APPLICATION OF SELF-ADAPTIVE ANT COLONY ALGORITHM IN MACHINE TECHNOLOGYMANUFACTURING PROCESS ROUTE OPTIMIZATION

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ABSTRACT: In allusion to the optimization scheme in computer aided process design, based on self-adaptive ant colony algorithm, this paper proposes a self-adaptive ant colony optimization method with the minimum resource replacement rate as the objective. By analyzing the features of parts, the manufacturing characteristics are decomposed according to the precision requirements, and the concept of processing element is put forward. The processing element is defined as a set of specific manufacturing features, processing stages, processing methods, and clamping positions. The determination of the process route is converted to the optimal sequence arrangement of the processing element. After giving constraints and taboo criteria, the processing element optimization principle is given, and then the processing cycle is shortened, processing quality is improved and the processing cost is reduced, which is taken as the comprehensive target, to express as the lowest replacement rate of manufacturing resource. The specific calculation method for transition probability and pheromone updating between the processing elements is given, to complete the mathematical modeling of the optimization objective function. Then, the algorithm proposed in this paper is analyzed with actual examples. The example analysis shows that the proposed method can reliably and effectively obtain the process route in line with the production reality.

KEY WORDS: processing element; ant colony algorithm; process route

1 INTRODUCTION

With the continuous progress of artificial intelligence, genetic algorithm, simulated annealing, ant colony algorithm and its hybrid algorithm have been used in recent years to solve the process route optimization. Even the researchers, in the existing enterprise resources constraints, use the genetic algorithm to make processing cost and efficiency optimization, but they ignore the influence of processing precision on product quality (Oliveira, J.R. et al.,2014); simulated annealing can be used to solve the sequence problem of one-time installation and multiple steps of processing in a machining center, but it also limits the method that it cannot be applied to the complete production process. The literature (Shao, Y et al.,2013)establishes a process route optimization decision model for green manufacturing, adopts the genetic simulated annealing hybrid algorithm to get the solution, which compensates for the shortcomings of genetic algorithm and simulated annealing algorithm, and improves the algorithm performance.

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Compared with these algorithms, ant colony algorithm, as a kind of probabilistic technique with positive feedback, distributed computing and greedy heuristic search characteristics, shows good performance in solving traveling salesman problem (TSP), vehicle routing planning, shop floor scheduling and so on discrete combinatorial optimization problem. The literature (Chen, T. & Xiao, R., 2014) and(Tang, B W et al.,2013)use the ant colony algorithm to optimize the process route, but the mathematical model is not established to construct processing sequence to constrain the optimization target, but simple knowledge reasoning.

If the most basic features of processing steps of a manufacturing machine, in determining the machine tools, clamping method and cutting tool are defined as the processing elements, then the processing element can be mapped to "city" in the TSP problem. The change of manufacturing resources in different processing elements is regarded as "the distance between the cities". Taking high manufacture precision, high production efficiency, and low manufacturing cost as optimization objectives, the process route decision problem is transformed into, in the common constraint of the processing sequence and manufacturing resources, seek the processing element optimization scheduling to make the manufacturing resource replacement rate the lowest. As a result, from the analysis of the optimization algorithm features, the ant colony algorithm is more suitable to solve the optimization problem of process route optimization. It was first proposed by Dorign et al. inspired by the discovery of path behavior by ants searching for food in nature. Ant colony algorithm has the characteristics of global optimization, information positive feedback, heuristic search and distributed computing. It performs good performance in solving TSP problem scheduling and resource twice allocation and so on combinatorial optimization problems.

Comprehensively considering the impact of manufacturing resources (machine, props, clamping etc.) on processing precision, processing efficiency and processing cost, based on the construction processing element concept, this paper puts forward a kind of process route optimization method based on self-adaptive ant colony algorithm. The paper constructs the optimization model of multi-process route decision problem, and improves the ant colony algorithm, effectively accelerates the convergence speed, and reduces the possibility of getting into the local optimal solution. The paper also verifies the reliability and validity of the method by an example.

