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ARTIFICIAL AND COMPUTATIONAL INTELLIGENCE

Digital twin-oriented dynamic optimization of multi-process route based on improved hybrid ant colony algorithm

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Abstract. To improve the dynamic adaptability and flexibility of the process route during manufacturing, a dynamic optimization method of the multi-process route based on an improved ant colony algorithm driven by digital twin is proposed. Firstly, based on the analysis of the features of the manufacturing part, the machining methods of each process are selected, and the fuzzy precedence constraint relationship between machining metas and processes is constructed by intuitionistic fuzzy information. Then, the multi-objective optimization function driven by the digital twin is established with the optimization objectives of least manufacturing cost and lowest carbon emission, also the ranking of processing methods is optimized by an improved adaptive ant colony algorithm to seek the optimal processing sequence. Finally, the transmission shaft of some equipment is taken as an engineering example for verification analysis, which shows that this method can obtain a process route that gets closer to practical production.

Keywords: digital twin; multi-process route; intuitionistic fuzzy information; adaptive ant colony algorithm; optimization.

1. INTRODUCTION

With the rapid development of a new generation of information technology, communication technology, and the Internet of Things technology, the manufacturing industry is leaping forward in the direction of digitalization, networking, and intelligence [1]. The traditional high-volume and large-scale manufacturing mode has been gradually eliminated, and the upgrading of new products is becoming increasingly frequent. The recent market demand is facing severe challenges such as diversification and personalization, small batches and multiple varieties, short cycles, and fast response [2]. The process route of the product stipulates the entire process of transforming the blank part into the finished product by using the workshop manufacturing resources. A scientific and reasonable process route is an important means to shorten the production cycle, reduce manufacturing costs, and improve processing quality. At the same time, it also has an important impact on reducing resource and energy consumption, mitigating environmental pollution, and promoting green and low-carbon development [3–5]. Therefore, it has attracted wide attention and is a technical difficulty that needs to be solved in the process of technological transformation and upgrading of manufacturing enterprises.

The optimization decision of the process route is not only affected by manufacturing resources (such as machine tools, cutting tools, checking fixtures, and measuring instruments) but also restricted by processing methods, process constraints, and other factors. At the same time, it is related to product types, product batches, design level of technicians, and even the limitation of enterprise process habits. So that it becomes an overly complex and constrained non-linear multi-factor planning problem [6,7]. The traditional methods (such as the Newton method, integer programming method, gradient descent method, and graph theory method) are used to conduct process route optimization with defects such as low efficiency, time consumption, poor consistency, and easily falling into local optimal solution [8–10]. Moreover, this single static process route cannot adapt to the dynamic change of manufacturing resources of an enterprise, resulting in greatly reduced or even invalid efficiency of process planning. In addition, the environmental impact on the manufacturing process is insufficiently considered, which cannot meet the development needs of low-carbon flexible manufacturing [11]. In recent years, with the development of artificial intelligence, scholars at home and abroad have proposed a variety of optimization algorithms, such as the Hopfield neural network, genetic algorithm, grey correlation method, ant colony optimization algorithm, tabu search, particle swarm optimization algorithm, etc., and achieve a large number of research results [12–15]. However, due to the defects of each algorithm itself, as well as the comprehensive impact of product diversity and dynamic changes in manufacturing resources, the use of

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a single optimization algorithm has certain limitations, and it is difficult to achieve the desired results. So, it is needed to adopt a mixture of multiple algorithms or the complementation between different optimizing algorithms to improve the optimization efficiency.

With the widespread application of digital manufacturing technology, digital twin technology, as synchronous interactive feedback between physical entities and virtual space, provides a feasible way for the dynamical adjustment and optimization of process routes to adapt to manufacturing resource changes during production and improve production management. Digital twin technology provides a scenario-aware means for collecting and utilizing dynamic information of process routes, expands the dynamic optimization decision-making capability of process routes through high-fidelity mapping evolution, data fusion analysis, and iterative optimization for decision-making, and meets the production management needs of enterprises.

During process planning, the process knowledge is complex, fuzzy, and discrete, and there are fuzzy constraint relationships among the process of different processing methods, which are suitable for analysis by the fuzzy mathematics theory. Intuitionistic fuzzy set, as an important extension and supplement of fuzzy set theory, comprehensively considers the information of membership, non-membership, and hesitation degree of elements [16], which is more flexible and objective in analyzing fuzzy and uncertain problems. Ant colony algorithm, which simulates the foraging behavior of ants, has strong local search ability, information positive feedback, distributed computing, and other features, and has significant advantages in solving combinatorial optimization problems. Given the features, this paper proposes a multi-process route dynamic optimization method based on digital twin technology, integrating intuitionistic fuzzy information and an improved ant colony algorithm. Intuitionistic fuzzy information is utilized to construct the fuzzy constraint relationship between machining metas and processes, and then the multi-objective optimization function driven by the digital twin is established with the minimum manufacturing cost and the least carbon emission as the optimization objectives. After that, the sorting efficiency of processing methods is optimized by an improved ant colony algorithm, and the convergence speed is effectively improved. Finally, the effectiveness and availability of this method are verified by engineering examples.

