

Modular Design Method for Active Recovery-Oriented Products

Zhang Chongyuan¹, Wei Wei², Zhan Yang², Li Rupeng³

1. Baotou Vocational & Technical college, Baotou 014035, Inner Mongolia, China

2. School of Mechanical Engineering and Automation, Beihang University, Beijing 100191, China

3. Shanghai Aircraft Manufacturing Co., Ltd., Shanghai 200436, China

Abstract: With the increase in environmental protection awareness, there has been a gradual increase in the demand for improving product recovery performance. Based on the traditional modular design method, this study integrates the idea of active recovery of products with the idea of modular design and proposes modularization criteria for the active recovery of products. It considers the active recovery, internal polymerization degree, and external coupling degree as the optimization targets for modular division. This paper proposes a clonal multi-objective optimization algorithm based on the mutation operation, optimized by removing antibodies that are more crowded. Finally, this method is applied to an internal combustion engine to compare its performance with that of a traditional non-optimized algorithm. The results prove the superiority of the improved immune algorithm.

Keywords: active recycling; multi-objective optimization; modular partition; improved immune algorithm; green design

1 Introduction

Since the reform and opening up of the economy, the Chinese manufacturing industry has been developing at a high speed, and it has achieved significant improvements on the technological front. The level of China's manufacturing industry is currently the fourth largest in the world after the United States, Germany, and Japan, and the export volume of the Chinese manufacturing industry accounts for approximately 20% of the world, ranking it first in the world. At the same time, 50% of the national financial revenue comes from the manufacturing industry [1]. Although China's manufacturing industry is developing rapidly, it is still far behind the above three countries in terms of recycling of scrap products. The objective for China's manufacturing industry is to realize both a prosperous economy and a green environment: "We want golden & silver mountains as well as green

hills and clear water." At present, when there is considerable advocacy for green development, the recycling of products has become a problem that China's manufacturing industry cannot ignore. The recycling of products not only reduces the damage to the environment but also recycles useful parts, thereby reducing the cost of production. To achieve this objective, we should consider not only the production process of a product during the initial stage of design but also its active end-of-life recovery. Thus, we introduce the idea of modular design, which involves combining a number of parts into a module and then combining that module with other modules to form a system. Based on the different methods of module division, the system can meet the different needs of the market. Through the idea of modular division, we can integrate the idea of product recycling into product design and take into account the recovery and utilization of the product when the product is designed and produced. Therefore,

Received date: February 15, 2018; **Revised date:** March 10, 2018

Corresponding author: Wei Wei, School of Mechanical Engineering and Automation, Beihang University, Lecturer. Major research fields include product family design, and digital design and manufacturing. E-mail: weiwei@buaa.edu.cn

Funding program: CAE Advisory Project "Research on Development Strategy of 'Internet Plus' Action Plan"(2016-ZD-03); Project of National Natural Science Foundation (51675028); Project of National Key R&D Plan (2017YFB1104200)

Chinese version: Strategic Study of CAE 2018, 20 (2): 042-049

Cited item: Zhang Chongyuan et al. Modular Design Method for Active Recovery-Oriented Product. *Strategic Study of CAE*, <https://doi.org/10.15302/J-SSCAE-2018.02.007>

the modular design method for active recovery-oriented products can effectively solve the problem of product handling during end of life, and deal with waste products reasonably to achieve green production.

Recently, many domestic and foreign experts and scholars have studied the recycling process of products nearing end of life. Li Fangyi and others [2] applied modularization technology to the development of green products, improving product maintainability, disassembly, recyclability, and performance. Gu and others [3] proposed the various phases of a product's life cycle and the corresponding design goals, and based on this, the modular design idea was extended to the full life cycle. Lu Yunwei [4] proposed the application of the same ratio to the modular classification of a product family, and combined it with the maintenance cycle, recovery relationship, and the possible green benefits of reuse. By analyzing the theory of disassembly and recovery in the life cycle of a product, Zeng Beichang [5] proposed a method of building a model through the modular dismantling of mixed model products. There have also been rich theoretical studies on the end of product life cycle for disassembly [6–10].

