Multi-objective disassembly sequence optimization aiming at quality uncertainty of end-of-life product

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ABSTRACT: Remanufacturing plays a vital role in circular economy due to its enormous contribution in promoting resources recycling and utilizing. Disassembly of end of life (EOL) products, as a prerequisite of remanufacturing, is an effective means to improve resource utilization and reduce environmental impact. However, because of the complex quality conditions of EOL products, different disassembly method and sequence for components may lead to different effects. Based on this, a multi-objective disassembly sequence optimization model considering the quality uncertainty of EOL products is proposed in this paper. Firstly, the remaining life of each component of an EOL product is calculated by using the Weibull distribution and artificial neural networks (ANN), and then the disassembly modes could be chosen according to their quality conditions. Secondly, a multi-objective disassembly sequence optimization model which takes minimum disassembly time and cost as the objective is established, and the particle swarm optimization (PSO) algorithm is employed to solve this model. Finally, a case study of drum washing machine disassembly is provided to verify the feasibility and superiority of the proposed methodology.

1. Introduction
Due to the prominent environmental problems and crisis of resources depletion and energy shortage, the effective disposal of EOL products has become a significant research problem in recent years. Remanufacturing, as an effective strategy for contributing to the development of the circular economy, can refurbish the EOL products of high value-added into like-new condition, and have great economic and environmental benefits, because it can not only reduce pollution and consumption of natural resources, but also improve companies economic performance by reducing production cost and increasing service level[1]. Disassembly, as a prerequisite for remanufacturing of EOL products, plays an important part in promoting the sustainable development of manufacturing industry, owning to its significant contribution to the remanufacturing, reuse, recycle, and reducing the environmental pollution of EOL products[2].

Because disassembly sequence optimization plays a significant role in finding the optimal
disassembly sequence, many researchers have explored it from various perspectives. Zhang et al. analyzed the multi-objective disassembly line balance problem with fuzzy disassembly time and employed a Pareto improved artificial fish swarm algorithm to solve this problem[3]. Jiao and Xu presented an improved bat algorithm, namely discrete bat algorithm approach to optimize the disassembly sequence planning (DSP) problem[4]. Marconi et al. studied how to incorporate data mining to disassembly sequence planning and proposed a approach for calculating the optimal disassembly sequence and time for industrial products[5].

Based on the existing researches done by[3-5], it can be concluded that most researches has employed various methods to conduct the disassembly sequence optimization, but only a few has considered the quality uncertainty of EOL products to be disassembled. Their quality uncertainty affect the choice of disassembly mode, which includes destructive disassembly, non-destructive disassembly and hybrid disassembly. Different disassembly modes correspond to different disassembly time and cost, thus affecting disassembly profit. Hence, it is vital to introduce a multi-objective disassembly sequence optimization model aiming at the quality uncertainty of EOL products to find the optimal disassembly sequence. The rest of this paper can be summarized as follows: Section 2 presents the disassembly problem and proposes the multi-objective disassembly sequence optimization model. The multi-objective solution procedures are shown in Section 3 and the proposed multi-objective optimization model is illustrated with a case study in Section 4. Finally, section 5 gives the conclusions of our research and describes some the future work.

2. Problem statement and modelling

2.1. Problem statement
In the actual disassembly process, because of the difference of disassembly sequences for EOL product components, different disassembly sequences can result in different effects on time and costs of disassembly. Meanwhile, due to the quality uncertainty of EOL products components, it is difficult for workers to conduct the disassemble work with high efficiency. They are worried about that their disassembly operations may destroy the components with good quality status and consequently, they use only the non-destructive disassembly mode in daily work which will obviously reduce their working efficiency compared to utilizing the hybrid disassembly mode. Hence, it is crucial to evaluate the quality conditions of different components of EOL products in a disassembly process.

On the basis of the analysis above, it can be concluded that how to get the optimal disassembly sequence under the quality uncertainty of EOL product components becomes a problem worthy of further consideration.

2.2. Multi-objective disassembly sequence optimization model
The multi-objective disassembly sequence optimization model comprehensively considers, disassembly time and cost of an EOL product under the quality uncertainty. And it is separated into three subsections to ensure better understanding of the model architecture. The first subsection illustrates the method applied to evaluate the quality of EOL products components. The second subsection introduces the first optimization objective - disassembly time. The third subsection presents the second optimization objective - disassembly cost.

