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A Dynamic Information Transfer and Feedback Model for Reuse-oriented Redesign of Used Mechanical Equipment

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Abstract

The intricate coupling relationship among the used parts make the reuse-oriented redesign process very complex, leading to the incompatible optimization between the used parts and used mechanical equipment. To this end, a dynamic information transfer and feedback method is proposed. In this method, the structure coupling model is established to characterize the relationship of parts. Remanufacturing cost, energy consumption and material consumption are taken as the redesign objectives. In accordance with these objectives and its constraints, a dynamic information transfer and feedback model (DITF) is adopted to achieve collaborative optimization between used mechanical equipment and used parts. An adaptive Teaching-Learning-Based Optimization (A-TLBO) algorithm is used to solve this model. Finally, a case in point is that a used machine tool (model C6132) is adopted to validate feasibility and effectiveness of the proposed method.

*Keywords:*Reuse-oriented redesign; Remanufacturing; Information transfer and feedback; Coupling; Teaching-Learning-Based Optimization

1. Introduction

Reuse-oriented redesign is a significant problem of implementing remanufacturing waste products. The redesign of used products is similar to new products design, which has a direct effect on product remanufacturing efficiency, quality, cost, resource efficiency and environmental pollution. Reuse-oriented redesign of used mechanical equipment is an innovative design process for new remanufactured product, in which used mechanical equipment and used parts are taken as the workblanks with an aim of reusing material and added value largely [1-3]. Compared to design of new mechanical equipment, reuse-oriented redesign is based on the remanufacturability of used mechanical equipment and considers the effect of the redesign of structure and process on quality, performance and second service life of remanufactured parts. Reuse-oriented redesign is a basis of remanufacturing and it has become a hot research topic of academic and industrial communities.

Currently, plenty of literature is focused on reuse-oriented redesign methods. For instance, Du et al. proposed a reuse-oriented redesign method based on Axiomatic theory and Quality Function Deployment (QFD) to normalize and optimize redesign process [4]. Zwolinski et al. developed a design tool that combines remanufacturing and production to facilitate designers implementing the initial product design [5]. Song et al. proposed an average life span of parts and multiple matching patterns and methods to achieve the optimal utilization of parts [6]. Cao et al. proposed a reuse-oriented redesign method based on machine tool function and structure characteristics for remanufacturing used machine tools [7]. The aforementioned literature illustrates that the current redesign methods take the maximal reuse of used resource and maximal life span of remanufactured product as the objectives

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to creatively conduct redesign process based on the structure of the used product. While few of them can effectively solve the complex coupling problem between the redesign of whole equipment and used parts. For instance, when the design of parts achieves the optimum, the redesign of the whole equipment may not reach the optimum, resulting in that the unreliable redesign schemes. On the grounds that, a structure coupling model is established to characterize the relationship of parts, and a dynamic information transfer and feedback model is built to achieve the goal of synthetical redesign from equipment level to component level and then to part level.

Compared to conventional design, reuse-oriented redesign is more complex and more factors should be considered due to the uncertainties in terms of quality condition of used mechanical equipment, remanufacturing process and market competition for remanufactured mechanical equipment. On top of that, the reuse-oriented redesign of used mechanical equipment is based on the existing used product, which is restricted by complex spatial structure and more parameters. To improve redesign efficiency, a couple of optimization algorithms such as genetic algorithm, particle swarm optimization and artificial bee colony are used to support complex problems solution. In detail, Núñez Cruz et al. adopted genetic algorithm to optimize design of humanoid robot based on the Limit Cycle Walking stability criterion [8]. Liu et al. developed a reliability-based design optimization (RBDO) method to tackle the lightweight design of battery box, in which particle swarm optimization was used to optimize design parameters [9]. While these algorithms are limited to the solution quality and speed when dealing with large scale complex multi-objective optimization problems. Based on this, the A-TLBO method is presented to optimize the redesign process. The use of adaptive of teaching factor increases the global exploration ability, embodying its advantages in solution quality and speed [10, 11].