For products in their end-of-life period, recycling is the top priority. However, the recovery of products involves disassembly, recycling of available components, and the treatment of harmful components. It is difficult to quantify this as an inherent function. Some of the existing methods aim to solve the recycling problem during the end of the product life cycle; however, the efficiency of recovery with such methods is low. In the proposed product design method, we consider the active recovery of the product; combine the modular design idea with the idea of active recycling of the product; quantify the property of active recovery; consider the active recovery, internal polymerization degree, and external coupling degree as the optimization targets; and obtain a more reasonable product modularization. Finally, taking the traditional internal combustion engine as an example, the practicability of the method is verified.

2 Modular model based on active recovery of product during end of life

2.1 Definition of modular design for active recovery-oriented products

The modular design of products, in simple terms, involves combining the product design, product attributes, functions, and other factors into the modular design, so that multiple parts of the product are divided into different modules [11]. The modular design for active recovery considers the active recovery and reuse of products in the modular design, so that the product can be completely recovered and reused at the end of life, thus solving the problems of environmental pollution and energy consumption to a great extent, in order to realize green production.

2.2 Modularization criteria for active recovery-oriented products

The process of active recovery of a product is complicated. The three main aspects of the process are as follows: ① reuse and remanufacture of components; ② recovery of materials that can be used; and ③ treatment of non-recyclable waste. The division of a product into modules during the design stage (considering active recovery) must follow the following four basic principles.

2.2.1 Easy disassembly criterion

Generally, the process of disassembling a product is not smooth because the disassembly problem is not considered during the initial design. This causes the parts to be damaged or unable to be disassembled during the disassembly process. In order to solve this problem, an easy dismantling criterion is proposed by defining the disassembly process factor $I_d(i, j)$:

$$I_d(i, j) = W_{dc} \frac{\sum_{h=1}^n I_{dc}(i, j)}{n} + W_{db} I_{db}(i, j) \quad (1)$$

where W_{db} is the weight value of the spatial constraint relation; W_{dc} is the weight of the disassembly relationship; $W_{dc} + W_{db} = 1$; $I_{dc}(i, j)$ is the spatial constraint relation value; $I_{db}(i, j)$ is the assembly relation value; h is the serial number of the connection point; and n is the number of connected relations.

2.2.2 Active recovery processing criterion

In the initial stage of product design, we should consider the reuse of components, the recovery of parts, and the processing methods for parts that cannot be recycled after the product is abandoned. In general, the treatment methods include methods such as centralized incineration and others. Through the process of module partition, we can take the above factors into account using the active recovery processing criterion. The interactive factor that defines active recyclability is

$$I_{RP}(i, j) = \frac{\min(RP_i, RP_j)}{\max(RP_i, RP_j)} \quad (2)$$

where RP_i and RP_j are the recovery values of parts i and j , respectively.

2.2.3 Economic criterion

According to the economic criterion, the product needs to be divided into modules based on an evaluation of the recovery value of the product in advance, so that the product can be recovered more reasonably and effectively when the parts are recovered, thus reducing the amount of labor and improving the recovery income. The economic criterion for active recovery, $I_V(i, j)$, is given as

$$I_V(i, j) = \frac{\min(V_p, V_j)}{\max(V_p, V_j)} \quad (3)$$

where $I_V(i, j)$ is the product value ratio between two products; and V_i and V_j are the recovery values for parts i and j , respectively.

2.2.4 Environmental norms

One of the important benefits of the active recovery of a product is the reduction in waste of resources and the production of harmful substances so that the impact of the product on the environment is minimized. Therefore, we introduce the ecological index (EI) of active recovery to evaluate the recovery value of the material in terms of the module value. The material is divided into parts that should be recovered actively and parts that can be discarded. The definition of the environmental interaction factor, $I_e(i, j)$, is as follows:

$$I_e(i, j) = \frac{\min(|EI_i|W_i, |EI_j|W_j)}{\max(|EI_i|W_i, |EI_j|W_j)} \quad (4)$$

where $I_e(i, j)$ represents the EI ratio between modules i and j ; EI_i and EI_j represent the recovery indices of parts i and j ; and W_i and W_j represent the weights of i and j , respectively.

The above four principles of active recovery modularization are analyzed. By using the relevant definition of active recovery, the attributes of any two parts are quantized and analyzed, and the attribute values of active recovery are obtained:

$$I(i, j) = \lambda_{RP}I_{RP} + \lambda_dI_d + \lambda_vI_v + \lambda_eI_e \quad (5)$$

where λ_{RP} , λ_d , λ_v , λ_e are the weighting factors of the corresponding criteria, and different weighting factors can be given as per the requirements during design.

