Optimization Strategy for Industrial Machinery Product Selection Scheme Based on DMOEA

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***Abstract*—With the continuous innovation and replacement of industrial machinery products, the traditional optional configuration plans are no longer able to complete product selection work with high quality. To further optimize the product selection process and solve the multi-objective selection problem of industrial machinery products, a multi-objective problem model for product selection is normalized and constructed based on the existing difficulties in industrial machinery product selection. A new product selection model is proposed by introducing a multi-objective evolutionary algorithm based on density calculation for model solving. The experimental results showed that the new model had the highest selection success rate of 97% and selection accuracy close to 95% when the iterations were 250. In addition, the maximum absolute error sum of the selected bearing and bearing seat diameters under this model was 0.002. The maximum relative error was 0.01%. The highest reliability of algorithm fitting was 99.9%. Simulation tests found that the average selection success rate was 93%. The average selection quality loss was 26%. In summary, the new selection model proposed in the study has certain advantages and feasibility. It can provide effective decision-making solutions for the design and selection of industrial machinery products.**

Keywords—Industrial machinery products; optional configuration plan; multi objective evolutionary algorithm; density calculation; selection success rate

I. Introduction

A. Background

As an important part of engineering design, industrial machinery product selection involves multiple objective problems [1]. Its complexity and diversity make the traditional optimization methods often can only give the optimal solution under a particular objective, and it is difficult to comprehensively consider the balance between multiple objectives [2].

B. Status of Research

To address this problem, scholars at home and abroad have proposed various method models using evolutionary algorithms and multi-objective optimization algorithms to achieve comprehensive optimization of industrial machinery product selection and matching. These methods find the most optimal selection and matching scheme that satisfies multiple objectives by comprehensively considering various objectives and constraints.

C. Problems with the Study

Although capable of effectively handling multi-objective optimization problems, evolutionary and optimization-only algorithms still have a number of challenges, including, but not limited to, the speed of convergence of the algorithms, the diversity of solutions, and the interpretability of the algorithms [3].

D. Research Purpose

In view of this, the main problem that the research aims to address is how to deal with multi-objective optimization problems efficiently, especially when facing complex scenarios where multiple conflicting objectives need to be optimized at the same time, to find a method that is both efficient and guarantees the diversity of solutions.

E. Research Methodology

Multi-Objective Optimization Algorithm (MOEA) is an effective way to solve the problem of industrial machinery product selection, among which Density-based Multi-objective Evolutionary Algorithm (DMOEA) shows better performance and stability than other algorithms when dealing with multi-objective optimization problems, especially when facing complex problems, it can effectively balance the trade-offs among objectives [4]. Algorithm (DMOEA) shows better performance and stability than other algorithms in dealing with multi-objective optimization problems, especially in the face of complex problems, it can effectively balance the trade-offs among the objectives. In view of this, the study is to improve the optimization on the basis of DMOEA and then solve the multi-objective problem model of product selection, so as to obtain the best selection plan.

F. Innovative Nature of the Research

The innovation of the research is that a DMOEA algorithm is proposed and the density function and reproduction process of the algorithm are pruned and optimized. For the complex multi-objective product selection problem, it can significantly improve the quality of the strategy and the solution efficiency.

G. Contribution of the Study

The contribution of the study is to propose a new complex multi-objective product selection optimization model and verify its superiority and feasibility, which has significant improvement compared with the existing methods and provides new ideas for the technical development in this field.

II. Related Works

With the continuous development of industrialization, industrial machinery plays an important role in the production process. The selection plan for industrial machinery products is the key to ensuring efficient and safe operation of the production process. Therefore, how to find the optimal matching solution among numerous products has become an important research question. Zhang et al. found that the rapid upgrading of mechanical products caused serious resource waste and environmental pollution. To improve the resource utilization, a mechanical product selection model utilizing big data analysis was proposed. The experimental results showed that the model could optimize the selection and assembly efficiency of in-service products, save manpower and material resources. It had certain feasibility and accuracy [5]. Guo et al. found that a large number of retired mechanical products caused resource waste. To transform the utilization rate of retired products, a new selection strategy for retired products was proposed by combining the generalized growth remanufacturing model. The experimental results indicated that this strategy could mine data associations between products, thereby increasing the utilization rate of retired products [6]. Li et al. found that the increase in richness and diversification of mechanical products often resulted in existing mechanical product assemblies being unable to meet the needs of users. Therefore, a mechanical product assembly model was proposed after combining digital twin technology. The experimental results indicated that the model could autonomously optimize the product selection process and operate with the highest rated product assembly plan for service evaluation [7]. Formentini et al. found that traditional manufacturing and assembly design strategies were no longer able to assemble new products with high standards, speed, and accuracy. Therefore, a new assembly design method was proposed by combining numerical maps. The experimental results showed that this method could adapt to the assembly of most existing mechanical products. The efficiency and accuracy were extremely high [8].

