve the PP problem, for example, a coding strategy based on natural numbers, selection operators based on the elitist model and tournament selection, and the use of nonconforming sequential searching crossover operators. Li et al. [3] proposed a tabu search-based approach to optimize the process plan. In their approach, process constraints among features are mapped to precedence constraints among operations according to their effects on the process plan. Li et al. [1] developed a hybrid approach integrating GA and SA approach to optimize process plans for prismatic parts. The combination of machine costs, cutting tool costs, machine change costs, tool changes, and setup costs was used to evaluate the performance of the process planning. Li et al. [22] proposed a novel PSO algorithm to optimize the process plan. Efficient encoding, updating, and random search methods have been developed to enhance the performance of the approach. Chan et al. [24] modeled the machine selection and operation allocation in a flexible manufacturing system and solved the process problem using an AIS-based fuzzy goal-programming approach.

Although significant achievements have been got for solving the PP problem, the potential for further improvement still remains [25, 26]. For example, a more flexible mathematical modeling for PP problem must be developed and the corresponding handling mechanism ought to be improved to suit the flexible process plan; additionally, some practical manufacturing environments should be considered.

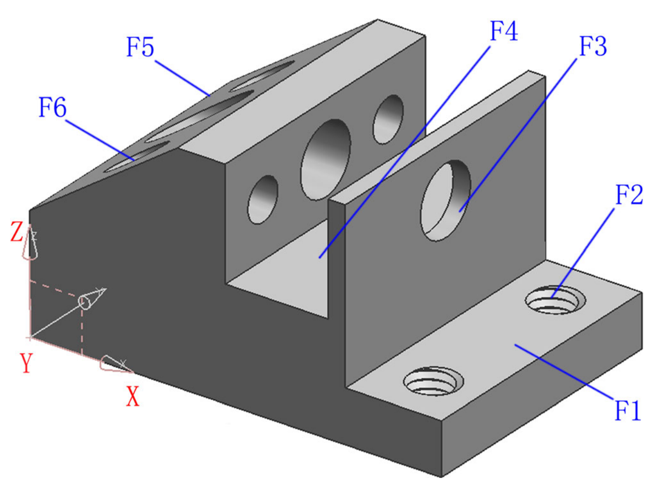


Fig. 1 An example part

Table 1 Operation selection for the example part

Feathers	Operations	Machines	Tools	TADs	Remarks	
F1	Milling (OP_1)	$M1$	$T1$	$+X, +Z$	M1: Vertical milling machine	$T1$: milling cutter
F2	Drilling (OP_2)	$M1, M2$	$T2$	$-Z$	M2: Drilling press	$T2$: drill1
	Tapping (OP_3)		$T3$			$T3$: tapping tool
F3	Drilling (OP_4)	$M1, M2$	$T4$	$-X$		$T4$: drill
	Reaming (OP_5)		$T5$			$T5$: reamer1
F4	Milling (OP_6)	$M1$	$T6$	$+Z$		$T6$: Slot cutter
F5	Milling (OP_7)	$M1$	$T7$	$-Z, +Y$		$T7$: chamfer cutter
F6	Drilling (OP_8)	$M1, M2$	$T8$	$+X$		$T8$: drill3
	Reaming (OP_9)		$T9$			$T9$: reamer2

3 Graph-based process planning problem

In CAPP, a part is described by its manufacturing features, such as holes, slots, etc., which can be recognized by analyzing the geometrical and topological information of the part, such as the position, dimensions, tolerance, surface finish, etc. A feature may be mapped to a set of operations (*OP*), which consists of one or several alternative operations [2]. An *AO* refers to a combination of machine (*M*), tool (*T*), and tool approach direction (*TAD*). As a result, for a part, the process plan is a set of operations, which is represented as follows:

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

OP_{i} is the *i*th operation of the part, which is defined as follows:

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

AO_{ij} is the *j*th alternative operation of the *i*th operation of the part, which is defined as follows:

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

M_{ij}, T_{ij}, and TAD_{ij} are the indices of the machine, tool, and *TAD*, respectively, by which the alternative operation AO_{ij} is executed.

In process planning for a part, two tasks must be performed, namely, selecting the operations and sequencing the operations. Due to the geometrical and manufacturing constraints among the manufacturing features, the operation sequencing must take into account the precedence constraints between operations. Many process constraints have been proposed [1–3, 7]. In general, these precedence constraints are as follows [17]:

(1) Primary surfaces prior to the secondary surface.
(2) Rough machining operation prior to finish machining operation.
(3) Datum surfaces prior to its associated features.
(4) Some good manufacturing practices.

To construct a process plan using the ACO approach, the process planning problem must be visualized and represented as a graph. The graph is denoted as $D=(O, C, R)$, where O is a set of nodes, C is a set of directed/undirected arcs, and R is a set of *OR* relations. The node set of O represents the alternative operations AO_{ij}. C represents the precedence constraints among the operations and the possible visited path for the ant colony. R represents the alternation of the operation associated with the same manufacturing feature.

The example part in Fig. 1 is used to illustrate the graph, which consists of six features and nine operations.

The operation selection for the example in Fig. 1 is listed in Table 1. The precedence constraints for the example are listed in Table 2.

Figure 2 shows the graph for the example part. The set of nodes includes 17 nodes, O_1–O_{17}, which are described in Table 3. For node O_{11}, there are 16 arcs connected with the other nodes. The eight undirected arcs are connected with nodes O_1, O_2, O_{12}, O_{13}, O_{14}, O_{15}, O_{16}, and O_{17}. The other eight directed arcs are connected with nodes O_3, O_4, O_5, O_6, O_7, O_8, O_9, and O_{10}. The relations of *OR* denote the alternation of the operations. For the relation of OR_1 in Fig. 2, O_2 has to be neglected if O_1 is chosen.