Overall, the current reuse-oriented redesign method for used mechanical equipment is short of the cooperation among the whole equipment, components and parts. On the grounds that, a multi-objective optimization redesign method based on dynamic information transfer and feedback is proposed. The novelty of this research lies in: 1) characterization of structural coupling of parts. A structural coupling model is established to characterize relationship of parts; 2) information transfer and feedback among equipment, components and parts. The dynamic information transfer and feedback model (DITF) is established to support the reuse-oriented redesign of used mechanical equipment; 3) adaptive optimization. The A-TLBO algorithm is presented to solve complex multi-objective optimization problems during the reuse-oriented redesign process. The effectiveness and feasibility are demonstrated by a case to provide a theoretical support for guaranteeing the quality of remanufactured mechanical equipment. The method is to enhance the core competitiveness of remanufacturing business.

2. Methodology

Reuse-oriented redesign (also called redesign) of used mechanical equipment aims to obtain the optimum design scheme. Firstly, a structure coupling model is established to characterize the relationship of parts. Then, remanufacturing cost, energy consumptionand material consumption are taken as the redesign objectives. Based on these objectives and its constraints, the dynamic information transfer and feedback model is presented to achieve the collaborative optimization between the whole equipment and parts. Finally, the A-TLBO method is used to solve this model. The process model is shown in Fig. 1.

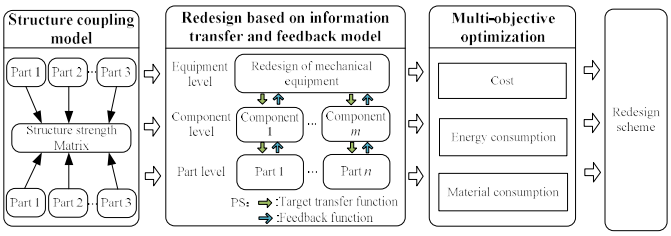

Fig. 1. Flow chart of reuse-oriented redesign of used mechanical equipment.

2.1. Structure coupling model of parts

There has a mutual relationship among the parts in an equipment, and the spatial structure between the adjacent parts may not only have an impact on its strength, but impacts the strength of other structures. The minimum strength of structures that are liable to failure determines the whole strength of parts [12]. To characterize the complex coupling of spatial structure of parts, simulation is adopted to analyze the structural strength with a specific spatial structure of parts. The structural coupling model of parts can then be established via a matrix, which is shown in Eq. (1).

$$SC = \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2n} \\ \vdots & \vdots & f_{ij} & \vdots \\ f_{m1} & f_{m2} & \cdots & f_{mn} \end{bmatrix} \tag{1}$$

Where f_{ij} represents the mapping function between structural strength and spatial structure between the adjacent parts. The row of the matrix represents the spatial structure strength influence rules of different parts from the adjacent parts. The column represents the structure strength impact rules of the certain part from the adjacent parts. Eq. (1) reflects the structure coupling relationship of parts, characterizing the rules between structural strength and spatial structure, which provides a guide for optimizing and designing the structure of parts.

2.2. Mechanism of information transfer and feedback model

Used mechanical equipment is consisted of many components and parts. Due to the restrictions in terms of space structure, parameters and function between parts, the redesign of components and parts becomes very complex. Based on this, the dynamic information transfer and feedback model is presented to transfer the redesign objectives from equipment level to component level and to part level. Transfer

objective and feedback functions are established to achieve a dynamic adjustment of redesign objectives. With several time iteration, the redesign from whole equipment to components and to parts can be implemented, and the method is shown in Fig. 2.