Multi objective optimization algorithms are a type of algorithms specifically designed to solve multi-objective optimization problems. The density based multi-objective evolutionary algorithm is an evolutionary algorithm used to solve multi-objective optimization problems. This algorithm combines density estimation and evolutionary strategy, aiming to find a set of approximate Pareto optimal solutions. Liang et al. found that traditional multi-objective algorithms couldn't handle the balance between population diversity well. Therefore, a DMOEA model combining decision variables was proposed. The experimental results showed that the model could stably output decision variables in both static and dynamic responses. It had better computational performance compared to traditional methods [9]. Li et al. proposed a multi-objective solution method combining DMOEA after summarizing and identifying the probability uncertainty problem in random resource allocation. The experimental results showed that this method performed better than other similar methods in most tests. It could successfully solve the random resource allocation [10]. Chen et al. proposed an evolutionary algorithm combining Coral algorithm and DMOEA to solve the Pareto optimal problem related to time and process in dynamic multi-objective optimization. The experimental results showed that the algorithm could achieve good solutions, with a fast completion speed and a high completion rate [11]. Feng et al. proposed a novel dynamic change prediction model by combining autoencoder and DMOEA to explore a solution for novel dynamic multi-objective optimization problems. The experimental results showed that the model could provide more accurate Pareto optimal solution prediction compared to multi-objective genetic algorithm. The iteration times were faster [12].

In summary, many scholars at home and abroad have explored the assembly schemes of mechanical products to varying degrees and have achieved remarkable results. Meanwhile, the DMOEA has been applied to different research fields, which has also solved many multi-objective problems. However, there is still little research on applying DMOEA to the assembly design of industrial machinery products. Therefore, this study attempts to combine the two, aiming to further improve the efficiency of product assembly and better address optimization issues in industrial machinery product selection schemes.

III. Industrial Machinery Product Selection Model Construction

To construct a new industrial machinery product selection model, the necessary multi-objective problem of machinery selection is first modeled. Different types of target problems are normalized. Secondly, the DMOEA was introduced for improvement. Then it is applied to the multi-objective solving process of the selection problem. Finally, a new assembly model is proposed.

A. *Modeling of Small Batch Multi-objective Matching Problems*

The selection of mechanical products follows the principle of group selection, which is to reasonably allocate and assemble parts based on their actual size, size, material, process, etc., in order to achieve high stability and rationality of product quality [13]. The formulation of mechanical product selection plans should consider multiple factors, including production scale, product requirements, environmental conditions, etc. Different mechanical products can achieve maximum benefits in specific production environments. The factors that generally affect the selection are shown in Fig. 1.

In Fig. 1, it is mainly divided into component level factors and optional level factors. At the part level, it is subdivided into structure, size, shape, indicating quality, and heat treatment. The selection level includes position, method, accuracy, plan, etc. These factors complement each other and work together on product selection work. There are a wide variety of mechanical products. There are certain differences in the selection mode of different types of products. Generally, large-scale product selection can rely on group selection for smooth assembly, while small batch products often lack consideration due to the primary and secondary relationships and assembly accuracy [14]. Therefore, this study focuses on small batch products as the main research object. Firstly, a selection correlation matrix for small batch products is constructed, as shown in Eq. (1).

$$R=\begin{bmatrix} r_{1,1},r_{1,2},\cdots,r_{1,k} \\ r_{2,1},r_{2,2},\cdots,r_{2,k} \\ \vdots \\ r_{m,1},r_{m,2},\cdots,r_{m,k} \end{bmatrix} \tag{1}$$