Table 2 Precedence constraints between operations

Features	Operations	Precedence constraint description	Hard or Soft
$F1$	OP_1	OP_1 is prior to OP_2 and OP_3.	Hard
		OP_1 is prior to OP_4 and OP_5.	Soft
$F2$	OP_2	OP_2 is prior to OP_3.	Hard
$F3$	OP_4	OP_4 is prior to OP_5.	Hard
	OP_4, OP_5	OP_4 and OP_5 are prior to OP_6.	Hard
$F6$	OP_8	OP_8 is prior to OP_9.	Hard
	OP_8, OP$_9$	OP_8 and OP_9 are prior to OP_7.	Hard

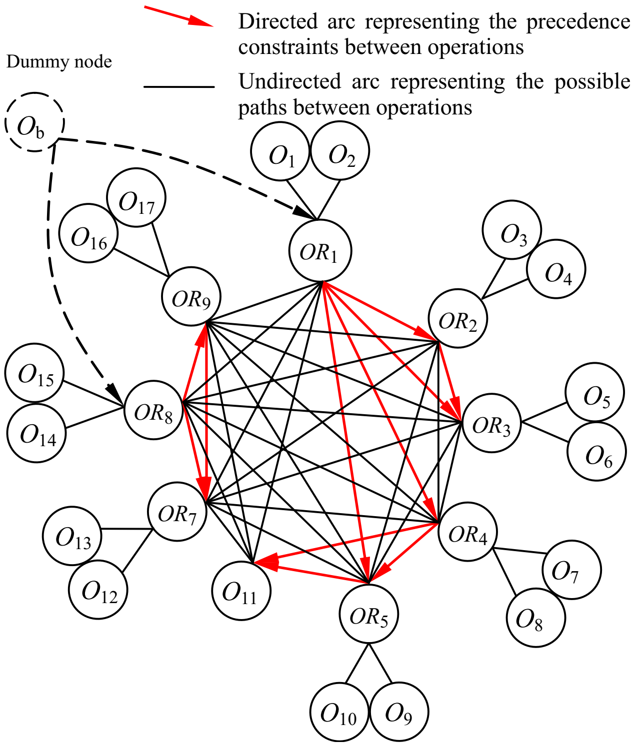


Fig. 2 Graph for the example part

While applying the ACO in the process planning using the graph, the ant colony will be placed on the initial node visited by the ant colony first. The initial node determines which operation can be executed first. For the graph in Fig. 2, the nodes O_1, O_2, O_{14}, and O_{15} are likely to be selected as the initial source node because operations OP_1 and OP_8 have no precedence operations. To facilitate the execution of ACO in process planning, a dummy node O_b acting as the initial node is added to connect the possibly executed operations first in the graph. The initial node O_b is used to connect nodes O_1, O_2, O_{14}, and O_{15}.

Table 3 Description of the alternative operations

Nodes	Operation	Alternative operation	Description
O_1	OP_1	AO_{11}	{$M1$,$T1$,+X}
O_2		AO_{12}	{$M1$,$T1$,+Z}
O_3	OP_2	AO_{21}	{$M1$,$T2$,–Z}
O_4		AO_{22}	{$M2$,$T2$,–Z}
O_5	OP_3	AO_{31}	{$M1$,$T3$,–Z}
O_6		AO_{32}	{$M2$,$T3$,–Z}
O_7	OP_4	AO_{41}	{$M1$,$T4$,–X}
O_8		AO_{42}	{$M2$,$T4$,–X}
O_9	OP_5	AO_{51}	{$M1$,$T5$,–X}
O_{10}		AO_{52}	{$M2$,$T5$,–X}
O_{11}	OP_6	AO_{61}	{$M1$,$T6$,+Z}
O_{12}	OP_7	AO_{71}	{$M1$,$T7$,–Z}
O_{13}		AO_{72}	{$M1$,$T7$,+Y}
O_{14}	OP_8	AO_{81}	{M1,$T8$,+X}
O_{15}		AO_{82}	{$M2$,$T8$,+X}
O_{16}	OP_9	AO_{91}	{$M1$,$T9$,+X}
O_{17}		AO_{92}	{$M2$,$T9$,+X}

4 Process plan evaluation criterion

Many process planning evaluation criteria have been proposed in the past literature. The criterion of minimum production cost is generally used. The production cost evaluating process plans are composed of six factors: machine processing cost (MC), tool processing cost (TC), machine change cost (MCC), tool change cost (TCC), set-up cost (SCC), and additional penalty cost (APC) [1–3, 7, 17]. The calculation procedures of these cost factors are described in detail below.

1) Total machine cost (TMC)

$$\mathrm{TMC} = \sum_{i=1}^{n} \mathrm{MC}_i \tag{4}$$

where MC_i is the machine cost of the ith machine for an operation and n is the number of operations.

2) Total tool cost

$$\mathrm{TTC} = \sum_{i=1}^{n} \mathrm{TC}_i \tag{5}$$

where TC_i is the tool cost of the ith tool.

3) Total machine change cost

$$\mathrm{TMCC} = \mathrm{MCC}^*\mathrm{NMC} \tag{6}$$

where MCC is considered to be the same for each machine change, and NMC is the number of machine changes, which can be calculated using Eq. (7) and Eq. (8).

$$\mathrm{NMC} = \sum_{i=1}^{n-1} \Omega_1(M_{i+1}, M_i) \tag{7}$$

$$\Omega_1(x,y) = \begin{cases} 1 & x \neq y \\ 0 & x = y \end{cases} \tag{8}$$

where M_i is the machine for the ith operation.

