Sequence optimization of machining elements for process model based on the genetic algorithm of matrix constrained

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Abstract. Process sequence planning is the permutation and combination orienting to product manufacturing process, which plays an important role in improving the manufacturing produce efficiency and reducing the manufacturing cost. In this paper, an improved constraint matrix method is proposed to transform the relation between manufacturing features into the constraint relation between machining elements, and to determine the sequence coefficient of machining elements according to the correlation relation of manufacturing features. Through constructing the interactive associative relationship of sequence constraint matrix and combined constraint matrix, the initial population with high adaptability is selected out, and can improves the adaptability of initial population of genetic algorithm by using the process sequencing algorithm of improved constraint matrix. In order to improve the convergence speed, the accuracy and efficiency of process sequencing, the genetic algorithm of elite preserving is used.

1. Introduction

Process sequence planning is the permutation and combination of product processing procedure, which plays an important role in improving the production efficiency and reducing the processing cost. The traditional process sequence planning[1] is based on the constraint drive process of hierarchical and phased mode[2], mainly including the trunk constraint matching method[3], which is based on the hierarchical structure of the model and completes the surface processing procedure planning based on the trunk process path and process constraints of the surface processing chain. Literature[4] conducts feature ranking based on knowledge rules and geometric reasoning. In literature[5], the priority realization constraint of feature processing is realized based on rule method, which is oriented to intersecting features. According to the principle of mechanical analysis, literature[6] obtained the priority sequence of intersection features by combining the type of feature intersection and the surface quality constraints of machining. Intelligent algorithm is applied to process sequence optimization[7-9], such as genetic algorithm, ant colony algorithm and simulated annealing algorithm. These algorithms optimize the sequence of processes from genetic algorithm factors, optimization objective function selection, inferior gene deletion and gene retention methods.

In this paper, an improved constraint matrix method is proposed to transform the constraint relation between manufacturing features into that between machining elements. The sequence coefficients of machining activities are determined according to the correlation of manufacturing features. The order
constraint matrix and combination constraint matrix are constructed, and the initial population with high fitness was selected according to their relationship. The fitness of the initial population in genetic algorithm is improved by using the process sequencing algorithm with improved constraint matrix. The convergence speed and accuracy of process sorting can be improved effectively by using elite retention strategy.

2. Machining element and its constraint matrix

2.1. Machining element and its sequence

According to the information such as the type, size and technical accuracy of the manufacturing features of a part, and combined with other processing step constraints, a processing method chain of processing features is formed. Each processing step operation is a machining element (ME). The ME information is created according to the manufacturing features, feature dimensions, precision, roughness, machining scheme, machining operations, machine tools and tools in the part model. Thus according to the basic features of the comprehensive information to form the processing scheme, processing operations, processing machine tools, tools and specific enabling information.

The information of ME is as follows: ME = {FM, OP, S, MA, TO, TAD, PA}. Where, FM is the manufacturing feature; OP is the processing method; S is the ME sequence coefficient; MA is the machine tools; TO is the tool information; TAD is the approach direction of the tool; PA is the process parameter.

An ordered set of ME is formed according to the processing sequence of ME, which is called machining element sequence, namely MES={ME1, ME2, ..., MEi, ..., MEN}, N is the total number of all machining elements.

2.2. The constraint matrix of the ME

Suppose a part contains n MEs, then the constraint matrix between MEs is expressed as[9]: C=(Cij)nxn, where, i, j = 1, 2, ..., n. The Cij represents the constraint precedence relationship between the ith ME and the Jth ME. When the ith ME is precedence over the Jth ME, then Cij=1 and Cji=0. In other cases Cij=Cji=0. According to the combination and priority relationship between MEs, the constraint relationship between them is represented. Thus the order constraint matrix(OCM) and the combination constraint matrix(CCM) of ME are constructed.