2 RESEARCH METHOD

2.1 Feature description of parts

Process route design includes manufacturing feature decomposition and manufacturing process scheduling of products design model. Manufacturing feature, as the carrier of manufacturing information, not only contains the geometric topological information of parts, but also includes the non-geometric information of manufacturing process, such as material, hardness, tolerance, surface quality and so on (Sun, W. et al.,2015). Generally speaking, in the process of making parts processing route, first of all, it is necessary to extract the parts features. The element of parts is composed of some of the most basic machining features with the process meaning, and the parts features can be divided into major features and minor features. The main features of parts are used to construct the whole structure of parts, such as outer circle, hole, plane and so on features unable to be decomposed again. Auxiliary features of parts are mainly further modifications for the major characteristics, such as slot, chamfer and so on features. Now, we give the following 3 definitions.

Definition 1: we define the most basic unit with machining meaning as the feature element of parts. All the features of the parts constitute a feature set, and we use F to represent.

$$F=1,2,3,4,5\cdots N \tag{1}$$

In (1), N represents the total number of parts features.

Definition 2: processing elements. The part is composed of a series of features. For each feature of the parts, we can complete the processing with several procedures, and the procedures completing the feature process can form a processing sequence. We call the most basic processing node in the processing sequence as the processing element. The processing element can be represented by a four-dimensional vector.

$$P_{ij} = \{F_i, S_j, T_l, D\} \tag{2}$$

In (2), Fi suggests the i feature in the parts, , and N is the number of manufacturing features in the parts; Sj indicates the j processing stage of Fi (rough processing, semi finishing processing and finishing processing); Tl represents the l processing method for the Sj stage of Fi; D refers to the clamping position of Fi in the Sj stage for processing.

Each of the processing stage of N features of the processing elements consists of the processing element of parts. That can be expressed as $A = P_{1j} + p_{2j} \ldots$, for the description convenience (Jadon, R.S.& Datta, U., 2013). Each processing stage of each feature is developed, then the processing element set can be expressed as $A = a_1 + a_2 \ldots$, in which n suggests the total number of processing elements. If all the parts are ordered according to a certain sequence, then the process route of the part is produced.

2.2 Mathematical model of process route based on ant colony algorithm

According to the principle of ant colony algorithm, the design process of process route can be described as: first of all, ants were placed in a processing element that can be taken as the starting point of the processing route. Ants move according to the pheromone concentration between the current node and the next phase selectable processing element node. When passing by a processing element, then it is put it into their taboo list; when all the elements have been passed, the traversal is completed, to generate a process route. Finally, after repeated cycles, the paths that ants walk through are bound to be stable, and then one or several optimal or better parts process route can be got.

2.2.1Optimization objective

Generally speaking, the design of process route must comprehensively consider the processing precision, processing cost, processing efficiency and so on factors. However, in a given manufacturing environment, the final process route is difficult to meet the above factors at the same time, which makes it difficult to determine the appropriate optimization objective function for the optimal algorithm. In view of this, starting from the manufacturing resources, the minimum replacement rate of manufacturing resources is used as the objective function of optimization, to make optimization solution for the process route (Shao, Y.et al., 2013). That is to say, in the case of meeting the processing sequence and the constraints of manufacturing resources, try to use more similar manufacturing resources to complete more parts feature processing, so as to reduce the replacement of manufacturing resources and change the benchmark.

Obviously, the decrease of replacement of the manufacturing resources rate can shorten the manufacturing cycle, and improve processing efficiency; while reducing clamping times can reduce the clamping error, avoid bench mark frequent conversion, so as to improve the machining accuracy, but also enhance the stability of the process; and the improvement of the processing accuracy and stability of the process, will inevitably lead to the products rejection rate reduced, thereby reducing the processing cost (Yavuz, G. et al.,2016). Therefore, taking the minimum replacement rate of manufacturing resources as the optimization goal, we can comprehensively reflect the common pursuit for short manufacturing cycle, high manufacturing precision and low manufacturing cost in process planning. Based on this, in the case of meeting the processing requirements, this paper takes reducing the times of manufacturing resources, such as machine tools, clamping tools, cutting tools and so on as the optimization objective.

