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Application of graph theory and hybrid GA-SA for operation sequencing in a dynamic workshop environment

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ABSTRACT
To solve the machining operation sequencing problem in the computer aided process planning, this paper presents a hybrid genetic algorithm and simulated annealing approach for machining operation sequencing optimization in a dynamic workshop environment. The directed graph used as an explicit constraint model is formulated based on precedence constraints among machining operations, and the graph search algorithms is embedded into framework of the optimization system. The initial solutions composed of all feasible operation sequences in GA optimization stage are produced by applying a stochastic topologic sort algorithm to the OPG. Production cost calculating model is taken as the criterion to evaluate the operation sequence quantitatively. The optimization approach can make a dynamical respond to the changes of plant resources and multiple optimal/suboptimal solutions could be obtained. Finally an illustrative example for a complicated part is given, and the test results testify the feasibility and validity of this developed method.

KEYWORDS
Operation sequencing; operation precedence graph; hybrid algorithm

1. Introduction

Computer-aided process planning (CAPP) plays a key role for integration of computer-aided design (CAD) and computer-aided manufacturing (CAM) systems [14]. A process plan describes the manufacturing processes for transforming a raw material to a completed part within the available machining resources. Manufacturing process planning activities involving: (1) choosing machining operations for every feature; (2)sequencing the aggregate of all the operations and allocating the available manufacturing resources; (3) determining setup plans; (4) calculating of cutting parameters; (5) tool path planning and generating NC part programs; and (6) designing of jigs and fixtures.

Of all the aforementioned activities, operation sequencing is considered as one of the most crucial and complicated tasks, and it generally includes the following two steps: (1) selecting the most reasonable combination of machines and cutting tools from the available machining resources, and find the correct tool approach direction (TAD) based on the feature geometry for each corresponding operation to be executed; (2) Determine the sequence of executing all the operations required for the part so that the precedence constraint relationship among all the operations are maintained. The decision-making tasks in (1) and (2) must be carried out simultaneously to achieve an optimal plan against a predetermined criterion, such as minimum production cost.

It is well-known that process planning is a NP-hard problem and which is very difficult to optimize using conventional techniques. In the last two decades, many optimization approaches based on intelligent algorithms, such as the simulated annealing (SA) [16], genetic algorithms (GAs) [1, 5, 15, 19, 20], particle swarm optimization (PSO) [2, 9], colony optimization(ACO) [7, 13], tabu search (TS) [10] and agent-based approach [8, 11] have been applied for solving process planning problem, and great progress have been made. However, the potential for further improvement is still remained. For example, a more reasonable constraint model needs to be formulate, and the optimization algorithms also need improved to be more efficient and robustness. Xu et al. [3,4,18] proposed a framework of processing multimedia resources.

In our proposed methodology, machining operations of a part and the precedence relationships among all the operations are formulated in a directed graph-based model, and the size of the solution space in operation sequencing can be reduced. The decision-making of selecting alternative manufacturing resources and tool approach direction for every operation, determining in what order to execute a set of operations so the resulting operation sequence obeys the precedence constraints

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established by both features and operations, is considered concurrently to achieve the optimal solution.

The remaining sections of the paper are organized as follows. In the second section, a brief review of the related research work is given. In the third section the machining operation sequencing problem is defined and the precedence constraint model of operations in sequence is analyzed and constructed. In the fourth section we present an overall hybrid GA-SA approach framework, the evaluation model of the operation sequence and population initialization problem are discussed in detail. In the fifth section a case is used to test the developed GA-SA optimization approach, the computing results are analyzed and compared. Finally, the conclusions and future work are given.

2. A literature review

Mohammad et al. [14] proposes a generic process sequencing approach can increase adaptability and flexibility of the system, due to its independency to available resources. The proposed method can be used by the Cloud-DPP (distributed process planning) in an integrated cyber-physical system.

The optimization approaches based on intelligent algorithms, such as the SA, GA, PSO, ACO and multi-agent algorithms, have been widely used to solve the operation sequencing problems in CAPP and significant progress has been made.

Nallakumarasamy et al. [16] proposed a metaheuristic for solving operation sequencing problem in CAPP, the feasible operation sequences were generated based on the precedence cost matrix and reward–penalty matrix by making use of simulated annealing technique. The main contribution of their work focused on improving the quality of the optimal solution with a fewer computational time along with generating more alternate optimal operation sequence plans. Zhang F et al. [19] developed a novel operation sequencing model for parts machined in a job shop manufacturing environment. The optimization approach based on GA was applied to accomplish the distribution of machining resources and sequencing operations simultaneously. The real-time status of machining resources in the job shop and alternative optimal plans were not considered. Zhang et al. [20] constructed a GAs approach comprising the coding scheme, the evaluation model and the objective function based on the analysis of various constraints in operation sequencing. The objective function was defined as a formula of the sum of compulsive constraints with each weighing, and the constraints were taken as the control strategy for the implementation of GAs. Ding et al. [1] proposed a hybrid approach to incorporate the GA, analytical hierarchical process (AHP) and artificial neural network (ANN) for operation sequencing for prismatic components. The strategy based on multi-objective optimization was presented, a globally objective function was defined comprising the calculation of machining time and cost, assessment of manufacturing rules. The relative weights of various evaluation factors were calculated quantitatively by using ANN techniques. Musharavati et al. [15] proposed a modified GA for manufacturing process planning in multiple parts reconfigurable manufacturing lines. A cyclic crossover operation for an integer-based representation was designed and executed to ensure that no violation of the processing constraints for each generated solutions in the iterative calculation process.