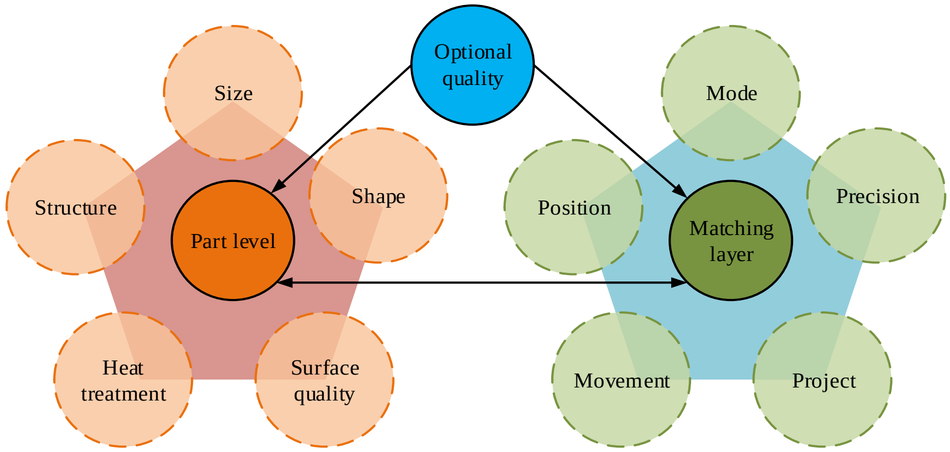


Fig. 1. Classification of factors affecting the selection accuracy.

In Eq. (1), $r_{m,k}$ represents the k-th dimension under the m-th dimension chain. At this point, the constraint matrix for small batch products is shown in Eq. (2).

$$G=\begin{bmatrix} g_{1,\min},g_{2,\min},\cdots g_{m,\min} \\ g_{1,\max},g_{2,\max},\cdots g_{m,\max} \end{bmatrix} \tag{2}$$

In Eq. (2), $g_{m,\min}$ and $g_{m,\max}$ represent the upper and lower deviations of the assembly accuracy related dimensions under the m-th dimension chain. If the size of a certain part is determined between $g_{m,\min}$ and $g_{m,\max}$, it is called a qualified size. The part dimensions are paired and coded. The obtained results are randomly arranged according to gene coding. The selection scheme code for small batch products is shown in Eq. (3).

$$X_i=(\beta_1,\beta_2,\beta_3,\cdots,\beta_n) \tag{3}$$

In Eq. (3), β_n represents the size number of the same group of parts. n represents the quantity of part dimensions. Based on the above coding patterns, the multi-objective selection problem model for small batch products is divided into three levels: selection success rate, selection quality, and multi-objective and multi quality selection. The success rate of small batch product selection represents the ratio of the current number of qualified products that have been selected to the total number of products that have been selected, as shown in Eq. (4).

$$\chi_m=\frac{n_e}{n}\times 100\% \tag{4}$$

In Eq. (4), χ_m represents the selection success rate. n_e represents the number of qualified products after completing the selection. n represents the quantity of all products that have been selected. In addition, the quality requirements for product selection are equally important, especially whether the gap docking of the selected parts is suitable, and whether the product operational functions can be achieved. The size of optional parts for the product is fixed. Therefore, the Taguchi model is selected for quality control in the study. The schematic diagram of this model is shown in Fig. 2.

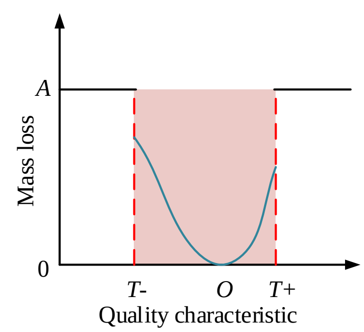


Fig. 2. Taguchi mass model diagram.

In Fig. 2, A represents the quality loss of unqualified products after completing the selection. T represents the reasonable tolerance range for the selected product dimensions. $T-$ and $T+$ represent the upper and lower limits of the tolerance range. When the gap size of the selected product is within the red range, the product quality is qualified. The quality loss function of the most optimal product is shown in Eq. (5).

$$C(g_{m,j})=\begin{cases} \dfrac{2A}{T_m}(g_{m,j}-g_o) \\ g_{m,j}\in\left[g_{m,\min},g_{m,\max}\right] \\ A,g_{m,j}\in(-\infty,g_{m,\min})\cup(g_{m,\max},+\infty) \end{cases} \tag{5}$$

