Matching technology of reducer bearing based on genetic algorithm

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Abstract. This paper presents a method of bearing selection for heavy reducer based on genetic algorithm. A mathematical model for the selection of key parts of bearing cap and adjusting ring is established, the coding mode of bearing cap and adjusting ring components is determined, the initial population is constructed, the fitness function is established, and the genetic calculations of selection, crossover and variation are carried out. Finally, through repeated experiments and 500 iterations, the value of the optimal objective function tends to be stable, and a good convergence effect is obtained. The assembly rate of the gearing cap-adjustment ring assembly is increased from the original 50\% to over 70\%, which greatly improves the assembly efficiency of heavy-duty reducer bearing, and thus the assembly cost is reduced, which is significant to the actual assembly of heavy-duty reducer.

1. Introduction
As the key basic transmission component of intelligent equipment, the reducer plays a decisive role in the heavy machinery of building materials, metallurgy and other industries, and the assembly performance of reducer is the bottleneck restricting the development of intelligent manufacturing equipment industry. In the process of assembly and adjustment, the existing heavy-duty reducer in China usually adopts the traditional manual installation method, relying only on the skills and experience of the workers to repeatedly test the installation until the assembly is qualified. This type of installation has large workload, long cycle, low efficiency, high cost, and it is difficult to meet the requirements of high quality and high precision product assembly. Among them, the assembly of the bearing cap and the adjusting ring is an important assembly and adjustment part of the reducer. It is necessary to adjust the thickness of the bearing cap and the adjusting ring by turning or grinding, and to repeatedly test the fitting in order to obtain a suitable bearing clearance, until qualified product assembly performance. If the bearing clearance is not satisfactory due to the low assembly accuracy, which will directly cause the failure of the reducer bearing assembly, then the gear shaft will become stuck or loose and affect the assembly performance of the reducer. If suitable matching parts can be selected according to the part size information measured before assembly, the final assembly products can not only meet the assembly requirements, but also shorten the assembly cycle and reduce the assembly cost.

In the process of assembling and adjusting mechanical products, parts selection will undoubtedly improve the assembly quality of mechanical equipment and ensure working performance. Through parts selection and matching, the quality of mechanical products can be improved without increasing
the machining accuracy [1]. Reasonable parts selection method to improve product accuracy, in order to maximize economic benefits [2]. The matching method of parts can be combined with intelligent algorithms such as genetic algorithm, ant colony algorithm and particle algorithm [3], to greatly improve the matching precision. And the automatic matching system of parts can be built by computer technology, finally the automatic matching of parts can be realized. Thereby the automation degree and the success rate of the assembly line of the mechanical equipment reducer can be improved. Kannan [4] et al. proposed to solve the single matching problem of single pair of parts with the minimum assembly deviation and the number of remaining parts of the assembly as the matching objective, and applied the genetic algorithm to the assembly line to obtain the most preferable matching scheme. Fei et al. proposed a new chromosome structure to describe the part fit scheme. This method is mainly suitable for the matching problem of the number of parts size group, and has achieved good matching effect. Liu Xiangyong [5] comprehensively considered the assembly qualification rate and the assembly precision rate of products, and proposed the concept of assembly precision index and assembly rate. Liu Jiandong [6], basing on the Taguchi quality loss model, improved the existing computer-aided selection assembly research, and compiled a multi-objective optimization genetic algorithm, which has the characteristics of maintaining population diversity.

Due to the large size and heavy weight of the large-scale reducer in engineering machinery, the strict assembly requirements, the low automation level, and the time-consuming and labor-intensive moving parts of the assembly components, the addition of parts selection in the reducer assembly process can not only reduce the number of parts moving and shorten the assembly cycle, but also the assembly precision of the components can be improved and the overall assembly performance of the reducer can be improved. In this study, aiming in the assembly process of the heavy-duty reducer bearing, the genetic algorithm is used to select the end cover and the adjusting ring assembly.