Huang et al. [5] modelled the operation sequencing as a combinatorial optimization problem with process constraints, and developed a hybrid graph and GA approach to operation sequencing in a concurrent manner by simultaneously sequencing operations and selecting manufacturing resources. Guo et al. [2] proposed a novel representation of process plans that is suited for five-axis machining environment, employed and modified a PSO algorithm to solve the operation sequencing problem effectively. Li et al. [9] proposed a modified PSO algorithm for the operation sequencing optimization problem, and the efficient encoding, updating, random search methods were developed in order to improve the performance of the PSO based approach. Liu et al. [13] developed an ACO based optimization approach for integrating process planning and production scheduling. The ACO algorithm is divided into two stages to solve the proposed mathematical model of integrated process planning and production scheduling problem. Krishna et al. [7] applied a newly developed ACO as a global search technique for the quick searching out the optimal operation sequence with considering various processing constrains. Li et al. [10] proposed a tabu search-based approach to solve the operation sequencing which was modelled as a constraint-based optimization problem. In order to improve the search efficiently in a large-size constraint-based space, a hybrid constraint-handling method was developed and embedded in the optimization algorithm. Li et al. [11] developed an agent-based approach to facilitate the integration of process planning and production scheduling, an agent based on an evolutionary algorithm was used to manage the interactions and communications between agents to make appropriate decisions. Leung et al. [8] present an agent-based system to integrate process planning and shopfloor scheduling. The search-based algorithm was incorporated into an established multi-agent system (MAS) platform, with advantages of flexible system architectures and responsive fault tolerance.

The potential for applying directed graph model to represent the space of solution (operation sequence) was addressed by Prabhu et al. [17]. Lin et al. [12] proposed a graph-search approach for operation sequencing in a prismatic part with interacting features. The graph model is built by considering the set of all machining operations in transforming a rough stock into the finished part. With the graph-search process, a high quality operation sequence plans could be generated. However, since these methods are developed based on some heuristic rules and reasoning process, the optimal operation sequence plans probably be missing during the graph-search processes. Irani et al. [6] explored in depth the integration of manufacturing precedence among part features with a complete and explicit graph representation for alternative process plans, developed the Hamiltonian path (HP) analogy for the process planning problem based on the precedence graph and operation cost matrix, and the Latin multiplication method (LMM) for constrained enumeration of all feasible HPs was implemented. The optimal process plan is an HP that corresponds to the least number of set-up required for machining each feature once and only once from a feature graph.

As reviewed in the previous related research, we could conclude that each algorithm has its own advantages and disadvantages. Although some literatures demonstrate that certain algorithm could be superior to other algorithms, most scholars believe that it will be able to get a more powerful search capability with the appropriate combination of different type of algorithms. Because of the open structure that has nothing to do with the nature of the problem to be solved of GA, it is easy for GA to combine with other type of algorithms, so in the research we propose a hybrid GA and SA approach for operation sequencing optimization in a dynamic workshop environment with an objective of minimizing the production cost.

3. Machining operation sequencing model

3.1. Problem description

For a part, an operation sequence is composed of valid operations to machine the features and the specified sequence of the operations, available machining resources, setup plans, machining parameters for each operation, etc. It is assumed that there are total n operations required for a part to be machined, and the operation aggregation is Op = {op1, op2, ..., op$n$}, each operation op-i can be executed by several alternative plans if different machines, cutting tools, or set-up plans are chosen for this operation. In this paper, a set-up is defined as a set of operations with the same TAD executed on the same machine. The class definition of an operation is listed in Fig. 1.

Class OperationType :	An operation
Variable	Description
operation_id	The ID of the operation
machine_id	The ID of the machine to to execute the operation
machine_list[]	The candidate machine list for executing the operation
tool_id	The ID of the tool to to execute the operation
tool_list[]	The candidate tool list for executing the operation
TAD_id	The ID of a TAD to apply the operation
TAD_list[]	The candidate TAD list for executing the operation

Figure 1. Class definition of an operation.

In this research, an operation sequence is represented using a vector comprises $\boldsymbol{n}$ bits, each bit represents an operation once and only once, and the order of those bits within the vector defines whose corresponding sequences. Any sequence of the bits set is a possible solution for an operation sequence in the solution space. An operation sequence vector is formulated as **Oper**[n], $\boldsymbol{n}$ is the whole number of machining operations to performed in a part with interacting features.

Fig. 1 illustrates a operation sequence comprising 6 operations: **Oper**[6]. The element "op5" represents the operation with the ID of 5, the elements m-01, t-02 and +x in the second column represent the machine, cutting tool and TAD applied to execute operation-5 respectively, so are the other columns. Here, as to the operation sequence vector **Oper**[6], the executing sequence starts with op-5, then op-4, ..., and the terminal is op-2.

In the initialization phase of GA-SA optimization, a single machine and tool from the candidates is randomly assigned to each corresponding operation, while in the process of optimization, the machine, tool and TAD for each operation must be adjusting dynamically according to the operation's practical position in the sequence. That is, the decision-making tasks of machining resources selection and sequencing operations are mutual influenced and restricted, which must be carried out simultaneously to achieve the optimal objective.

3.2. Precedence constraints analyzing and modeling

The preliminary precedence constraints among operations come from the consideration of geometrical and manufacturing interactions between features, as well as technological requirements in a certain type of part. The constraints imply precedence relationships of determining in what order to perform an aggregation of operations so the resulting operation sequence satisfies the

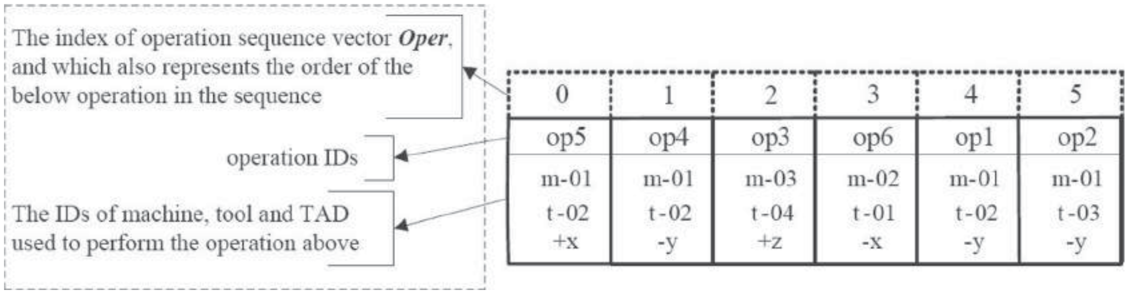


Figure 2. Representation of an operation sequence.