3 Module division for active recovery-oriented products

3.1 Optimization goal of module division

3.1.1 Establishing the interrelated matrix between parts

In a product, there are functional and structural relationships between different parts and components. We use a fuzzy relationship to express the similarity between two parts, and the range of values is [0,1].

The comprehensive interrelated matrix is given by

$$\begin{bmatrix} \xi_{1,1} & \xi_{1,2} & \cdots & \xi_{1,q} & \cdots & \xi_{1,M_{NM}} \\ \vdots & \vdots & & \vdots & & \vdots \\ \xi_{N_1,1} & \xi_{N_1,2} & \cdots & \xi_{N_1,q} & \cdots & \xi_{N_1,M_{NM}} \\ \vdots & \vdots & & \vdots & & \vdots \\ \xi_{i_p,1} & \xi_{i_p,2} & \cdots & \xi_{i_p,q} & \cdots & \xi_{i_p,M_{NM}} \\ \vdots & \vdots & & \vdots & & \vdots \\ \xi_{M_{NM},1} & \xi_{M_{NM},2} & \cdots & \xi_{M_{NM},q} & \cdots & \xi_{M_{NM},M_{NM}} \end{bmatrix} \quad (6)$$

where ξ_{i_p,j_q} is the comprehensive association degree between part p in module M_i and part q in module M_j .

3.1.2 Internal polymerization degree of product parts

The degree of internal polymerization is defined as an index of similarity between different parts of the same module. A greater internal polymerization degree indicates greater similarity between the components in the module. Therefore, it is better to have a higher degree of internal polymerization. The degree of internal polymerization is often used as a criterion for module partition; therefore, a mathematical model is created for the relative polymerization degree between components.

The internal polymerization degree can be represented by the comprehensive correlation matrix of the parts. According to incidence matrix (6), the aggregation index of the cluster i in the product module is

$$O_i = \sum_{p=1}^{N_i-1} \sum_{q=p+1}^{N_i} \varepsilon_{i_p,j_q} / \sum_{p=1}^{N_i-1} \sum_{q=p+1}^{N_i} 1 \quad (7)$$

The internal polymerization degree of all modules in the product is

$$O_i = \sum_{i=1}^M (\sum_{p=1}^{N_i-1} \sum_{q=p+1}^{N_i} \varepsilon_{i_p,j_q} / \sum_{p=1}^{N_i-1} \sum_{q=p+1}^{N_i} 1) \quad (8)$$

where N represents the total number of parts in a module unit; B indicates the comprehensive correlation degree; and the lower corners p and q refer to the p -th and q -th parts.

3.1.3 Relative coupling degree of product parts

The external independence of the product refers to the degree of independence between different modules. The greater the external independence, the lower the degree of similarity between modules; the external independence is usually measured in terms of relative coupling, and is the most important index in the module partition. The independence of modules is generally evaluated by the function and structure of components. Next, a mathematical optimization model of the integrated relative coupling between modules is created.

According to incidence matrix (6), the relative coupling between module M_i and module M_j is

$$M_j^i = \sum_{p=1}^{N_i} \sum_{q=1}^{N_j} \varepsilon_{i_p,j_q} / \sum_{p=1}^{N_i} \sum_{q=1}^{N_j} 1 \quad (9)$$

The degree of relative coupling among the modules is as follows:

$$M = \sum_{i=1}^{M-1} \sum_{j=i+1}^M (\sum_{p=1}^{N_i} \sum_{q=1}^{N_j} \varepsilon_{i_p,j_q} / \sum_{p=1}^{N_i} \sum_{q=1}^{N_j} 1) \quad (10)$$

The degree of relative coupling between module M_i and M_j is expressed in formula (10), which indicates the relative coupling between the modules.