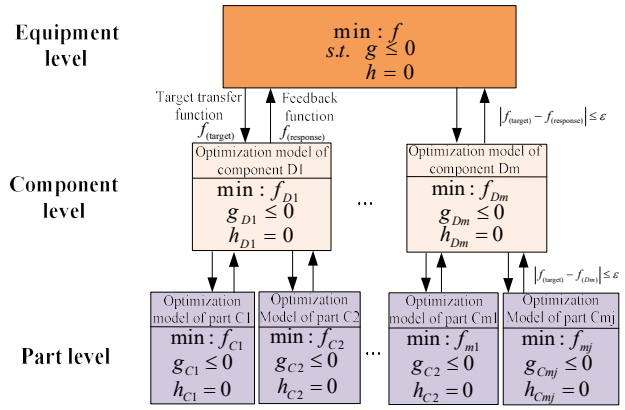

Fig. 2. Structure of reuse-oriented redesign of used mechanical equipment.

2.3. Multi-objective optimization model

To increase redesign efficiency, the multi-objective optimization model and its constraints are established. The remanufacturing companies focus on economic profits and environmental benefits. Therefore, remanufacturing cost, energy consumption and material consumption are taken as the objectives. The mathematical model and its constraints are shown as follows.

$$\begin{cases} \min C = \sum_{i=1}^{N}(C_{P1}^{*}+C_{T1}^{*})\cdot t_{di}+\sum_{j=1}^{a}C_{Nj}^{*}+\sum_{k=1}^{c}C_{M}^{*}\cdot t_{rk}+\sum_{m=1}^{Q}(C_{P2}^{*}+C_{T2}^{*})\cdot t_{am} \\ \min E = \sum_{k=1}^{c}E_{k} \\ \min M = \sum_{j=1}^{a}m_{1j}+\sum_{k=1}^{c}m_{2k} \end{cases} \tag{2}$$

s.t.

$$\sum_{i=1}^{N}(C_{P1}^{*}+C_{T1}^{*})\cdot t_{di}+\sum_{m=1}^{N}(C_{P2}^{*}+C_{T2}^{*})\cdot t_{am}<C<\sum_{i=1}^{N}(C_{P1}^{*}+C_{T1}^{*})\cdot t_{di}+\sum_{j=1}^{N_0}C_{Nj}^{*}+\sum_{m=1}^{M}(C_{P2}^{*}+C_{T2}^{*})\cdot t_{am}\le 0.5C_0 \tag{3}$$

$$0\le c<N;0\le a<M;0<N_0<M \tag{4}$$

$$c\cdot E_{0\min}<E<c\cdot E_{0\max}\le 0.4E_0 \tag{5}$$

$$0\le m_1<M;0\le m_2<M;0<M\le 0.3M_0 \tag{6}$$

Where C and N represent the remanufacturing cost of used mechanical equipment and the total number of parts of mechanical equipment respectively; C_{P1}^{*} and C_{T1}^{*} represent the unit labor cost and tool cost for disassembly operations respectively; t_{di} and C_{Nj}^{*} represent the mean disassembly time for the *ith* part and the cost of purchasing new parts respectively; a and c represent the total number of new parts and parts that need to be remanufactured respectively; C_{M}^{*} and t_{rk} represent the unit remanufacturing cost and mean time to remanufacturing the *kth* used part respectively; C_{P2}^{*} and C_{T2}^{*} represent the unit labor cost and tool cost for reassembly operations respectively; t_{am} and Q represent the mean time to reassembly the *mth* part and the total number of parts of the equipment respectively; M, m_{1j} and m_{2k} represent the material consumption for remanufacturing, the material weight of the *jth* new partand the material consumption for remanufacturing the *kth* used part respectively. Eq. (3) represents that the total remanufacturing cost should be no less than disassembly and reassembly cost when the used equipment does not need remanufacturing processing operations and should be no more than the cost of new components without remanufacturing processing operations, and should be no more than the 50% cost of new equipment. N_0 represents the total number of new components for used equipment. Eq. (4) represents that the number of components that need to be remanufactured. This should be less than the total number of parts of the remanufactured equipment. Eq. (5) represents that energy consumption during the remanufacturing processing. This should be no less than the minimum and should be no more than the maximum processing energy consumption of used equipment and should be no more than 40% of new product energy consumption. Eq. (6) represents that the quality of new components and processed components. This should be less than the total quality of the whole remanufacturing material. M_0 represents the quality of the type of mechanical equipment, and the total material consumption should be no more than 30% of total quality of new equipment.