2. Establishment of mathematical model for bearing selection

2.1. Extraction of the end cap-adjustment ring assembly dimension chain

The extraction procedure of the end cap-adjustment ring component assembly dimension chain are as follows:

2.1.1. Determination of closed loop. Due to the assembly process of the end cap-adjustment ring component, this study mainly considers the accuracy requirements of the assembly clearance and specifies the reasonable assembly clearance range. Therefore, the assembly clearance, naturally formed after the assembly of the end cap and the adjustment ring, is used as a closed loop of the assembly dimension chain.

![Figure 1. The structure diagram of end cap - adjustment ring component](image)
2.1.2. Lookup of assembly dimension chain. It can be seen from the above that after the assembly clearance is determined as the closed loop, the parts forming assembly clearance are used as the starting point. And the influence needs to be carefully looked up in the assembly relationship of the structure of the end cap-adjustment ring according to the specified search direction, until the end of the same datum is found. The assembly is all parts of the gap until the same datum is finally found. Thus, between the two assembly datum planes, the dimensions and interrelationships of the relevant parts that affect the assembly are the constituent rings of the extracted assembly dimension chain.

The specific structure diagram of the input shaft drive assembly of the reducer, in which the End cap-adjustment ring component is located, is shown in Figure 1.

After analyzing the structure of the selected accessory, according to the assembly factors and the extraction method of assembly dimension chain that affect the performance of this reducer, the assembly dimension chain of the selected end cap-adjustment ring component was extracted, as shown in Figure 2 below.

![Figure 2. The assembly dimension chain of end cap-adjustment ring component.](image)

\[ A_0 \text{ - Closed ring, bearing clearance; } \\
A_1 \text{ - The thickness of the outer ring of the bearing; } \\
A_2 \text{ - The thickness of the adjusting ring; } \\
A_3 \text{ - The thickness of the end cap; } \\
A_4 \text{ - The thickness of the assembly side of the reducer.} \]

2.2. Part selection target

In this study, referring to the actual assembly conditions of the factory, the adopted selection target is the assembly success rate \( R(S) \) (\( S \) indicates the part matching scheme), so that, after the end cap-adjustment ring is matched, the remaining parts are the least and the assembly success rate is improved under the premise of meeting the assembly accuracy requirements specified by the reducer.

2.3. Assembly clearance calculation

![Figure 3. Rolling bearing clearance.](image)

The bearings used in this reducer assembly are the rolling bearings, and the axial clearance of the bearings is strictly regulated during the assembly of the reducer. It can be known from the specific structure of the reducer that the assembly clearance formed after the assembly of the end cap-adjustment ring is the axial clearance of the bearing of the structure, as shown in Figure 3. Therefore, after referring to the actual assembly situation and querying the assembly process file, we can obtain the assembly clearance requirements for the end cap-adjustment ring component. According to the
assembly dimensional chain relationship of the end cap-adjustment ring component extracted previously, the required clearance calculation formula is listed. The established clearance calculation formula will be used to calculate the assembly clearance of each individual in the assembly scheme, and then directly use the part matching mathematical model to evaluate the advantages and disadvantages of the part fit scheme.

As shown by the second dotted line of the structural drawing in Figure 1, it is assumed that the input shaft shoulder and the inner wall of the reducer are always kept in the same straight line, and the shoulder is in close contact with the inner ring of the bearing, which is the fixing of bearing inner ring. And as shown in Figure 4, the reducer bearing clearance is used as a closed loop in the assembly size chain, and the inner wall surface (contacting with the shoulder) is used as one end of the closed loop in the assembled dimension chain, and the surface of bearing outer ring is used as the other end. Taking the manufacturing error of the end cap and the adjusting ring into account, the actual thickness dimension measurement value is used as the raw data of the part selection ignoring the manufacturing error of other parts; the bearing outer ring surface is moved to the extreme position of the shoulder when the bearing clearance is 0, the bearing clearance of the reducer is the difference between the outer surface of the bearing and the limit position of the shoulder.