3.1.4 Active recovery degree

The active recovery modular calculation of a product involves dividing the product into different modules according to

the product's active recovery criteria, easy disassembly criteria, economic criteria, and environmental standards, so that the maximum active recovery of the product is achieved and the product can be recovered well. Let N be the total number of parts of the product and M be the number of units of the product module. N_i refers to the number of parts in the i -th module M_i , where the value of i ranges from 1 to M . We need to calculate only the interaction factors of the corresponding criteria and obtain the weight of each criterion through expert scoring. In this way, the relative active recovery matrix for the entire product family can be obtained as follows:

(1) Establish the part relative active recovery matrix:

$$[I] = \begin{pmatrix} \gamma_{1,1_1} & \gamma_{1,1_2} & \cdots & \gamma_{1,1_{j_q}} & \cdots & \gamma_{1,1_{M_{NM}}} \\ \vdots & \vdots & & \vdots & & \vdots \\ \gamma_{1_{N_1},1_1} & \gamma_{1_{N_1},1_2} & \cdots & \gamma_{1_{N_1},j_q} & \cdots & \gamma_{1_{N_1},M_{NM}} \\ \vdots & \vdots & & \vdots & & \vdots \\ \gamma_{i_p,1_1} & \gamma_{i_p,1_2} & \cdots & \gamma_{i_p,j_q} & \cdots & \gamma_{i_p,M_{NM}} \\ \vdots & \vdots & & \vdots & & \vdots \\ \gamma_{M_{NM},1_1} & \gamma_{M_{NM},1_2} & \cdots & \gamma_{M_{NM},j_q} & \cdots & \gamma_{M_{NM},M_{NM}} \end{pmatrix} \quad (11)$$

where r_{i_p,j_q} is the comprehensive recovery between the p -th part in module M_i and the q -th part in module M_j .

(2) Establish a mathematical optimization model for integrated relative active recovery among the modules.

The relative active recovery of module M_i and module M_j is

$$I_j^i = \frac{\sum_{p=1}^{N_i} \sum_{q=1}^{N_j} r_{i_p,j_q}}{\sum_{p=1}^{N_i} \sum_{q=1}^{N_j} 1} \quad (12)$$

The comprehensive relative active recovery degree among the modules is as follows:

$$I = \sum_{i=1}^{M-1} \sum_{j=i+1}^M \left(\frac{\sum_{p=1}^{N_i} \sum_{q=1}^{N_j} r_{i_p,j_q}}{\sum_{p=1}^{N_i} \sum_{q=1}^{N_j} 1} \right) \quad (13)$$

where I_j^i is the relative active recovery degree between module cluster M_i and module cluster M_j ; and I is the comprehensive relative active recovery degree among the cluster modules.

3.2 Module division based on the NICA-II

In the design of a product based on module division, there are three optimization objectives—active recovery degree, internal aggregation, and external independence. Therefore, the problem is a multi-objective optimization problem. The mathematical translation of this concept is as follows:

$$\begin{cases} F(X) = [I(X), M(X), O(X)], \\ \begin{cases} g_j(x) \leq 0, j=1, 2, 3, \dots, J \\ h_k(x) = 0, k=1, 2, 3, \dots, K \end{cases} \\ X = (\delta_1, \delta_2, \dots, \delta_N) \\ \delta_i \in (0, M) \end{cases} \quad (14)$$

where $I(X)$ and $O(X)$ are the maximization objective functions; $M(X)$ is the minimization objective function; $h_k(x)$ is a constraint in the optimization problem; K is the number of constraints; $g_j(x)$ is another constraint; and j is the number of constraints.

In order to solve this problem, we propose an original method based on an improvement in the multi-target optimization algorithm. The artificial immune system [12] is a new computational intelligence method associated with the biological immune system. The immune algorithm can efficiently solve many mathematical problems; however, it has some limitations. Based on a previous immune algorithm, Coello and others [13] developed the multi-objective immune system algorithm (MISA). The MISA is widely used in multi-objective optimization problems because of its convergence speed and solving precision; however, it has low efficiency when solving a number of multi-objective optimization problems divided into modules. Therefore, we have improved the traditional method.

Fig. 1 shows the flow chart of the novel immune clonal algorithm II (NICA-II) for multi-objective problems in modular division.