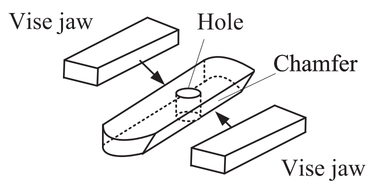
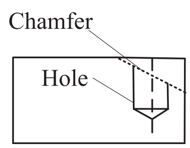
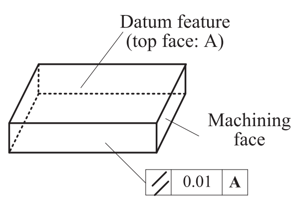
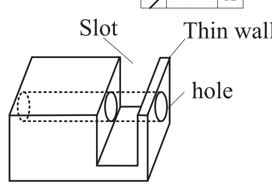
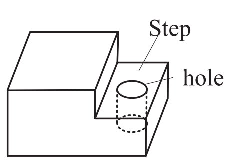
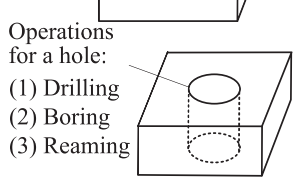
Constraint	Example	Explanation
Fixture interactions		The hole should be machined before the chamfer; otherwise it cannot be fixtured
Tool interactions		In order to position a drilling tool correctly, the drilling of the hole should precede the machining of the chamfer.
Datum interactions		The top face (the datum feature) should be machined prior to the base face.
Technological structure interactions		Good practice should involve drilling the hole,then machining the slot to avoid deformation of the thin wall.
Material-removal interactions		The step should be machined prior to the hole for achieving high machining efficiency (milling is faster than drilling) and surface quality.
Fixed order of machining operations		A typical sequence of machining a hole is drilling, boring, and reaming.

Figure 3. Examples of precedence of constraints.

precedence constraints. It is compulsory for an operation sequence to obey any of the precedence constraints. The precedence constraints between features and operations are generally divided into six types, as listed in Fig. 3.

In this paper, an operation precedence graph (OPG) model is developed for representing the precedence relationships among all the operations. OPG = (V, A), where the vertices set $V = \{\text{op}1,\ \text{op}2,\ \ldots,\ \text{op}n\}$is the set of n-operation of a part; A denotes the set of directed edges between operation vertices, $A = \{\ a_t =< \text{opt}(i),\ \text{opt}(j) > \ |t = 1,\ 2, \cdots,\ m; \text{opt}(i),\ \text{opt}(j) \in V\}$. Every element of the operation aggregation is mapped to the corresponding vertex of an OPG. The precedence relationship between two operations is represented as an directed edge to which two vertices are linked, i.e., one vertex that the arrow points to must be executed after the other. As shown in Fig. 4, where the directed edge a_t starts from vertex "op-i" and points to vertex "op-j", which means op-i must be performed prior to op-j, and the vertex "op-i" is the **immediate predecessor** to "op-j". When two vertices have no edge linked, it indicates that there is no specific precedence relationship between them. A feasible operation sequence can be generated by traversing the vertices of an OPG through the directed edges according to topological relations.

$$\mathrm{op}_i \xrightarrow{a_t} \mathrm{op}_j$$

Figure 4. A pair of vertices and a directed edge.

In order to facilitate generating the feasible operation sequences in the optimization process, e.g., executing the random depth first search of OPG in the initial optimization stage, judging the feasibility of solutions, the repairing of infeasible solutions and implementing of the operator for GA-SA, an adjacency matrix is used to store the OPG. In this research, the adjacency matrix is also called precedence relationships matrix which is developed for use in the proposed GA-SA optimization approach, and the general form is modelled as follows:

$$m[i][j] = \begin{cases} 1, & \exists a_t =< \mathrm{op}i,\ \mathrm{op}j >, a_t \in A \\ 0, & else \end{cases} \quad (i,j = 1, 2, \cdots, n)$$

Where: n is the number of operations; "m$[i][j] = 1$" represents that operation op-i must be performed before op-j; and "m$[i][j] = 0$" represents that there is no precedence relationship between the two operations of op-i and op-j.

4. Hybrid GA and SA optimization approach

4.1. Overall framework of the optimization approach

The hybrid GA-SA approach is applied for operation sequencing optimization in a dynamic workshop environment. The overall implementation procedure is described in the following:

(1) The initialization of information for all the machining operations for GA, and generating the initial solutions which comprises a specified number of operation sequences. After that executing the iterative calculation process in the GA optimization phase, which including several steps as follows: (a) solution reproduction according to specified selection strategy; (b) applying the crossover and mutation operators for every solution in the current generation to get new solutions; (c) identifying and adjusting the infeasible solutions to the feasible domain; (d) the three steps are repeated sequentially and repetitively until the pre-specified termination criterion has been reached.

(2) When the running times of GA program has been achieved to the specified number of iterations, the individuals of the last generation are sorted according to the evaluation value. Then the N_2 individuals with high evaluation values are taken as the initial solution for SA stage and starting to perform the SA iteration calculation. When the running times of SA program has been achieved, selecting a certain number of solutions from the current N_2 solutions as the optimal/suboptimal solutions. The whole flowchart is shown as Fig. 5.

4.2. The evaluation model of the operation sequence

The criteria for an operation sequence evaluation generally include minimum number of setups, shortest process time, minimum production cost, etc. Because the detailed information such as tool paths and machining parameters is unavailable up to now, the total machining time is inadequate to be used for evaluation. Production cost, as the frequently used criterion to evaluation process plans in the macro-planning stage, is used to evaluate the operation sequence quantitatively. Production cost is composed of five cost factors: machine cost (MC), tool cost (TC), machine change cost (MCC), tool change cost (TCC) and set-up cost (SC), the calculation procedures of the five cost factors have been described in detail as follows.