3. Multi-objective optimization solution

Currently, many algorithms such as genetical algorithm, particle swarm optimization and artificial bee colony are used to solve multi-objective optimization problems. While these algorithms are limited to solution quality and speed for large scale optimization problems. Based on this, the A-TLBO method is adopted. This method simulates a process that students learn from the teacher through adjusting teaching factor, which is used to solve large scale complex multi-objective optimization problems. The process of this algorithm is shown in Fig. 3.

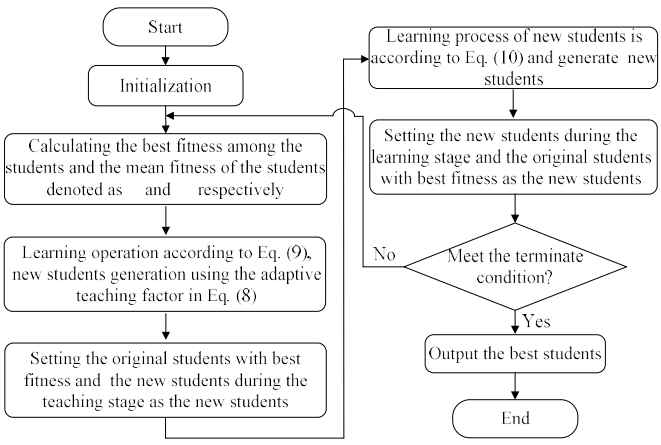

Fig. 3. Flow chart of A-TLBO algorithm.

3.1. Teaching stage

When conducting the ith iteration, the M_i is set as the mean value of the student score and T_i as the teacher. The teaching process is in accordance with the following difference as showed in Eq. (7).

$$Difference = r_i \cdot \left(M_{new} - TF \cdot M_i \right) \tag{7}$$

Where r_i represents the random number of [0, 1]; TF represents the teaching factor and its value is dependent on the Eq. (8).

$$TF = round\left[1 + rand\left(0,1\right)\right] \tag{8}$$

The value after teaching is determined by the Eq. (9):

$$X_{new,i} = X_i + Difference \tag{9}$$

Where X_i and $X_{new,i}$ represent the ith student's knowledge degree before and after teaching respectively.

If $f\left(X_{new,\mathrm{i}}\right) < f\left(X_{\mathrm{i}}\right)$, then the X_{i} is replaced by $X_{new,\mathrm{i}}$ and the individuals are updated.

3.2. Learning stage

In this stage, students learn and update according to the difference between itself and other students. The learning process is presented as follows:

$$X_{new,\mathrm{i}} = \begin{cases} X_i + r_i \cdot \left(X_i - X_j\right), f\left(X_i\right) < f\left(X_j\right) \\ X_i + r_i \cdot \left(X_j - X_i\right), f\left(X_i\right) > f\left(X_j\right) \end{cases} \tag{10}$$

Where r_i represents a random number of [0,1], X_i and $X_{new,i}$ represent the knowledge degree of the ith student before and after teaching respectively, X_j represents the knowledge degree of the jth student before teaching.

If $f\left(X_{new,i}\right) < f\left(X_i\right)$, then the X_i is replaced by $X_{new,i}$ and the individuals are updated.

3.3. Teaching factor

In TLBO algorithm, the teaching factor (*TF*) determines the mean value. In the pre-teaching stage, students and teachers are different because the students are strange for the knowledge they will learn. Thus, studying efficiency of students is high and they can learn a lot quickly. With time going by, students have learnt a lot of knowledge and the difference between students and teachers decreases gradually. The studying efficiency of students decreases and they can learn little knowledge slowly. In this algorithm, the smaller of *TF* means the higher exploration ability of the algorithm but the lower searching ability; the larger of *TF* means the lower exploration ability of the algorithm but the higher searching ability. To solve this problem, this paper improves the teaching factor and proposes the A-TLBO algorithm. *TF* value decreases linearly with the increase of iterations and the detail is shown as follows:

$$TF\left(t\right) = \frac{1}{2}\left[\left(TF_{\max} - TF_{\min}\right)\cdot\left(\frac{t_{\max} - t_i}{t_{\max}}\right)^2 + \left(TF_{\max} - TF_{\min}\right)\cdot\left(\frac{t_{\max} - t_i}{t_{\max}}\right)\right] + TF_{\min} \tag{11}$$