- (1) Initialize population;
- (2) Input the basic parameters of the algorithm, including initial algebra $i = 0$, antibody group size N , clone size M , and maximum iteration number G ;
- (3) Randomly generate an antibody group with a size $N(i)$, and perform the immune clone operation, $N^{(1)}(i) = I_C(N(i))$;
- (4) Carry out immune gene operation and complete cross-variation, $N^{(2)}(i) = I_C(N^{(1)}(i))$;
- (5) The antibody was divided into a dominant antibody and a non-dominant antibody. The non-dominant antibody in the modular antibody group was selected to update the antibody group $N^{(3)}(i) = I_S(N^{(2)}(i))$;
- (6) The calculation result obtained $N^{(4)}(i) = I_{RS}(N^{(3)}(i))$ and the new target-function value matrix $F(N^{(4)}(i))$;
- (7) It is judged that when i is greater than j , it directly outputs the module antibody group $A(i)$ and its objective function matrix $F(N(i))$; when i is less than j , let

$$\begin{cases} N(i+1) = N^{(4)}(i) \\ F(N(i+1)) = F(N^{(4)}(i)), i = i+1 \end{cases}$$

and return to step (2) with the result.

In order to achieve a global search, the algorithm proposed in this paper uses a cloning operation, in which the mutation operation is the main part, and the 4-bit and 2-digit form is used to counter the gene value of the antibody and its gene position. In this case, the internal combustion engine has 19 parts, of which five are coded 0011; while $p=0.2$, the variation is 0010. The compilation process is shown in Fig. 2.

In order to ensure the uniformity of the Pareto-optimal solution distribution, a modular clonal selection operation and a module-element antibody-group-update operation are adopted.

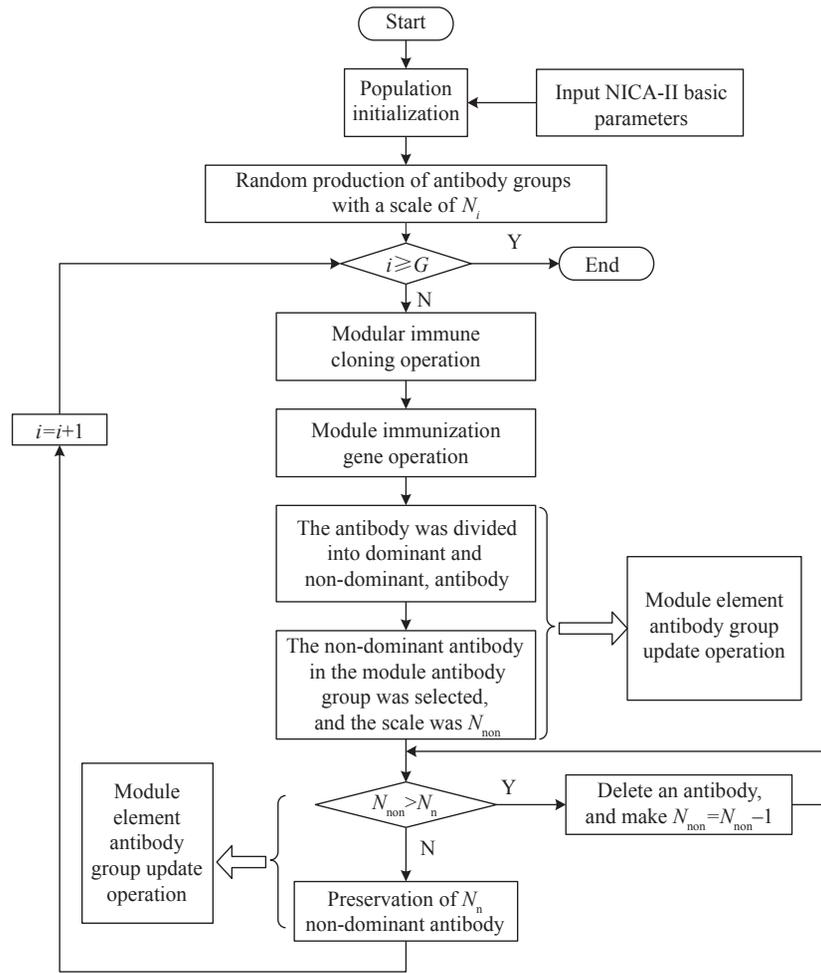


Fig. 1. NICA-II flow chart.

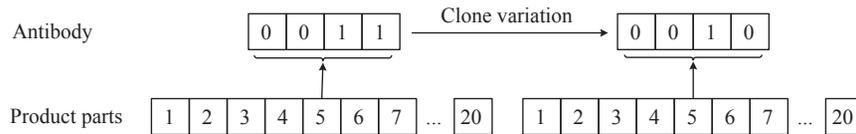


Fig. 2. Schematic diagram of antibody coding and clone variation of internal combustion engine parts.