(1) Machine cost (**MC**). **MC** is the whole costs of the machines used to accomplish an operation sequence **Oper**$[n]$, and it is calculated as:

$$\mathrm{MC} = \sum_{i=0}^{n-1} \mathrm{MCI}j, \quad j = \mathrm{Oper}[i].machine\_id \quad (4.1)$$

Where $\boldsymbol{n}$ is the number of operations, which is equal to the length of operation sequence vector **Oper**$[n]$. $\mathbf{MCI}_{\boldsymbol{j}}$ is the machine cost index for using machine-j, and it is a constant for a specific machine.

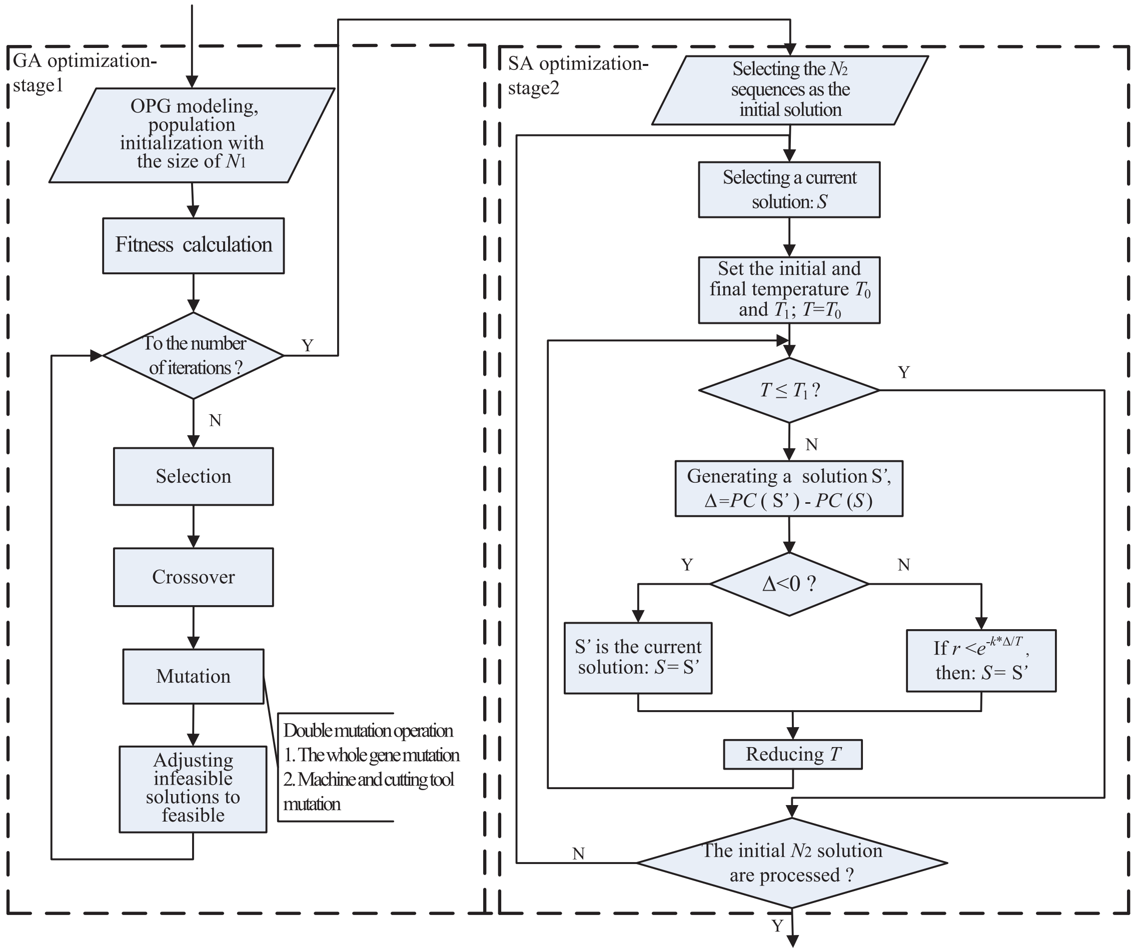


Figure 5. Flowchart of the hybrid GA-SA approach.

(2) Tool cost (**TC**). **TC** is the whole costs of the cutting tool used to accomplish **Oper**[n], and it can be calculated as:

$$\mathrm{TC} = \sum_{i=0}^{n-1} \mathrm{TCI}j, \quad j = \mathrm{Oper}[i].tool\_id \tag{4.2}$$

Where $\mathbf{TCI}_j$ is the tool cost index for using tool-j, and which is a constant for a specific cutting tool.

(3) Number of machine changes (**NMC**) and whole machine change cost (**MCC**): when two adjacent operations are performed on different machines separately, it means that one machine change occurs. **NMC** and **MCC** for an operation sequence **Oper**[n] is calculated as:

$$\mathrm{NMC} = \sum_{i=0}^{i=n-2} \Omega1(\mathrm{Oper}[i].machine\_id, \times \mathrm{Oper}[i+1].machine\_id) \tag{4.3}$$

$$\mathrm{MCC} = \mathrm{NMC} * \mathrm{MCCI} \tag{4.4}$$

$$\Omega1(X, Y) = \begin{cases} 1, & X \neq Y \\ 0, & X = Y \end{cases} \tag{4.5}$$

Where **MCCI** is defined as the machine change cost index, and it is considered to be a constant for each machine change of an operation sequence. Oper[i].*machine_id* is the ID of the machine used to perform operation-Oper[i].*operation_id*.