2.2.1. Order constraint matrix

Let the OCM be: A=(Aij)nxn, where: i, j = 1, 2, ..., n. Aij represents the OCM element value of the ith ME and the jth ME. According to the corresponding relationship between MEs, the value of OCM element is:

\[
A_{ij} = \begin{cases} 
1 & S_i < S_j \\
0 & S_i = S_j \\
-1 & S_i > S_j 
\end{cases}
\]

Where: Si is the sequence coefficient of MEi, which represents the processing priority of ME; Aij = 1 means that MEi is processed before MEj; Aij = 0 means that there is no definite processing order between MEi and MEj. Aij = -1 indicates that MEi is processed after MEj.

2.2.2. Combination constraint matrix

Let the CCM be: B=(Bij)nxn, where: i, j = 1, 2, ..., n. The Bij represents the CCM element value of the ith and jth ME, and is the combination degree of the two adjacent MEs. The larger the coefficient value is, the higher the combination degree is, the stronger the necessity is. The element value of CCM is:
\[
B_{ij} = \begin{cases} 
1 & \text{only } r^i_j \\
m & \text{and the post m-1 rule } r^i_j \\
0 & \text{not } r^i_j 
\end{cases}
\] (2)

Where: \( m \in [0,4] \), 4 represents the total number of Combination constraint rules.

2.2.3. Rules for Combination constraint

Set \( M_{ij} = \{ r^1_{ij}, r^2_{ij}, r^3_{ij}, r^4_{ij} \} \) as the combination rule set of \( ME_i \) and \( ME_j \), indicating whether the combination constraint condition satisfies the decision rule:

(1) Rule for machine tool resources
\( r^1_{ij} : \phi_1(ME_i, ME_j) = 1 \) means that two MEs meet the same machine tool resource combination rule; \( \phi_1(ME_i, ME_j) = 0 \) means that the above rule is not met.

(2) Rule for same datum
\( r^2_{ij} : \phi_2(ME_i, ME_j) = 1 \) means that the two MEs meet the same datum combination rule; \( \phi_2(ME_i, ME_j) = 0 \) means that the above rule is not met.

(3) Rule for the tools
\( r^3_{ij} : \phi_3(ME_i, ME_j) = 1 \), means that the two MEs meet the same tool combination rule; \( \phi_3(ME_i, ME_j) = 0 \) means that the above rule is not met.

(4) Rule for tools approaching direction
\( r^4_{ij} : \phi_4(ME_i, ME_j) = 1 \) means that the two MEs meet the combination rule of the same cutter approach direction; \( \phi_4(ME_i, ME_j) = 0 \) means that the above rule is not met.

The calculation method of \( B_{ij} \) is as follows: the rules in \( M_{ij} \) are determined from front to back, and the coefficient is increased by 1 for each meeting rule. If \( r^1_{ij} = 0 \), then \( B_{ij} = 0 \), the calculation is finished.

3. Construction of ME constraint matrix

3.1. Constructing OCM

S--The machining element sequence coefficient is determined by the processing order between manufacturing features and the position of ME in the standard processing sequence. It is composed of five-digit natural number coding, and its calculation formula is as follows:

\[
S_{ij} = b_j \times 1000 + c_{ij} \times 100 + a_i
\] (3)

Where: \( b_j \) is the number corresponding to the jth machining element in the standard processing sequence of \( FM_i \); \( c_{ij} \) indicates whether the machining feature is a reference datum or not. If so, the value is 0. If not, the value is 1. \( a_i \) is the sequence coefficient of the manufacturing feature \( FM_i \).

Based on the search principle of depth-first traversal and breadth-first traversal, the correlation diagram of manufacturing characteristics was traversed to determine the sequence coefficient of manufacturing characteristics, and the last two values of \( S \) could be obtained. At the same time, it identifies whether the feature is a reference benchmark, determines the value of the middle bit, and then determines the first two digits of \( S \) by searching the standard processing sequence of manufacturing features, then the five-digit natural number \( S \) can be all determined.

The machining elements are rearranged according to the sequence coefficient of the machining elements from small to large, and the resulting machining element sequence is taken as the row and column of the constraint matrix, and then the corresponding element value in OCM is determined by comparing the sequence coefficient of different machining elements.