4. Total tool change cost

$$\mathrm{TTCC} = \mathrm{TCC}^*\mathrm{NTC} \tag{9}$$

where TCC is considered to be the same for each tool change, and NTC is the number of tool changes, which can be calculated using Eq. (8), Eq. (10) and Eq. (11).

$$\mathrm{NTC} = \sum_{i=1}^{n-1} \Omega_2(\Omega_1(M_{i+1}, M_i), \Omega_1(T_{i+1}, T_i)) \tag{10}$$

$$\Omega_2(x, y) = \begin{cases} 0 & x = y = 0 \\ 1 & \text{otherwise} \end{cases} \tag{11}$$

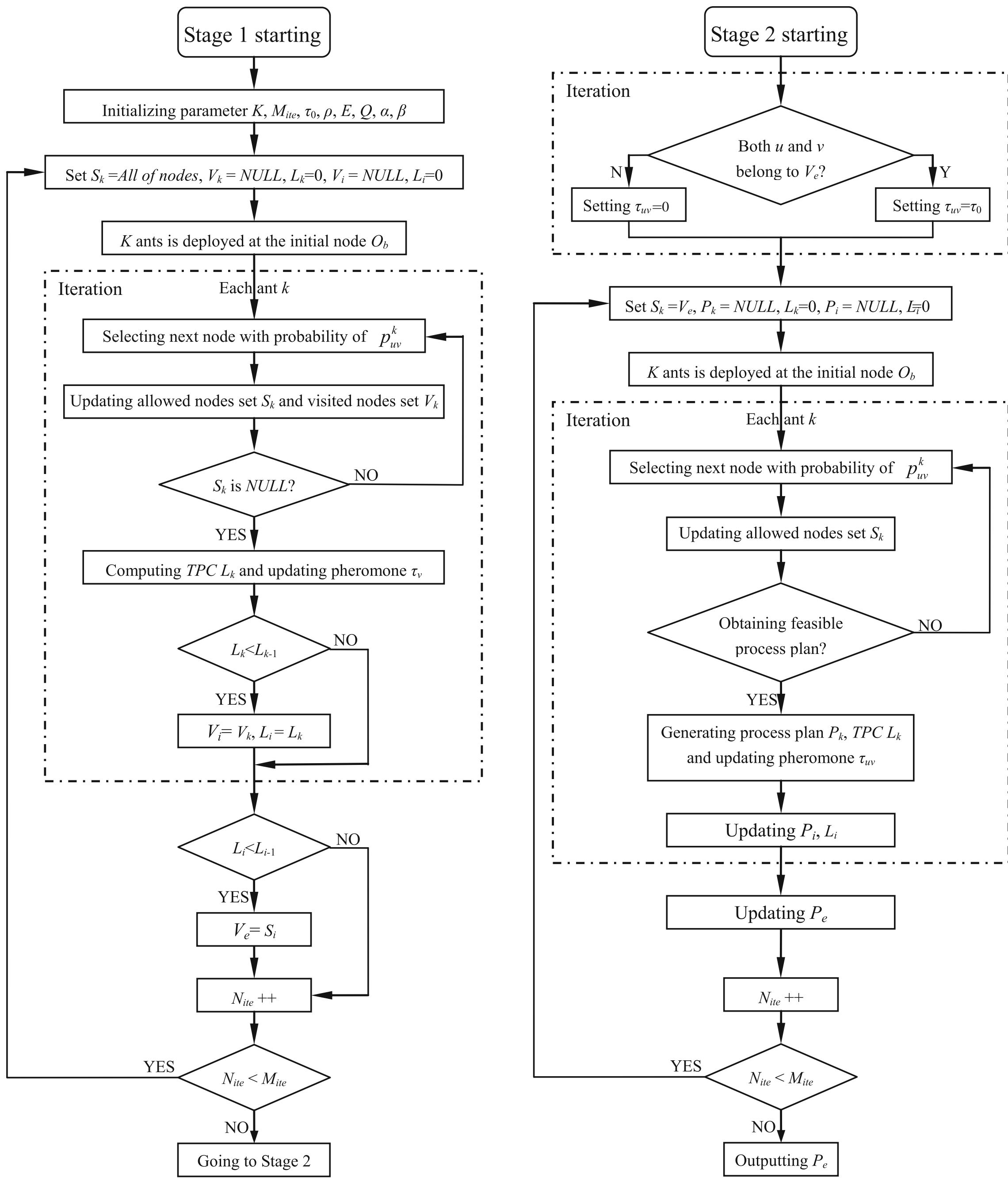
where T_i is the tool for the ith operation.

5) Total set-up cost

$$\mathrm{TSCC} = \mathrm{SCC}^{*}\mathrm{NS} \tag{12}$$

where the SCC is considered to be the same for each set-up, and NS is the number of set-ups, which can be calculated using Eq. (13) and Eq. (14).

$$\mathrm{NS} = \mathrm{NSC} + 1 \tag{13}$$



(a) Stage 1 (b) Stage 2

Fig. 3 Two-stage ACO approach

Table 4 Definitions of symbols

Symbol	Meaning
K	Number of ants
k	Index of ant, $k\in[1,K]$
u	Source node
v	Destination node
τ	Pheromone
η	Heuristic information
α	Relative weight of pheromone τ_{uv}
β	Relative weight of heuristic information η_{uv}
ρ	Pheromone evaporation rate
E	Algorithm constant to determine η_{uv}
Q	Algorithm constant to determine $\Delta\tau$
τ_0	Initial value of the pheromone
S_k	Set of nodes allowed at the next step by ant k.
V_k	Set of nodes visited by ant k
P_k	Process plan achieved by ant k
L_k	*TPC* achieved by ant k
P_i	Iteration-best process plan
V_i	Set of nodes generated by the iteration-best process plan
L_i	Iteration-best *TPC*
V_e	Final set of nodes
P_e	Final process plan
M_{ite}	Maximum number of iterations
N_{ite}	Number of iteration

$$\mathrm{NSC} = \sum_{i=1}^{n-1} \Omega_2(\Omega_1(M_{i+1}, M_i), \Omega_1(\mathrm{TAD}_{i+1}, \mathrm{TAD}_{ii})) \quad (14)$$

where TAD_i is the TAD for the ith operation.