2.2.2Constraint conditions and taboo criteria

1) Constraint conditions

Each processing node of the parts all the eigenvectors, according to a certain order, is processed and able to generate parts processing route. But the processing nodes cannot be arbitrarily combined. Ants must be restricted by constraint conditions in the process of traversing the processing nodes. The constraints can be divided into two types (Kim, Y. M. et al., 2012): 1) the inherent principle must be followed in the process, such as coarse to fine, the surface to the hole, and the superior to the inferior; 2) when the processing object is too complex, the constraints are set in advance by process staffs combining with enterprises manufacturing resources.

2) Taboo criterion

In the process of using ant colony algorithm to make process routing decision, when ants choose the next node in the current process node, there are two kinds of nodes will be placed in the taboo list, and temporarily removed in the selection. One is the processed node, and the other is the processing node that does not meet the constraints.

2.2.3Process optimization principle

When the ants transfer from the current processing element to the next processing element, it will randomly select all the processing elements filtered by the taboo list. Calculate the random selection probability according to the optimization principle, and the optimization principle is that the closer the ants' selection to the current processing element, the higher probability the processing element has.

The determination principle of distance between the different processing elements includes the following three points (Dong, X. et al., 2014): 1) the machine tools that the two processing elements use are the same, the closer the distance; 2) the clamping position between the two processing elements is the same, the closer the distance; 3) the cutters that the two processing elements use are the same, the closer the distance. The distance between arbitrary processing elements can be calculated by (3).

$$C_{ai,aj} = \lambda_1 R_y + \lambda_2 R_t + \lambda_3 R_f \tag{3}$$

In (3), respectively indicates the weight coefficient that machine tools, cutting tools and fixtures replaced. The change of machine tools is bound to cause cutters and clamping position change (Yin, T. et al.,2014). According to the effect of change of machine tool, cutters, and clamping position on the production efficiency in the actual production, in this paper, is given. is determined by the specific situation of the processing elements i and j, and the calculation method of is shown in (4).

$$R_y = \begin{Bmatrix} 0(X_{ai} = X_{aj}) \\ 1(X_{ai} \neq X_{aj}) \end{Bmatrix}, R_t = \begin{Bmatrix} 0(Y_{ai} = Y_{aj}) \\ 1(Y_{ai} \neq Y_{aj}) \end{Bmatrix}, R_f = \begin{Bmatrix} 0(Z_{ai} = Z_{aj}) \\ 1(Z_{ai} \neq Z_{aj}) \end{Bmatrix} \tag{4}$$

In (4), X_{ai} represents the machine tool that a_i uses, Y_{ai} suggests the cutters that a_i uses, and Z_{ai} indicates the clamping position of a_i.

2.3 Transition probabilities between processing elements

In the process of the ants traversing all the processing elements, the choice of the next processing node from the current node is required to follow the relevant transition probability function. The function determines the transition probability of ants to transfer from the current processing element i to the next processing element j. The greater the value, then the greater the probability for the next processing node to choose j. At t moment, the probability $P_{ij}^k(t)$ that the ant k moves from the processing element i to the processing element j can be expressed as (5).

$$P_{ij}^k(t)=\begin{cases}\dfrac{[\tau_{ij}(t)]^\alpha\bullet[\eta_{ij}(t)]^\beta}{\sum\limits_{s\in allowed_k}[\tau_{is}(t)]^\alpha\bullet[\eta_{is}(t)]^\beta}, j\in allowed_k\\ 0, others\end{cases} \tag{5}$$

In (5), $\tau_{ij}(t)$ is the pheromone between the processing element i and j at the moment of t. At the initial moment, the pheromone on each path is equivalent, set as $\tau_{ij}(0)=c$. α is the information heuristic factor, indicating the relative importance of the trajectory. β is the expectation elicitation factor, representing the degree of importance of heuristic factors in ant selection path. $\eta_{ij}(t)$ suggests the desired degree of the processing element i to move to the processing element j, defined as the reciprocal of manufacturing resource replacement rate between two adjacent processing elements i and j [9].The smaller the replacement rate, the larger $\eta_{ij}(t)$. $allowed_k=\{C-Tab(i_k)\}$ represents a collection of allowing choosing processing element node of ants at the moment of t.