2. PROBLEM DESCRIPTION

The optimization of the process route is extraordinarily complex, and its optimization variables are sequential rather than regular numerical optimization. Meanwhile, the constraints and optimization objectives are difficult to express by explicit analytical expressions, which further increases the difficulty of solving.

2.1. Part features and constraints

The optimization decision of the process route is essentially the decomposition and extraction of part manufacturing features and the sequencing optimization of the manufacturing process. As a carrier of various information in the product development process, manufacturing features not only involve geometric topology information of parts but also contain non-geometric information required for design and manufacturing, such as material information, tolerance information, heat treatment information, tool information, surface quality information, etc. Usually, part features are divided into several categories, such as key features, auxiliary features, and management features [17]. There is usually an interrelationship between each basic feature, and the part can be represented by a feature set as $F = \{f_1, f_2, \cdots, f_m\}$, m is the number of features.

During the part machining process, each part feature can be achieved by multiple operations, and the processes that complete the machining of all part features constitute a processing sequence, in which each machining node is called a machining meta and can be described as a six-tuple:

$$P_{ij} = \left\{PI_e,\ PF_i,\ PS_j,\ PM_l,\ PW_r,\ PD\right\}, \tag{1}$$

where PI_e is the machining meta number; PF_i is the part feature; PS_j is the machining stage j of feature i; PM_l is the method l available for the feature i in the machining stage j; PW_r is the manufacturing resource r available for the feature i in the machining stage j; PD is the clamping position of the feature i in the machining stage j.

Therefore, the set of machining meta in each machining stage of a part can be expressed as $A = \left\{P_{1j}, P_{2j}, \cdots, P_{nj}\right\}$, for ease of presentation, the machining stages are expanded and constituted as $A = \{a_1, a_2, \cdots, a_n\}$, n is the total number of machining meta. When each machining meta performs a reasonable allocation and sequencing of manufacturing resources under certain constraint conditions, a process route will form. A typical process route generation process is shown in Fig. 1 below.

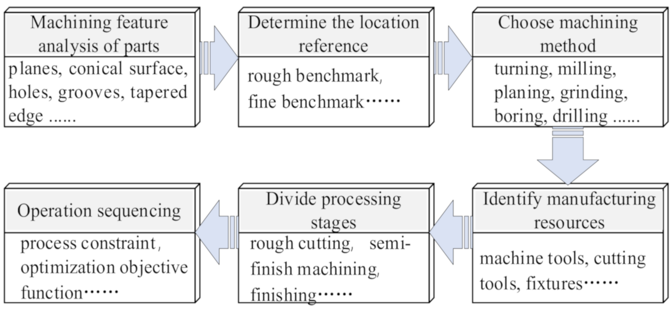

Fig. 1. Generation steps of process route

The sorting of each machining meta in the process route is not arbitrary, it is necessary to consider the constraints of processing methods, processing stages, process rules, and other factors to ensure the effectiveness of the optimization efficiency. Constraints include the following aspects:

1. Benchmark and location constraints: the machining features used as the benchmark should be processed first. If there are multiple precise data, the principle of reference surface transfer order and gradually improving machining accuracy

should be abided by for machining processes; when there is a location relationship between the machining features, the locating feature shall be dealt with first.
2. Processing stage constraints: from coarse to precise, from primary surface to secondary surface. That is, in the order of roughing → semi-finishing machining → finishing → smoothing. At the same time, the main surfaces (working surface, assembly surface, etc.) are processed first, and the secondary surface (non-working surface, auxiliary surface, etc.) should be post-processing.
3. Non-destructive constraints: the features of post-processing cannot destroy the properties generated by the previous processing. For example, chamfering is earlier than thread processing, and groove is processed after cylinder processing.
4. Constraints formed by the feature properties: the hole expansion or reaming of an inner hole must be processed after the drilling of it.
5. The uniqueness constraint of a machine tool and cutting tool: each processing can only be conducted on one machine tool, and only one cutting tool can be selected for machining operation.
6. Constraints of energy-saving and consumption-reduction: under the premise of ensuring machining quality, as many as possible machining features should be dealt with for one clamping, and the tool path of each processing should be the shortest, which not only shortens the processing time but also reduces tool consumption and machine tool wear.

Among them, 1 to 5 are mandatory constraints, which must be satisfied during the dynamic optimization of the process route; 6 belongs to selective constraints, which are maximally satisfied during the dynamic optimization process of the process route. Due to the overlapping and fuzziness of the constraint relationship between the part features, to accurately express this state between machining metas, the intuitionistic fuzzy information introduced below will be adopted to establish the precedence constraint relationship of the machining metas.