From the assembly dimension chain of end cap-adjustment ring component extracted previously, the closed loop $A_0$ is:

$$A_0 = A_4 - A_3 - A_2 - A_1$$

Therefore, referring to the assembly dimension chain, as can be seen from Figure 5, the bearing clearance of the reducer can be obtained. The assembly clearance formed after the assembly of the end cap-adjustment ring is:

$$\Delta = H - B - T - D = 42 - (T + D)$$

In which:

- $\Delta$ —— Bearing clearance, get from the table: 0.20mm ~ 0.30mm
- $B$ —— Bearing width, the bearing used in the reducer is a standard piece of single row tapered roller bearing, checked: $B = 86$mm
- $H$ —— Box thickness $H = 128$mm
- $T$ —— The thickness of the adjustment ring $31^{0.0}_{-0.20}$ mm
- $D$ —— The thickness of the end cap $11^{+0.10}_{-0.10}$ mm
2.4. Matching mathematical model
In this study, the mathematical model of the end cap-adjustment ring component selection is established by satisfying the assembly clearance in requirement accuracy and minimizing the number of unsuitable parts. As mentioned above, the number of end caps and adjusting rings that are matched with each other is as large as possible, which means the number of remaining parts is minimized, and the assembly success rate $R(S)$ is generally used ($S$ indicates a part matching scheme).

The assembly success rate refers to the proportion of that the number of fittings meeting the assembly requirements after the end cap and the adjusting ring are matched in the maximum number when all the parts participate in the matching. The mathematical expression is:

\[ R(S) = \frac{n_s}{N} \times 100\% \]

where:
- $n_s$: Number of assembly that meet requirements (successful matching)
- $N$: The maximum number when all parts can be assembled

Obviously, the assembly success rate $R(S)$ is a parameter value ranging from 0 to 1. The larger the value, the higher the assembly success rate, that is, the more the number of components meeting the assembly requirements after the matching, and the fewer the number of remaining parts that is not adapted. On the contrary, it means that the number of remaining parts is more after matching, and the utilization rate of parts is low. In this study, the number of the assembly whose clearance formed by the end cap and the adjustment ring can meet the assembly requirements can be directly calculated in the part assembly scheme, and the assembly success rate can be calculated.

3. Implementation of bearing selection algorithm

3.1. Correspondence between genetic concepts and parts selection
Genetic algorithm is an adaptive global optimization probability search algorithm that simulates the genetic and evolutionary processes of biological in the natural environment. In this study, the part selection is simulated into a biological evolution process to design a genetic algorithm of part selection. Therefore, in order to better apply the genetic algorithm to the part selection, we first need to combine the biological evolution process and algorithm characteristics to clarify the correspondence between the biological genetic concept and the matching problem of the part, as shown in Table 1 below. It is necessary to design a suitable genetic matching algorithm.

| biological genetic concepts | The meaning expressed in the part selection |
|----------------------------|---------------------------------------------|
| gene                      | Part coding                                 |
| individual                | A feasible selection solution               |
| Chromosome                | Code of selection solution                  |
| Population                | Randomly generated series of selection options |
| Individual fitness        | Value of the objective function             |
| Survival of the fittest   | The better the combination of the objective function values, the greater the possibility of retention |
| intersect                 | The two feasible options will be selected to obtain new combinations by exchanging partial components |
| variation                 | Change a component of an option             |

3.2. Coding method
In this study, when the N-piece end cap and the N-piece adjustment ring are selected, the part size serial number is a discrete point. Therefore, the natural number coding method can be adopted, and the part size serial number is directly used as the code of the part. This coding method of the parts is relatively simple. Specifically, the dimensions of each part of the same batch that needs to be selected
is measured, and the measured values of the parts of the batch are sequentially represented by natural numbers 1, 2, ..., N, and the part dimension numbers are formed. Take the end cap-adjustment ring as an example, when N = 10, assume that there are 10 end caps and 10 adjustment rings, measuring the part dimension of the end cap and the adjusting ring, and write the code number of part dimensions. The part coding result is shown in Table 2 below, and an adjustment ring chromosome code is: \{1, 2, 3, 4, 5, 6, 7, 8, 9, 10\}. The row corresponding to the code in the table represents a pair of paired parts. When the genetic operation is performed, the first column code sequence number remains unchanged, and only the second column code sequence number (adjustment ring chromosome code) is selected, crossed, mutated, etc.

