Journal of Zhejiang University-SCIENCE A (Applied Physics & Engineering)
ISSN 1673-565X (Print); ISSN 1862-1775 (Online)
www.zju.edu.cn/jzus; www.springerlink.com
E-mail: jzus@zju.edu.cn

A novel approach for parallel disassembly design based on a hybrid fuzzy-time model*

Zhi-feng ZHANG, Yi-xiong FENG†‡, Jian-rong TAN, Wei-qiang JIA, Guo-dong YI

(*The State Key Laboratory of Fluid Power Transmission and Control, Zhejiang University, Hangzhou 310027, China*)

†E-mail: fyxtv@zju.edu.cn

Received May 29, 2015; Revision accepted Aug. 21, 2015; Crosschecked Aug. 25, 2015

Abstract: This paper investigates the problem of parallel disassembly with the consideration of fuzziness. A novel approach is proposed based on optimized dispatching for parallel disassembly in which disassembly time is characterized by the fuzzy sets due to inevitable uncertainties. The proposed approach consists of three parts: in the first part, the fuzzy time-based dispatching disassembly process model is established; in the second part, the boundary conditions of the fuzzy time and the disassembly are derived, and the components' disassembly order and available stations are encoded together to find the optimal disassembly path; in the final part, the approach is optimized by using genetic algorithm (GA) to minimize the total time and cost, and the solution is compared with other algorithms. Finally, a case study for a hydraulic press disassembly is presented to verify the effectiveness and feasibility of the proposed approach.

Key words: Disassembly sequence planning, Dispatching disassembly process, Fuzzy time, Genetic algorithm (GA)
doi:10.1631/jzus.A1500155 **Document code:** A **CLC number:** TB491

1 Introduction

Environmental problem has been a serious challenge to our society, and many measures have been promoted to ease this issue, such as public opinions, industrial standards, and environmental laws (Tian *et al.*, 2014). Disassembly, an important step of product recycle, involves methodical extraction that departs reusable components and valuable materials from end-of-life products via certain operations.

There exist many research studies on disassembly. Most researchers focus on three relative issues: disassembly modeling, disassembly path planning, and disassembly evaluation. Disassembly modeling is the logical and informational basis for disassembly that contains physics data, assembly data, and constraint data. Disassembly path planning involves a sequence of components removed from product ontology. Disassembly evaluation is to assess the disassembly scheme during the design to ensure disassembility and efficiency of the products. Over the decades, the issue on disassembly path planning has attracted the attention of many researchers because it relies not only greatly on environmental factors but also on the efficient use of natural resources.

A number of researchers have proposed disassembly sequencing approaches. Kang *et al.* (2001) proposed an approach based on an integer programming formulation and considered sequence-dependent operation times to obtain the optimal disassembly sequence. Li *et al.* (2005) presented an object-oriented disassembly sequence for

‡ Corresponding author

* Project supported by the National Natural Science Foundation of China (No. 51322506), the Zhejiang Provincial Natural Science Foundation of China (No. LR14E050003), the National High-Tech R&D Program (863 Program) of China (No. 2013AA041304), the National Key Technology Support Program (No. 2013BAF02B10), the Fundamental Research Funds for the Central Universities, and the Innovation Foundation of the State Key Laboratory of Fluid Power Transmission and Control, China

ORCID: Zhi-feng ZHANG, http://orcid.org/0000-0002-7197-9557; Yi-xiong FENG, http://orcid.org/0000-0001-7397-2482

maintenance based on the disassembly constraint graph and the genetic algorithm (GA). González and Adenso-Díaz (2006) adopted the scatter search metaheuristic to deal with the disassembly cost of complex products, when only one component can be released at each time. Lambert (2006) modified the two-commodity network flow approach to address complex disassembly problems and to find out the exact solutions, particularly, useful for evaluating heuristic and metaheuristic approaches. Aguinaga *et al.* (2008) analyzed the differences between the disassembly path-planning problem and the general one, and modified the rapidly-growing random tree-based (RRT) algorithm to address these differences. Tang (2009) introduced a fuzzy Petri net model to explicitly represent the dynamics inherent in disassembly. Li *et al.* (2013) proposed a modular disassembly method to solve the inflexibility in a single modular of complex mechatronics products. Aydemir-Karadag and Turkbey (2013) dealt with a stochastic disassembly line balancing problem and proposed a new GA for multi-objective optimization. The objectives related to line balance and design costs were optimized by using an AND/OR graph. Rickli and Camelio (2013) proposed a GA based on disassembly operation costs, recovery reprocessing costs, revenues, and environmental impacts to optimize partial disassembly sequences. Tian *et al.* (2013) presented some chance constrained programming models for disassembly cost from the perspective of stochastic planning. Moreover, two hybrid intelligent algorithms, namely, one integrating stochastic simulation and neural network (NN), and another integrating stochastic simulation, GA and NN, were proposed to solve the proposed model. Liu and Lu (2014) researched on the alternation of processes for path generation during the disassembly of the synthesized product. Zhang *et al.* (2014) proposed a parallel disassembly sequence planning (PDSP) method to reduce the time complexity.

At the same time, researchers have accomplished great achievements on the optimal time and cost of disassembly. Zussman and Zhou (1999) proposed a mathematically sound disassembly Petri net (DPN) for the modeling and adaptive planning of disassembly processes. The planning algorithm guaranteed the optimal remanufacturing value when each node's utility function (benefit of a subassembly or part and cost of a disassembly operation) is fixed. Das *et al.* (2000) presented a multi-factor model to compute the disassembly effort index, which represented the total operating cost of disassembly. Gungor and Gupta (2001) discussed the disassembly line balancing problem with task failures. Tseng *et al.* (2008) added engineering attributes to the liaison graph model for the evaluation of part connections, which served as criteria for evaluating component liaison intensity during the design stage. Li *et al.* (2011) proposed a platform reconfiguration path-planning method using sensitivity analysis with robust design theory, which can improve the efficiency of disassembly. Xia *et al.* (2014) presented a simplified teaching-learning-based optimization algorithm for solving disassembly sequence planning problems effectively. Liu *et al.* (2014) introduced the prospect theory for the disassembly problem of sharing product service system. Ilamparithi *et al.* (2015) proposed a novel scheme for monitoring the conditions of dynamic eccentricity faults in salient-pole synchronous machines through the standard short-circuit test.

However, previous studies mainly focus on the sequential disassembly problem and pay little attention to parallel disassembly, which is widely adopted during the productive process. As an important method to disassemble a large and complex product, parallel disassembly can reduce the total work time and cost, and increase the productivity.