(4) Number of cutting tool changes (**NTC**) and whole cutting tool change cost (**TCC**): when two adjacent operations are performed on different machines, it means that one cutting tool change occurs. **NTC** and **TCC** for an **Oper**[n] are respectively calculated as:

$$\mathrm{NTC} = \sum_{i=0}^{i=n-2} \Omega2\{\Omega1(\mathrm{Oper}[i].machine\_id, \times \mathrm{Oper}[i+1].machine\_id), \times \Omega1(\mathrm{Oper}[i].tool\_id, \mathrm{Oper}[i+1] .tool\_id)\} \tag{4.6}$$

$$\mathrm{TCC} = \mathrm{NTC} * \mathrm{TCCI} \tag{4.7}$$

$$\Omega2\{X, Y\} = \begin{cases} 0, & X = Y = 0 \\ 1, & \text{otherwise} \end{cases} \tag{4.8}$$

Where TCCI is defined as the tool change cost index, and it is a constant for each cutting tool change.

(5) Number of set-up changes (**NSC**), the number of set-ups (NS) and whole set-up change cost (**SC**): when two adjacent operations are performed on different machines, it means that one cutting tool change occurs. **NTC** and **TCC** for an **Oper**[n] are respectively calculated as:

$$\mathrm{NSC} = \sum_{i=0}^{i=n-2} \Omega 2\{\Omega 1(\mathrm{Oper}[i].\mathit{machine\_id}, \times \mathrm{Oper}[i+1].\mathit{machine\_id}), \Omega 1(\mathrm{Oper}[i].\mathrm{TAD\_}\mathit{id}, \mathrm{Oper}[i+1].\mathrm{TAD\_}\mathit{id})\} \quad (4.9)$$

$$\mathrm{NS} = \mathrm{NSC} + 1, \quad \mathrm{SC} = \mathrm{NS} * \mathrm{SCI} \quad (4.10)$$

Where **SCI** is the set-up change cost index, and it is considered to be a constant for each set-up change of an operation sequence.

Finally, the production cost (**PC**) of an operation sequence **Oper**[n] is the sum of the above five cost factors, thus:

$$\mathbf{PC} = \mathbf{MC} + \mathbf{TC} + \mathbf{MCC} + \mathbf{TCC} + \mathbf{SC} \quad (4.11)$$

4.3. Population initialization for GA optimization

Due to the precedence relationship constraints among machining operations, certain operation sequences obtained randomly are infeasible because of the violation of constraints, which brings adverse effects on the performance of GA optimization. In the research, all the initial solutions (operation sequences) must obey the precedence constraints formulated by OPG, it is necessary to design a search algorithm based on OPG so that the initial population composed of all feasible solutions could be obtained.

In order to eliminate the infeasible operation sequences, a randomly topologic sort algorithm for OPG is designed. Firstly, some variables are predefined:

G The OPG of operation aggregate for a part
g A directed graph with the same format as **G**.
L A linear list to store the operation vertices in **G**, and **L** is initialized to empty.
V A vector to sequentially store the operation vertices in **G**, and **L** is initialized to empty.

(1) Copy **G** to **g**, the variable **L** and **V** is initialized to empty.
(2) Store the operation vertices with no immediate predecessors in **L**.
(3) Randomly select one operation op-i from **L** and insert it into the vector **V**, meanwhile, delete op-i from the **L and** delete the vertex op-i and the directed edge attached to op-i in **g**.
(4) Randomly select a machine, cutting tool and TAD from the candidates which can be applied for performing the operation op-i and assign them to op-i.
(5) If there are new vertices with no immediate predecessors in **g**, store them in **L**.
(6) Repeat steps (3)–(5) until the **g** or **L** is empty.
(7) Repeat steps (1)–(5) until the number of prescribed initial solutions is reached.

By Applying the initialization approach, the initial solutions which are all in the feasible domain can be generated.

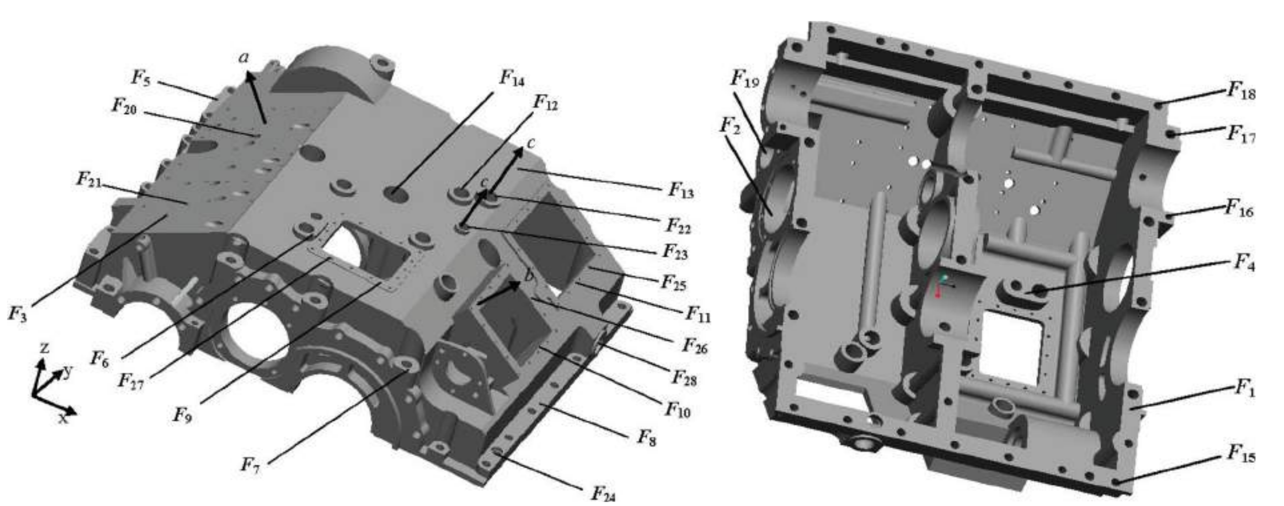


Figure 6. A sample part with 28 machining features.