In Eq. (5), T_m represents the design tolerance for optional parts. g_o represents the optimal clearance value of the part. When the actual selection gap approaches $g_{m,\min}$ or $g_{m,\max}$, the mass loss is greater, that is, closer to the A value. The average selection quality loss function at this time is shown in Eq. (6).

$$Q_m = \frac{\sum_{j=1}^{n} C(g_{m,j})}{n} \tag{6}$$

If the value of Q_m is small, it indicates that the accuracy and quality of the selected product are high. Therefore, the multi-objective and multi quality selection scheme is selected to approximate the minimum value. The definition of this process is shown in Eq. (7).

$$\min \mathit{fitness}(x) = (M_1(X), M_2(X), \cdots, M_m(X)) \tag{7}$$

In Eq. (7), $M_m(X)$ represents the comprehensive optimization objective function of the m-th product. $\mathit{fitness}(x)$ represents the fitness function. The expression curve is shown in Fig. 3.

In Fig. 3, γ represents the actual common difference of the selected dimensions. The fitness value range for parts selection is between γ and 1. When the actual selected size tolerance is H, the maximum quality loss is 1. When the actual selected size common difference approaches $T-$ and $T+$, the fitness function value is the lowest at γ. In summary, the optimal selection size common difference and the lowest quality function can achieve the best production selection work.

B. Modeling of Selection Strategies for Small-lot Products

After constructing a multi-objective problem model for selecting small batch products, the study attempts to use optimization algorithms for solution. General optimization algorithms include genetic algorithm, ant colony algorithm, particle swarm algorithm, and simulated annealing algorithm [15]. These algorithms have wide adaptability and strong applicability, but simple optimization algorithms cannot quickly and completely solve multi-objective problems. Therefore, a multi-objective evolutionary algorithm using density calculation, DMOEA, is proposed for the assembly problem of small batch products. The operation process of this algorithm is shown in Fig. 4.

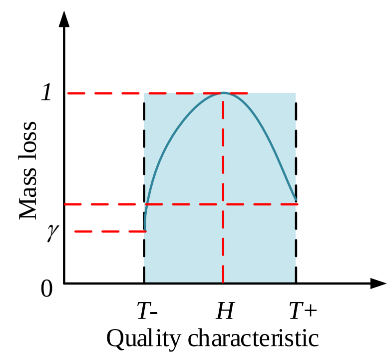


Fig. 3. Fitness function curve of multi-object and multi-mass selection.

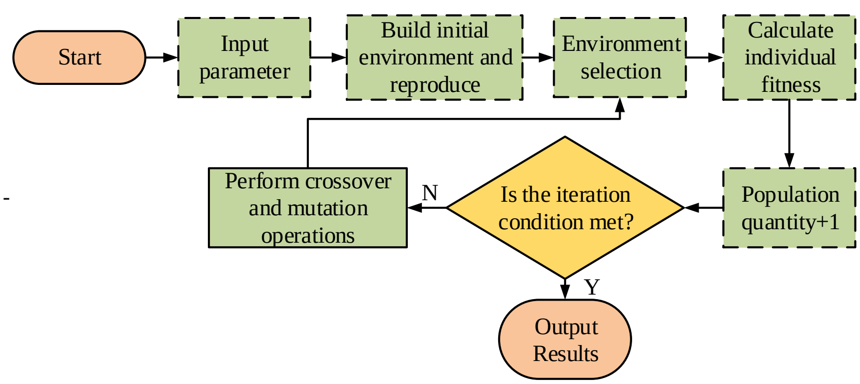


Fig. 4. The process of DMOEA.

In Fig. 4, the DMOEA first determines the algorithm parameters and selection problem parameters, such as population size, cross mutation probability, iteration number, size chain constraint relationship, part data, etc. Secondly, the initial environment is constructed for population reproduction and evolution. The environment is selected and a non-dominated set is constructed for replication. Then the individual fitness is calculated or the population size is increased. Finally, after satisfying the iteration conditions, the result is output. If not, operations such as crossover and mutation are performed again. The environment selection and non-dominated set replication are repeated. The fitness function of the entire algorithm is mainly calculated using clustering density. To quantify the influence degree between individuals, the density function is calculated using a normal distribution, as shown in Eq. (8).