In fact, to a great extent, disassembly time depends on the environment and other factors, such as physical strength of workers and actual product effect. Therefore, it is of vital importance to study disassembly path-planning problem with imprecise time. To deal with this problem, the fuzzy set theory has provided an appropriate method. With precise time, the disassembly path planning is an idealization. In the general sense, these factors are described with linguistic variables. For example, we can use the linguistic variables to indicate the physical strength of workers, with the values being super, excellent, good, average, poor, etc. Apparently, none of these linguistic variables are digitized. Moreover, the fuzzy model makes it possible that the output of a model is a clearly defined value.

In terms of the disassembly problem, the time of working procedure will vary with uncertain factors. Additionally, in view of the continuity and parallelism, the time change in a single working procedure will cause huge differences in disassembly path solution, due to which the solution achieved cannot be the optimal. For instance, we may solve a disassembly problem involving six processes in two stations. When we display the time of disassembly working procedure with a precise time, all the working procedures will be assigned to the two stations for getting a similar total operation time between these two stations. If a worker's mistake leads to a process using a longer time than the usual case, there would be interference between the processes. It is useful to build up a fuzzy model for increasing environment adaptiveness and uncertainty adaptiveness. In this paper, we get the probability distribution of time through statistics, which is suitable for practice. Generally, we can get the shortest time, the longest time, and the most probable time of process easily; therefore, triangular fuzzy numbers (TFNs) are appropriate to represent imprecise time.

We propose a novel approach of parallel disassembly based on a hybrid fuzzy time model. The parallel disassembly path-planning method dispatches all workstations synergistically; hence, it shortens the disassembly time and reduces the cost. Note that the cost defined here means the overall cost, including additional stations cost, cost of operators necessary for a parallel disassembly, and the project management cost relating to the total time. Because the disassembly process is influenced by several uncertain factors and the time cannot be controlled in every process, we express the removal time of each component with TFNs. Additionally, we also encode components and available stations together within a chromosome sequence to simplify the algorithm. With the introduction of Gaussian function into GA, the rate of convergence is improved thus contributing to an optimal result.

In this paper, we first describe the problem characteristics and mathematical model. Then, a comprehensive explanation of the proposed GAs is given. At last, a case study of a hydraulic press is presented to verify the effectiveness and feasibility of the proposed approach.

2 Preliminaries and problem statement

2.1 Preliminaries

In this study, we represent disassembly time by TFNs. The definition of TFNs and their relevant operations are discussed further in this section.

Suppose that X is a nonempty set. A fuzzy set $\tilde{A}$ in X is defined as a pair $\tilde{A}$:=(x, $\mu_A(x)$), where x is an element belonging to the set $\tilde{A}$. $\mu_A(x)$ is called the membership function, where $\mu_A(x)\in[0, 1]$. The mathematical form of a TFN is denoted by $\tilde{a}=(a_{\mathrm{L}}, a_{\mathrm{M}}, a_{\mathrm{H}})$, while the membership functions are represented as (Zimmermann, 2001)

$$\mu_{\tilde{a}}(x)=\begin{cases}\dfrac{x-a_{\mathrm{L}}}{a_{\mathrm{M}}-a_{\mathrm{L}}}, & a_{\mathrm{L}}\le x<a_{\mathrm{M}},\\ \dfrac{a_{\mathrm{H}}-x}{a_{\mathrm{H}}-a_{\mathrm{M}}}, & a_{\mathrm{M}}\le x\le a_{\mathrm{H}},\\ 0, & \text{otherwise.}\end{cases} \tag{1}$$

The basic arithmetic operations between any two TFNs are shown as follows. If $\tilde{a}=(a_{\mathrm{L}}, a_{\mathrm{M}}, a_{\mathrm{H}})$ and $\tilde{b}=(b_{\mathrm{L}}, b_{\mathrm{M}}, b_{\mathrm{H}})$ are two TFNs, then:
addition operation:

$$\tilde{a}\oplus\tilde{b}=(a_{\mathrm{L}}+b_{\mathrm{L}}, a_{\mathrm{M}}+b_{\mathrm{M}}, a_{\mathrm{H}}+b_{\mathrm{H}}); \tag{2}$$

subtraction operation:

$$\tilde{a}\ominus\tilde{b}=(a_{\mathrm{L}}-b_{\mathrm{L}}, a_{\mathrm{M}}-b_{\mathrm{M}}, a_{\mathrm{H}}-b_{\mathrm{H}}); \tag{3}$$

multiplication operation:

$$\tilde{a}\otimes\tilde{b}=(a_{\mathrm{L}}\cdot b_{\mathrm{L}}, a_{\mathrm{M}}\cdot b_{\mathrm{M}}, a_{\mathrm{H}}\cdot b_{\mathrm{H}}); \tag{4}$$

division operation:

$$\tilde{a}/\tilde{b}=(a_{\mathrm{L}}/b_{\mathrm{L}}, a_{\mathrm{M}}/b_{\mathrm{M}}, a_{\mathrm{H}}/b_{\mathrm{H}}); \tag{5}$$

reciprocal of a TFN $\tilde{a}$:

$$1/\tilde{a}=(1/a_{\mathrm{H}}, 1/a_{\mathrm{M}}, 1/a_{\mathrm{L}}); \tag{6}$$

maximization operation:

$$\tilde{a} \vee \tilde{b} = (a_\mathrm{L} \vee b_\mathrm{L},\ a_\mathrm{M} \vee b_\mathrm{M},\ a_\mathrm{H} \vee b_\mathrm{H}); \tag{7}$$

minimization operation:

$$\tilde{a} \wedge \tilde{b} = (a_\mathrm{L} \wedge b_\mathrm{L},\ a_\mathrm{M} \wedge b_\mathrm{M},\ a_\mathrm{H} \wedge b_\mathrm{H}). \tag{8}$$

The following criteria are adopted to rank any two given TFNs $\tilde{a}=(a_\mathrm{L}, a_\mathrm{M}, a_\mathrm{H})$ and $\tilde{b}=(b_\mathrm{L}, b_\mathrm{M}, b_\mathrm{H})$:

Criterion 1 If $a_\mathrm{L}+2a_\mathrm{M}+a_\mathrm{H}/4>b_\mathrm{L}+2b_\mathrm{M}+b_\mathrm{H}/4$, then $\tilde{a} \succ \tilde{b}$. If $a_\mathrm{L}+2a_\mathrm{M}+a_\mathrm{H}/4<b_\mathrm{L}+2b_\mathrm{M}+b_\mathrm{H}/4$, then $\tilde{a} \prec \tilde{b}$. If $a_\mathrm{L}+2a_\mathrm{M}+a_\mathrm{H}/4=b_\mathrm{L}+2b_\mathrm{M}+b_\mathrm{H}/4$, use Criterion 2.

Criterion 2 If $a_\mathrm{M}>b_\mathrm{M}$, then $\tilde{a} \succ \tilde{b}$. If $a_\mathrm{M}<b_\mathrm{M}$, then $\tilde{a} \prec \tilde{b}$. If $a_\mathrm{M}=b_\mathrm{M}$, use Criterion 3.