| End cap part number | First column code | Adjustment ring part number | Second column encoding |
|---------------------|-------------------|-----------------------------|------------------------|
| DG001               | 1                 | TZH001                      | 1                      |
| DG002               | 2                 | TZH002                      | 2                      |
| DG003               | 3                 | TZH003                      | 3                      |
| DG004               | 4                 | TZH004                      | 4                      |
| DG005               | 5                 | TZH005                      | 5                      |
| DG006               | 6                 | TZH006                      | 6                      |
| DG007               | 7                 | TZH007                      | 7                      |
| DG008               | 8                 | TZH008                      | 8                      |
| DG009               | 9                 | TZH009                      | 9                      |
| DG0010              | 10                | TZH010                      | 10                     |

3.3. Constructing the initial population
According to the actual situation of participating parts and part coding method above, the population quantity is set to M, the adjustment ring population \( P = \{S_1, S_2, L, S_i, L, S_m\} \) is generated randomly. In the adjusted ring population, the size numbers of the parts included in each chromosome are generated by random numbers. When the initial population is set to 50, the initial population of the resulting adjustment loop is shown in Table 3 below.

| chromosome | The sequence adjustment ring dimensions number (encoding) |
|------------|---------------------------------------------------------|
| \( S_1 \)  | 3, 5, 6, 10, 9, 3, 2, 4, 8, 7                           |
| \( S_2 \)  | 1, 2, 4, 7, 9, 10, 3, 5, 6, 8                           |
| \( S_3 \)  | 4, 3, 5, 7, 9, 8, 1, 6, 2, 10                           |
| \( S_4 \)  | 5, 2, 3, 8, 7, 6, 4, 1, 10, 9                           |
| \( S_5 \)  | 8, 9, 7, 4, 3, 6, 5, 10, 1, 2                           |
| \( S_6 \)  | 10, 1, 8, 9, 6, 7, 2, 5, 3, 4                           |
| ...        | ...                                                      |
| \( S_{49} \)| 2, 7, 1, 5, 4, 3, 10, 9, 8, 6                          |
| \( S_{50} \)| 9, 2, 1, 10, 3, 5, 8, 7, 6, 4                          |

3.4. Establish fitness function
In the part selection process of this study, part \( D \) (end cover) and part \( T \) (adjustment ring) are matched as a component. Referring to the mathematical selection model established previously, we can define the fitness function as:

\[
F(S_m) = R(S) = \frac{n_S}{N} = \sum_{i=1}^{N} \frac{b_i}{N}
\]
In which,
\[ b_i = \begin{cases} 1 & \text{(The i-th mating component satisfies the following constraints)} \\ 0 & \text{(The i-th mating component does not satisfy the following constraints)} \end{cases} \]

Restriction:
\[ \delta_i \leq \Delta_i \leq \delta'_i \quad (i = 1, 2, 3 \ldots N) \]

In which,
- \( S_m \) — Part selection scheme
- \( \delta_i \) — The specified lower clearance limit for the part \( D \) and part \( T \)
- \( \delta'_i \) — The specified upper clearance limit for the part \( D \) and part \( T \)
- \( \Delta_i \) — The assembly clearance part \( D \) and part \( T \)

The above formula ensures that the part \( D \) of the i-th mating component and the matching part \( T \) meet the required fit clearance requirements. Obviously, the more the number of components that meet the above constraints, the larger the value of the adaptation function obtained according to the formula, indicating that the obtained part matching scheme is superior.

3.5. Optional scheme population evolution

3.5.1. Select operator. Selecting operator, also known as the replicating operator, essentially is the replication of the chromosomes of the population, which is the main reason why the organism can maintain certain excellent traits in the process of inheritance and evolution, whose basic principle is: the probability that each individual in the population is selected is proportional to the value of its fitness function value, and the probability that each body is selected according to each individual fitness is calculated as follows.

