Fuzzy-Clustering Based Cost Modeling of Disassembly Planning for EOL Products

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Abstract: Cost model is a key issue in the disassembly process planning. Because the optimized disassembly sequence is determined by ranking several possible disassembly operation. In this study, a fuzzy cost model for disassembly processes was developed which based on the fuzzy clustering method. The objective is to solve the problems in the practical applications of the currently used quantitative models of disassembly cost model, which is based on the change times of the tools operation or the disassembly time. The sample data were obtained through the disassembly tests of the typical EOL (end-of-life) products. Then, the transitive closure operations were performed after standardization and normalization. Dynamic clustering was conducted on the basis of above results, and appropriate clustering results were selected to construct the membership function of fuzzy costs. This study also proposed a method of proportional interpolation to expand the directly built membership function to the uncovered discourse domain, resulting in a more practical fuzzy cost models. Finally, the disassembly process of a general reducer was adopted as an example to verify the feasibility of the above method.

Keywords: Disassembly, disassembly cost model, fuzzy clustering, recycling, remanufacturing.

1. INTRODUCTION

The disassembly and recycling of EOL products has attracted increased attention. Reasonable disassembly and recycling of EOL products can not only reduce environmental pollution, but also significantly reduce the consumption of natural resources. Therefore, there have been lots of studies on the disassembly theory of EOL products in recent years. H.Srinivasan and R.Gadh presented a method of wave propagation to modeling the single selective disassembly [1]. then, Jianjun Yi, et al. improved this method, a geometric algorithm was took into account for disassembly strategy [2]. Lu Zhong, et al. put forward a method of Component-fastener graph to modeling the structure of product [3]. Shana Smith, et al. present a method of disassembly sequence structure graph which based on the matrix of contact constraint and motion constraint [4]. Ying Tang et al. presented a fuzzy petri net based approach to construct the model EOL product and obtain the optimal disassembly sequence [5]. Ahmed Elsayed et al. use bill of material (BOM) and genetic algorithm to generate the near optimal disassembly sequence for end-of-life electronic products [6]. The current strategy research on disassembly mainly focuses on how to find an optimal sequence for disassembly, so that the valuable parts of EOL products can be reused or remanufactured and the rest is recycled as material.

In order to comparing different disassembly sequences, disassembly cost is a matter of the main concern. Usually, the least-cost path is selected as the optimal path among various disassembly sequences. In current studies, the disassembly time or the change times of the tool operation pose is mostly adopted as the quantitative model of disassembly cost. S.Kara et al. use disassembly time of each operation as cost model to determine the optimal disassembly sequence [7]. Shana S et al. use number of direction change, number of components and fasteners need to be removed as cost model for disassembly sequence planning [8]. Li Hsing et al. proposed a cost model include disassembly time, cost of disassembly equipment and labor to determine the optimal disassembly sequence [9]. T.F. Go et al. also use disassembly time as cost model, furthermore, they proposed a penalty index for direction change [10].

Above mentioned cost model depends on the disassembly time or tools direction change method is feasible for simple products, but would be more difficult to use for EOL products with complex structure and large number of parts, because not only simple hand tools, but also various electric and hydraulic tools need to be used in the disassembly of EOL products. The change times of the tool are difficult to represent the disassembly cost. In addition, the disassembly time for the same component may be different due to the uncertainty in the joint strength between parts resulting from
corrosion, clogging or other reasons. Therefore, accurate quantification models are inappropriate in the modeling of disassembly cost. In this study, the difficulty degree of the disassembly cost representation is denoted using fuzzy variable based on the fuzzy theory, which can be easily accepted by disassembly operators. Therefore, it is needed to build fuzzy cost models to adapt to the features of EOL products, which use fuzzy sets to denote the difficulty in disassembly with different joints.

According to fuzzy theory, the common methods to build fuzzy sets are expert experience method, statistical test method, and minimum fuzzy method, etc. However, there are some disadvantages for these methods in building the fuzzy sets of disassembly cost. For example, large errors may exist due to the subjective intuition for the expert experience method, while large amounts of data samples are required for the statistical test method and minimum fuzzy method. In this study, a modeling method of disassembly cost based on fuzzy clustering is proposed. Firstly, a small number of samples were collected based on the disassembly of typical EOL products, and then analyzed using fuzzy clustering method. Furthermore, fuzzy sets of the disassembly cost were constructed according to the clustering results.