2.2. Objective functions

Usually, in a certain manufacturing environment, the manufacturing resources of the actual production process are unchanged, that is, under the condition that the machine tool, cutting tool, and fixture are known. Their variation will cause changes in processing time, production cost, carbon emission, and product quality.

Therefore, the order optimization of processing methods can be conducted by taking the lowest manufacturing cost and the least carbon emission as objective functions, namely:

$$\min C(x) = MC(x) + CE(x), \tag{2}$$

where $MC(x)$ is manufacturing cost, which mainly includes the machining costs of machine tools and cutting tools, as well as the changing costs caused by changes in machine tools, cutting tools, and fixtures, can be expressed as follows:

$$\begin{aligned} MC(x) &= \sum_{i=1}^{n} JC(x) + \sum_{i=1}^{n} DJ(x) + \sum_{i=1}^{n} JC_d(x) \\ &\quad + \sum_{i=1}^{n} DJ_d(x) + \sum_{i=1}^{n-1} JJ_d(x) \\ &= JC\sum_{i=1}^{n} t_i + DJ\sum_{i=1}^{n} t_i + JC_d \sum_{i=1}^{n-1} \delta(JC_i, JC_{i+1}) \\ &\quad + DJ_d \sum_{i=1}^{n-1} \delta(DJ_i, DJ_{i+1}) \\ &\quad + JJ_d \sum_{i=1}^{n-1} [1-\delta(JC_i, JC_{i+1})]\,\delta(JJ_i, JJ_{i+1}), \end{aligned} \tag{3}$$

where JC, DJ are the unit machining cost coefficients of machine tools and cutting tools, respectively. JC_d, DJ_d, JJ_d are the unit variable cost coefficients of machine tools, cutting tools, and fixtures, respectively. $\delta(x_i, x_{i+1})$ is the discriminant function [18], which can be expressed as:

$$\delta(x_i, x_{i+1}) = \begin{cases} 1 & (x_i \neq x_{i+1}), \\ 0 & (x_i = x_{i+1}). \end{cases} \tag{4}$$

$CE(x)$ is the carbon emission, which mainly contains carbon emission from energy consumption of machine tools during machining, carbon emissions from tool wear, and carbon emissions from chip fluid, which can be expressed as follows:

$$\begin{aligned} CE(x) &= f_e \sum_{i=1}^{n} P_i \cdot t_i + f_d \sum_{i=1}^{n} \frac{t_i}{T_i} \cdot m_i \\ &\quad + \sum_{i=1}^{n} \frac{t_i}{T_{yi}} \left(f_y Q_c + f_y^r Q_c / \rho \right), \end{aligned} \tag{5}$$

where f_e, P_i, t_i are the carbon emission coefficient of electric energy, machine power, and corresponding machining time during machining, respectively; f_d, T_i, m_i are the cutting tool carbon emission coefficient, tool life, and weight, respectively; f_y, f_y^r, T_{yi}, Q_c, ρ are the carbon emission coefficient of chip fluid, carbon emission coefficient of chip waste disposal, cutting fluid replacement cycle, cutting fluid dosage and cutting fluid concentration, respectively.

In the optimization process, these two objective functions will be constrained by each other, and it is difficult to meet their optimal conditions simultaneously. The multi-objective problem can be transformed by a weighted combination according to the importance of a single objective function. The objective function can be expressed as:

$$\min C(x) = \gamma_1 \min MC(x) + \gamma_2 \min CE(x), \tag{6}$$

where γ_1, γ_2 are weight coefficients, and $\gamma_1, \gamma_2 \in [0, 1]$, $\gamma_1 + \gamma_2 = 1$.

To eliminate the influence of magnitude on the calculation results, the smaller type of normalization is adopted for $MC(x)$, $CE(x)$, and then the objective function is converted to:

$$\min C(x) = \gamma_1 \min \frac{MC(x) - MC(x)_{\min}}{MC(x)_{\max} - MC(x)_{\min}} + \gamma_2 \min \frac{CE(x) - CE(x)_{\min}}{CE(x)_{\max} - CE(x)_{\min}}. \tag{7}$$

Due to the dynamic nature of manufacturing, the uncertainty of the pre-determined process route increases in practical application. Therefore, based on information collection, the digital twin technology is used to fully consider the influence of manufacturing processes and their changes on process route optimization in the time dimension, such as manufacturing environment, production scheduling, and workshop control, and to build a dynamic process route optimization framework based on digital twinning as shown in Fig. 2.