2.2.1 The method for evaluating the quality of EOL product components
The quality condition is usually illustrated with components’ remaining life, so in this subsection, the method which incorporates Weibull distribution[6] and ANN[7] for remaining life evaluation of EOL product components is proposed. The main evaluation steps are shown as follows and the flow chart of remaining life evaluation of EOL product components is shown in figure 1.
The EOL product component
Historical failure data
Characterizing component degradation characteristics data
Weibull distribution
Shape parameter $\beta$
Scale parameter $\eta$
Position parameter $\gamma$
The average service life $T_M$
The remaining life $T_R = T_M - T_A$

Non-destructive disassembly group
Destructive disassembly group

Figure 1. The flow chart of remaining life evaluation of EOL product components

Step 1: Due to the average service life of the EOL components reflects the normal running time of the parts, it can be calculated from the failure data of the components to establish its Weibull distribution model. Meanwhile, the three-parameter Weibull distribution has the characteristic of high fitting precision, and can more accurately reflect the actual operation of the components. Consequently, three-parameter namely $\beta$, $\eta$, $\gamma$ Weibull distribution is used to calculate the life distribution as well as reliability distribution of the components. Its distribution form can be represented with fault density function shown as Eq1 and cumulative fault distribution function shown as Eq2, where the shape parameter $\beta$, Scale parameter $\eta$ and Position parameter $\gamma$ respectively denote failure mode, Characteristic life as well as minimum guaranteed life.

$$f(t) = \frac{\beta}{\eta} \left( \frac{t - \gamma}{\eta} \right)^{\beta-1} \exp \left[ -\left( \frac{t - \gamma}{\eta} \right)^{\beta} \right] \quad t \geq \gamma$$

(1)

$$f(t) = 1 - \exp \left[ -\left( \frac{t - \gamma}{\eta} \right)^{\beta} \right]$$

(2)

Based on shape parameter $\beta$, scale parameter $\eta$ and position parameter $\gamma$, the average service life of components $T_M$ can be calculated by the Eqs 3 and 4.

$$\Gamma(x) = \int_0^\infty u^{-1} \exp(-u) du = \frac{\Gamma(x_1, x_2, \ldots, x_n)}{\Gamma(x_1, x_2, \ldots, x_n)}$$

(3)

$$T_M = \gamma + \eta \left( 1 + \frac{1}{\beta} \right)$$

(4)

Step 2: Firstly, select the appropriate characterization indicators to characterize component degradation. By means of the ANN, the characteristic index value that characterizes the performance degradation of the component is taken as the input of the neural network, and the actual service life corresponding to the characteristic index value is taken as the output of the neural network. Through network training, establish the relationship between the characteristic index values that characterize the degradation of component performance and the actual service life of components. Thirdly, detect the performance degradation characteristic value of a component, namely $x_1, x_2, \ldots, x_n$, in which $x_1, x_2, \ldots, x_n$ respectively denotes the different characteristic index values that characterize performance degradation of the components. Then input these values into trained artificial neural network model and obtain the output which is the actual service life of the component, $T_A$.

Step 3: Combining the average service life $T_M$ obtained from step 1 and the actual service life $T_A$ obtained from step 2, we can get the calculation result of the remaining life $T_R$ by utilizing Eq5, to know the quality condition of the component. when $T_R$ is positive, it means that the EOL product component has remaining life and possesses a good quality status, so it can be classified into the non-destructive disassembly group. On the contrary, when $T_R$ is negative, it means that the EOL has not...
remaining life and its quality situation is terrible, so it can be classified into the destructive disassembly group.

\[ T_d = T_m - T_a \]  

(5)

Finally, according to the group classification of the EOL product components, we can adopt a hybrid disassembly mode to disassemble the EOL product, namely respectively disassembling the components belonging to the non-destructive disassembly group and destructive disassembly group with non-destructive disassembly mode and destructive disassembly mode.