3.2. Constructing CCM

According to the definition of CCM, matrix element \( B_{ij} \) is the combination coefficient between \( ME_i \) and \( ME_j \). In the combination rule set \( M_{ij} = \{ r^1_{ij}, r^2_{ij}, \ldots, r^4_{ij} \} \), the number of adjacent MEs conforms to
the rule, which reflects the degree of the combination of the two adjacent MEs. The higher the coefficient value, the stronger the combination degree is required.

4. Process sequencing based on constraint matrix genetic algorithm
Genetic algorithm is used to select, copy, cross and mutate ME chromosomes to optimize ME sequence, and finally a convergent sequence individual, namely the optimal solution, is obtained.

4.1. Obtaining initial population
The size of QRS(t) of the initial population is selected based on experiments and experience, generally 20~100[10]. The composition of the initial population is: QRS(0)={MES1, MES2, ..., MESk}. Where: K represents the total number of MES in the population. The combination of MES coefficient(Score) computation formula is as follows:

\[
\text{Score} = \sum_{i=1}^{M-1} B_{i(i+1)}
\]  

(4)

Where Bi(i+1) represents the combination coefficient of two adjacent MEs in CCM, and M represents the total number of ME.

4.2. Optimizing the sequence of machining elements
The elite retention strategy is as follows: the elite individuals appearing periodically in the evolution process of ME group are directly copied to the next generation[9].

4.2.1. Machining fitness function
Two important parameters, processing time and production cost, were considered to construct the fitness function.

1) Processing time function
The calculation formula of the total processing time is:

\[
f(x): T = \sum_{i=1}^{n} t_i
\]  

(5)

Where, T is the total processing time, n is the number of MEs, and ti is the ith ME total processing time. In order to calculate ti, set MAi as used machine tools for machining MEi, and TOi as the processing tool used in MEi, and t1i as the processing conversion time of MEi to MEi+1, and t2i as the tool conversion time of MEi to MEi+1, t3i as the clamping conversion time of MEi to MEi+1, t4i as the machining time of MEi. The calculation operator is as follows:

\[
f_i(x, y) = \begin{cases} 
1 & X \neq Y \\
0 & X = Y 
\end{cases}
\]  

(6)

\[
f_i(x,y) = \begin{cases} 
1 & X = 0, Y = 1 \\
0 & \text{others}
\end{cases}
\]  

(7)

The calculation formula of machine tool transformation time of MEi is:

\[
T_{MC_i} = t_{i1} \cdot f_i(MA_i, MA_{i+1})
\]  

(8)

The calculation formula of tool conversion time of MEi is as follows:

\[
T_{TO_i} = t_{i2} \cdot f_i(MA_i, MA_{i+1}, f_i(TO_i, TO_{i+1}))
\]  

(9)

The calculation formula of clamping conversion time of MEi is as follows:

\[
T_{SC_i} = t_{i3} \cdot f_i(MA_i, MA_{i+1}, f_i(TAD_i, TAD_{i+1}))
\]  

(10)

Therefore, the ti formula for the processing time of MEi is:

\[
t_i = T_{MC_i} + T_{TO_i} + T_{SC_i} + t_u
\]  

(11)

Thus, the total time of all processing sequences is:

\[
T = \sum_{i=1}^{n} (T_{MC_i} + T_{TO_i} + T_{SC_i} + t_u)
\]  

(12)
(2) Production cost calculation
There are three main factors affecting production cost: machining operation method, tool life and tool cost. The simplified production cost calculation formula is as follows:

\[
P = \sum_{i=1}^{n} \left( M + \frac{x_i}{Z_i} G_i \right)
\]

Where, \( P \) is the total production cost of a ME sequence; \( n \) is the number of ME; \( M \) is the unit time cost of the workplace; \( x_i \) is the processing operation coefficient of MEi; \( Z_i \) is the tool life of MEi; \( G_i \) is the tool cost of MEi.