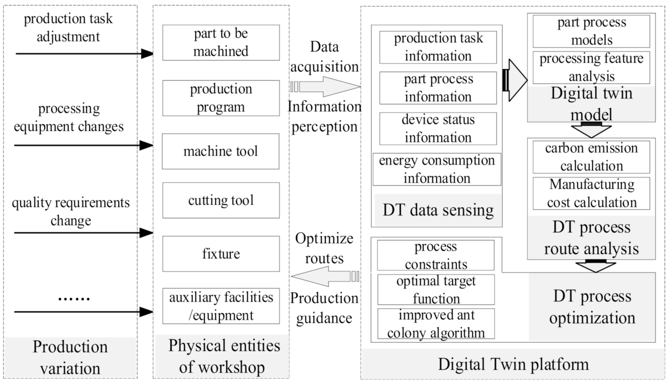

Fig. 2. Dynamic optimization framework of process route based on the digital twin

3. HYBRID OPTIMIZATION ALGORITHM

3.1. Intuitionistic fuzzy information

The intuitionistic fuzzy set considers three aspects of elements information: membership, non-membership, and hesitation, which is more flexible and practical in solving fuzzy and uncertain decision problems. Usually, the intuitionistic fuzzy set is defined as:

$$B = \left\{ \langle x_i, \mu_B(x_i), \nu_B(x_i) \rangle \middle| x_i \in X \right\}. \tag{8}$$

B is an intuitionistic fuzzy set of X (a given non-empty set), where $\mu_B\colon X \to [0, 1]$, $\nu_B\colon X \to [0, 1]$ represents the membership and non-membership of B, respectively, and they satisfy $\mu_B(x_i) + \nu_B(x_i) \in [0, 1]$, $\forall x_i \in X$. In addition, $\pi_B(x_i) = 1 - \mu_B(x_i) - \nu_B(x_i) \in [0, 1]$, $\forall x_i \in X$ is the hesitation degree of$B$. When $\pi_B(x_i) = 0$, it is obvious that $\mu_B(x_i) = 1 - \nu_B(x_i)$, then the intuitionistic fuzzy set degenerates into a traditional fuzzy set [19]. The elements of B are called intuitionistic fuzzy numbers and are abbreviated as follows for the convenience of calculation:

$$b = \langle \mu, \nu \rangle = \langle \mu_B(x_i), \nu_B(x_i) \rangle. \tag{9}$$

When determining the constraint relationship between any machining meta P_{ij} by intuitionistic fuzzy information, the intuitionistic fuzzy value corresponding to each semantic evaluation information should be defined in advance. That is, according to membership $\mu_B(x_i)$ given by the semantic evaluation information and the hesitation $\pi_B(x_i)$ given by the technologist, the intuitionistic fuzzy number is calculated:

$$b_i = \langle \mu_B(x_i) - \alpha \cdot \pi_B(x_i), \mu_B(x_i) + \beta \cdot \pi_B(x_i) \rangle, \tag{10}$$

where $\alpha + \beta = 1$, and α, $\beta \in [0, 1]$, α and β are the higher and lower levels of hesitation, respectively.

The precedence constraint relationship between machining metas is divided into five categories, namely, extremely strong constraint B_1, strong constraint B_2, general constraint B_3, weak constraint B_4, and extremely weak constraint B_5. Each constraint type corresponds to an intuitionistic fuzziness with hesitation, as shown in Table 1 so that technologists can easily find it.

Table 1
Fuzzy semantic information and its intuitionistic fuzzy value

Semantic information of precedence constraints	Intuitionistic fuzzy value	The value of α and β
extremely strong constraint B_1	$1 - \alpha\pi$, $1 + \beta\pi$	$\alpha = 1, \beta = 0$
strong constraint B_2	$0.75 - \alpha\pi$, $0.75 + \beta\pi$	$\alpha = 0.5, \beta = 0.5$
general constraint B_3	$0.5 - \alpha\pi$, $0.5 + \beta\pi$	$\alpha = 0.5$,$\beta = 0.5$
weak constraint B_4	$0.25 - \alpha\pi$, $0.25 + \beta\pi$	$\alpha = 0.5, \beta = 0.5$
extremely weak constraint B_5	$0 - \alpha\pi$, $0 + \beta\pi$	$\alpha = 0, \beta = 1$

For example, $B_2(0.3)$ means that two adjacent machining metas have strong constraints, and the hesitation given by a technologist is 0.3, then the corresponding intuitionistic fuzzy value is $\langle 0.6, 0.9 \rangle$. Therefore, it is easy to judge the precedence relationship between machining metas, which provides free operating space for decision-making and also conforms to the actual status. Obviously, when the hesitation given by a technologist is 0, there are two extreme situations, namely, mandatory precedence constraint $\langle 1, 1 \rangle$ and no precedence constraint $\langle 0, 0 \rangle$.