The population size is \( M \), where the fitness of \( S_m \) is \( F(S_m) \), then the probability \( P_m \) of the individual being selected is:
\[ P_m = \frac{F(S_m)}{\sum_{k=1}^{M} F(S_k)} \quad (k = 1, 2 \ldots m \ldots M) \]

It can be seen from the above formula that the higher the value of \( F(S_m) \), the higher the value of \( P_m \); conversely, the lower the fitness, the smaller the corresponding probability.

Randomly generate a random number \( P_c \) in the range of \([0,1]\). If
\[ \sum_{j=1}^{m-1} P_j \leq P_c \leq \sum_{j=1}^{m} P_j \quad (j = 1, 2 \ldots m - 1, m) \]
then select the individual \( S_m \). And in the subsequent genetic operation process, it is crossed and mutated.

3.5.2. Crossover operator. It can be seen from the above that before the cross-reorganization operation of the individual populations is performed, the parents of the parent populations need to be paired according to certain rules. The most commonly used pairing rule at present is the random matching strategy. This study also adopts this strategy to randomly form \( M \) individuals against the parent population to form a \( M/2 \) pair paired individual group, and perform cross-recombination operations between the two bodies of the paired individual group to generate a new individual.

In this study, the PMx (Partial Mapping Crossover) operator is used to process the crossover operation of the selected part chromosomes. The basic operational idea of which is to randomly select two points between them is the part that needs to be crossed on the chromosome firstly, then to cross-element elements in order and modify the overlapping part. The following takes the end cap and adjustment ring selection process as an example to illustrate the operation process of partial mapping intersection.
During the genetic manipulation of the chromosomes of the regulatory loop, it is assumed that two chromosomes in the population of the regulatory loop are $S_x$ and $S_y$, and the chromosomes after the crossover become $S'_x$ and $S'_y$. Randomly two intersections are gotten, as shown in Figure 6, the two vertical line positions, all elements of the two chromosomes between the two vertical lines must be crossed one by one. First, cross the chromosome 4 and gene 6. In order to avoid generating invalid chromosomes, it is necessary to modify the overlapping elements existing outside the two vertical lines. For example, two genes 6 will appear after the first line is crossed, and the second line will appear. The two genes 4 must be modified so that there are no repeating elements in each row. By analogy, each line continues to be cross-modified, and finally the new two adjustment ring chromosomes $S'_x$ and $S'_y$ are obtained.

\[
\begin{align*}
S_x &= (2 \ 1 \ 7 \ 4 \ 9 \ 8 \ 10 \ 3 \ 6 \ 5) \\
S_y &= (4 \ 7 \ 2 \ 6 \ 3 \ 5 \ 1 \ 9 \ 10 \ 8) \\
&\longrightarrow (2 \ 1 \ 7 \ 6 \ 9 \ 8 \ 10 \ 3 \ 4 \ 5) \\
&\longrightarrow (6 \ 7 \ 2 \ 4 \ 3 \ 5 \ 1 \ 9 \ 10 \ 8) \\
&\longrightarrow (2 \ 1 \ 7 \ 6 \ 3 \ 8 \ 10 \ 9 \ 4 \ 5) \\
&\longrightarrow (6 \ 7 \ 2 \ 4 \ 9 \ 5 \ 1 \ 3 \ 10 \ 8) \\
&\longrightarrow (2 \ 1 \ 7 \ 6 \ 3 \ 5 \ 10 \ 9 \ 4 \ 8) = S'_x \\
&\longrightarrow (6 \ 7 \ 2 \ 4 \ 9 \ 8 \ 1 \ 3 \ 10 \ 5) = S'_y
\end{align*}
\]

**Figure 6.** Partial mapping cross operation diagram.

### 3.5.3. Mutation operator

In this study, according to the need of solving the part selection problem, the basic bit mutation operator is used to mutate the chromosome of the selected component. It is also the most widely used mutation operator. The basic operation process is as follows: firstly, select the mutation position on the chromosomal gene coding according to the mutation probability $P_m$, then replace the selected gene values with other gene values on the chromosome to generate a new chromosome. In the end cap-adjustment ring part selection, in order to avoid the generation of meaningless chromosomes, after the mutation operation of the selected mutation position in the mutation operation, the overlapping parts of other parts of the chromosome need to be modified.