2.2.2 The first optimization objective - disassembly time

The disassembly time is an intuitive reflection of the disassembly efficiency. Considering the different disassembly tools and levels, the total disassembly time \( T \), includes the tool change time \( T_1 \) and disassembly process time, in which the disassembly process time can be divided into two parts, namely destructive disassembly time \( T_2 \) and non-destructive disassembly time \( T_3 \).

1) Tool change time \( T_1 \). It can be expressed with Eq 6.

\[ T_1 = \sum_{j=1}^{n} t_j \cdot \phi_{j-1,j} \]  

(6)

Where, \( t_j \) is the tool change time of component \( j \), \( \phi_{j-1,j} \) is the chosen function, and it can be expressed as follow:

\[ \phi_{j-1,j} = \begin{cases} 0 & \text{No tool change} \\ 1 & \text{Tool change} \end{cases} \]

Disassembly process time. For the same product and applying the same connection method among components, the different disassembly methods lead to the difference of disassembly time. According to different quality conditions, the components can be classified shown as follows:

\[ \omega_j = \begin{cases} 1, & \text{non-destructive components} \\ 0, & \text{destructive components} \end{cases} \]

Hence, the loss time of the non-destructive disassembly components and destructive disassembly components of the EOL product can respectively be expressed with Eq 7 and Eq 8:

\[ T_2 = \sum_{j=1}^{n} t(j) \cdot \omega_j (j=1,2,...,n) \]  

(7)

\[ T_3 = \sum_{j=1}^{n} t(j) \cdot (1 - \omega_j) (j=1,2,...,n) \]  

(8)

Where \( \omega_j \) represents a collection of classification of the components of EOL products and \( t(j) \) represents the time it takes to disassemble part \( j \).

Finally, according to the Eq 9, we can get the total disassembly time \( T \).

\[ T = T_1 + T_2 + T_3 = \sum_{j=1}^{n} t(j) \cdot \omega_j + \sum_{j=1}^{n} t(j) \cdot (1 - \omega_j) + \sum_{j=1}^{n} t(j) \cdot \phi_{j-1,j} (j=1,2,...,n) \]  

(9)

2.2.3 The second optimization objective - disassembly cost \( C \)

Disassembly cost is an important indicator of the size of the disassembly gain. Generally speaking, the total disassembly cost majorly includes employee expenditure \( C_1 \), tools loss and energy consumption cost \( C_2 \), and loss cost of the residual value of the components \( C_3 \).

1) The Employee expenditure \( C_1 \) shown in Eq 10:

\[ C_1 = S_w \cdot T \]  

(10)

Where \( S_w \) indicates workers wages per unit of time and \( T \) indicates the disassembly time of EOL products.

2) The tools loss and energy consumption cost \( C_2 \) presented in Eq 11:
\[ C_2 = C_d \cdot \text{P} \cdot T \cdot (1 - \omega_j) \]  

Where \( C_d \) represents the life loss of the tools per unit time and \( \text{P} \)—represents the unit price of electricity.

3) The loss cost of the residual value of the components \( C_3 \):

Assume that the product has been used for \( L_R \) years when it is recycled and meanwhile, its design life is \( L_N \) years. When it is destructively disassembled, its depreciation rate can be denoted with Eq 12.

\[ \mu = \frac{L_N - L_R}{L_N} \]  

Further, the loss cost of the residual value of the components \( C_3 \) can be expressed with Eq 13.

\[ C_3 = \sum_{j} M_j \cdot (1 - \omega_j) \cdot \mu \]  

Finally, the total disassembly costs \( C \) can be denoted with Eq14:

\[ C = C_1 + C_2 + C_3 = (s_\omega + c_{\omega}) \cdot \text{P} \cdot T \cdot (1 - \omega_j) + \sum_{j} M_j \cdot (1 - \omega_j) \cdot \mu \]  

3. Multi-objective solution procedure

3.1. The basic principle of the particle swarm optimization (PSO) algorithm

For any particle generated randomly, each particle represents an answer to the question and possesses a different motion speed, and according to the value of the fitness function, it can judge its performance and position condition during its movement and update its position and change its own speed by continuously Pursuing for the best individual to obtain the most ideal solution. Suppose that \( N \) particles are employed to search in a \( D \)-dimensional space, and each particle corresponds to a property of corresponding sequence and flies in its space as required.