3.2. Precedence constraint matrix

The precedence constraint matrix $Y = \left(y_{ij}\right)_{n \times n}$ can be established from the intuitionistic fuzzy values of machining metas. Since the elements y_{ij} in the matrix Y belong to the interval $[0, 1]$, it is necessary to use the relevant knowledge of fuzzy theory to sort the intuitionistic fuzzy values to obtain the accurate fuzzy precedence constraints of all machining metas. Let $b_1 = \langle \mu_1, \nu_1 \rangle$, $b_2 = \langle \mu_2, \nu_2 \rangle$ as any intuitionistic fuzzy value, the probability $P(b_1 \geq b_2)$ of $b_1 \geq b_2$ is expressed as follows:

$$P(b_1 \geq b_2) = \begin{cases} \dfrac{\max(0, L_1 + L_2 - \max(0, \nu_2 - \mu_1))}{L_1 + L_2}, & L_1 + L_2 \neq 0, \\ 1, & L_1 + L_2 = 0,\ \mu_1 \geq \mu_2, \\ 0, & L_1 + L_2 = 0,\ \mu_1 < \mu_2, \end{cases} \tag{11}$$

where $L_1 = \mu_2 - \mu_1$, $L_2 = \nu_2 - \nu_1$ [20]. In the obtained precedence constraint matrix Y, the modulus of its row vector $\|H_i\| = \sum_{j=1}^{n} y_{ij}$ is calculated to represent the number of processing constraints provided by the machining meta i, and the modulus of its column vector $\|L_j\| = \sum_{i=1}^{n} y_{ij}$ is calculated to represent the number of processing constraints accepted by the machining meta j. When $\|H_i\| \neq 0$ and $\|L_i\| = 0$, the machining meta i can be the beginning of a processing route; when $\|H_i\| = 0$ and $\|L_i\| \neq 0$, the machining meta i acts as the endpoint of a processing route. If $\|H_i\| \neq 0$ and $\|L_i\| \neq 0$, the machining meta i can be used as the intermediate process of a processing route, interspersed between the starting and ending operations.

3.3. Improved ant colony algorithm

The ant colony algorithm is a simulated evolutionary algorithm proposed by Dorigo *et al.* [21]. It was adopted to solve combinatorial optimization problems such as traveling salesman problems, job-shop scheduling, and quadratic programming problems, but it is apt to appear premature convergence or stagnation behavior, moreover, it takes longer time than some other algorithms. In this paper, the adaptability of the optimization process is improved by improving the heuristic information function and adjusting the volatile concentration of local pheromone and global pheromone, to be used for the optimization decision of the multi-process route. The search procedure is as follows.

1. Initialization

At the initial time, ants m are randomly placed on any candidate machining meta corresponding to the roughing stage of the manufacturing feature n, and the first element of the tabu list is set as the current machining meta node. Currently, the pheromone of each path is equal, which is a small constant, namely, $r_{ij}(0) = c$.

2. Path transition rules

When ants search all the machining meta, they need to determine how to move from the current machining meta i to the next machining meta j according to the transition probability function $P_{ij}^{k}(t)$. The larger the function value, the greater the probability of selecting the next machining meta j, the formula is as follows [22]:

$$P_{ij}^{k}(t) = \begin{cases} \dfrac{\left[r_{ij}(t)\right]^{\alpha} \cdot \left[\eta_{ij}(t)\right]^{\beta}}{\sum\limits_{s \subset \mathrm{allowed}_k} \left(\left[r_{is}(t)\right]^{\alpha} \cdot \left[\eta_{is}(t)\right]^{\beta}\right)} & j \in \mathrm{allowed}_k\,, \\ 0 & \text{others}, \end{cases} \tag{12}$$

$$\eta_{ij}(t) = \frac{1}{d_{ij} + d_{jm}}, \tag{13}$$

$$a_k = \{1 - Tab(PF_k)\}, \tag{14}$$

where $r_{ij}(t)$ is the pheromone between machining meta i and j at the moment t; α is the information heuristic factor, which indicates the relative importance of the trajectory; β is the expected heuristic factor, which represents the relative importance of the heuristic factor; a_k is the set of optional machining meta nodes for ant k at the current moment. $\eta_{ij}(t)$ is the heuristic information function, it is usually taken as the inverse of distance transferred from i to j. In this paper, it is taken as the reciprocal of the sum of manufacturing cost and carbon emission between two adjacent machining metas, i.e., $d_{ij} = 1/(MC_{ij} + CE_{ij})$. This search method does not consider the relationship between the current node and endpoint and is easy to fall into the local optimum. Therefore, the distance d_{jm} between the machining meta j and the final machining meta m is introduced into the heuristic information function to improve the pertinence of the search. If $d_{ij} < d_{jm}$, j is defined as a closer node; otherwise, it is a remote node. When the ant searches, it only calculates several nodes near the closer node, to reduce the calculation amount and accelerate the convergence rate.

At the same time, when the ant k moves from the current machining meta i to the next machining meta j, it will put the nodes that meet the tabu criteria into the tabu list $Tab(PF_k)$, and remove them when selecting. There are two types of tabu nodes: one is the processed machining meta node, and the other is that does not meet process constraints.

3. Pheromone update rules

After each step, the ant k locally updates the path pheromone to avoid falling into the local optimum. Meanwhile, the pheromone concentration is limited to the interval $[r_{\min}, r_{\max}]$ to prevent it from increasing indefinitely. The local update rule of pheromone is as follows:

$$r_{ij}(t+1) = \begin{cases} r_{\min}\,, & r_{ij} \le r_{\min}\,, \\ (1-\theta_1) r_{ij}(t) + \theta_1 r_{\max}\,, & r_{\min} < r_{ij} < r_{\max}\,, \\ r_{\max}\,, & r_{ij} \ge r_{\max}\,, \end{cases} \tag{15}$$

where θ_1 is the volatilization coefficient of the local pheromone, $\theta_1 \in (0, 1)$.