(3) Fitness function
The value of fitness function reflects the advantages and disadvantages of individuals in genetic algorithm. Based on the total processing time requirements, the fitness function of chromosomes is defined as:

\[
F(x) = \frac{\omega_1}{T} + \frac{\omega_2}{C}
\]

In the formula, \( \omega_1 \) and \( \omega_2 \) are the weight coefficients of corresponding parameter indexes. Since processing time has a great influence on process sequencing optimization, the weight values of the two coefficients are 0.8 and 0.2 respectively.

4.2.2. Processing coding method
By selecting "natural number coding" for gene coding, ME sequence is mapped to natural number sequence to form chromosome set. Figure 1 shows the encoding and decoding process of genes, and Figure 2 shows the manufacturing resource information corresponding to each ME.

4.2.3. Elitist retention strategy of machining element sequence
Elite retention strategies are used to select elite individuals and are copied directly into the next generation. The number of elite retention in each generation is determined by the replication probability \( Pr \), which is usually set at 10%~20%[9]. In the calculation process, the total processing time of each MES in QRS(\( i \)) of the population of the \( i \)th generation is calculated according to the fitness function \( F(x) \). If MES (\( n \)) is an elite individual in the \( n \) generation, the MES (\( n \)) is operated as follows:

\[
MES (n+1) = MES (n)
\]

4.2.4. Crossover operator
The crossover probability \( Pc \) is the number of chromosomes to set the crossover operation. If the number of individuals in the population is \( N \), \( N \ast Pc \) individuals in each generation in the genetic
algorithm participate in cross genetics, and $P_c$ is usually taken as 50% ~ 80%[9]. Figure 3 shows how the crossover operator operates.

4.2.5. Mutation operator
From the parent population, the mutation probability $P_v$ is used to generate new individuals in the mode of random gene encoding exchange, and $P_v$ is usually set at 1%~10%[9]. Figure 4 shows how the mutation operator operates.

As new individuals generated by mutation operator may be invalid, the validity of chromosomes needs to be judged according to the process constraints of ME. If it is effective, it will be passed on to the next generation; if it is invalid, it will be deleted and another intersection or mutation point will be selected for variation.

4.2.6. Termination conditions
In the process of cross selection, the termination conditions of the optimal population selection iteration were set as follows:

$$G(TC) = \{ Cov.1 \} \lor (Cov.2 \lor Cov.3)$$  \hspace{1cm} (16)

Where, Cov.1 is the default calculation number $N$. When the genetic algebra reaches the maximum value, the operation terminates. Cov.2 means when the fitness value of the optimal individual remains unchanged or changes little after several generations of genetic calculation, the operation is terminated. Cov.3 is when the average fitness of the population is infinitely close to the fitness of the optimal individual, the operation is terminated.

5. Example verification
With VS2012 and NX10 as the development environment, NXOpen and C++ as the development language, the feasibility of the proposed method is verified.

As shown in Figure 5(a), the neutral block B1 is the main manufacturing feature in the model. There are overlapping feature surfaces between manufacturing feature B1 and P3 and P5, so both cavities depend on B1. Figure 5(b) shows the correlation between manufacturing features.
Figure 5. 3D model and its associated model.

Table 1 shows the sequence coefficients of each manufacturing feature. Table 2 shows the relevant information of the processing element.