The former effectively accelerates the convergence rate, and the latter removes a more crowded antibody to ensure uniformity.

4 Example of module division of traditional internal combustion engine

The internal combustion engine is a type of power machine. It transforms the chemical energy stored in the fuel into kinetic energy. Its invention promoted the production of cars, and it has an important place in people’s lives. However, due to the imperfect recycling process, the problem of environmental pollution caused by a large number of discarded internal combustion en-

gines cannot be ignored. Fig. 3 shows a schematic diagram of a certain type of internal combustion engine. Table 1 lists the main parts of the simplified internal combustion engine.

First, based on the four active recovery criteria proposed in the previous section, each standard value of any two parts in the internal combustion engine is calculated. Then the conclusion is obtained by expert consultation. It is concluded that the difficulty of active recovery of the internal combustion engine mainly lies in the economic criterion and the easy disassembly criterion. The weight index between the criteria is: $\lambda = \{0.09, 0.33, 0.52, 0.06\}$, and according to formula (12), the normalized calculation of the active recovery matrix is as follows:

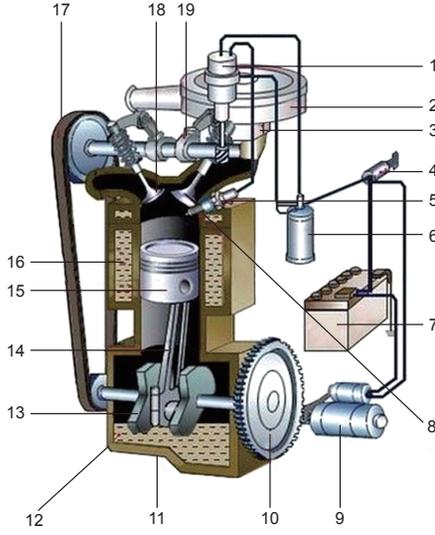


Fig. 3. A type of combustion engine.

Table 1. The main parts of a certain type of internal combustion engine after simplification.

Serial number	Part	Serial number	Part
1	Distributor	11	Oil sump
2	Air filter	12	Base cabin
3	Carburetor	13	Crankshaft
4	Ignition switch	14	Connecting rod
5	Spark plug	15	Piston
6	Ignition coil	16	Inner cabin
7	Battery	17	Timing chain
8	Intake valve	18	Exhaust valve
9	Engine	19	Camshaft
10	Free wheel		

When the module is divided, if the number of modules is the square root of the total number of parts, then the result of the module division is optimal. Therefore, the number of modules is set to be the square root of the total number of parts N , and the constraint conditions are

$$\begin{cases} i, j < \sqrt{N} + 1 \\ i, j > 0 \\ i, j \in 1, 2, \dots, n \end{cases} \quad (16)$$

where N represents the total number of parts; and i and j represent any two modules in the module division.

Taking δ_i as the optimization object, the objective function is the minimum degree of coupling between the internal combustion engines and the maximum degree of polymerization inside the module. The formula for the multi-objective optimization of internal combustion engines is as follows: $A(i) = \{a_1(i), a_2(i), \dots, a_{100}(i)\}$, where i represents the superposition algebra. Using the module division method of the NICA-II, the maximum iteration number G is 200, the mutation probability P is 0.2, the clone proportion R is 4, and the Pareto solution set is calculated as shown in Fig. 4.

In order to prove the superiority of the NICA-II, the non-dominated sorting genetic algorithm (NSGA) is introduced. From the comparison shown in Fig. 4, it is clear that the Pareto solution set of the NICA-II is more intensive.

From another perspective (as in Table 2), the average computing time of the two algorithms is compared under the same conditions. It is found that the average operation time of the NICA-II is shorter than that of the NSGA.

Finally, the number of non-dominated individuals of the two algorithms is compared (Table 3). Obviously, the results show that the number of NICA-II non-dominated individuals is greater, and the accuracy of the final solution set is relatively high.

The comparison shows that the improved algorithm has a considerable advantage over the previous algorithm.