Criterion 3 If $(a_\mathrm{H}-a_\mathrm{L})>(b_\mathrm{H}-b_\mathrm{L})$, then $\tilde{a} \succ \tilde{b}$. If $(a_\mathrm{H}-a_\mathrm{L})<(b_\mathrm{H}-b_\mathrm{L})$, then $\tilde{a} \prec \tilde{b}$.

Here, a_L and b_L are the lower bounds of $\tilde{a}$ and $\tilde{b}$, a_M and b_M are the middle values of $\tilde{a}$ and $\tilde{b}$, and a_H and b_H are the upper bounds of $\tilde{a}$ and $\tilde{b}$, respectively.

2.2 Problem statement

There are several notations to represent the disassembly path planning as presented in Table 1.

The problem is about the disassembly of a product containing L components. Each component has $W(i)$ processes to disassemble from the product. All processes are completed on N stations. What we have to do is to find the best disassembly path with the best balance between time and cost.

The time is not precise that is expressed with TFN. We assign the upper bound, the middle value, and the lower bound as the longest time, the average time, and the shortest time of a disassembly process, respectively, according to the historical records.

The considered assumptions are listed as follows:

Assumption 1 Each station can hold only one process at a time, and each operation cannot be started until the last process is finished.

Assumption 2 The time of setting up station and the time of moving items are negligible.

Assumption 3 Stations and processes are mutually independent of each other.

Assumption 4 There are no precedence constraints among the operations of different processes.

2.3 The proposed fuzzy time model

The problem is concerned with parallel disassembly path planning of products that disassembled on several stations at the same time. The advantage of this model is that all stations are used synergistically, so we can get a disassembly path planning with an optimal balance between time and cost.

The disassembly time and cost of product are respectively described as

$$T = \sum_{k=1}^{N} \sum_{h=1}^{\mathrm{NU}(k)} t(\mathrm{st}_k, \mathrm{so}_{k,h}), \tag{9}$$

$$C = \sum_{k=1}^{N} \sum_{h=1}^{\mathrm{NU}(k)} c(\mathrm{st}_k, \mathrm{so}_{k,h}). \tag{10}$$

Because of discrepancy in magnitudes between the time value and the cost value, we normalize the data through the function as follows:

$$x = \frac{x - x_{\min}}{x_{\max} - x_{\min}}. \tag{11}$$

Table 1 Several notations in the disassembly path-planning problem

Notation	Description
AP={$\mathrm{ap}_1 \ldots \mathrm{ap}_i \ldots \mathrm{ap}_L$}	Set of components, where ap_i is the ith component
OP={$\mathrm{op}_1 \ldots \mathrm{op}_i \ldots \mathrm{op}_L$}	Set of process orders
OP_i={$\mathrm{op}_{i,1} \ldots \mathrm{op}_{i,j} \ldots \mathrm{op}_{i,W(i)}$}	Process order of certain component ap_i
ST={$\mathrm{st}_1 \ldots \mathrm{st}_k \ldots \mathrm{st}_N$}	Set of stations, where st_k is the kth station
SO_k={$\mathrm{so}_{k,1} \ldots \mathrm{so}_{k,h} \ldots \mathrm{so}_{k,\mathrm{NU}(k)}$}	$\mathrm{so}_{k,h}$ is the total processes finished in the certain station st_k, and the fiction NU(k) is the total number of the processes
$f=t(\mathrm{st}_k, \mathrm{so}_{k,h})$	Fiction to represent the time that each process needs in each station
$g=c(\mathrm{st}_k, \mathrm{so}_{k,h})$	Fiction to represent the cost that each process needs in each station

The optimization purpose is to shorten the time and reduce the cost. Based on the known constraints, the product's disassembly path plan can be described as

$$\min E[T], \tag{12}$$

$$\min E[C], \tag{13}$$

s.t.

$$\begin{cases} \sum_{k=1}^{N} \mathrm{NU}(k) = \sum_{i=1}^{L} W(i), \\ 1 \le \mathrm{NU}(k) \le \sum_{i=1}^{L} W(i) + 1 - N, \\ W(i) \ge 1, \\ \mathrm{so}_{k,h} \in \mathrm{OP}, \\ t(\mathrm{st}_k, \mathrm{so}_{k,h}) = (t_{k,h}^1 \ t_{k,h}^2 \ t_{k,h}^3). \end{cases} \tag{14}$$

GA is one of the most popular evolutionary computing methods used to search for the optimal solution. To solve multi-objective optimization problem, Pareto solution-based GA is widely used when the decision-maker's preference of objectives is without priority. In this study, the preference in the time and cost of the disassembly has already been identified. We translate the multi-objective optimization problem into a single-objective optimization via the weighted average summation approach.

We need to find the optimal disassembly path, and not all the domination solution is needed. We compute a weighted sum of time and cost to find the optimal solution and use decision matrix to find the corresponding weights.

$$\min E\left[\varphi \sum_{k=1}^{N} \sum_{h=1}^{\mathrm{NU}(k)} t(\mathrm{st}_k, \mathrm{so}_{k,h}) + \varepsilon \sum_{k=1}^{N} \sum_{h=1}^{\mathrm{NU}(k)} c(\mathrm{st}_k, \mathrm{so}_{k,h}) \right], \tag{15}$$

where φ and ε stand for the weights of time and cost in solution, respectively.

We construct a decision matrix with two indexes and l samples, which is similar to that proposed by Li (2005):

$$\boldsymbol{R}_{l,2} = \begin{bmatrix} A_{1,1} & A_{1,2} \\ A_{2,1} & A_{2,2} \\ \vdots & \vdots \\ A_{l,1} & A_{l,2} \end{bmatrix} = \begin{bmatrix} T_1 & C_1 \\ T_2 & C_2 \\ \vdots & \vdots \\ T_l & C_l \end{bmatrix}. \tag{16}$$

The introduced systemic principle is used to translate decision matrix into membership matrix that smaller score means more optimal:

$$\mu_{j,i} = \frac{\min A_{j,i}}{A_{j,i}}. \tag{17}$$

Also, the membership matrix ($\overline{\boldsymbol{R}_{l,2}}$) is equal to the correlation coefficient matrix $\boldsymbol{R}_\xi$:

$$\boldsymbol{R}_\xi = \overline{\boldsymbol{R}_{l,2}} = \begin{bmatrix} \mu_{1,1} & \mu_{1,2} \\ \mu_{2,1} & \mu_{2,2} \\ \vdots & \vdots \\ \mu_{l,1} & \mu_{l,2} \end{bmatrix}. \tag{18}$$