6) Total additional penalty cost

$$\mathrm{TAPC} = \mathrm{APC} * \mathrm{NPC} \quad (15)$$

where APC is the fixed penalty cost and NPC is the number of violating constraints, which can be calculated using Eq. (16) and Eq. (17).

$$\mathrm{NPC} = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \Omega_3\left(OP_i, OP_j\right) \quad (16)$$

$$\Omega_3(x,y) = \begin{cases} 1 & \text{The sequence of } x \text{ and } y \text{ operations violates constraints} \\ 0 & \text{The sequence of } x \text{ and } y \text{ operations meets constraints} \end{cases} \quad (17)$$

The definitions of machine change, tool change, and setup change have been previously described in detail [1, 3]. In this paper, the combination of TWC, TTC, TMCC, TTCC, TSCC, and TAPC will be used as the objective of the process planning problem, which can be defined as TPC, as calculated by Eq. (18).

$$\mathrm{TPC} = w_1 * \mathrm{TMC} + w_2 * \mathrm{TTC} + w_3 * \mathrm{TMCC} + w_4 * \mathrm{TSCC} + w_5 * \mathrm{TTCC} + w_6 * \mathrm{TAPC} \quad (18)$$

In Eq. (18), w_1, w_2, w_3, w_4, w_5, and w_6 are the weights of TMC, TTC, TMCC, TTCC, TSCC, and TAPC, respectively, the value of which is limited to {0, 1}. These weights can be assigned by referring to the active situations; this approach

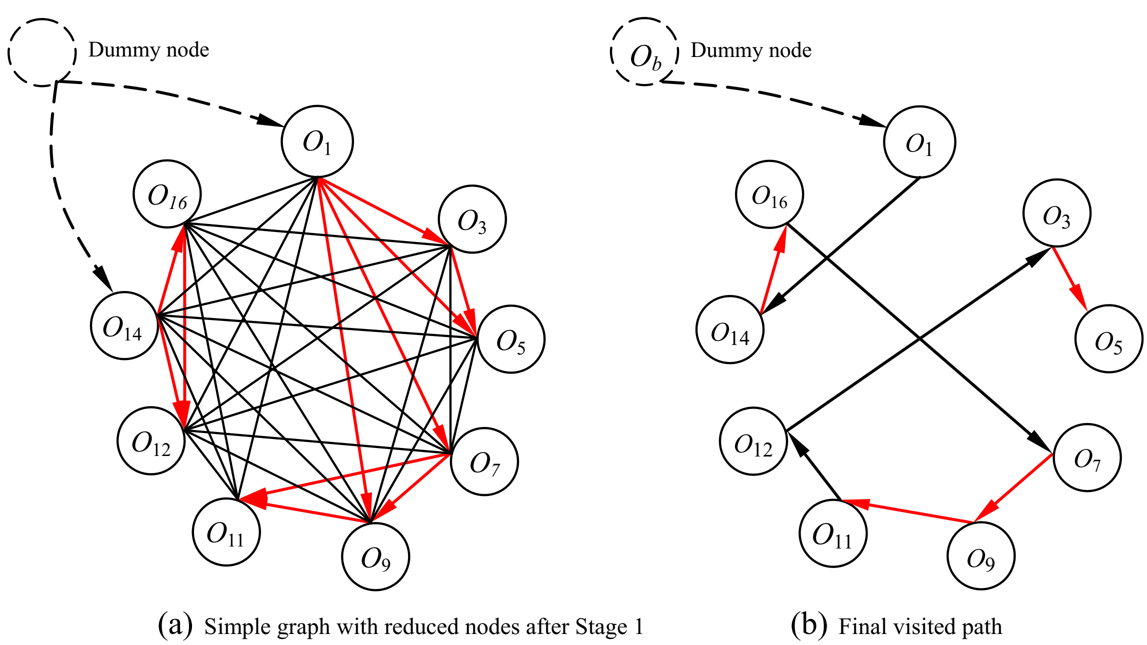


Fig. 4 Disjunctive graph and ant-visited path in stage 2

provides the flexibility to customize the optimization objective function according to various situations [3]. w_6 can be used to switch the penalty function of the "soft" constraints on or off. If no "soft" constraints are considered, it is assigned as 0. Otherwise, it is 1.

5 Two-stage ACO approach

As described in Section 3, selecting the operations and sequencing the operations must be performed in the PP problem. Accordingly, the two-stage ACO approach in this paper is used to perform the operation selection and sequencing process in two consecutive stages. The first stage corresponds to operation selection. The ant colony is deployed on the initial node of the graph, and these ants traverse the necessary nodes to identify the set of preferred nodes with the smaller TPC. The character of this stage is that the nodes of the graph are pheromone carriers. The second stage corresponds to operation sequencing; the unselected nodes in the first stage will be ignored completely in subsequent ant visits, and the ants will deposit pheromones at the arcs, with the aim of identifying the most favorable visited path. The arcs among the nodes are pheromone carriers in this stage, which is different from the first stage. The procedures of the two stages are outlined in Fig. 3, and the explanations for the symbols used are listed in Table 4.