If the new adjustment loop individual $S'_x$ generated after the above crossover need be mutated, the mutation point 1 is randomly selected according to the mutation probability $P_m = 0.1$. As shown in Figure 7, the mutated gene value can only be selected from \{2, 3, 4, 5, 6, 7, 8, 9, 10\}. Assuming that the gene value taken is 2, then after modifying the overlap, the resulting new adjustment loop is $S'_x$.

\[
\begin{align*}
S'_x &= (2 \ 1 \ 7 \ 4 \ 9 \ 8 \ 10 \ 3 \ 6 \ 5) \\
&\rightarrow (2 \ 1 \ 7 \ 6 \ 9 \ 8 \ 10 \ 3 \ 4 \ 5) \\
&\rightarrow (6 \ 7 \ 2 \ 4 \ 3 \ 5 \ 1 \ 9 \ 10 \ 8) \\
&\rightarrow (2 \ 1 \ 7 \ 6 \ 3 \ 8 \ 10 \ 9 \ 4 \ 5) \\
&\rightarrow (6 \ 7 \ 2 \ 4 \ 9 \ 5 \ 1 \ 3 \ 10 \ 8) \\
&\rightarrow (2 \ 1 \ 7 \ 6 \ 3 \ 5 \ 10 \ 9 \ 4 \ 8) = S'_x \\
&\rightarrow (6 \ 7 \ 2 \ 4 \ 9 \ 8 \ 1 \ 3 \ 10 \ 5) = S'_y
\end{align*}
\]

**Figure 7.** Schematic diagram of the mutation operation.
3.6. Calculation process of part selection genetic algorithm

In the calculation of the part selection algorithm, there is also an important parameter - $T$, terminating algebra. It determines whether the genetic algorithm is running or done, which means that the optimization calculation stops when it reaches the set termination algebra. Usually the value is 100~1000. This study chooses $T = 500$. As mentioned above, as shown in figure 8, the calculation process of the end cap-adjustment ring selection based on genetic algorithm is as follows:

1) Determine the part coding method and the genetic parameters such as the crossover probability $P_c$, the mutation probability $p_m$, and the termination algebra $T$.
2) Construct an initial population $P(k)$ of size $M$ using a method of randomly generating initial populations, and $k = 0$.
3) Calculate the fitness $F(S_m)$ of each generation of individual populations through the fitness function and determine whether it is equal to $N$. If $F(S_m) = N$, it means that the best part matching scheme has been found, go to step (9); if $F(S_m) \neq N$, it means that the optimization process still needs to be continued, go to step (4). Where $S_m$ represents the part matching scheme.
4) Select $P(k)$ by the operator selection and select a good individual to copy.
5) Cross-reorganization is performed on the selected excellent individuals by the crossover operator.
6) The variation is achieved by the mutation operator on the crossed individuals.
7) Generate a new generation of population $P(k+1)$ and set $k = k+1$.
8) Determine if $k$ is equal to the set termination algebra $T$. If $k = T$, stop the operation, go to step (9); if $k \neq T$, go to step (3) to continue the operation.
9) Output the optimal part selection scheme.

![Figure 8. Genetic algorithm flow of part selection.](image-url)
4. Application examples and analysis of operation results

4.1. data preparation
In this study, the end cap-adjustment ring matching example of the reducer is used, and Matlab programming is used to verify the genetic algorithm of the part selection. The 10 end caps and 10 adjustment rings are matched. The assembly parameter is as follow: 2 kinds of parts; the algorithm parameter are as follows: population size $M = 50$, crossover probability $P_c = 0.6$, mutation probability $P_m = 0.1$, and the termination condition is the number of iterations $T = 500$. The thickness of the end cap to be selected is $D = 11^{0.10}_{-0.10} \text{mm}$, the thickness of the adjustment ring $D$ to be selected is $T = 31^{0.20}_{-0.20} \text{mm}$, and the original dimension data are measured. As shown in Table 4 to 5, the actual dimension data of a set of end caps and adjustment rings to be installed are given.