2. FUZZY COST MODEL FOR DISASSEMBLY PROCESS PLANNING

The disassembly sequence planning based on fuzzy disassembly cost is shown in Fig. (1). Firstly, a small number of samples were extracted from a type of EOL products to carry out disassembly tests. During the disassembly process, the disassembly torque and energy consumption, etc., were measured using torque wrench, current power meter and other tools, or otherwise using sensors installed in tools. After disassembly, the obtained data were used for fuzzy clustering analysis. Finally, according to the results of dynamic clustering, appropriate cluster state was selected to build fuzzy sets of disassembly cost.

After the completion of the fuzzy sets of disassembly cost, an appropriate searching program for the optimal disassembly sequence can be adopted to solve the disassembly and recycling strategies of EOL products. There are already many such algorithms and procedures for this purpose, which can be used for the disassembly process planning. Ahmed ElSayed et al. apply the genetic algorithm in disassembly sequence for EOL products [11]. J.F. Wang et al. use ant colony algorithm to search optimal disassembly sequence in disassembly process planning [12]. Elif Kongar et al. present a genetic algorithm to determine the best disassembly sequence [13]. By L.M. et al. Implemented a genetic algorithm based fuzzy logic approach for disassembly process [14]. Wei-Chang Yeh et al. presents a revised simplified swarm optimization algorithm for disassembly sequencing problem [15]. Belarmino et al. presented an efficient GRASP algorithm for disassembly sequence planning [16].

3. PROCEDURE OF FUZZY CLUSTERING WITH SAMPLING DATA

The fuzzy clustering process of sample data obtained from disassembly tests are shown in Fig. (2). Firstly, a sample data list needs to be established. Generally, each row of the table represents a group of sample data, i.e., all the data collected in a disassembly process for particular joint. And each column is a corresponding test indicator, such as the dismounting force, the energy consumption, the time. Then, the sample data list is standardized. The purpose of standardization is to eliminate the influence due to different dimensions for different indicators. The maximum and minimum method is used here (as shown in Eq. 1). Where, maxj and minj are the maximum and minimum values of column j (the jth indicator), respectively. Advantage of this method is not only excluding the effect of dimensions, but also avoiding the submergence of the role played by the minimum value. By this means, all the data are compressed into the region of [0,1].

\[ X_{ij} = \frac{A_{ij} - \min_j}{\max_j - \min_j} \quad (j=1,2,3,4) \]  

(1)

In order to build a similarity relationship between disassembly operations, i.e. to build a similarity relationship matrix. The maximum and minimum approaching method (shown in Eq. 2) is used here for calculation, \( X_{ik} \) is the element value of row i and column j after the standardization of original materials; and are the maximum and minimum Zadeh operators respectively.

\[ R_{ij} = \frac{\sum_{k=1}^{11} (X_{ik} \land X_{jk})}{\sum_{k=1}^{11} (X_{ik} \lor X_{jk})} \]

(2)

After the treatment above, the similarity relationship matrix \( R_{ij} \) can be obtained. \( R_{ij} \) is used to indicate the association degree between various constraints, i.e., the judgment of the interrelated association between disassembly operations. On this basis, fuzzy clustering can be carried out. Therefore, the similarity matrix is the constraint correlation.

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**Fig. (1).** Procedure of fuzzy cost based disassembly process planning.
function. The element \( r_{i,j} \) in the similarity matrix represents the similarity degree between the disassembly operations \( D_i \) and \( D_j \); \( r_{i,j}=0 \) denotes that they are completely different; while \( r_{i,j}=1 \) denotes that they are the same and the diagonal elements of this matrix are all equal to one.

Here, there are only two cases including 0 and 1 for the elements in \( R' \). By selecting different thresholds \( \lambda \), a series of logical matrixes \( R' \) can be obtained. Using appropriate program tools such as Matlab, the corresponding dynamic clustering map can be drawn. Thereby, the change of \( \lambda \) and the clustering state of the sample data can be easily observed. Then, an appropriate cluster state can be selected according to the size of fuzzy sets, which can be used to establish fuzzy sets of disassembly cost.

4. FUZZY COST MODELING FOR DISASSEMBLY PROCESS PLANNING

Fuzzy cost models in the disassembly process are represented by fuzzy sets. Namely, the linguistic variables such as "very difficult", "difficult", "medium", "easy" and "very easy" are used to describe the ease degree of disassembly. Then, the total cost of various disassembly sequences was determined by computing the fuzzy variables in the disassembly sequence planning algorithm, such as addition, multiplication, size comparison, etc., resulting in an optimal disassembly sequence.