Based on the results of the Pareto solution set and the char-

	K_1	K_2	K_3	K_4	...	K_{16}	K_{17}	K_{18}	K_{19}
K_1	1.000	0.511	0.207	0.542	...	0.524	0.813	0.778	0.629
K_2	0.511	1.000	0.686	0.388	...	0.366	0.534	0.314	0.538
K_3	0.207	0.686	1.000	0.779	...	0.518	0.486	0.487	0.760
K_4	0.542	0.388	0.779	1.000	...	0.789	0.354	0.218	0.163
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
K_{16}	0.524	0.366	0.518	0.789	...	1.000	0.596	0.747	0.213
K_{17}	0.813	0.534	0.486	0.354	...	0.596	1.000	0.515	0.311
K_{18}	0.778	0.314	0.487	0.218	...	0.747	0.515	1.000	0.109
K_{19}	0.629	0.538	0.760	0.163	...	0.213	0.311	0.109	1.000

Each module is based on the correlation degree matrix (6), which is used to obtain the degree of relative correlation between the components in the product; the results after normalization are as follows:

	K_1	K_2	K_3	K_4	...	K_{16}	K_{17}	K_{18}	K_{19}
K_1	1.000	0.381	0.523	0.451	...	0.534	0.457	0.158	0.379
K_2	0.381	1.000	0.221	0.775	...	0.076	0.241	0.531	0.624
K_3	0.523	0.221	1.000	0.146	...	0.239	0.819	0.437	0.136
K_4	0.451	0.775	0.146	1.000	...	0.356	0.165	0.325	0.277
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
K_{16}	0.534	0.241	0.819	0.165	...	1.000	0.247	0.186	0.394
K_{17}	0.457	0.241	0.819	0.165	...	0.247	1.000	0.569	0.724
K_{18}	0.158	0.531	0.437	0.325	...	0.186	0.569	1.000	0.253
K_{19}	0.379	0.624	0.136	0.277	...	0.394	0.724	0.253	1.000

A multi-objective optimization mathematical model for the internal combustion engine is established. Its objective function is

$$F(X) = \begin{cases} \min f_1(x) = I_j^i = \sum_{i=1}^{M-1} \sum_{j=i+1}^M \left[\frac{\sum_{p=1}^{N_i} \sum_{q=1}^{N_j} r_{i_p j_q}}{\sum_{p=1}^{N_i} \sum_{q=1}^{N_j} 1} \right] \\ \min f_2(x) = M_j^i = \sum_{i=1}^{M-1} \sum_{j=i+1}^M \left[\frac{\sum_{p=1}^{N_i} \sum_{q=1}^{N_j} r_{i_p j_q}}{\sum_{p=1}^{N_i} \sum_{q=1}^{N_j} 1} \right] \\ \min f_3(x) = O_j^i = \sum_{i=1}^{M-1} \sum_{j=i+1}^M \left[\frac{\sum_{p=1}^{N_i-1} \sum_{q=p+1}^{N_j} r_{i_p j_q}}{\sum_{p=1}^{N_i-1} \sum_{q=p+1}^{N_j} 1} \right] \end{cases} \quad (15)$$

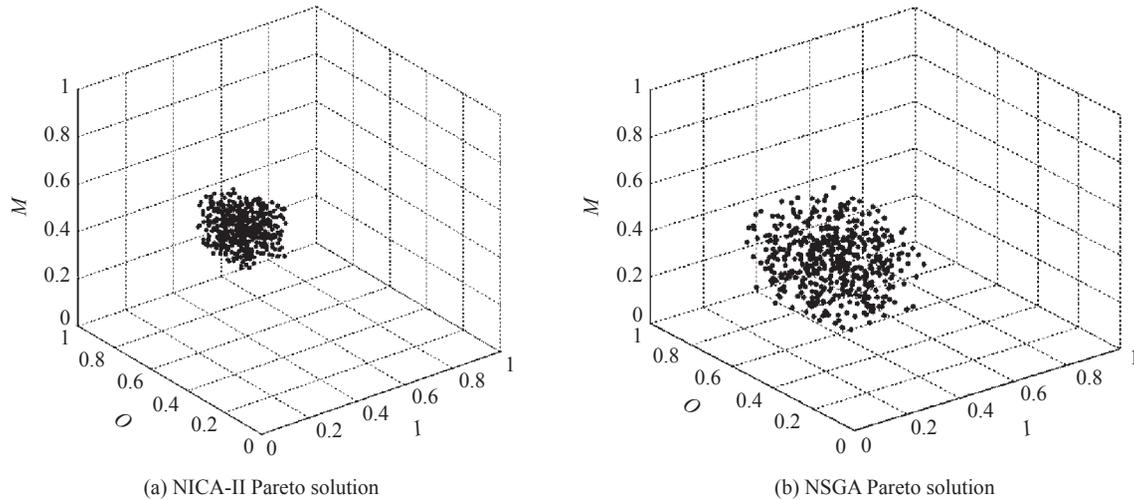


Fig. 4. Pareto solution.