Where $TF_{\max}$ and $TF_{\min}$ represent the maximum and minimum teaching factor respectively, $t_{\max}$ and t_i represent the maximum iteration and the current iteration respectively.

4. Case study

Turning lathe is a very common machine tool applying to process axis parts, sleeve parts and other types of rotary workpieces, and the demands and inventory of it are very large. Used turning-lathe (model C6132) is taken as the example to demonstrate the effectiveness of the proposed redesign method. This type of lathe is mainly consisted of gearbox, feeding box, sliding box, turntable, tool rest, tailstock, lathe bed, light bar and screw bar. In accordance with the fault feature characterization method in reference [13], the failure mode, fault features and its damage volume can be obtained. According to the method in reference [14], the remaining service life prediction of these used parts can be obtained.

4.1. Redesign model based on dynamic information transfer and feedback model

In accordance with spatial structure analysis in Section 2.1, the coupling relationship between parts can be understood. Then the used turning-lathe (model C6132) is studied from equipment level, component level and part level. A dynamic information transfer and feedback model of this lathe are established as showed in Fig. 4.

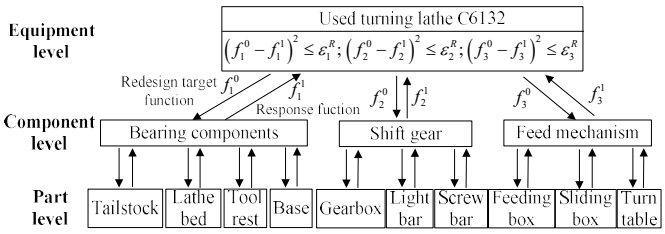

Fig. 4. Reuse-oriented redesign method for used turning lathe C6132

In Fig. 4, f_1^0, f_2^0 and f_3^0 represent the distributed redesign objectives from equipment level to component level, in which each objective contains remanufacturing cost, energy consumption and material consumption under a normalization operation and an equal weighted operation; f_1^1, f_2^1 and f_3^1 represent the response functions from component level to equipment level; $\varepsilon_1^R, \varepsilon_2^R, \varepsilon_3^R$ represent the response deviation capacity of bearing components, shift gear and feed mechanism respectively, determining by the range of redesign objectives.

4.2. Multi-objective optimization redesign of used turning lathe

Each experiment has undergone 50 iterations and Table 1 records 14 iterations of the experiment. According to Figs. 5-6, TLBO algorithm converges to 0.251 at 13 iterations, while A-TLBO algorithm converges to 0.245 at 11 iterations. Table 2 records the best global minimum, worst global minimum and mean global minimum in six experiments of the two algorithms. These three indicators reflect the performance of stability and result during the solution process.

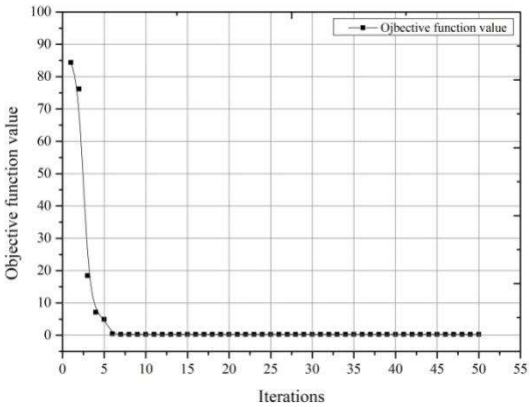

Fig. 5. Solution process of TLBO.