The \( V_i = (V_{i1}, V_{i2}, \ldots, V_{in}) \), \( X_i = (X_{i1}, X_{i2}, \ldots, X_{in}) \) are respectively used to indicate the flight speed and Spatial location of particle \( i \). The \( p_i = (p_{i1}, p_{i2}, \ldots, p_{in}) \) is used to indicate the individual extremum searched out by the particle swarm. The \( g \cdot p_i = (p_{g1}, p_{g2}, \ldots, p_{gn}) \) are respectively used to denote the whole population, and the set of optimal positions obtained by a series of iterations and searching for all the particles. When \( N \) particles are employed to search in a \( D \)-dimensional space, their changing positions and speeds can be expressed with Eq 15.

\[
\begin{align*}
V_{id}^{t+1} &= V_{id}^t + c_1 r_1 (p_{id}^t - X_{id}^t) + c_2 r_2 (p_{gd}^t - X_{id}^t) \\
X_{id}^{t+1} &= X_{id}^t + V_{id}^{t+1}
\end{align*}
\]  

Where \( r_1 \), \( r_2 \) represent two functions that are randomly taken values in the interval (0, 1). The \( c_1 \), \( c_2 \) represent the acceleration factors in which \( c_1 \), \( c_2 \) are respectively used to adjust the speed of individual particle in local search and global search. \( D \) and \( t \) respectively represent the dimension of a particle in \( D \)-dimensional space, and the number of iterations of the algorithm.

3.2. The iterative search steps of the PSO algorithm

Step1: Initialize the particle swarm, including initial position, velocity, and population size, and determine parameters such as acceleration factors \( c_1 \), \( c_2 \), maximum number of iterations \( \text{Max} \), individual extremum \( p_{\text{best}} \) and Global extremum \( p_{\text{gbest}} \). Where individual extremum \( p_{\text{best}} \) is the current fitness value of the particle and Global extremum \( p_{\text{gbest}} \) is the optimal fitness value for all particles in the particle swarm.

Step2: Evaluate the fitness value of each particle. If the particle fitness value obtained by this iteration is better than \( p_{\text{best}} \), update \( p_{\text{best}} \) and record its position. If the optimal fitness value of all
particles is better than pbest, update pbest and record its position.

Step3: Update the speed and position of particles. When particles are employed to search in a D-dimensional space, their changing positions and speeds can be updated.

Step4: Determine whether the end condition is met. If number of iterations reaches maximum value or the particle fitness value meets the expected requirements, the process ends and the optimal result is obtained. Otherwise, return to step2.

4. case study

The proposed multi-objective optimization methodology for choosing the optimal disassembly sequence is illustrated with a case of optimizing drum washing machine disassembly sequence. In the process of optimizing the disassembly sequence of drum washing machine, the PSO algorithm is applied to solve the optimal disassembly sequence and Matlab is utilized to compile the program. In a calculation example, set the weighting coefficient of the objective function $\lambda_1=\lambda_2=0.5$, the inertia weighting coefficient $c_t$=0.5, and the acceleration constant $c_2$=1. The parameter settings of the particle swarm are as follows: the size of population - swarm size, is defined as 40, the maximum number of iterations - Max, is defined as 20 and the initial value of each particle is randomly selected when it meets the corresponding condition. In addition, in order to compare the results obtained by using PSO with those obtained by using the non-dominated genetic algorithm (NSGA-II), the parameters of NSGA-II are needed to be set as follows: its population size - swarm size is defined as 40, the maximum number of iterations - Max, is defined as 20 and the probability of its crossover and variation are respectively defined as 0.9 and 0.1. Finally, through the operations of PSO and NSGA-II, their convergence graph is shown in figure 2. It can be analyzed from figure 2 that PSO performs better compared with NSGA-II in the speed of solving and accuracy of results. Moreover, the partial optimization results obtained by the operations of PSO and NSGA-II are shown in table 1.