5.1 Stage 1—operation selection

Ant colony K is deployed at the dummy start node O_b initially. The ants traverse all of the necessary nodes in accordance with the precedence constraints until all of the required operations are completed and a process plan is generated. Due to the alternative operations, not all of the nodes in the weight graph must be visited by the ants. After a node is visited by an ant, all of the alternative nodes belonging to the same operation will be ignored. In this stage, the nodes of the weight graph are the pheromone carriers. To choose the next node v among all of the possible operation nodes connected to the current node u, an ant k is guided by a pheromone amount τ_v and heuristic information η_v. The heuristic information η_v is calculated as follows:

$$\eta_v = \frac{E}{\mathrm{PC}} \tag{19}$$

where E is a positive constant, and PC is the processing cost of the selected node operation, which is calculated as follows:

$$\mathrm{PC} = w_1 * \mathrm{MC} + w_2 * \mathrm{TC} \tag{20}$$

Eq. (19) shows that the node with a smaller processing cost has a higher information value, that is, it is more attractive to the ants.

The pheromone amount is initially set at τ_0 on every node. The pheromone intensity on the nodes is dynamically updated after the ant colony has completed the process plans. To avoid unlimited accumulation of the pheromone, the pheromone also evaporates at every round of iterations. The pheromone amount τ_v can be given as follows:

$$\tau_v = (1-\rho)^* \tau_v + \Delta\tau_v^k \tag{21}$$

where ρ is an evaporation coefficient of the pheromone on the destination node v. $\Delta\tau_v^k$ is the quantity of the pheromone increments on the node v generated by the ant k after each iteration. The amount of pheromone deposited on the node v by an ant k is proportional to a respective L_k. The process plans with smaller L_k will accumulate a greater amount of pheromone on their corresponding nodes. $\Delta\tau_v^k$ can be given as follows:

$$\Delta\tau_v^k = \begin{cases} \dfrac{Q}{L_k} & \text{if ant } k \text{ passes the node } v \\ 0 & \text{otherwise} \end{cases} \tag{22}$$

where Q is a positive constant. L_k is the TPC of the process plan generated by ant k.

The heuristic information η_v and the pheromone amount τ_v determine the probability of moving from one node to another node for an ant. The greater the pheromone amount and the heuristic information on the nodes, the higher is the selective probability. For ant k, the selective probability p_v^k from the source node u to the destination node v can be calculated as follows:

$$p_v^k = \begin{cases} \dfrac{[\tau_v]^\alpha [\eta_v]^\beta}{\sum\limits_{w \in S_k} [\tau_w]^\alpha [\eta_w]^\beta} & v \in S_k \\ 0 & v \notin S_k \end{cases} \tag{23}$$

where α and β denote the weighting parameters controlling the relative importance of the pheromone amount and the heuristic information, respectively.

Table 5 Cost indices for the example part

MC		TC									MCC	SCC	TCC	APC
*M*1	*M*2	*T*1	*T*2	*T*3	*T*4	*T*5	*T*6	*T*7	*T*8	*T*9				
40	10	10	3	7	3	8	10	10	3	8	300	60	20	200

Table 6 Optimal process plans for the example part in Fig. 1

Node	O_1	O_{14}	O_{16}	O_7	O_9	O_{11}	O_{12}	O_3	O_5
Operation	OP_1	OP_8	OP_9	OP_4	OP_5	OP_6	OP_7	OP_2	OP_3
Machine	$M1$	$M1$	$M1$	$M1$	$M1$	$M1$	$M1$	$M1$	$M1$
Tool	$T1$	$T8$	$T9$	$T4$	$T5$	$T6$	$T7$	$T2$	$T3$
TAD	$+X$	$+X$	$+X$	$-X$	$-X$	$+Z$	$-Z$	$-Z$	$-Z$

NMC=0, NCC=8, NSC=3. TMC=360, TTC=62, TMCC=0, TTCC=160, TSCC=240, TPC=822.

5.2 Stage 2—operation sequencing

If the set of node V_e is determined after stage 1, then the ants will only be allowed to travel among these nodes. Those nodes that were not selected in stage 1 will be ignored in Stage 2. In contrast to stage 1, the arcs of the weight graph are the pheromone carriers in stage 2. All of the pheromone values on the arcs (u, v) that involve those unselected processes would be set to 0.

For the example part in Fig. 1, after stage 1, the graph in Fig. 2 is effectively reduced to a simple graph depicted in Fig. 4a, which contains only the nodes included in set V_e. The ants must visit all of the nodes on the simple graph along the arcs connected to each pair of nodes. Thus, the ants deposit pheromones on the arcs of the graph. The transition probability from node u to v for ant k is given as follows:

$$p_{uv}^k = \begin{cases} \dfrac{[\tau_{uv}]^\alpha [\eta_v]^\beta}{\sum\limits_{w \in S_k} [\tau_{uw}]^\alpha [\eta_w]^\beta} & v \in S_k \\ 0 & v \notin S_k \end{cases} \tag{24}$$

The heuristic information η_v is calculated using Eq. (19) and Eq. (20). The pheromone amount τ_{uv} on the arcs (u, v) can be given as follows:

$$\tau_{uv} = (1-\rho)^* \tau_{uv} + \Delta\tau_{uv}^k \tag{25}$$

$$\Delta\tau_{uv}^k = \begin{cases} \dfrac{Q}{L_k} & \text{if} \quad \text{ant } k \text{ uses the arc}(u,v) \text{ in its tour} \\ 0 & \text{otherwise} \end{cases} \tag{26}$$

6 Experiments and results

Two experiments were conducted to illustrate and validate the feasibility of the two-stage ACO approach. In the first experiment, a walk-through example is used to illustrate the two-stage ACO approach. The second experiment was conducted to evaluate the performance of the two-stage ACO approach. Some computational results for two different parts under different conditions are used to compare this approach with typical ACO, TS, GA, and SA methods.