$\boldsymbol{R}_\mathrm{w}$ is the evaluation index of multiple decision weighting factors for each solution and $\boldsymbol{R}_\mathrm{k}$ is the multiple fuzzy correlation decision factors consisting of correlation degrees. $\boldsymbol{R}_\mathrm{w}$ is operated with weighted average to get $\boldsymbol{R}_\mathrm{k}$ as follows:

$$\boldsymbol{R}_\mathrm{k} = \boldsymbol{R}_\mathrm{w} \odot \boldsymbol{R}_\xi, \tag{19}$$

where $\boldsymbol{R}_\mathrm{w}=(W_1, W_2)$. The mark $\odot$ stands for certain calculation:

$$\boldsymbol{R}_\mathrm{k} = (K_1 \ \ K_2) = \left(\sum_{i=1}^{n} W_1 \mu_{i,1} \ \ \sum_{i=1}^{n} W_2 \mu_{i,2} \right). \tag{20}$$

We rank the final correlation degree and find the maximum from $\boldsymbol{R}_\mathrm{k}$:

$$K^* = \max(K_1 \ K_2). \tag{21}$$

The weights (φ and ε) are based on the calculation of K_1 and K_2:

$$\begin{cases} \varphi = \dfrac{K^*}{K_1 + K_2}, \ \varepsilon = 1 - \dfrac{K^*}{K_1 + K_2}, \quad K_1 \ge K_2, \\ \varepsilon = \dfrac{K^*}{K_1 + K_2}, \ \varphi = 1 - \dfrac{K^*}{K_1 + K_2}, \quad K_1 < K_2. \end{cases} \tag{22}$$

Finally, the fuzzy time-based dispatching disassembly process model (FTDDPM) is described as follows:

for $K_1 \geq K_2$,

$$\min E\left[\frac{K^*}{K_1+K_2}\sum_{k=1}^{N}\sum_{h=1}^{\mathrm{NU}(k)} t(\mathrm{st}_k,\ \mathrm{so}_{k,h}) + \left(1-\frac{K^*}{K_1+K_2}\right)\sum_{k=1}^{N}\sum_{h=1}^{\mathrm{NU}(k)} c(\mathrm{st}_k,\mathrm{so}_{k,h})\right], \tag{23}$$

and for $K_1 < K_2$,

$$\min E\left[\left(1-\frac{K^*}{K_1+K_2}\right)\sum_{k=1}^{N}\sum_{h=1}^{\mathrm{NU}(k)} t(\mathrm{st}_k,\mathrm{so}_{k,h}) + \frac{K^*}{K_1+K_2}\sum_{k=1}^{N}\sum_{h=1}^{\mathrm{NU}(k)} c(\mathrm{st}_k,\mathrm{so}_{k,h})\right], \tag{24}$$

s.t.

$$\begin{cases} \sum_{k=1}^{N}\mathrm{NU}(k)=\sum_{i=1}^{L}W(i), \\ 1\leq \mathrm{NU}(k)\leq \sum_{i=1}^{L}W(i)+1-N, \\ W(i)\geq 1, \\ \mathrm{so}_{k,h}\in \mathrm{OP}, \\ t(\mathrm{st}_k,\mathrm{so}_{k,h})=(t_{k,h}^1\ \ t_{k,h}^2\ \ t_{k,h}^3). \end{cases} \tag{25}$$

3 Optimization of the disassembly sequence based on GA and fuzzy time model

Being widely used to solve optimization problem, GA is used in this section to get an optimal solution. Table 2 lists the pseudocode of GA. We encode disassembly order and processes of the components together as a sequence of nonnegative integers. Moreover, Gaussian mutation operator is introduced to GA to get a better solution.

Algorithm 1 Pseudocode of GA

```
Input: AP, OP, ap_i, ST, T, C.
Output: optimal solution.
Begin
//Initialization:
Generate an initial chrom;
Generate an initial fitness;
Repeat
  //Fitness assignment:
    Fitnv=ranking(objv);
  //Selection
    Selch=select('rws', chrom, fitnv, GGAP);
  //Acrossing
    Selch=across(selch, XOVR, Jm, T);
  //Mutation
    Selch=mutate(selch, MUTR, Jm, T);
  //Compute the fitness
    [PVal ObjVSel P S]=cal(SelCh, JmNumber, T,
    Jm);
  //Reinsert the chrom to population
    [Chrom ObjV]=reins(Chrom, SelCh,1, 1, ObjV,
    ObjVSel);
  //Save the optimal solution
    Trace(1, gen)=min(ObjV);
Until gen>maxgen
  Print out the optimal solution;
End
```

Step 1: encode

Each chromosome contains two parts (the total length is $2\sum_{i=1}^{k} n_i m_j$): the front half depicts the disassembly sequence order of the components, and the latter half depicts the station sequence according to the disassembly sequence of components.

In other words, a chromosome is a matrix with line number 1 and column number $2\sum_{i=1}^{k} n_i m_j$. The matrix represents a disassembly sequence of k components. Component n_i ($i\in(1, 2, \ldots, k)$) involves m_j processes, and the total number of processes is $\sum_{i=1}^{k} n_i m_j$. Additionally, there is a one-to-one correspondence between the processes and the stations, due to which the length of the latter half chromosome representing station is $\sum_{i=1}^{k} n_i m_j$. The initial chromosome is randomly based on the number of components, processes, and stations.

For example, the chromosome of one component is presented in Table 2. There has been a disassembly problem involving four components and five stations, where there are four working procedures in component 1 and three, two, and three working procedures in components 2, 3, and 4, respectively. The sequence of component processing is 1, 3, 4, 2, 4, 1, 3, 2, 1, 4, 1, 2, with the corresponding station sequence being 2, 5, 3, 3, 1, 4, 2, 5, 4, 2, 1, 5. The completed chromosome is 1, 3, 4, 2, 4, 1, 3, 2, 1, 4, 1, 2 | 2, 5, 3, 3, 1, 4, 2, 5, 4, 2, 1, 5. Moreover, the 1st, 6th, 9th, and 11th genes represent the four working procedures of component 1, which are accomplished on station 2, station 4, station 4, and station 1, respectively. Accordingly, the station genes are the 13th, 18th, 21st, and 23rd genes in chromosome; the corresponding relation between components and stations is presented in Table 3.

Step 2: fitness assignment

Fitness is the criterion to select offspring. In general, the total disassembly time is an accurate value denoted as fitness=q/ZT, where ZT represents the total time of the disassembly process, and q represents variable coefficient; less time means better chromosome. However, cost cannot be ignored in the real disassembly process. In this study, the cost is considered as a factor for the decision-making process. Fitness is represented as

$$\text{fitness}=\frac{\varphi}{\sum_{j=1}^{m}\sum_{i=0}^{n}t_{i,j}+t+1}+\frac{\varepsilon}{\sum_{j=1}^{m}\sum_{i=0}^{n}c_{i,j}+c+1}. \quad (26)$$

Step 3: selection

We use roulette method to select the chromosome with better fitness, which could be inherited by the next generation. The probability for every individual is $\text{pi}(i)=\text{Fitness}(i)\Big/\sum_{i=1}^{n}\text{Fitness}(i)$, where Fitness($i$)=1/fitness($i$). With higher fitness, there would be higher probability of optimal evolution.