| Table 1. Manufacturing feature sequence coefficients. |
|---|---|---|---|---|---|---|---|---|---|---|
| $F_{M_i}$ | $B_i$ | $P_5$ | $P_1$ | $P_2$ | $H_9$ | $H_1$–$H_2$ | $H_3$–$H_8$ | $H_{10}$ | $S_i$ | $M_i$ | $S_i$ | $T_i$ |
| 1. Rough milling plane#1 | B | 01001 | M1 | S1 | T1 | 16. Fine milling cavity | P1–P2 | 02103 | M1 | S1 | T6 |
| 2. Fine milling plane#1 | B | 02001 | M1 | S1 | T2 | 17. Point drill | H9 | 01103 | M2 | S1 | T7 |
| 3. Rough milling plane#2 | B | 01001 | M1 | S2 | T1 | 18. Drilling | H9 | 02103 | M2 | S1 | T8 |
| 4. Fine milling plane#2 | B | 02001 | M1 | S2 | T2 | 19. Chambering | H9 | 03103 | M2 | S1 | T9 |
| 5. Rough milling plane#3 | B | 01001 | M1 | S1 | T1 | 20. Reaming | H9 | 04103 | M2 | S1 | T10 |
| 6. Fine milling plane#3 | B | 02001 | M1 | S1 | T2 | 21. Point drill | H10 | 01104 | M2 | S1 | T7 |
| 7. Rough milling plane#4 | B | 01101 | M1 | S2 | T1 | 22. Drilling | H10 | 02104 | M2 | S1 | T8 |
| 8. Fine milling plane#4 | B | 02101 | M1 | S2 | T2 | 23. Chambering | H10 | 03104 | M2 | S1 | T11 |
| 9. Rough milling plane#5 | B | 01101 | M1 | S3 | T1 | 24. Reaming | H10 | 04104 | M2 | S1 | T12 |
| 10. Fine milling plane#5 | B | 02101 | M1 | S3 | T2 | 25. Point drill | H1–H2 | 01104 | M2 | S1 | T7 |
| 11. Rough milling plane#6 | B | 01101 | M1 | S3 | T1 | 26. Drilling | H1–H2 | 02104 | M2 | S1 | T8 |
| 12. Fine milling plane#6 | B | 02101 | M1 | S3 | T2 | 27. Reaming | H1–H2 | 03104 | M2 | S1 | T13 |
| 13. Rough milling cavity | P5 | 01102 | M1 | S1 | T3 | 28. Point drill | H3–H8 | 01104 | M2 | S1 | T7 |
| 14. Fine milling cavity | P5 | 02102 | M1 | S1 | T4 | 29. Drilling | H3–H8 | 02104 | M2 | S1 | T8 |
| 15. Rough milling cavity | P1–P2 | 01103 | M1 | S1 | T5 | 30. Reaming | H3–H8 | 03104 | M2 | S1 | T14 |

| Table 2. Relevant information of machining element. |
|---|---|---|---|---|---|---|
| number | Processing operations | $F_{M_i}$ | $S_i$ | $M_i$ | $S_i$ | $T_i$ |
| 1 | Rough milling plane#1 | B | 01001 | M1 | S1 | T1 |
| 2 | Fine milling plane#1 | B | 02001 | M1 | S1 | T2 |
| 3 | Rough milling plane#2 | B | 01001 | M1 | S2 | T1 |
| 4 | Fine milling plane#2 | B | 02001 | M1 | S2 | T2 |
| 5 | Rough milling plane#3 | B | 01001 | M1 | S1 | T1 |
| 6 | Fine milling plane#3 | B | 02001 | M1 | S1 | T2 |
| 7 | Rough milling plane#4 | B | 01101 | M1 | S2 | T1 |
| 8 | Fine milling plane#4 | B | 02101 | M1 | S2 | T2 |
| 9 | Rough milling plane#5 | B | 01101 | M1 | S3 | T1 |
| 10 | Fine milling plane#5 | B | 02101 | M1 | S3 | T2 |
| 11 | Rough milling plane#6 | B | 01101 | M1 | S3 | T1 |
| 12 | Fine milling plane#6 | B | 02101 | M1 | S3 | T2 |
| 13 | Rough milling cavity | P5 | 01102 | M1 | S1 | T3 |
| 14 | Fine milling cavity | P5 | 02102 | M1 | S1 | T4 |
| 15 | Rough milling cavity | P1–P2 | 01103 | M1 | S1 | T5 |
By rearranging the ME sequence coefficients from small to large, the feasible MES were obtained, and the initial feasible OCM and CCM were established. When MES was: \{ME1, ME3, ME5, ME7, ME9, ME11, ME13, ME15, ME17, ME21, ME25, ME28, ME2, ME4, ME6, ME8, ME10, ME12, ME16, ME18, ME22, ME26, ME29, ME19, ME27, ME20, ME24\}, Score was the highest, so this sequence was the best selected object of the initial population.