When the ant k traverses all the machining meta nodes of the process route once, the pheromone of each path is globally adjusted to avoid the pheromone remaining too much to annihilate the heuristic information and to make better use of the existing optimal solution. The pheromone global update rules are as follows:

$$r_{ij}(t+1) = (1-\theta_2) r_{ij}(t) + \theta_2 \sum_{k=1}^{m} \Delta r_{ij}^{k}(t), \tag{16}$$

$$\Delta r_{ij}^{k}(t) = \frac{Q}{\min(L_k)}, \tag{17}$$

where θ_2 is the global pheromone volatilization coefficient, $\theta_2 \in (0, 1)$; $\Delta r_{ij}^{k}(t)$ is information left on the path by the ant k during this traversal; L_k is the path of the ant k between time t and $t+1$. Q is pheromone intensity, it usually is a constant.

In summary, the flow chart of process routes optimization by hybrid ant colony algorithm with intuitionistic fuzzy information is shown in Fig. 3.

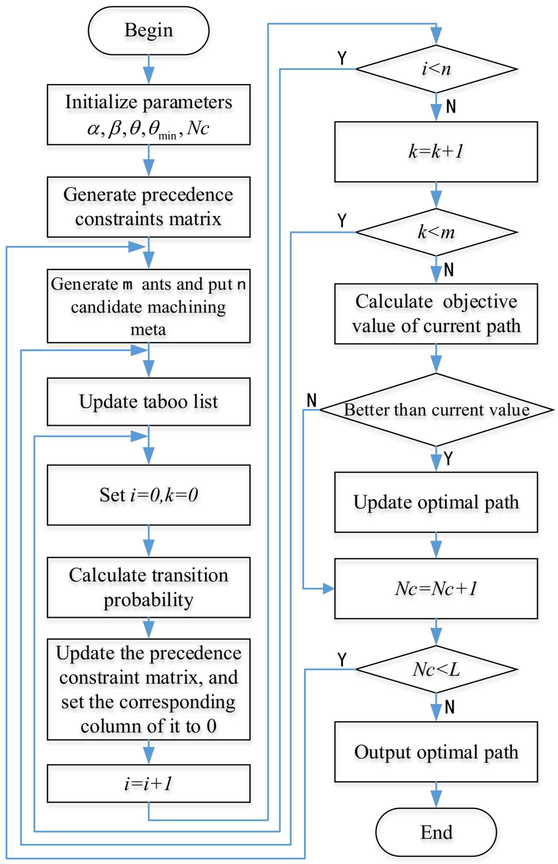

Fig. 3. Flow chart of process routes optimization

4. CASE STUDY AND DISCUSSION

4.1. Transmission shaft machining information

In this paper, a transmission shaft part produced by an enterprise is considered as an example for analysis and verification. The main structure shape, physical dimensions, and machining accuracy of the part drawing are shown in Fig. 4, and its material is 40 MnB. Based on analyzing the manufacturing features of this part, the processing methods and available manufacturing resources corresponding to each manufacturing feature are selected by comprehensively considering factors such as machining quality, processing accuracy, and manufacturing cost. Feature properties and machining methods of this part are shown in Table 2, and the available manufacturing resources of machining metas are shown in Tables 3 and 4.

Table 3
Machine tool information

Machine tool number	Machine tool type	Power [kW]	Coefficient JC
M1	ordinary lathe	7.5	10
M2	CNC lathe	11	15
M3	vertical miller	10	13
M4	CNC miller	15	20
M5	grinder	5.5	30
M6	driller	2	10