Step 4: crossover

Integer crossing method is used to promote the whole evolution. First, we select the first half of two chromosomes randomly, while at the same time, the genes are swapped in optional cross position selected. For example, Fig. 1 shows a chromosome crossover with the extreme and the cross location is 6.

After the crossover, the information of individual may be redundant or missing. In this example, components 3 and 4 are missing and component 1 is redundant. According to the original station order, we add the missing information to the chromosome of the offspring.

Table 2 Information interpreted from the chromosome

Chromosome	1,3,4,2,4,1,3,2,1,4,1,2 | 2,5,3,3,1,4,2,5,4,2,1,5
Disassembly sequence	Component 1→Component 3→Component 4→Component 2→Component 4 →Component 1→Component 3→Component 2→Component 1→Component 4 →Component 1→Component 2
Station sequence	Station 2→Station 5→Station 3→Station 3→Station 1→Station 4→Station 2 →Station 5→Station 4→Station 2→Station 1→Station 5
Component 1	Four processes in total
Component 2	Three processes in total
Component 3	Two processes in total
Component 4	Three processes in total

Table 3 Corresponding relation between components and stations

Component	Process	Station	Component	Process	Station	Component	Process	Station
1	1st	2	4	2nd	1	1	3rd	4
3	1st	5	1	2nd	4	4	3rd	2
4	1st	3	3	2nd	2	1	4th	1
2	1st	3	2	2nd	5	2	3rd	5

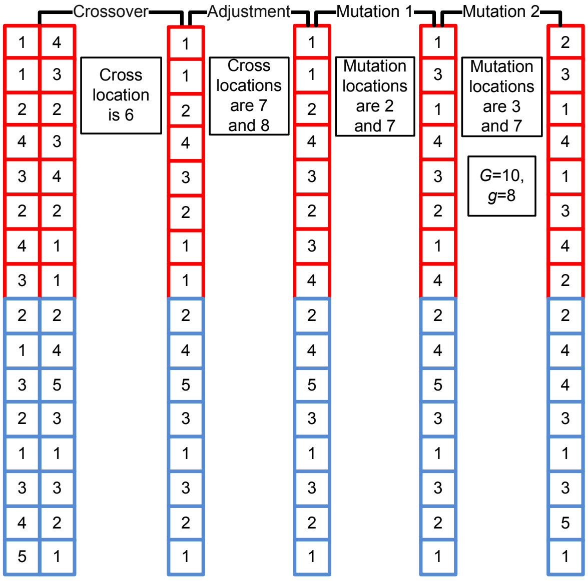

Fig. 1 An example of GA

Step 5: mutation

Mutation can bring new genes to population and ensure the gene diversity over the evolution. The individuals are selected randomly, and the chromosomes would mutate with a known probability. With the adoption of the mutation method for the first half part code, pos1 and pos2 (pos means the position of gene in chromosome) that are chosen randomly are swapped with each other. For the second half part code, Gaussian mutation operator, similar to that proposed by Shi *et al.* (2011), is introduced. We choose mutations named pos3 and pos4, in which pos3 is mutated by the Gaussian mutation operator. Additionally, pos4 is used to be adjusted for filling constraint. Gaussian probability density function is as follows:

$$f(x)=\frac{1}{\sqrt{2\pi}\sigma}\mathrm{e}^{-(x-\mu)^2/(2\sigma^2)},\quad -\infty<x<\infty, \tag{27}$$

where σ is the variance of Gaussian distribution and μ is the expectation.

In terms of evolution, the following rule needs to be followed:

$$y_k'=y_k-\lfloor y_k\times N(\mu,\sigma)\rfloor, \tag{28}$$

where y_k' represents the varied gene k of offspring, y_k is the corresponding gene k of father, $N(\mu, \sigma)$ is the Gaussian amplifier variable with expectation μ and variance σ, and $\lfloor\rfloor$ stands for the integral operator. For an ideal solution, it is assumed that μ is 0, and σ is changed with iterations as

$$\sigma(t)=1-0.9\times\frac{g}{G}, \tag{29}$$

where g is genetic algebra at present and G is the total genetic algebra.

As an example, the mutation locations are as follows: pos1=2, pos2=7, pos3=3, and pos4=7. We assume that G=10 and g=8, and the result is shown in Fig. 1.

4 Case study

To verify the effectiveness of the proposed approach, the disassembly process of a hydro-press has been simulated. As shown in Fig. 2, the hydro-press contains seven components with less than six disassembly processes. In addition, there are 10 available stations for disassembly. With the available station assignment based on the historical data, the available station set of removal cost and corresponding TFNs set of removal time are presented in Tables 4–6.

The basic parameters for the proposed approach are as follows: the number of population is 40;

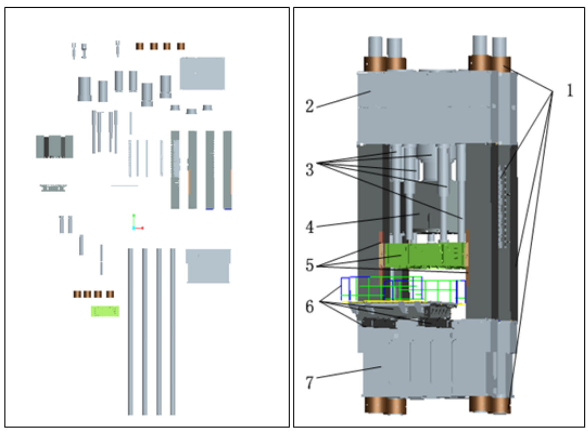

Fig. 2 Components of a hydro-press

1: vertical post; 2: upper beam; 3: oil cylinder; 4: drawing slide; 5: blank holder slide; 6: worktable; 7: lower beam

Table 4 Available station assignment for each process

Component	Available station assignment					
	Process 1	Process 2	Process 3	Process 4	Process 5	Process 6
ap_1	2	1	[4, 6]	[2, 8]	5	–
ap_2	9	[7, 8]	4	–	–	–
ap_3	[7, 9]	5	3	[5, 7]	1	6
ap_4	5	6	[2, 4]	7	–	–
ap_5	3	[4, 8]	[2, 5]	7	2	–
ap_6	3	4	[5, 9]	1	[6, 8]	2
ap_7	[1, 8]	7	9	5	[3, 8]	–