$$\psi(r) = \left[1/\sigma\sqrt{2\pi}\right] e^{-r^2/2\sigma^2} \tag{8}$$

In Eq. (8), r represents the Euclidean distance between individuals. σ represents the standard deviation of the distribution. The density calculation for individuals at this time is shown in Eq. (9).

$$D(x_y)=\sum_{i=1}^{N}\psi\left[d(x_i,x_y)\right] \tag{9}$$

In Eq. (9), $d(x_i,x_y)$ represents the Euclidean distance between individual x_i and individual x_y. x_i and x_y belong to the evolved individuals after reproduction. The density fitness function is shown in Eq. (10).

$$F(X_i)=\frac{fitness(X_i)}{D(X_i)} \tag{10}$$

In Eq. (10), all algebraic meanings are consistent with the previous explanation. According to this equation, individuals with higher density fitness values have lower individual density, meaning their mutual influence is relatively small. Therefore, to preserve the diversity of individuals after iteration, individuals with higher density fitness values should be selected [16]. In addition, the random change method is used to transform the correlation matrix R for small batch parts selection. The transformed matrix is shown in Eq. (11).

$$X_0=\begin{bmatrix} x_{1,1},x_{1,2},\cdots x_{1,k} \\ x_{2,1},x_{2,2},\cdots x_{2,k} \\ \vdots \\ x_{j,1},x_{j,2},\cdots x_{j,k} \end{bmatrix} \tag{11}$$

In Eq. (11), $x_{j,k}$ represents a separate part with the number k in group j. When generating the initial population, its individual distribution maintains randomness, that is, it is arranged according to a random sequence. This arrangement represents an optional solution, which can be obtained by repeating multiple arrangements. For the initial population reproduction, to ensure that the population size after reproduction matches the evolutionary scale, a pruning method is adopted, which eliminates the individuals with the highest density [17]. The reproduction process is shown in Fig. 5.

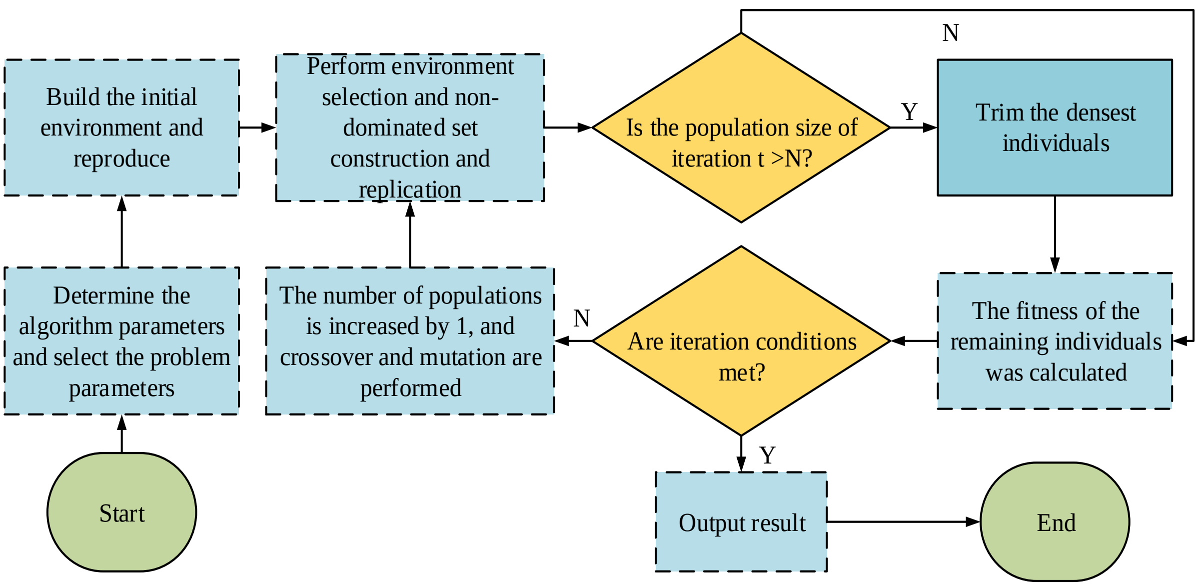


Fig. 5. Pruning and breeding process of DMOEA.