Table 2
Feature properties and machining methods of part

Feature number	Dimensions and tolerances	Machining methods	Machining chain	Optional machining tools	Optional cutting tools	Lamping points
f1	20	turning	rough turning a_1; semi-finish turning a_2	M1, M2	T1, T2	6
f2	$\phi\ 20^{+0.023}_{+0.002}$	turning, grinding	rough turning a_3; semi-finish turning a_4; rough grinding a_5; fine grinding a_6	M1, M2, M5	T1, T2, T5, T6	6
f3	$\phi\ 26^{0}_{-0.021}$	turning, grinding	rough turning a_7; semi-finish turning a_8; rough grinding a_9; fine grinding a_{10}	M1, M2, M5	T1, T2, T5, T6	6
f4	M36	turning	rough turning a_{11}; semi-finish turning a_{12}	M1, M2	T1, T2	6
f5	$\phi\ 28^{0}_{-0.021}$	turning, grinding	rough turning a_{13}; semi-finish turning a_{14}; rough grinding a_{15}; fine grinding a_{16}	M1, M2, M5	T1, T2, T5, T6	2
f6	$\phi\ 20^{+0.023}_{+0.002}$	turning, grinding	rough turning a_{17}; semi-finish turning a_{18}; rough grinding a_{19}; fine grinding a_{20}	M1, M2, M5	T1, T2, T5, T6	2
f7	20	turning	rough turning a_{21}; semi-finish turning a_{22}	M1, M2	T1, T2	2
f1-1	B2.5	turning/drilling	drilling a_{23}	M1, M6	T1, T7	6
f2-1	$1\times45°$	turning	rough turning a_{24}; semi-finish turning a_{25}	M1, M2	T1, T2	6
f2-2	2×1.5	turning	rough turning a_{26}; semi-finish turning a_{27}	M1, M2	T1, T2	6
f3-1	8N9	milling	rough milling a_{28}; fine milling a_{29}	M3, M4	T3, T4	6, 2
f3-2	2×1.5	turning	rough turning a_{30}; semi-finish turning a_{31}	M1, M2	T1, T2	6
f4-1	–	turning	turning screw a_{32}	M1, M2	T2	6
f4-2	2×1.5	turning	rough turning a_{33}; semi-finish turning a_{34}	M1, M2	T1, T2	6
f5-1	$3\times45°$	turning	rough turning a_{35}; semi-finish turning a_{36}	M1, M2	T1, T2	2
f6-1	$1\times45°$	turning	rough turning a_{37}; semi-finish turning a_{38}	M1, M2	T1, T2	2
f7-1	B2.5	turning/drilling	drilling a_{39}	M1, M6	T1, T7	2

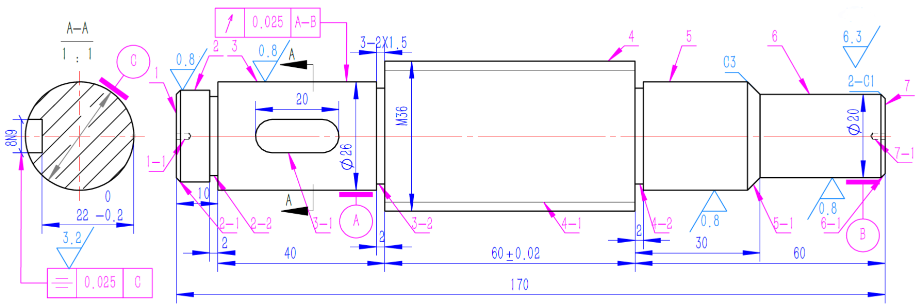

Fig. 4. The model of a transmission shaft

Table 4
Cutting tool information

Cutting tool number	Cutting tool type	Weight [g]	Tool life [min]	Coefficient DJ
T1	lathe tool	9	60	11
T2	lathe tool	10	110	9
T3	milling cutter	8	240	12
T4	milling cutter	40	180	15
T5	grinding tool	650	24	15
T6	grinding tool	800	15	25
T7	drilling bit	325	55	8

In this figure, 1, 7: end face, 2, 3, 5, 6: cylindrical face, 4: thread face, 1-1, 7-1: center hole, 2-1, 5-1, 6-1: chamfer, 2-2, 3-2, 4-2: withdrawal groove, 3-1: flat keyway, and 4-1: external thread.

In this case, the unit variable cost coefficients of machine tools, cutting tools, and fixtures are set as: $JC_d = 7$,$DJ_d = 1$, $JJ_d = 4$, respectively. At the same time, the carbon emission coefficient of electric energy with machine tool in the machining process is $f_e = 2.41$ kgCO$_2$e/kWh, the carbon emission coefficient of chip fluid is $f_y = 2.86$ kgCO$_2$e/L, the carbon emission coefficient of chip waste disposal is $f_y^r = 0.2$ kgCO$_2$e/L, the cutting fluid replacement cycle is $T_{yi} = 3.6 \cdot 10^4$ min, the cutting fluid dosage is $Q_c = 15$ L, and the cutting fluid concentration is $\rho = 0.04$.

4.2. Analysis of optimization results

According to the fuzzy priority constraint relationship between machining metas, the precedence constraint matrix is established, and then the improved ant colony algorithm is applied for iterative optimization. This algorithm is programmed by MATLAB R2016b. The computer configuration used for simulation is as follows: Windows 7 system, Intel (R) Xeon (R) CPU @3.07 GHz, and 8GB RAM. In this experiment, the ant colony number $m = 25$, the machining meta number $n = 39$, the cycle number $N_{\max} = 250$, the information heuristic factor $\alpha = 1.0$, the expected heuristic factor $\beta = 1.5$, and the pheromone volatilization coefficient $\theta_1 = 0.9$, $\theta_2 = 0.9$. At the same time, to compare the process route optimization method proposed in this paper with the conventional method that only focuses on manufacturing cost or carbon emissions, five groups of different weight combinations are set, and the optimized results are shown in Table 5.