Table 5 TFNs set of removal time for each process

Component	TFNs set of removal time (h)					
	Process 1	Process 2	Process 3	Process 4	Process 5	Process 6
ap_1	(8, 9, 10)	(4, 5, 6)	[(4, 5, 6), (7, 8, 9)]	[(7, 8, 9), (8, 9, 10)]	(3, 4, 5)	–
ap_2	(3, 4, 5)	[(4, 5, 6), (9, 10, 11)]	(4, 5, 6)	–	–	–
ap_3	[(3, 4, 5), (3, 4, 5)]	(8, 9, 10)	(7, 8, 9)	[(7, 8, 9), (1, 2, 3)]	(7, 8, 9)	(3, 4, 5)
ap_4	(8, 9, 10)	(3, 4, 5)	[(5, 6, 7), (10, 11, 12)]	(3, 4, 5)	–	–
ap_5	(4, 5, 6)	[(4, 5, 6), (3, 4, 5)]	[(3, 4, 5), (8, 9, 10)]	(10, 11, 12)	(8, 9, 10)	–
ap_6	(2, 3, 4)	(1, 2, 3)	[(0, 1, 2), (4, 5, 6)]	(3, 4, 5)	[(3, 4, 5), (6, 7, 8)]	(1, 2, 3)
ap_7	[(2, 3, 4), (3, 4, 5)]	(7, 8, 9)	(2, 3, 4)	(6, 7, 8)	[(2, 3, 4), (7, 8, 9)]	–

Table 6 Cost of each process

Component	Cost ($\times10^3$ CNY)					
	Process 1	Process 2	Process 3	Process 4	Process 5	Process 6
ap_1	4	6	[10, 7]	[6, 2]	7	–
ap_2	3	[8, 7]	12	–	–	–
ap_3	[11, 5]	9	8	[6, 6]	4	2
ap_4	2	8	[7, 3]	4	–	–
ap_5	4	[3, 6]	[9, 11]	3	6	–
ap_6	5	9	[2, 7]	9	[7, 4]	10
ap_7	[4, 5]	8	11	6	[7, 5]	–

crossover probability is 0.8; mutation probability is 0.6; and the generation gap value is 0.9. According to Li *et al.* (2005)'s study and experiments, the above-mentioned parameters are selected. Considering the redundancy and incompleteness, the initial crossover probability and mutation probability are set to be as large as possible. An algorithm is used to estimate and adjust mutation probability from the 2nd iteration through the Gaussian mutation operator.

Figs. 3a–3c show the solutions of algorithm after 150 iterations when the initial mutation probabilities are 0.6, 0.3, and 0.1. The result proves that the algorithm is endowed with robustness.

Figs. 4 and 5 show the optimal parallel disassembly sequence after 50 iterations.

Table 7 presents a comparison between the algorithm proposed in this study and the rapidly-growing random tree-based (RRT) algorithm proposed by Aguinaga *et al.* (2008) with the same initialization. The set of iterations are 50, 100, and 150 in the test.

Initially, RRT algorithm sets an initial point as the root node in the state space, after which the number of leaf nodes increases until a rapidly-growing random tree is obtained. When the set of leaf nodes contains the target point, path planning, which consists of several leaf nodes starting from the initial point and ending in the target point, is finished. The effectiveness of search can be enhanced by RRT algorithm without modeling.

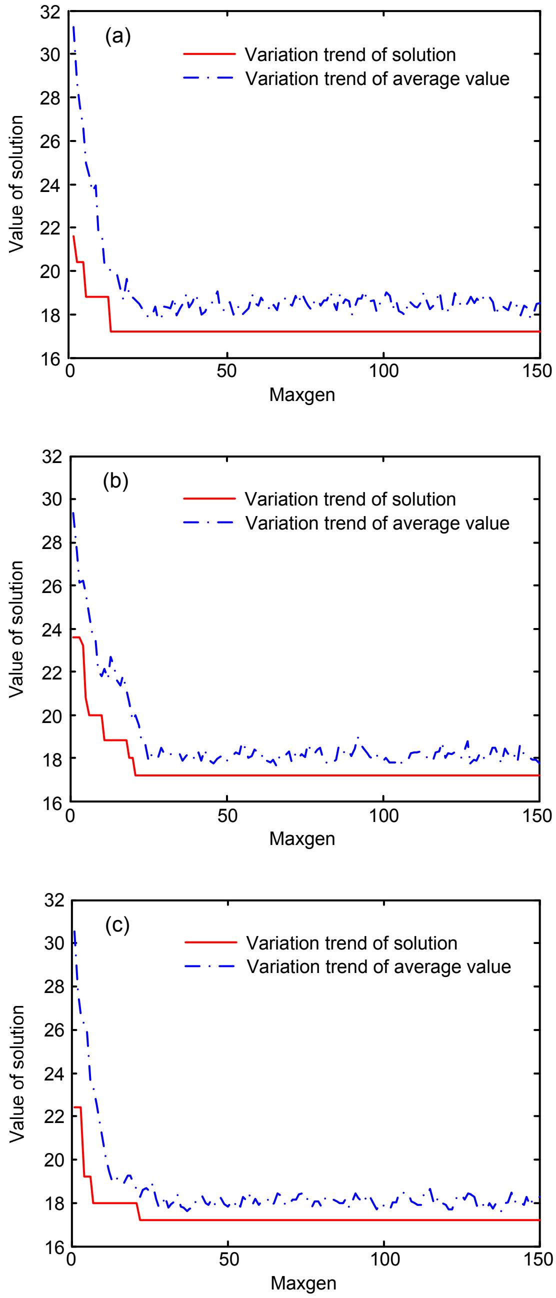

Fig. 3 The solutions of algorithm after 150 iterations under different initial mutation probabilities: (a) 0.6; (b) 0.3; (c) 0.1 (Maxgen is the maximal iteration)

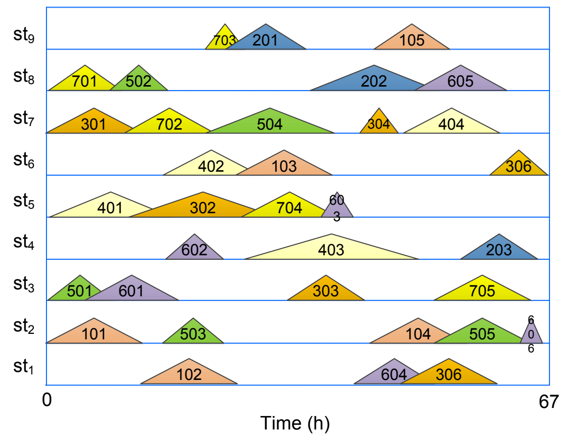

Fig. 4 Fuzzy time distribution under the optimal parallel disassembly sequence of seven components in nine stations