2.4 Pheromone update function

In order to avoid residue information submerged heuristic information caused by excessive residual pheromone, each ant traversal of all nodes, according to (6), update the residual information.

$$\tau_{ij}(t+n)=(1-p)\bullet\tau_{ij}(t)+\Delta\tau_{ij}(t) \tag{6}$$

I In (6), $p\in[0,1]$ represents pheromone volatile function; $1-p$ indicates the residual coefficient of information; $\Delta\tau_{ij}(t)$ refers to the pheromone increment of ant k in this loop traversal between processing meta i and j. The calculation method of $\Delta\tau_{ij}(t)$ is shown in (7). $\Delta\tau_{ij}^k(t)$ is the pheromone left between the processing element i and j in the ergodic of ant k. This paper uses Ant - Cycle Model to calculate.

$$\Delta\tau_{ij}(t)=\sum_{k=1}^{m}\Delta\tau_{ij}^k(t) \tag{7}$$

2.5 Self-adaptive adjustment

When the number of machining parts elements is large, in order to improve the searching ability of ant colony algorithm, prevent the slow convergence rate and fall into the local optimal solution, the method of adaptively adjusting the information evaporation coefficient θ is adopted (Tang, B. W.et al.,2013). When the optimal solution obtained by ant colony algorithm has not been improved obviously after several cycles, adjust according to (8).

$$\theta(t+1)=\begin{cases}0.95\theta(t), 0.95\theta(t)>\theta_{min}\\ \theta_{min}, others\end{cases} \tag{8}$$

In (8), θ_{min} is the minimum of θ, which can prevent reducing the convergence rate of the algorithm for too small θ.
The algorithm flow chart diagram presented in this paper is shown in figure 1.

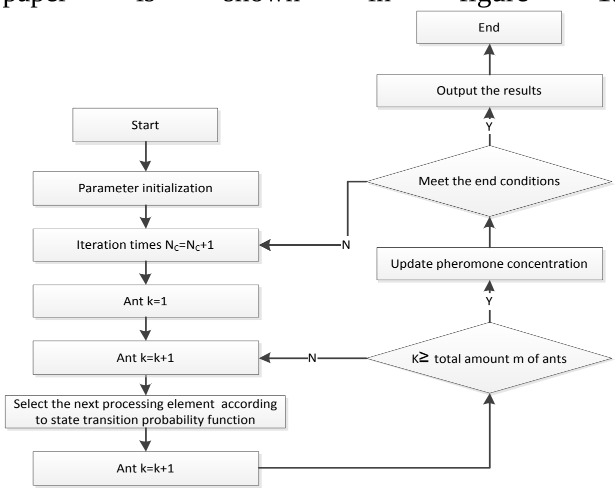

Figure 1. The flow chart of the algorithm

3 RESEARCH RESULTS

In this paper, the transmission shaft produced by an enterprise is taken as an example, and through the analysis of the parts in the gear shaft design model, it gets the characteristic attribute table of the parts, as shown in table 1.

Table 1. Transmission shaft characteristic attribute table

Major features	Category	Size	Tolerance	Auxiliary features	Category	Size	Tolerance
f1	End face	40		f1-1	Center hole		
f2	Cylindrical surface	$\phi 40$	+0.018 +0.002	f2-1	Chamfer	$1*45^{\circ}$	
f3	Cylindrical surface	$\phi 60$		F2-2	Back-cutter groove		
f4	Cylindrical surface	$\phi 52$	+0.032 +0.007	f4-1	Key groove	Width 16	
f5	External screw thread	M48		f4-2	Back-cutter groove		
f6	Cylindrical surface	$\phi 40$	+0.0018 +0.002	f5-1	Chamfer	$1*45^{\circ}$	
f7	End face	40		f5-2	External screw thread		
				f6-1	Back-cutter groove		
				f6-2	Chamfer	$1*45^{\circ}$	
				f7-1	Center hole		

And in accordance with the premise of meeting the processing accuracy requirements, minimize the length of the processing chain, and list the corresponding processing methods and processing chain of each feature, as shown in table 2.