5. Case study

In this case, a complex part shown in Fig. 6 is used to test the developed GA-SA optimization approach. The part, which is assumed to be manufactured in a job shop manufacturing environment, consists of 28 machining features which include planes, holes, pockets, etc. These features can be machined with 46 operations ($n = 46$), the relevant information of machining feature, operations and manufacturing resources are given in Fig. 7. Complying with the precedence of constraints among operations, the corresponding OPG of the sample part can be established, as shown in Fig. 8, and the corresponding PR matrix is given in Fig. 9.

5.1. Setting parameters in GA and SA

To Parameters in GA : *population size* $N_1 = 80$, crossover probability $P_c = 0.9$, the mutation probability of whole genome $P_{m1} = 0.1$, the mutation probabilities for machine and tool $P_{m2} = 0.1$, the maximal iteration times $m = 600$. Parameters in SA: initial temperature $T_0 = \mathrm{PC}_{max}/10$ termination temperature $T_1 = T_0 *$

Features	Feature descriptions	TAD	Operation id	Machine candidates	Tool candidates
F_1	flat surface	+z	rough turning(op1)	01,02	01, 02, 03
			half finished turning(op2) finished turning(op3)	02	01, 02, 03
F_2	bearing hole	-y, +y	rough boring(op4)	07, 08	04
			half finished boring(op5) finished boring(op6)	06, 07, 08	05
F_3	angular surface	-a	rough milling(op7)	05, 07, 08	07, 08, 09
			finished milling(op8)	03, 04, 06	07, 08, 09
F_4	four bosses	+z	rough milling(op9)	03, 04, 05	08, 09
F_5	plane 1	-z	rough milling(op10)	03, 04, 05	08, 09
F_6	top boss	-z	rough milling(op11)	03, 04, 05	08, 09
			finished milling(op12)	04, 05	
F_7	six bosses	-z	rough milling(op13)	03, 04, 05	08, 09
F_8	plane 2	-z	rough milling(op14)	03, 04, 05	08, 09
F_9	top window surface	-z	rough milling(op15) finished milling(op16)	03, 04, 05	07, 08
F_{10}	inclined plane 1	-b	rough milling(op17) finished milling(op18)	03,04,06,07	07, 08
F_{11}	inclined plane 2	-b	rough milling(op19) finished milling(op20)	03,04,06,07	07, 08
F_{12}	the top holes	-z, +z	drilling(op21)	09, 10	10
F_{13}	top plane	-z	rough milling(op22)	04, 05	07, 08, 09
F_{14}	counterbore hole	-z	spot facing (op23)	09, 10	20
F_{15}	Ø18H7 hole	+z	drilling(op24)	09, 10	11
			reaming(op25)		22
F_{16}	2-Ø12.5 hole	+z	drilling (op26)	09, 10	12
F_{17}	12-Ø21 hole	+z	drilling (op27)	09, 10	13
F_{18}	18-Ø17 hole	+z	drilling (op28)	09, 10	14
F_{19}	side hole	-y	rough boring(op29)	07, 08	06
			finished boring(op30)	06, 07, 08	06
F_{20}	5-Ø20 holes	-a	drilling(op31)	07,08,09,10	15
F_{21}	24-Ø8 holes	-a	drilling(op32)	07,08,09,10	16
			tapping(op33)		23
F_{22}	Oil passage hole 1	-c	reaming(op34)	06, 07, 08	28
			tapping(op35)		24
F_{23}	Oil passage hole 2	-c	drilling(op36)	06, 07, 08	17
			tapping(op37)		25
F_{24}	Ø23 counterbore hole	-z	spot facing(op38)	03,04,09,10	21
F_{25}	holes in inclined plane 1	-b	drilling(op39)	09, 10	18
			tapping(op40)		26
F_{26}	holes in inclined plane 2	-b	drilling(op41)	09, 10	18
			tapping(op42)		26
F_{27}	top holes	-z	drilling(op43)	03,04,09,10	18
			tapping(op44)		26
F_{28}	Oil passage hole 3	-x	drilling(op45)	06, 07, 08	19
			tapping(op46)		27

Available machining resources

Machine id	Model number	Machine Type	Cost indices
01	C5112A	Vertical lathe	20
02	CK5116D	CNC lathe	45
03	XK5763A/1	CNC milling machine	50
04	XK5763A/2	CNC milling machine	55
05	X53T	Milling machine	20
06	TK6111	Boring-milling machine	80
07	TSPX619	Boring-milling machine	45
08	TX6111T	Boring-milling machine	48
09	Z3050	Radial drilling machine	16
10	Z3060	Radial drilling machine	18

Tool id	Tool type	Cost indices
t-01	Turning tool	5
t-02		6
t-03		7
t-04	Boring cutter	12
t-05		13
t-06		9
t-07	Milling cutter	8
t-08		9
t-09		10
t-10	Drill	4
t-11		4
t-12		3
t-13		4
t-14		3
t-15		4
t-16		3
t-17		4
t-18		2
t-19		2
t-20	Countersink drill	4
t-21		3
t-22	reamer	5
t-23	tapping tool	3
t-24		4
t-25		4
t-26		3
t-27		4
t-28	Reaming drill	3

Machine change cost index-MCCI: 120
Set-up cost index- SCI: 90
Tool change cost index-TCCI: 15

Figure 7. The features, operations and manufacturing resources information of the sample part.