In order to create a fuzzy set according to the above clustering results, the form of the membership function must be firstly determined. Although there are several types of membership functions, the triangular membership function has been widely applied in engineering due to the simple form and convenience in use. The triangular membership function is also used in the fuzzy modeling of disassembly cost. The form of triangular membership functions is shown in Fig. (3). It is represented by a ternary array \((L, M, N)\). Where, \( L \) is the minimum value of the domain which is able to represent the linguistic variables; \( M \) represents the domain value with the largest membership value; and \( N \) is the maximum value of the domain, which is able to represent the linguistic variables.

![Triangular membership function](image)

**Fig. (2).** Process of fuzzy clustering for sample data.

The transitivity must be satisfied for the clustering of the matrix \( R_{ip} \), i.e., \( R \circ R \) is contained in \( R \). The symbol \( \circ \) denotes the convolution operation. In order to quickly solve the transitive closure \( t(R) \), the square algorithm, which is mostly commonly used, is adopted here. Namely, by calculating the relationship sequence as follows until no new relationship generates, we have \( R^1 \circ R^2 = R^3 \). The transitive package is \( t(R) = R^4 \).

\[
R \rightarrow R^2 \rightarrow R^4 \rightarrow \cdots \rightarrow R^{2k} = t(R)
\]  

Finally, different confidence levels i.e., the threshold \( \lambda \) can be selected. The above transitive closure is clustered, resulting in a corresponding logical matrix \( R' \). The approach is shown in Eq. (4), where, \( r'_{ij} \) is the element in \( R' \).

\[
r'_{ij} = \begin{cases} 
0 & r_{ij} \leq \lambda \\
1 & r_{ij} \geq \lambda
\end{cases} \quad (i,j=1,2,\cdots,n)
\]  

**Fig. (3).** Triangular membership function.

According to the clustering results obtained in the previous section, the centroid method can be used to calculate the center of each data cluster, namely the domain value where the point \( M \) locates.

\[
v'_k = \frac{1}{n} \sum_{i=1}^{n} x_i'(k = 1, 2, 3, 4)
\]
Then, the minimum and the maximum values in each set of data were used to replace the above L and M, and the domain distribution of the corresponding linguistic variables can be obtained. However, the developed fuzzy cost model should be able to cover all possible domain regions for the EOL products. Otherwise, the data may be lost due to the discontinuity of the fuzzy domains in the fuzzy processing of particular connection relationships. As shown in Fig. (4), two fuzzy linguistic variables K3 and K4 constructed using the method described above are not covered in the regions where the domains D5 and D6 locate. If the domain values in this region are input, appropriate language variable cannot be generated. Therefore, this paper proposes a method of proportion interpolation. Firstly, the midpoint of the uncovered domain region is calculated, i.e., the domain value of the midpoint H between D5 and D6. Then, the interpolation point P is calculated according to the following proportional relationship.

\[
M_{H} = \frac{D_{p}P}{HM_{4}}
\]

(6)

After the reprocessing of the domain values for linguistic variables, a fuzzy cost model of disassembly process is obtained to meet the actual requirements.

5. CASE STUDY

In this study, the disassembly process of a common reducer was adopted as an example for fuzzy cost modeling. The reducer has different structural forms, including one-level reducer, two-level reducer, single output and dual output. But the joint modes of its components are roughly the same, and therefore they generally belong to the same category of products. For modeling convenience, a small and medium-sized one-level reducer was selected as the typical product for disassembly testing. The structure of this one-level reducer is shown in Fig. (5).

Disassembly was operated by special disassembly tools and testing tools for main components. Four indicators including disassembly duration, disassembly moment, disassembly energy consumption, and tool cost are selected. Among them, the tool cost means the cost of each operation calculated from the tool purchase price and service life. Eleven data sets were obtained by testing, and the data sample list is shown in Table I.

![Fig. (4). Proportional interpolation.](image)

![Fig. (5). The disassembly structure of reducers.](image)
was carried out using the obtained test data, and then the dynamic clustering chart were created using Matlab, as shown in Fig. (6).