Table 1. Processing methods and equipment for part features

Feature No.	Processing methods	Processing equipment	Processing chain
f1	Vehicles	Lathe	Rough turning a_1 -Half finished turning a_2
f2	Vehicles and milling	Lathe and cylindrical grinding machine	Rough turning a_3 -Half finished turning a_4 -Coarse grinding a_5 -Fine grinding a_6
f3	Vehicles	Lathe	Rough turning a_7 -Half finished turning a_8
f4	Vehicles	Lathe	Rough turning a_9 -Half finished turning a_{10} -Finish turning a_{11}
f5	Vehicles	Lathe	Rough turning a_{12} -Half finished turning a_{13}
f6	Vehicles and milling	Lathe and cylindrical grinding machine	Rough turning a_{14} -Half finished turning a_{15} -Coarse grinding a_{16} - Fine grinding a_{17}
f7	Vehicles	Lathe	Rough turning a_{18} -Half finished turning a_{19}
f1-1	Vehicles	Lathe	Drill a_{20}
f2-1	Vehicles and pliers	Lathe	Rough turning a_{21} -Half finished turning a_{22}
F2-2	Vehicles	Lathe	Rough turning a_{23} -Half finished turning a_{24}
f4-1	Milling	Vertical milling machine	Rough milling a_{25} -Fine milling a_{26}
f4-2	Vehicles	Lathe	Rough turning a_{27} -Half finished turning a_{28}
f5-1	Vehicles and pliers	Lathe	Rough turning a_{29} -Half finished turning a_{30}
f5-2	Vehicles	Lathe	Screw thread a_{31}
f6-1	Vehicles	Lathe	Rough turning a_{32} -Half finished turning a_{33}
f6-2	Vehicles and pliers	Lathe	Rough turning a_{34} -Half finished turning a_{35}
f7-1	Vehicles	Lathe	Drill a_{36}

This example selects ant colony number is 24, the number of cycles for 200 times, parts processing element number for 36, , , , and , using Matlab 2010 software to calculate then an optimal solution can be obtained, the machine tool changing for 3 times, the clamping changing for 6 times, and tool changing for 13 times. Machining meta priority sequence is:

$a_{18}-a_{14}-a_{12}-a_{9}-a_{19}-a_{36}-a_{1}-a_{3}-a_{7}-a_{2}-a_{20}-a_{15}-a_{13}-a_{10}-a_{27}-a_{32}-a_{34}-a_{29}-a_{35}-a_{30}-a_{4}-a_{8}-a_{23}-a_{21}-a_{22}-a_{24}-a_{28}-a_{33}-a_{31}-a_{11}-a_{25}-a_{26}-a_{5}-a_{16}-a_{6}$

The current enterprise popular process route, machine tool changes for 4 times, tool changes for 15 times, clamping changes for 8 times, higher than the results obtained in this paper optimization program. The scheme effectively improves the technical route of the part. At the same time, analyzing and calculating the current enterprise existing process resource replacement rate index (Z=7) (Dong, X. et al., 2015). By comparison, the process resource replacement rate index obtained by the algorithm is decreased by 18.57%. This algorithm effectively reduces the resources replacement rate in the process, and improves the stability of the processing process.

4 CONCLUSION

In order to solve the parts optimal scheme selection for in the machining process, the ant colony algorithm is applied to the machining process optimization, the process route optimization method with a minimum resource replacement rate for the optimization goal is put forward. In addition, through analyzing features of parts, the appropriate processing method is selected according tothe machining precision, and the processing element concept is proposed. Then, the mathematical model with a minimum resource replacement rate for the optimization goal is constructed, and self-adaptive ant colony algorithm is used to get the solution.The example proves that the method can get the optimal process route processingsatisfying the processing requirements. In this paper, the main processing route is inserted into the heat treatment, inspection and other auxiliary processes, thus forming a complete parts process route.

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