6.1 Walk-through example

This paper considers the example part in Fig. 1 to illustrate the two-stage ACO approach. All of the cost indices are presented in Table 5, and it is assumed that all of the machines and tools are available, namely w_1–w_6 in Eq. (18) and Eq. (20) are set to 1.

In stage 1, the ant colony travels freely on the graph. More pheromones will be accumulated on the favorable nodes for the ant colony. The unfavorable nodes or the alternative operation nodes will be eliminated from the graph. While the ant colony

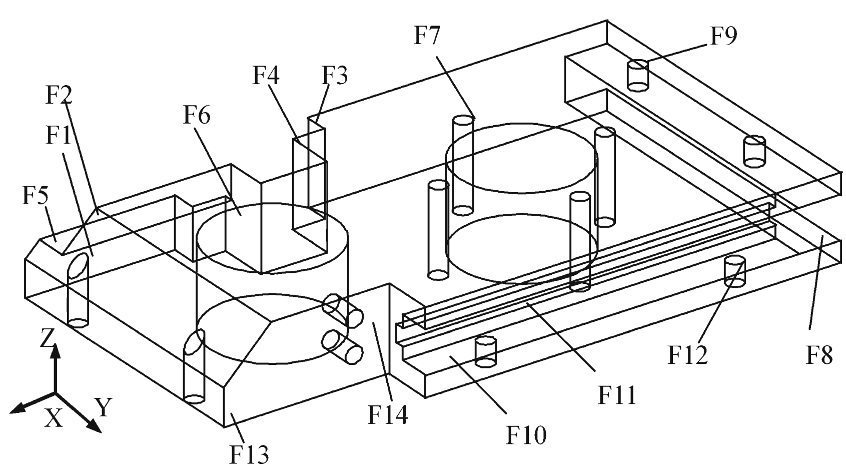


Fig. 5 A sample part with 14 features and 14 operations—part 1

finishes the visit of all of the necessary nodes, the graph in Fig. 2 will be reduced to a simple graph, as shown in Fig. 4a.

In stage 2, the ant colony travels through the nodes and arcs that are still remaining, as shown in Fig. 4a. The pheromone amount on the arcs and the heuristic information on the nodes will guide the ants to visit all of the nodes. The final visited path generated by the ant colony represents the process planning result with the minimum TPC. Based on the simple graph in Fig. 4a, the final visited path is shown in Fig. 4b, and the corresponding process plan is presented in Table 6.

6.2 Comparative experiments

Two prismatic parts are used for the simulated experiments. The first prismatic part (part 1) is first introduced by Zhang et al. [2], which consists of 14 features and 14 operations. The