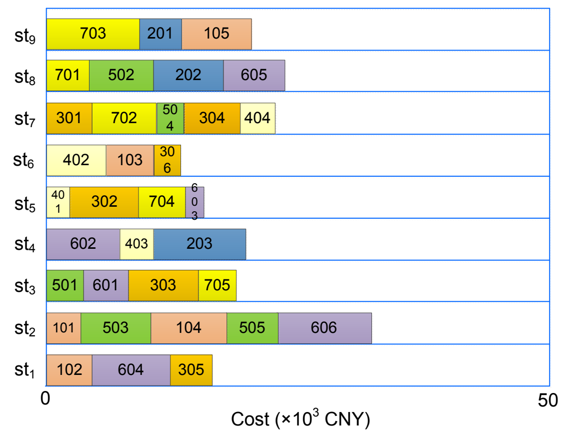

Fig. 5 Cost under the optimal parallel disassembly sequence of seven components in nine stations

Table 7 Comparing result between algorithms

Algorithm	Maxgen	Fitness	Computing time (s)
GA in this study	50	17.5	6.3
	100	17.3	12.8
	150	16.8	16.9
RRT algorithm	50	19.6	6.8
	100	20.4	13.7
	150	23.3	18.1

Let A be a set of components being disassembled on several stations called workspace N. p_1, p_2, …, p_q are processes distributed in N, and q represents the total number of processes. In the processes, it is assumed that A, p_1, p_2, …, p_q, and N are accurately known. The path-planning problem is as follows: it will generate a path τ specifying a continuous sequence of processes for A, with an initial process and a goal process of A finished on N.

We make a conclusion from Table 7 that the algorithm proposed in this study can usually get a better solution. Furthermore, the running time of the new algorithm is shorter. Fig. 6 shows that this algorithm has a faster rate of convergence.

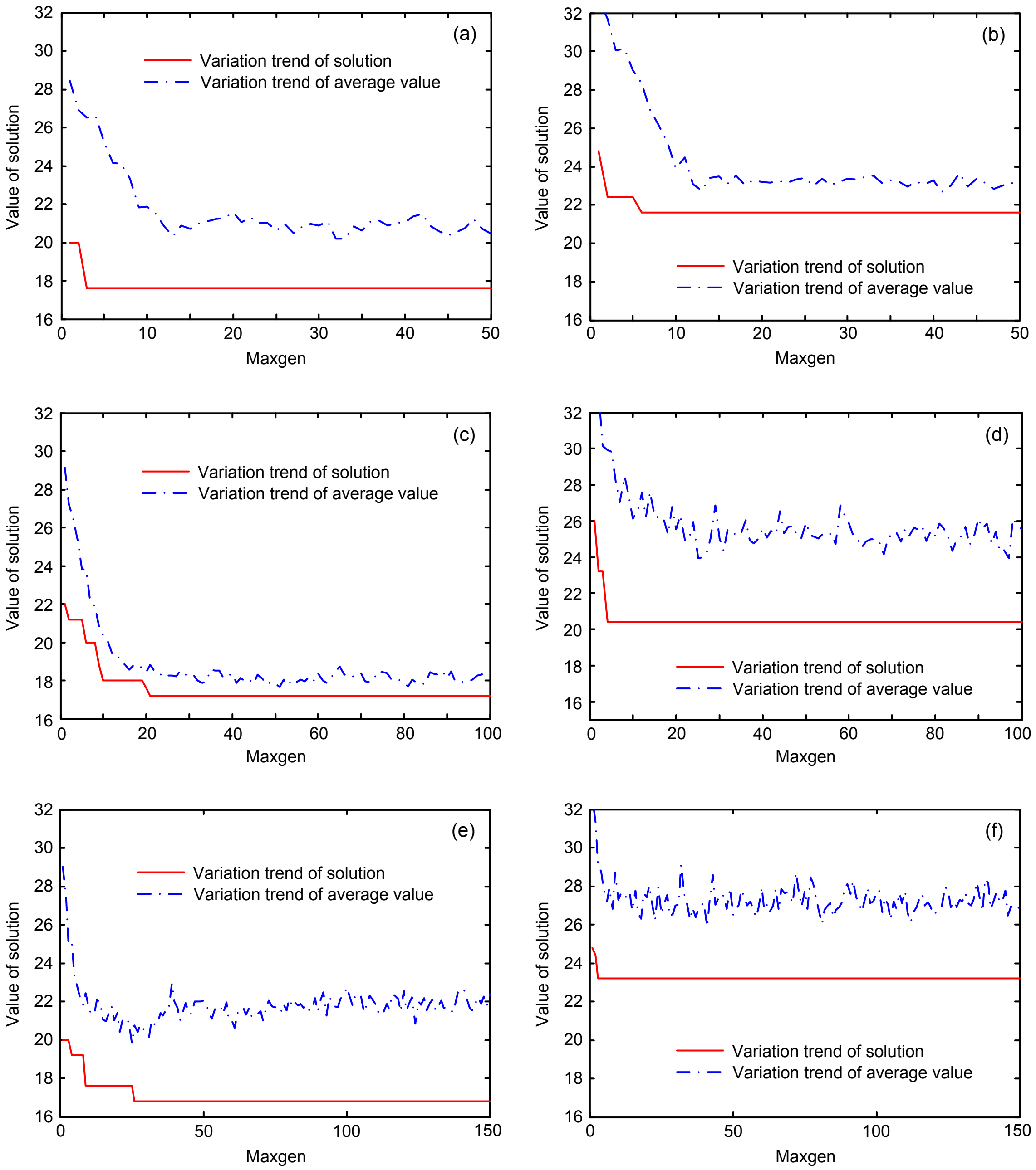

Fig. 6 Variation trend of solution and average value of the algorithm proposed in this study (a), (c), and (e) and RRT algorithm (b), (d), and (f)

5 Conclusions

In this paper, we consider a parallel disassembly path-planning problem with fuzzy time focusing on minimum overall operation time and cost. To embody the disassembly path planning and fuzzy time of processes, a disassembly path-planning problem with N stations and L components has been introduced. Then, FTDDPM is proposed, based on which the constraints are deduced. Gaussian mutation operator is introduced into GA to optimize the result, for better solution, and shorter time.

An application of the proposed approach is illustrated with disassembly of a hydro-press. The result shows that the problem can be solved perfectly within a reasonable amount of computing time and cost.

This research can be extended in several ways. First, the proposed approach should be applied to more case studies so as to prove the effectiveness. Furthermore, it is necessary to improve the algorithm to suit large-size products. Additionally, in terms of a problem involving a large number of components, a coding method for large-scale data than GA shall be useful and thus adopted.