Setting the machine tool exchange time \(t_{1i}\) as 30s, tool tool change time \(t_{2i}\) as 3s, clamping exchange time \(t_{3i}\) as 4s, and processing time \(t_{4i}\) as 5s. Table 3 and Table 4 show the parameters in the production cost. The elite retention method was applied, in which the population number was set as 50, \(P_{c}\) as 0.7 and \(P_v\) as 0.02, and the optimal individual gene sequence was obtained as follows: \{3, 7, 9, 11, 1, 5, 13, 15, 17, 21, 25, 28, 4, 8, 10, 12, 2, 6, 14, 16, 18, 22, 26, 29, 19, 23, 20, 24, 27, 30\}, and then the corresponding processing element sequence could be obtained through decoding.

| Table 3. Processing operation coefficient. |
|-------------------------------------------|
| Machining method | Rough/fine milling | Drillin | Reamin | Chamberin |
| \(X_i\) | 1 | 2 | 2 | 3 |

| Table 4. Tools life and cost. |
|------------------------------|
| Tool s | T1 | T2 | T3-6 | T7-10 | T11-14 |
| \(Z_i\) | 100 | 90 | 80 | 70 | 50 |
| \(G_i\) | 4 | 6 | 5 | 3 | 3 |

In order to verify the superiority of the method proposed in this paper, the calculation results of the improved method and the standard genetic algorithm are compared, as shown in Figure 6, Figure 7. The number of convergent iterations is shown in Table 5.

| Table 5. The comparison of the results of the two methods. |
|-----------------------------------------------------------|
| Algorithm | Selected method | \(K\) | \(P_r\) | \(P_c\) | \(P_v\) | iterations |
| Improved genetic algorithm | Based on improved constraint matrix | 50 | 0.7 | 0.02 | 24 |
| standard genetic algorithm | Randomly selected | 50 | 0.7 | 0.02 | 70 |

![Figure 6. Standard GA mean change of population fitness.](image1)

![Figure 7. Improved GA mean change of population fitness.](image2)
Through contrast figure 6 and figure 7, the mean value of the population obtained by using the standard genetic algorithm is gradually stable and convergent in about 70 generations. However, the improved genetic algorithm proposed in this paper starts to converge around the 25th generation, and the population fitness mean in the early stage is more stable than the standard algorithm. This is because the order constraint matrix (OCM) and combination constraint matrix (CCM) are introduced to strictly screen out poor quality chromosome sequences in the initial stage of algorithm iteration, and good quality chromosomes in the population are retained to the descendants as much as possible in the process of iteration with elite retention strategy. Thus, the reliability of the final MES optimal chromosome processing sequence was increased.

Through the secondary development of UG, manufacturing feature recognition, machining element acquisition, sequence coefficient acquisition and initial population of constraint matrix are realized, as shown in Figure 8; the initial population code is sorted by genetic algorithm to obtain the optimal sequence of machining elements, as shown in Figure 9; the machining elements with the same processing conditions are combined to form a processing procedure, and the optimal sequence of operations is obtained as shown in Figure 10.

![Figure 8. The initial population.](image)

![Figure 9. The optimal machining sequence.](image)

![Figure 10. The optimal ME sequence.](image)

6. Conclusion
The genetic algorithm of constraint matrix is applied to process sequence planning. Feature machining elements and their attribute information are determined according to the features and their relationship, which mainly includes the processing operation, process precision level, manufacturing resources and sequence coefficient of feature machining elements. Therefore, an improved constraint matrix is
constructed. The genetic algorithm with improved constraint matrix is used to select the initial population, so as to obtain the minimum processing time and the optimal sequence of operations. Although the proposed method can better solve the problem of process sequence optimization, it needs further improvement. It can be applied to the semantic model of process and the release of process constraint information.

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