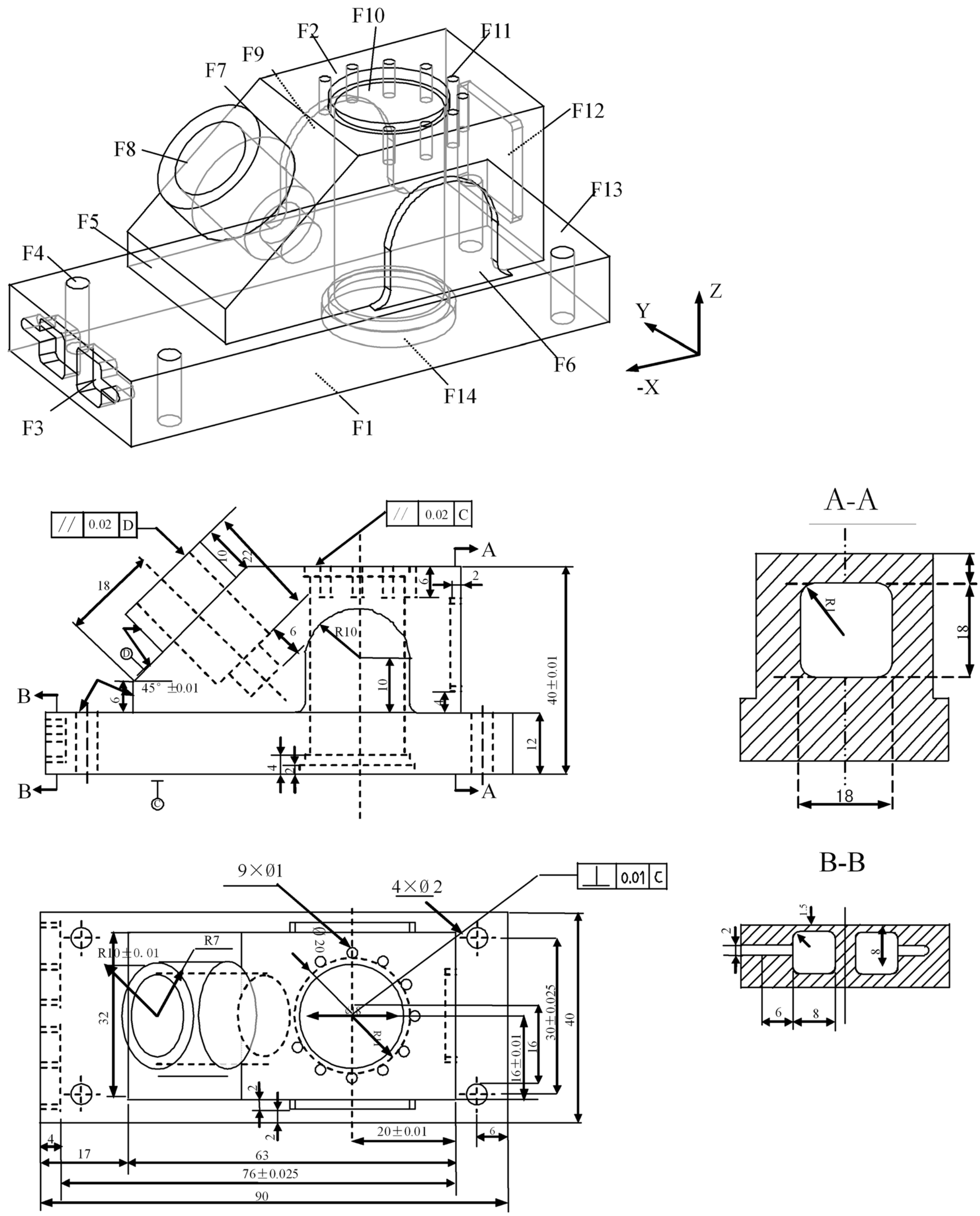


Fig. 6 A sample part with 14 features and 20 operations—part 2

Table 7 The best process plans for part 1 corresponding to conditions (1) and (2)

Condition (1)														
Operation	6	1	7	9	12	5	3	4	8	10	11	13	14	2
Machine	2	2	2	2	2	2	2	2	2	2	2	2	2	2
Tool	2	1	1	1	1	5	5	5	5	5	5	5	1	8
TAD	$-Z$	$-Z$	$-Z$	$-Z$	$-Z$	$-Z$	$+Y$	$+Y$	$+X$	$-Y$	$-Y$	$-Y$	$-Y$	$-Y$
NMC=0, NTC=4, NSC=3, NPC=1, TMCC=0, TTCC=60, TSCC=480, TMC=490, TTC=98, TAPC =200, TPC=1328														
Condition (2)														
Operation	6	7	12	1	9	2	5	13	8	3	4	10	11	14
Machine	2	2	2	2	2	2	2	2	2	2	2	2	2	2
Tool	2	1	1	1	1	8	5	5	5	5	5	5	5	1
TAD	$-Z$	$-Z$	$-Z$	$-Z$	$-Z$	$-Z$	$-Z$	$-Z$	$+X$	$+Y$	$+Y$	$-Y$	$-Y$	$-Y$
NMC=0, NSC=3, NPC=1, TMCC=0, TSCC=480, TMC=490, TAPC=200, TPC=1170														

detail is illustrated in Fig. 5. The second prismatic part (part 2) is first introduced Li et al. [1], which consists of 14 features and 20 operations. The detail is illustrated in Fig. 6. The machining information and precedence constraints of part 1 and part 2 are illustrated in detail in the work of Li et al. [3]

Two conditions are used to test the proposed approach on part 1 in Fig. 5:

(1) All machines and tools are available, and w_1–w_6 in Eq. (18) and Eq. (20) are set to 1.
(2) All machines and tools are available, and w_2=w_5=0, w_1=w_3=w_4=w_6=1.

For part 1, 20 trials were independently carried out to evaluate the two-stage ACO approach under conditions (1) and (2). Experimental observation has demonstrated that K=25, ρ=0.75, α=1, β=1, E=50, Q=2000, τ_0=1, and M_{ite}=200 are the best choices of these parameters. The best process plans generated under conditions (1) and (2) are listed in Table 7.

Table 8 Comparison of the results of the proposed approach to those of other algorithms for part 1

Condition	Proposed approach	ACO	TS	SA	GA
(1)					
Mean	1329.0	1329.5	1342.6	1373.5	1611.0
Maximum	1348.0	1343.0	1378.0	1518.0	1778.0
Minimum	1328.0	1328.0	1328.0	1328.0	1478.0
(2)					
Mean	1170.0	1170.0	1194.0	1217.0	1482.0
Maximum	1170.0	1170.0	1290.0	1345.0	1650.0
Minimum	1170.0	1170.0	1170.0	1170.0	1410.0

Comparison of the results with those of the GA, the SA approach by Li et al. [1], the TS by Li et al. [3], and the ACO by Liu et al. [17] are presented in Table 8.

Under condition (1), among 20 trial results, TPC (1328.0) occurs 18 times, TPC (1348) occurs 1 time, and TPC (1343) occurs 1 time. The mean TPC (1329.0) is the best results among all of five algorithms. Under condition (2), TPC (1170.0) occurs 20 times in 20 trials, which is better than the performances of TS [3], SA, and GA [1] and is the same as the performance of ACO [17].

In addition to the above two conditions, an additional condition is used to test the two-stage ACO approach for part 2 in Fig. 6, which is described as follows:

(3) Machine M2 and tool T7 are down, w_2=w_5=0, w_1=w_3=w_4=w_6=1.

For part 2, 20 trials were independently carried out to evaluate the proposed approach under conditions (1), (2), and (3). Experimental observation has demonstrated that K=40, ρ=0.75, α=1, β=1, E=100, Q=3000, τ_0=1, and M_{ite}=200 are the best choices of these parameters. The best process plans generated under conditions (1), (2), and (3) are listed in Table 9. The comparison of the results of the proposed approach with those of the GA, the SA approach by Li et al. [1], the TS by Li et al. [3], and the HGA by Huang et al. [6] are presented in Table 10.