According to the general requirements of the disassembly process, it is reasonable to classify the difficulty for the component disassembly into five levels, which maintains a certain degree of differentiation and is easy to use. The language variable "very low" (VL), "low" (L), "moderate" (M), "high" (H), "very high" (VH) are used to represent the disassembly costs. Namely, when the confidence level \( \lambda \) located in the region of \([0.504, 0.657]\), the sample data are clustered into five categories: \{D5, D9\}, \{D6, D7\}, \{D5\}, \{D1, D2, D3, D4\} and \{D10, D11\}.

Finally, the triangular membership functions were built for the above aggregate of data using centroid method and proportion interpolation, and then extended to the uncovered domain regions. The final fuzzy cost set model can be obtained, and its membership function is shown in Fig. (7). Fig. (8) is the fuzzy cost set model constructed by the expert experience method [17]. It can be seen that there are obvious differences between the two results and the fuzzy set obtained by fuzzy clustering is more practical.

**CONCLUSION**

At present, the cost model based on the change times of the tool operation pose and the disassembly time is difficult to apply in practice. The disassembly cost described by fuzzy linguistic variables is easier to estimate in engineering applications. However, it is critical to establish a disassembly cost model based on fuzzy domain according to the specific features of the EOL products. The expert experience method in fuzzy theory often leads to big deviation in fuzzy set due to the subjective errors and incomplete experience. And the statistical method requires a lot of sample data. In this study, the disassembly tests were conducted for some EOL products. Fuzzy clustering analysis was carried out using the obtained test data, and then the

<table>
<thead>
<tr>
<th>No.</th>
<th>Disassembly Part</th>
<th>Disassembly Time/SD</th>
<th>Disassembly Torque/ N·M</th>
<th>Energy Consumption/ J</th>
<th>Tool Costs/T</th>
<th>Component Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1</td>
<td>M8×10</td>
<td>5.8</td>
<td>1.25</td>
<td>125.6</td>
<td>8</td>
<td>Oil level indicator</td>
</tr>
<tr>
<td>D2</td>
<td>M3×10</td>
<td>7.2</td>
<td>1.25</td>
<td>157</td>
<td>5</td>
<td>Felt blade screw</td>
</tr>
<tr>
<td>D3</td>
<td>M3×10</td>
<td>6.6</td>
<td>1</td>
<td>125.6</td>
<td>5</td>
<td>Observation window positioning screw</td>
</tr>
<tr>
<td>D4</td>
<td>M8×10</td>
<td>10</td>
<td>1.50</td>
<td>113.04</td>
<td>8</td>
<td>Observation window air hole bolt</td>
</tr>
<tr>
<td>D5</td>
<td>M8×10</td>
<td>8.9</td>
<td>7</td>
<td>351.68</td>
<td>8</td>
<td>Oil discharge bolt</td>
</tr>
<tr>
<td>D6</td>
<td>M6×64</td>
<td>23.7</td>
<td>6.75</td>
<td>1780.38</td>
<td>42</td>
<td>Fastening Bolt 1 of upper and lower tank</td>
</tr>
<tr>
<td>D7</td>
<td>M6×35</td>
<td>20.7</td>
<td>6</td>
<td>1318.8</td>
<td>33</td>
<td>Fastening Bolt 2 of upper and lower tank</td>
</tr>
<tr>
<td>D8</td>
<td>M4×20</td>
<td>10.9</td>
<td>14</td>
<td>2512</td>
<td>18</td>
<td>End cover (through cover) positioning screw</td>
</tr>
<tr>
<td>D9</td>
<td>M4×20</td>
<td>8.3</td>
<td>13</td>
<td>2332.57</td>
<td>18</td>
<td>End cover (stuffy cover) positioning screw</td>
</tr>
<tr>
<td>D10</td>
<td>30205</td>
<td>1.2</td>
<td>0.26</td>
<td>24.5</td>
<td>13</td>
<td>Clearance Fit 1 of tapered roller bearings</td>
</tr>
<tr>
<td>D11</td>
<td>30206</td>
<td>1</td>
<td>0.34</td>
<td>37.37</td>
<td>17</td>
<td>Clearance Fit 2 of tapered roller bearings</td>
</tr>
</tbody>
</table>

**Table 1.** The sample data list of disassembly.

Fig. (6). Dynamic clustering chart of fuzzy clustering.

Fig. (7). Fuzzy cost model by fuzzy clustering.

order from small to large, the corresponding logical matrixes are calculated respectively, and the dynamic clustering chart were created using Matlab, as shown in Fig. (6).

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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