| Intelligent Algorithm | Number of iterations | Swarm size | Disassembly direction change times | Disassembly tool change times | Optimal or approximate optimal disassembly sequence | Fitness value |
|-----------------------|----------------------|------------|-----------------------------------|-------------------------------|---------------------------------------------------|---------------|
| PSO                   | 10                   | 40         | 9                                 | 11                            | 1-6-4-3-1-9-15-17-19-16-18-2                       | 1.23          |
| NSGA-II               |                      |            |                                   |                               | 11-1-2-4-3-6-9-15-17-19-16-18-10-12-13-20-21-14-8-5-7 | 1.74          |
| PSO                   | 20                   | 40         | 8                                 | 7                             | 6-1-4-3-2-2-21-20-16-18-11-12-15-17-19-9-5-13-10-14-8-7 | 0.48          |
| NSGA-II               |                      |            |                                   |                               | 11-6-16-10-3-15-9-17-19-16-1-8-4-2-16-20-21-14-8-5-7 | 0.99          |
| PSO                   | 30                   | 40         | 6                                 | 5                             | 6-11-16-13-12-17-19-1-2-1-4-3-20-9-18-5-10-14-8-7-15 | 0.47          |
| NSGA-II               |                      |            |                                   |                               | 6-16-11-12-15-17-19-1-2-1-4-3-20-9-18-5-10-13-14-8-7 | 0.68          |

Figure 2. Algorithm iteration convergence graph

Table 1. Partial optimization results obtained by the operations of PSO and NSGA-II
Table 2 shows the disassembly time and cost comparison results of the partial disassembly sequences between non-destructive disassembly method and hybrid disassembly method. Where \( T_m \), \( C_m \) respectively denote disassembly time and disassembly cost of the drum washing machine in the non-destructive disassembly mode, and \( T_m \), \( C_m \) respectively denote disassembly time and disassembly cost of the drum washing machine in the hybrid disassembly mode which is utilized in this paper.

Table 2. Comparison of disassembly time and cost of partial disassembly sequences in two disassembly modes

| The optimal or near optimal disassembly sequences | \( T_m/\text{s} \) | \( C_m/\text{yuan} \) | \( T_m/\text{s} \) | \( C_m/\text{yuan} \) |
|-----------------------------------------------|----------------|----------------|----------------|----------------|
| 1-6-4-3-11-9-15-17-19-16-18-2-10-12-13-20-21-14-8-5-7 | 2936 | 14.28 | 2374 | 12.52 |
| 6-1-4-3-2-21-20-16-18-11-12-15-17-19-9-5-13-10-14-8-7 | 2874 | 13.95 | 2168 | 11.36 |
| 6-11-16-13-12-17-19-1-2-4-3-20-21-9-18-5-10-14-8-7-15 | 2842 | 13.97 | 2053 | 10.49 |

According to the table 2, We can draw some conclusions. Firstly, the optimal disassemble sequence of drum washing machine is 6-11-16-13-12-17-19-1-2-4-3-20-21-9-18-5-10-14-8-7-15. Then, when the optimal disassemble sequence and the hybrid disassembly mode are utilized to disassemble the drum washing machine, the disassembly time \( T_m \) is 2053s and disassembly cost \( C_m \) is 10.49 yuan. When the optimal disassemble sequence and the non-destructive disassembly mode is applied to disassemble the drum washing machine, the disassembly time \( T_m \) is 2842s and disassembly costs \( C_m \) is 13.97 yuan. Finally, Compared to the non-destructive disassembly mode, the hybrid disassembly mode utilized in this paper can reduce the cost by 24.9% and improve the efficiency by 27.8%.

5. Conclusions

In this paper, a multi-objective disassembly sequence optimization model is proposed considering the quality uncertainty of EOL products. The model is targeted at two indicators, namely disassembly time and costs to maximize the disassembly profit. Where the quality evaluation is achieved by integrating the Weibull distribution and ANN to assess the remaining life of EOL products components. The PSO algorithm is designed to solve the proposed model so as to converge to the optimal or near-optimal disassembly sequence. A disassembly case of drum washing machine is presented to verify the feasibility and superiority of the proposed methodology. The research results can be utilized to guide the decision makers to choose the optimal disassembly sequence while conducting the disassembly work of EOL products. In the future, with the stricter environmental governance and the increasing awareness of corporate environmental responsibility, multi-objective optimization should not only focus on the economic dimension, but also on the environmental dimension to achieve the coordinated development of economic growth and environmental protection. In addition, with the development of modelling and optimizing methods, this paper can be extended by utilizing more advanced disassembling sequence planning model and optimizing methods.

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