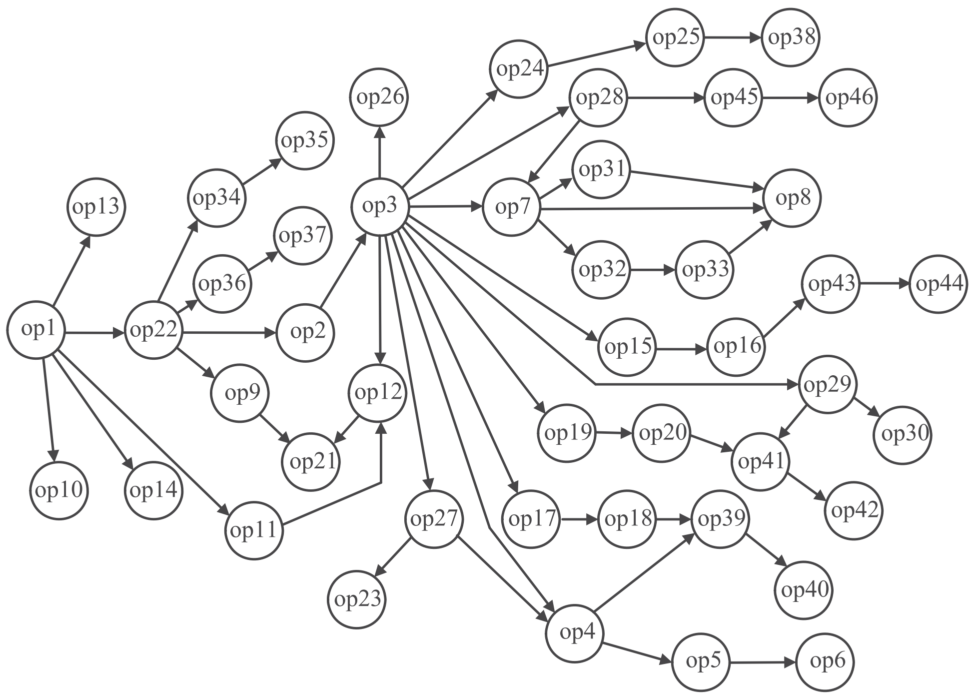


Figure 8. The OPG of the sample part.

Operation id	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46
1	0	0	0	0	0	0	0	0	0	1	1	0	1	1	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
2	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	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	1	0	0	1	0	0	0	0	1	0	0	1	0	1	0	1	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
4	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	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
5	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	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	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
7	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	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	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
9	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
10	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
11	0	0	0	0	0	0	0	0	0	0	0	1	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
12	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
13	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	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	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
15	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	0	0	0	0	0
16	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	0	0	0
17	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	0	0	0
18	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	0	0	0	0	0	0	0
19	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	0
20	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	0	0	0	0	0
21	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
22	0	1	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	1	0	1	0	0	0	0	0	0	0	0	0	0
23	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
24	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	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	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	0	0	0	0	0	0	0	0
26	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
27	0	0	0	1	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
28	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	0	0	0	0	0	0	0	0	0	0	0	0	1	0
29	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	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
30	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
31	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	0	0	0	0	0	0	0	0	0	0	0	0	0
32	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	0	0	0	0	0	0	0	0	0	0	0	0	0
33	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	0	0	0	0	0	0	0	0	0	0	0	0	0
34	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	0	0	0	0	0	0	0	0	0	0	0
35	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
36	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	0	0	0	0	0	0	0	0	0
37	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
38	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
39	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	0	0	0	0	0	0
40	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
41	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	0	0	0	0
42	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
43	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	0	0
44	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
45	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
46	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

Figure 9. The precedence relationship matrix.

The optimal/sub-optimal solutions **1**

machining sequences	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Operation ID	1	22	11	2	3	19	20	17	18	14	10	13	15	12	16	28	27	26	24	25	9	7
Machine ID	01	05	05	02	02	03	03	03	03	03	03	03	03	03	03	09	09	09	09	09	05	05
Tool ID	01	08	08	01	01	08	08	08	08	08	08	08	08	08	08	14	12	13	11	22	08	08
TAD	+z	-z	-z	+z	+z	-b	-b	-b	-b	-z	-z	-z	-z	-z	-z	+z	+z	+z	+z	+z	+z	-a

Continued	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45
	29	4	45	46	36	37	34	35	8	5	6	30	21	23	38	43	44	31	32	33	39	41	40	42
	07	07	07	07	07	07	07	07	06	06	06	06	09	09	09	09	09	09	09	09	09	09	09	09
	06	04	19	27	17	15	28	24	07	05	05	06	10	20	21	18	26	15	16	23	18	18	26	26
	-y	-y	-x	-x	-c	-c	-c	-c	-a	-y	-y	-y	-z	-z	-z	-z	-z	-a	-a	-a	-b	-b	-b	-b

NMC= 8, NS= 15, NTC= 30, MCC= 960, SC= 1350, MC= 1572, TCC= 300, TC=186 **PC**= 4368

The optimal/sub-optimal solutions **2**

machining sequences	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Operation ID	1	11	22	2	3	14	10	13	12	15	16	17	18	19	20	26	28	24	25	27	7	9
Machine ID	01	05	05	02	02	03	03	03	03	03	03	03	03	03	03	09	09	09	09	09	05	05
Tool ID	01	08	08	01	01	08	08	08	08	08	08	08	08	08	08	12	14	11	22	13	08	08
TAD	+z	-z	-z	+z	+z	-z	-z	-z	-z	-z	-z	-b	-b	-b	-b	+z	+z	+z	+z	+z	-a	+z

Continued	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45
	4	29	45	46	34	35	36	37	32	33	31	39	41	40	42	43	44	21	23	38	5	6	30	8
	07	07	07	07	07	07	07	07	09	09	09	09	09	09	09	09	09	09	09	09	06	06	06	06
	04	06	19	27	28	24	17	15	16	23	15	18	18	26	26	18	26	10	20	21	05	05	06	07
	-y	-y	-x	-x	-c	-c	-c	-c	-a	-a	-a	-b	-b	-b	-b	-z	-z	-z	-z	-z	-y	-y	-y	-a

NMC= 8, NS= 15, NTC= 30, MCC= 960, SC= 1350, MC= 1572, TCC= 300, TC= 186 **PC**= 4368

Figure 10. The optimal/sub-optimal solutions under condition 1.

α^{1000}, cooling coefficient $\alpha = 0.995$, shift probability in the neighborhood $Ps = 0.35$, the probability of exchange $P_{as} = 0.3$, mutation probability $P_{am1} = P_{am2} = 0.3$, the number of initial solutions $N2 = 6$.

5.2. Computational results under different conditions

To test the capability and flexibility of the proposed GA-SA approach in dynamic workshop environment, we carried out the operation sequencing under two different conditions.