References

Aguinaga, I., Borro, D., Matey, L., 2008. Parallel RRT-based path planning for selective disassembly planning. *International Journal of Advanced Manufacturing Technology*, **36**(11-12):1221-1233. [doi:10.1007/s00170-007-0930-2]

Aydemir-Karadag, A., Turkbey, O., 2013. Multi-objective optimization of stochastic disassembly line balancing with station paralleling. *Computers and Industrial Engineering*, **65**(3):413-425. [doi:10.1016/j.cie.2013.03.014]

Das, S.K., Yedlarajiah, P., Narendra, R., 2000. An approach for estimating the end-of-life product disassembly effort and cost. *International Journal of Production Research*, **38**(3):657-673. [doi:10.1080/002075400189356]

González, B., Adenso-Díaz, B., 2006. A scatter search approach to the optimum disassembly sequence problem. *Computers and Operations Research*, **33**(6):1776-1793. [doi:10.1016/j.cor.2004.11.018]

Gungor, A., Gupta, S.M., 2001. A solution approach to the disassembly line balancing problem in the presence of task failures. *International Journal of Production Research*, **39**(7):1427-1467. [doi:10.1080/00207540110052157]

Ilamparithi, T., Nandi, S., Subramanian, J., 2015. A disassembly-free offline detection and condition monitoring technique for eccentricity faults in salient-pole synchronous machines. *IEEE Transactions on Industry Applications*, **51**(2):1505-1515. [doi:10.1109/TIA.2014.2358797]

Kang, J.G., Lee, D.H., Xirouchakis, P., *et al.*, 2001. Parallel disassembly sequencing with sequence-dependent operation times. *CIRP Annals-Manufacturing Technology*, **50**(1):343-346. [doi:10.1016/S0007-8506(07)62136-2]

Lambert, A.J.D., 2006. Exact methods in optimum disassembly sequence search for problems subject to sequence dependent costs. *Omega*, **34**(6):538-549. [doi:10.1016/j.omega.2005.01.005]

Li, H., 2005. Fuzzy Mathematics and Practical Calculation Method. Science Press, Beijing, China, p.352-364 (in Chinese).

Li, J.R., Khoo, L.P., Tor, S.B., 2005. An object-oriented intelligent disassembly sequence planner for maintenance. *Computers in Industry*, **56**(7):699-718. [doi:10.1016/j.compind.2005.03.005]

Li, Z., Cheng, Z., Feng, Y., *et al.*, 2013. An integrated method for flexible platform modular architecture design. *Journal of Engineering Design*, **24**(1):25-44. [doi:10.1080/09544828.2012.668614]

Li, Z.K., Li, X.R., Zhu, Z.C., 2011. Scalable platform robust reconfiguration method with sensitivity analysis and fuzzy clustering. *Applied Mechanics and Materials*, **52-54**:1026-1031. [doi:10.4028/www.scientific.net/AMM.52-54.1026]

Liu, A., Lu, S.C.Y., 2014. Alternation of analysis and synthesis for concept generation. *CIRP Annals-Manufacturing Technology*, **63**(1):177-180. [doi:10.1016/j.cirp.2014.03.094]

Liu, A., Wuest, T., Wei, W., *et al.*, 2014. Application of prospect theory on car sharing product service system. The 6th CIRP Conference on Industrial Product-Service Systems, Ontario, Canada, p.350-355. [doi:10.1016/j.procir.2014.02.022]

Rickli, J.L., Camelio, J.A., 2013. Multi-objective partial disassembly optimization based on sequence feasibility. *Journal of Manufacturing Systems*, **32**(1):281-293. [doi:10.1016/j.jmsy.2012.11.005]

Shi, Y., Li, B., Zhang, Z., 2011. Layout design of satellite module using a modified artificial bee colony algorithm. *Advanced Science Letters*, **4**(8-10):3178-3181. [doi:10.1166/asl.2011.1370]

Tang, Y., 2009. Learning-based disassembly process planner for uncertainty management. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, **39**(1):134-143. [doi:10.1109/TSMCA.2008.2007990]

Tian, G., Zhou, M., Chu, J., 2013. A chance constrained programming approach to determine the optimal disassembly sequence. *IEEE Transactions on Automation Science and Engineering*, **10**(4):1004-1013. [doi:10.1109/TASE.2013.2249663]

Tian, G., Chu, J., Hu, H., *et al.*, 2014. Technology innovation system and its integrated structure for automotive components remanufacturing industry development in China. *Journal of Cleaner Production*, **85**:419-432. [doi:10.1016/j.jclepro.2014.09.020]

Tseng, H.E., Chang, C.C., Li, J.D., 2008. Modular design to support green life-cycle engineering. *Expert Systems with Applications*, **34**(4):2524-2537. [doi:10.1016/j.eswa.2007.04.018]

Xia, K., Gao, L., Li, W., *et al.*, 2014. Disassembly sequence planning using a simplified teaching-learning-based optimization algorithm. *Advanced Engineering Informatics*, **28**(4):518-527. [doi:10.1016/j.aei.2014.07.006]

Zhang, X.F., Yu, G., Hu, Z.Y., *et al.*, 2014. Parallel disassembly sequence planning for complex products based on fuzzy-rough sets. *International Journal of Advanced Manufacturing Technology*, **72**(1-4):231-239. [doi:10.1007/s00170-014-5655-4]

Zimmermann, H.J., 2001. Fuzzy Set Theory—and Its Applications. Kluwer Academic Publishers, Boston, USA, p.57-60. [doi:10.1007/978-94-010-0646-0]

Zussman, E., Zhou, M., 1999. A methodology for modeling and adaptive planning of disassembly processes. *IEEE Transactions on Robotics and Automation*, **15**(1):190-194. [doi:10.1109/70.744614]

中文概要

题　目： 一种基于混合模糊模型的新型并行拆卸设计方法

目　的： 解决考虑模糊环境条件影响下的复杂机械产品并行拆卸路径规划问题，并给出成本和模糊时间最优的拆卸方案。

创新点： 建立混合模糊模型，引入三角模糊数表示拆卸工序加工时间，提高拆卸路径规划的环境适应性；采用并行加工方法，尽可能地提高生产资源利用效率，缩短加工时间和降低加工成本；使用混合编码方式，用同一条染色体表示拆卸工序和工位信息，简化模型表达和运算；在遗传算法中引入高斯变异方法，提高算法的收敛速度。

方　法： 1. 引入一个包含 N 个工位和 L 个零部件的拆卸序列规划问题，提出混合模糊拆卸模型实现对此问题的数学描述；2. 采用包含高斯变异算子的遗传算法，对结果进行优化计算，以得到最短的模糊加工时间和加工成本；3. 将本文所述方法的计算结果与快速搜索随机树算法的运行结果进行比较。

结　论： 在算法分别迭代 50 次、100 次和 150 次的情况下，本文所述方法得到的最优解均优于快速搜索随机树算法的解，并且运行时间均短于快速搜索随机树算法。

关键词： 并行拆卸；序列规划；模糊时间；遗传算法