| Part number | D    |
|-------------|------|
| DG001       | 11.03|
| DG002       | 11.07|
| DG003       | 10.91|
| DG004       | 10.94|
| DG005       | 10.96|
| DG006       | 10.92|
| DG007       | 10.98|
| DG008       | 10.95|
| DG009       | 10.97|
| DG010       | 10.93|

| Part number | T    |
|-------------|------|
| TZH001      | 30.98|
| TZH002      | 30.94|
| TZH003      | 30.82|
| TZH004      | 30.88|
| TZH005      | 30.89|
| TZH006      | 30.97|
| TZH007      | 30.85|
| TZH008      | 30.83|
| TZH009      | 30.86|
| TZH010      | 30.81|

4.2. Analysis of operation results
As shown in Figure 9, after repeated experiments and 500 iterations, the optimal objective function values of the selection algorithm tend to be stable, that is, the highest assembly success rate of each generation parts matching scheme eventually stabilizes. It shows that the part selection algorithm has a good convergence effect.

The value curve of optimal objective function calculated by the above algorithm can help obtain the optimal part selection scheme of the selected example, as shown in the following Table 6: end cap 1 matching adjustment ring 6, end cap 2 matching adjustment ring 1... end cap 10 is matching adjustment ring 7.
Figure 9. The value curve of optimal objective function.

Table 6. The most preferred solution of the end cap - adjustment ring selection

| First column code (End cap) | Second column encoding (Adjustment ring) | Matching clearance Δ (mm) | Whether the assembly requirements are met (0.20–0.30mm) |
|-----------------------------|-----------------------------------------|--------------------------|--------------------------------------------------------|
| 1                           | 6                                       | 0.10                     | No                                                     |
| 2                           | 1                                       | —                        | No                                                     |
| 3                           | 5                                       | 0.20                     | Yes                                                    |
| 4                           | 9                                       | 0.20                     | Yes                                                    |
| 5                           | 8                                       | 0.21                     | Yes                                                    |
| 6                           | 4                                       | 0.20                     | Yes                                                    |
| 7                           | 3                                       | 0.20                     | Yes                                                    |
| 8                           | 10                                      | 0.24                     | Yes                                                    |
| 9                           | 2                                       | 0.09                     | No                                                     |
| 10                          | 7                                       | 0.22                     | Yes                                                    |

From the calculation results of the above selection algorithm, it can be known, when the end cap and the adjustment ring are randomly selected by experience only, the assembly success rate is at least 50%; but when the end cap-adjustment ring selection is adopted by the genetic algorithm and the optimization process reaches the iteration number of 500, the optimal objective function value has converged to 0.7, the end cap-adjustment ring assembly success rate has increased to 70%. Therefore, the part selection algorithm greatly improves the assembly success rate, saves the assembly time, and has an significance for the actual assembly of the reducer.

5. Conclusions

In this study, the bearing cap-adjustment ring component of the heavy-duty reducer is taken as the research object to be selected by the genetic algorithm. Firstly, the assembly dimension chain is extracted, and the matching clearance of the component is calculated to meet the requirements of the assembly clearance requirements and minimize the number of unsuitable parts. Since the mathematical model of the end cap-adjustment ring assembly is established. Then according to the actual situation and needs of the end cap-adjustment ring component selection, the part coding method and the initial population is constructed, the fitness function is established, furthermore the genetic calculations such as selection, crossover and mutation are carried out. Finally, through repeated experiments and 500 iterations, the value of the optimal objective function tends to be stable, and a good convergence effect
is obtained; the assembly success rate of the end cap-adjustment ring component is increased from the original 50% to over 70%, the assembly efficiency is greatly improved, reduce and the assembly cost is reduced, which has a significance for the actual assembly of the reducer.

Acknowledgments

This research was supported by a National Defense Fundamental Research Project of China (Grant Number: JCKY2018601C205) and a ASIC Product Innovation Research Project (Grant Number: 237099000000170006) and the National Key Research and Development Program of China (No. 2019YFB2004400).

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