Note: M is the degree of coupling, O is the degree of polymerization, and I is the degree of active recovery.

Table 2. Comparison of the average time for two algorithms.

algorithm	NICA-II	NSGA
Response t/s	75.34	94.24

acteristics of the product structure of the internal combustion engine, the comprehensive optimal solution of multi-objective programming for the modular unit of the internal combustion engine is obtained. The final module division scheme is composed of five modules: the power module {5,7,9,15}, the fuselage module: {8,11,16,18,12}, the switch module {4,6}, the transmission module {10,13,14,17,19}, and the auxiliary module {1,2,3}.

5 Conclusions

(1) We quantified the active recovery of a product into an optimization goal in the multi-objective optimization of module division, and constructed a mathematical model based on active recovery, degree of cohesion, and external coupling of the product.

(2) We used an improved immune genetic algorithm to solve the multi-objective optimization problem and compared it with the traditional immune genetic algorithm. The comparison results showed that the algorithm can effectively improve the convergence speed, and results in a more efficient multi-objective optimization problem.

References

- [1] Li S. An empirical study of the impact of structural change on manufacturing technology efficiency [D]. Dalian: Dalian University of Technology (Master's thesis), 2009. Chinese.
- [2] Li F Y, Liu G, Wang J S, et al. A study on fuzzy AHP method in

Table 3. Comparison of the number of non-dominant individuals for two algorithms.

Algorithm	NICA-II	NSGA
Number	37.6%	31.8%

- green modularity design [J]. *China Mechanical Engineering*, 2000, 11(9): 997–1000. Chinese.
- [3] Gu P, Hashemian M, Sosale S, et al. An integrated modular design methodology for life-cycle engineering [J]. *CIRP Annals-Manufacturing Technology*, 1997, 46(1): 71–74.
- [4] Lu Y W. Different than the modular green product family design method [D]. Shanghai: Shanghai Jiao Tong University(Master's thesis), 2013. Chinese.
- [5] Zeng B H. Research on design and technology of disassembly and recycling for household appliances [D]. Suzhou: Soochow University (Master's thesis), 2010. Chinese.
- [6] Su X W, Zuo F. Generation and optimization of the disassembly sequence of small household appliances based on hierarchical modularization [J]. *Journal of Hubei University of Technology*, 2017, 32(4): 6–11. Chinese.
- [7] Guo W X, Liu Z F, Liu G F, et al. Disassembly sequence planning based on modularization [J]. *Journal of Computer-Aided Design & Computer Graphics*, 2005, 17(3): 498–504. Chinese.
- [8] Rong K Q, Xu X M, Li F H. Research on modular method of disassembly of products [J]. *Mechanical and Electrical Engineering Technology*, 2009, 38(4): 88–91, 132. Chinese.
- [9] Wei W, Peng G W, Ji J, et al. A product module partition method based on improved immune algorithm [J]. *Aeronautical Manufacturing Technology*, 2017, 527(8): 64–69. Chinese.
- [10] Hou K F, Li Z K. The method of product redesign for green modularization [J]. *Modern Manufacturing Engineering*, 2017 (12): 139–145. Chinese.
- [11] Muhamad A S, Deris S. An artificial immune system for solving production scheduling problems: A review [J]. *Artificial Intelligence Review*, 2013, 39(2): 97–108.

- [12] Quan N, Xia X H. Research on modular design of auto products for active recovery research [J]. *Logistics Technology*, 2014, 33(5): 148–150. Chinese.
- [13] Coello C A C, Cortes N C. Solving multiobjective optimization problems using an artificial immune system [J]. *Genetic Programming & Evolvable Machines*, 2005, 6(2): 163–190.