Condition 1: assuming that all the machining resources are available. Running the optimization program and 3 optimal/sub-optimal solutions are obtained, two of them are shown in Fig. 10.

Condition 2: In a dynamic workshop environment, some machines or cutting tools may be in the state of bottleneck usage or breakdown. Supposing that tool-08, machines 03 and 07 are down. Running the optimization program and 2 optimal or sub-optimal solutions are obtained, one of them are shown in the Fig. 11.

5.3. Test results analysis and comparison

Also take the above part as a sample with all the machining resources are available, experiments have been conducted to illustrate the computational results of the GA, SA and hybrid GA-SA approach. The calculation results show that the single GA and SA algorithm is easy to converge to local optimum, and the optimal solution obtained by SA is much closer to the global optimum comparing with GA, but it needs more computation time. In the early stage the convergence rate of GA is higher but it falls into stagnation in the latter stage. The hybrid GA-SA approach can switch from GA in the terminal iterations to SA by perform neighborhood random operations with the current optimal solutions, and the final solutions quality are significantly improved. In terms of computational efficiency, the time spent by GA-SA in generating

machining sequences	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Operation ID	1	11	22	2	3	24	25	26	28	27	7	9	17	18	19	20	15	16	13	10	14	12
Machine ID	01	05	05	02	02	09	09	09	09	09	05	05	04	04	04	04	04	04	04	04	04	04
Tool ID	01	09	09	01	01	11	22	13	14	12	09	09	07	07	07	07	07	07	09	09	09	09
TAD	*+z*	*-z*	*-z*	*+z*	*+z*	*+z*	*+z*	*+z*	*+z*	*+z*	*-a*	*+z*	*-b*	*-b*	*-b*	*-b*	*-z*	*-z*	*-z*	*-z*	*-z*	*-z*

Continued	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45
	4	29	45	46	34	35	36	37	38	23	21	43	44	39	41	40	42	31	32	33	30	5	6	8
	08	08	08	08	08	08	08	08	09	09	09	09	09	09	09	09	09	09	09	09	06	06	06	06
	06	04	19	27	28	24	17	15	21	20	10	18	26	18	18	26	26	15	16	23	06	05	05	07
	-y	*-y*	*-x*	*-x*	*-c*	*-c*	*-c*	*-c*	*-a*	*-a*	*-a*	*-b*	*-b*	*-b*	*-b*	*-z*	*-z*	*-z*	*-z*	*-z*	*-y*	*-y*	*-y*	*-a*

NMC= 8, NS= 15, NTC= 31, MCC= 960, SC= 1350, MC= 1642, TCC= 310, TC= 188 **PC**= 4450

Figure 11. The optimal/sub-optimal solutions under condition 2.

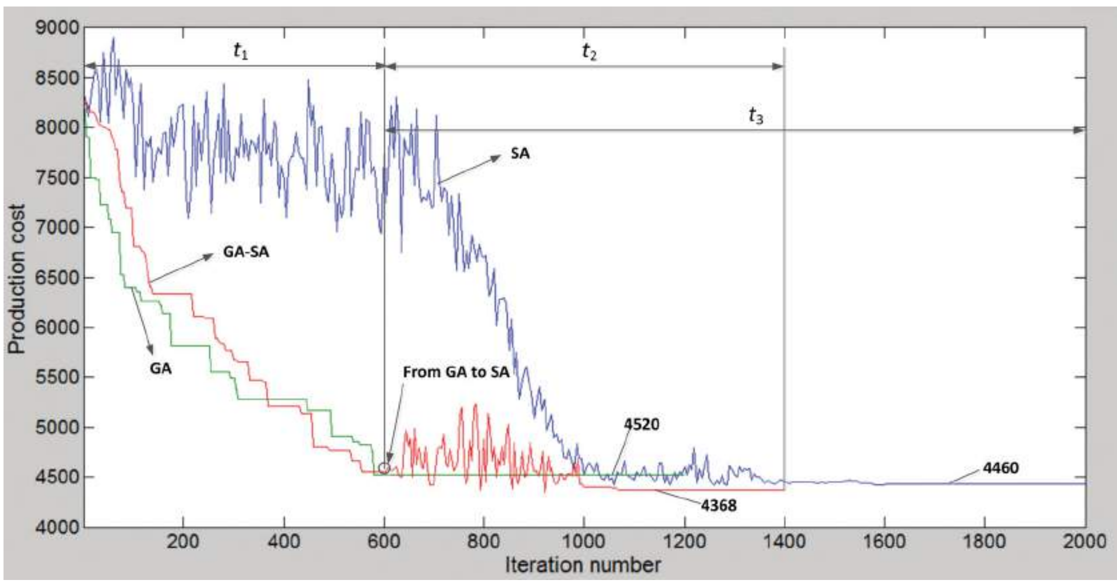


Figure 12. The iterative curves comparison of the GA, SA and GA-SA approach.

3 optimal/suboptimal solutions is t_1+3t_2, while the time spent by SA is $3(t_1+t_2)$.

6. Conclusion and future work

One hybrid algorithm approach which mixed by the GA with strong global searching ability and SA search with strong local searching ability has been proposed to solve operation sequencing optimization problem. The directed graph model representing precedence constraints among machining operations is formulated and the graph search algorithms is embedded into framework of the system. From the results obtained, it is clear that the proposed GA-SA optimization approach produces improved optimal solutions with a fewer computational time. The test results show that the optimization method could not only search the optimal solution with efficiency, but also conveniently simulate a practical dynamic workshop environment. The availability of alternative optimal or suboptimal operation sequences could provide the production scheduling module with the flexibility to select different plans depending on the real-time status of manufacturing resources. Finally, the computing results of case study demonstrate that the developed optimization approach is also efficient and effective in solving the large-scale combinatorial optimization problems such as the machining operation sequencing in CAPP. Finally, how to elaborate the evaluation criterion of production cost to make it more applicable to production practice is our work in the future.

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