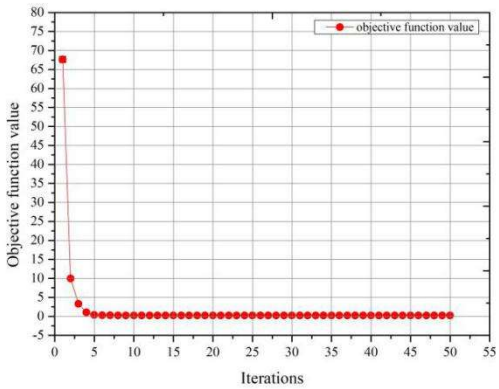

Fig. 6. Solution process of A-TLBO.

Table 1.Objectives value of two algorithm.

Algorithm	Iteration						
	1	2	3	4	5	6	7
TLBO	84.367	76.139	18.440	7.098	4.948	0.425	0.272
A-TLBO	67.628	9.974	3.277	1.073	0.386	0.295	0.273
Algorithm	Iteration						
	8	9	10	11	12	13	14
TLBO	0.257	0.255	0.254	0.253	0.252	0.251	0.251
A-TLBO	0.259	0.252	0.249	0.245	0.245	0.245	0.245

Table 2.Experimental result comparisons.

Algorithm	TLBO			A-TLBO		
Experiment	Best global minimum	Worst global minimum	Mean global minimum	Best global minimum	Worst global minimum	Mean global minimum
1	0.2512	69.7255	4.8056	0.2451	0.2491	0.2452
2	0.2512	69.7255	4.7043	0.2451	0.2491	0.2452
3	0.2512	69.7255	4.6075	0.2451	0.2491	0.2452
4	0.2512	69.7255	4.5148	0.2451	0.2491	0.2452
5	0.2512	69.7255	4.4259	0.2451	0.2491	0.2452
6	0.2512	69.7255	4.5116	0.2451	0.2491	0.2452

Through a comparison of the best global minimum and worst global minimum in Table 2, the two algorithms keep the stability of solutions, while the best global minimum of TLBO algorithm is distinctly different from other values. The mean global minimum of TLBO algorithm tends to decrease, while A-TLBO algorithm always keep stable and its solutions are better than TLBO algorithm. This is because the utilization of adaptive adjustment strategy speeds up the solution process and improves solution performance during the learning stage. Table 3 shows a comparison of redesign schemes and the corresponding results through two algorithms.

Table 3. Comparisons of redesign schemes and its results.

Algorithm	Redesign schemes of used parts				Cost/RMB	Energy/kJ	Material/kg
	Sliding box	Tool rest	Light bar	Screw bar			
TLBO	U	R	U	R	7756	13530	95.13
A-TLBO	U	U	R	R	7240	12705	82.68

Note: U represents upgrade; R represents remanufacturing.

In accordance with Table 3, compared to TLBO algorithm, A-TLBO algorithm can reduce cost up to 6.65%, energy consumption up to 6.10% and save material up to 13.1%. The proposed results show that A-TLBO algorithm is better than TLBO with respect to solution speed and quality.

5. Conclusion

A redesign method for used mechanical equipment is presented. Firstly, the complex coupling relationship between the whole equipment and components and parts is analyzed. The dynamic information transfer and feedback method is applied to cooperate and control the equipment redesign, components and parts objectives synergistically. Then, the multi-objective optimization model is established and A-TLBO algorithm is proposed to solve this model and obtain the optimal redesign scheme of used mechanical equipment. Finally, the used turning-lathe (model C6132) is taken as the example to demonstrate the effectiveness of the proposed method. Comparisons of the results demonstrate that the proposed redesign method could improve the solution speed,

stability and the quality, whilst could reduce remanufacturing cost, energy consumption and material consumption of used mechanical equipment. This research fails to consider some factors such as the whole life cycle carbon emission and government policy about remanufacturing used mechanical equipment. Taking these factors into consideration can be the future research direction.

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