Table 5
Comparison of optimization results

Optimized values		Weight coefficients ($\gamma1$, $\gamma2$)				
		(1, 0)	(0.6, 0.4)	(0.5, 0.5)	(0.4, 0.6)	(0, 1)
MC	Convergence	148.72	153.56	157.43	162.47	168.13
	Iterations	53	65	76	92	0
CE	Convergence	3.87	3.64	3.49	3.27	3.16
	Iterations	0	94	81	70	50

As can be seen from Table 5, when the lowest manufacturing cost is taken as the optimization objective, the machine tool and cutting tool with low machining cost coefficient are preferred, and the number of machine tool changes and the change times of the cutting tool are reduced as much as possible, to shorten the processing time accordingly. However, reducing the machining time will inevitably increase the cutting amount or the spindle speed of the machine tool, which leads to an increase in tool wear and machine power consumption, resulting in increased carbon emissions. When the lowest carbon emission is taken as the optimization goal, the machine tool with less power consumption and the processing route with less tool wear and less cutting fluid usage during the machining process is preferred, but it also causes frequent switching of machine and cutting tool and increases the machining time and auxiliary time, which leads to higher manufacturing cost. In the process route that considers both manufacturing cost and carbon emission, the weight coefficients of manufacturing cost and carbon emission can be comprehensively evaluated according to product batch, order urgency, and workshop production conditions, to meet the dual demands of economic and environmental benefits in the production process. However, under normal production conditions, when the weighting coefficients of the two are equal, the process result is the best. The optimal process route of this case is shown in Table 6, in which the machine tool changes twice, the cutting tool changes three times, and the clamping position changes ten times. It is better than the existing process route of the enterprise, and the priority order of each optimized processing meta is as follows.

$a_{21} \succ a_{17} \succ a_{13} \succ a_{11} \succ a_{22} \succ a_{39} \succ a_1 \succ a_3 \succ a_7 \succ a_2 \succ a_{23} \succ a_{18} \succ a_{14} \succ a_{12} \succ a_{33} \succ a_{35} \succ a_{37} \succ a_{38} \succ a_{36} \succ a_4 \succ a_8 \succ a_{30} \succ a_{26} \succ a_{24} \succ a_{25} \succ a_{27} \succ a_{31} \succ a_{34} \succ a_{32} \succ a_5 \succ a_9 \succ a_{15} \succ a_{19} \succ a_6 \succ a_{10} \succ a_{16} \succ a_{20} \succ a_{28} \succ a_{29}$.

Table 6

The optimal process route of low cost and low carbon emission

Feature number	Process content	Machine tool	Cutting tool
f7, f6, f4	rough turning of the right end face and outer circle surface	M2	T1
f7, f7-1	semi-finish turning of the right end face and center hole	M2	T1
f1, f2, f3	rough turning of the left end face and outer circle surface	M2	T1
f1, f1-1	semi-finish turning of the left end face and center hole	M2	T1
f6, f5, f4	semi-finish turning of the outer circle surface	M2	T1
f4-2, f5-1, f6-1	rough turning of run-out groove and chamfer	M2	T1
f6-1, f5-1, f2, f3	semi-finish turning of chamfer and outer circle surface	M2	T1
f3-2, f2-2, f2-1	rough turning of run-out groove and chamfer	M2	T1
f2-1, f2-2, f3-2, f4-2	semi-finish turning of chamfer and run-out groove	M2	T1
f4-1	turning thread	M2	T2
f3-1	milling key slot	M4	T4
F2, f3, f5, f6	cylindrical grinding	M5	T6

The process route of this scheme includes the main processes of that part, according to the specific processing conditions and technical requirements, some auxiliary processes (such as material preparation, blanking, and the scribing process in the previous stage, the intermediate heat treatment process, inspection and storage in the later stage) just need to add in the scheme to constitute an acceptable process route that meets the manufacturing cost and carbon emission demands.

5. CONCLUSIONS

The dynamic optimization decision of the process route is a nonlinear programming problem with multiple constraints and multi-objective. Considering the diversity and ambiguity between processes, as well as the subjectivity of a technician in decision-making, the digital twin technology is adopted to fully consider the influence of the manufacturing process and its changes on the process route optimization in the time dimension. Taking the least manufacturing cost and the minimum carbon emission as the optimization objectives, an improved ant colony algorithm integrating intuitionistic fuzzy information is used to conduct the global optimization of multi-process routes. Finally, the transmission shaft of equipment is taken as an engineering example to verify the effectiveness and feasibility of this scheme, which can provide a reference for manufacturing enterprises to make process optimization decisions and has practical application prospects.

In addition, this method can also be used to solve other similar multi-objective optimization problems. However, due to the wide categories and various structural shapes of parts, the expansibility of this method needs to be verified by more types of parts. At the same time, the excessive feature information and constrained relationship of parts may reduce the applicability of this method, which still needs more thorough follow-up research and verification in the future. In addition, the process route optimization should also be combined with process parameter selection and production scheduling management to adapt to the dynamic change of production conditions.

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