Under condition (1), compared to the other approaches, the improved performance of the two-stage approach, with a minimum TPC (2525.0), was demonstrated. In addition, all of the costs, including mean TPC (2552.4), maximum TPC (2557), and minimum TPC (2525.0), are better than the costs achieved by the other four algorithms. Under condition (2), a lower TPC (2090.0) was found using the two-stage ACO approach compared to the other approaches. The maximum TPC (2380.0) is the same as the result of the SA and is superior to the results of the TS and GA. Under condition (3), the minimum TPC (2590) is inferior to the result of the TS and

Table 9 The best process plans corresponding to conditions (1), (2), and (3)

Condition (1)																				
Operation	1	3	5	6	2	18	11	12	13	17	7	8	9	19	14	20	10	4	15	16
Machine	2	2	2	2	2	2	2	2	2	2	2	2	2	2	4	4	4	1	1	1
Tool	6	6	6	6	6	6	7	3	9	7	7	2	9	9	10	10	10	2	1	5
TAD	$+Z$	$+X$	$+X$	$-Z$	$-Z$	$-Z$	$-Z$	$-Z$	$-Z$	$-X$	$-a$	$-a$	$-a$	$+Z$	$-Z$	$+Z$	$-a$	$-Z$	$-Z$	$-Z$
NMC=2, NTC=10, NSC=10, TMCC=320, TTCC=200, TSCC=1000, TMC=770, TTC=235 TPC=2525																				
Condition (2)																				
Operation	1	2	18	11	6	12	13	19	17	3	5	7	8	9	10	20	14	4	15	16
Machine	2	2	2	2	2	2	2	2	2	2	2	2	2	2	4	4	4	1	1	1
Tool	7	7	7	7	7	3	9	9	7	7	7	7	3	9	10	10	10	2	1	5
TAD	$+Z$	$-Z$	$-Z$	$-Z$	$-Z$	$-Z$	$-Z$	$+Z$	$-X$	$+X$	$+X$	$-a$	$-a$	$-a$	$-a$	$+Z$	$-Z$	$-Z$	$-Z$	$-Z$
NMC=2, NSC=8, TMCC=320, TSCC=1000, TMC=770, TPC=2090																				
Condition (3)																				
Operation	1	6	2	5	11	12	13	14	18	17	7	8	9	10	19	20	3	4	15	16
Machine	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	1	1	1
Tool	6	6	6	6	8	2	9	10	6	8	8	2	9	10	9	10	6	2	1	5
TAD	$+Z$	$-Z$	$-Z$	$-Z$	$-Z$	$-Z$	$-Z$	$-Z$	$-X$	$-X$	$-a$	$-a$	$-a$	$-a$	$+Z$	$+Z$	$+X$	$-Z$	$-Z$	$-Z$
NMC=1, *NSC*=6, *TMCC*=160, *TSCC*=700, *TMC*=1730, *TPC*=2590																				

is the same as the result of the SA. The mean TPC (2600.8) using the proposed approach is better than the results of the TS, SA, and GA. In general, the performance of the proposed approach for part 2 is better than the performances of the other four algorithms.

7 Conclusions

A two-stage ACO approach was proposed to solve the PP problem for prismatic parts. In the proposed approach, a directed graph is used to represent the PP problem. The graph consists of nodes, directed/undirected arcs, and OR relations. Artificial ants travel freely on the graph to construct process plans in two stages. The operation nodes are selected in the first stage, which reduces the graph to a simple graph. In the second stage, the selected operations on the simple graph are sequenced to generate the feasible process plans. As evident from the experimental results, the two-stage approach is able to provide a feasible solution method for the PP problem. For the different complex prismatic parts considered, the approach can effectively generate several optimal process plans with the same minimal TPC. In comparison with the other algorithm, the two-stage ACO approach was found to have better performance on some aspects under the same conditions.

Table 10 Comparison of the results of the proposed approach to those of other algorithms for Part 2

Condition	Proposed approach	HGA	TS	SA	GA
(1)					
Mean	2552.4	–	2609.6	2668.5	2796.0
Maximum	2557.0	–	2690.0	2829.0	2885.0
Minimum	2525.0	2527.0	2527.0	2535.0	2667.0
(2)					
Mean	2120.5	–	2208.0	2287.0	2370.0
Maximum	2380.0	–	2390.0	2380.0	2580.0
Minimum	2090.0	2120.0	2120.0	2120.0	2220.0
(3)					
Mean	2600.8	–	2630.0	2630.0	2705.0
Maximum	2740.0	–	2740.0	2740.0	2840.0
Minimum	2590.0	–	2580.0	2590.0	2600.0

The results of this paper illustrated the application of a two-stage ACO in the PP problem. On the basis of the simulation results, the two-stage ACO approach was found to be competitive with the other algorithms considered. However, some improvements to this approach should be pursued in future studies. First, due to the complexity of the setting of parameters for the ACO approach, a detailed consideration of the simplification of the parameters setting process for the ACO approach should be performed, and tests for large-scale PP problems should be conducted to verify the feasibility of this approach. Furthermore, a self-adjustment mechanism on those parameter values could be made to reduce the amount of time spent on tuning the experiments. Second, more appropriate criteria should be used to evaluate the process plans. For example, considering the effect of carbon dioxide pollution on the environment caused by the machining process, minimization of the amount of carbon emissions should be used to evaluate the process plans.

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Compliance with ethical standards

Conflict of interest All of authors declare that there is no conflict of interests regarding the publication of this paper.

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