From Fig. 5, this process is roughly similar to the general genetic algorithm process, but the difference is that it has an additional pruning step. After eliminating individuals with high fitness, to avoid mutual influence between individuals, this step recalculates the fitness of the remaining individuals. After completing population reproduction, population strategies such as crossover and mutation should be implemented. Among them, single point crossing method is a classic crossing method. Although its computational speed is not as fast as multi-point crossing and mixed crossing, its positional damage is significantly smaller than the other two types of methods. It is more conducive to the precise size positioning of the selection scheme [18]. The expression for single point crossing is shown in Eq. (12).

$$X_a=\begin{bmatrix} x_{1,1}^a,x_{1,2}^a,\cdots,x_{1,n}^a \\ x_{2,1}^a,x_{2,2}^a,\cdots,x_{2,n}^a \\ \vdots \\ x_{m,1}^a,x_{m,2}^a,\cdots,x_{m,n}^a \end{bmatrix} \Rightarrow X_a^{`}=\begin{bmatrix} x_{1,1}^a,x_{2,2}^a,\cdots,x_{2,n}^a \\ x_{2,1}^a,x_{1,2}^a,\cdots,x_{1,n}^a \\ \vdots \\ x_{m,1}^a,x_{m,2}^a,\cdots,x_{m,n}^a \end{bmatrix} \tag{12}$$

In Eq. (12), X_a represents offspring. $X_a^{`}$ represents the parent. From this formula, the arrangement sequence after single point crossing changes, but the position of individual individuals remains. Mutation induces individual positional changes through genetic alterations. The code of the mutated small batch product is shown in Eq. (13).

$$X_i=\left[\beta_1,\beta_2,\beta_3,\cdots,\beta_n\right]\Rightarrow X_i^{`}=\left[\beta_1,\beta_3,\beta_2,\cdots,\beta_n\right] \tag{13}$$

In Eq. (13), X_i is the code of the small batch product before mutation. $X_i^{`}$ represents the code of small batch products after mutation. At this point, the individual position of the product has changed. Therefore, it is possible to create unique new individuals. In summary, a new industrial machinery product selection model is proposed by combining the optimized DMOEA. The model structure is shown in Fig. 6.

In Fig. 6, the entire optional system is roughly divided into three main gates and 8 small gates. The three main gates are part data collection, dimension chain calculation, and selection planning. Among them, part data collection includes batch, size, and quantity of parts. The size chain calculation includes the calculation of increase or decrease cycles and the refinement of size chain. The selection plan includes DMOEA selection algorithm calculation, selection result validation, and selection result analysis.

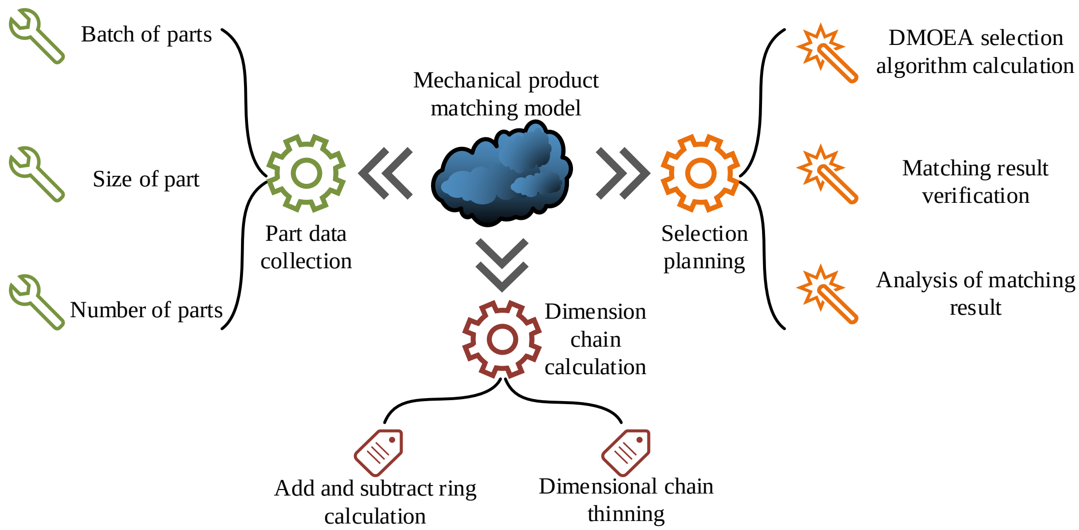


Fig. 6. Mechanical product selection model combined with DMOEA optimization.

IV. Product Option Model Performance Testing

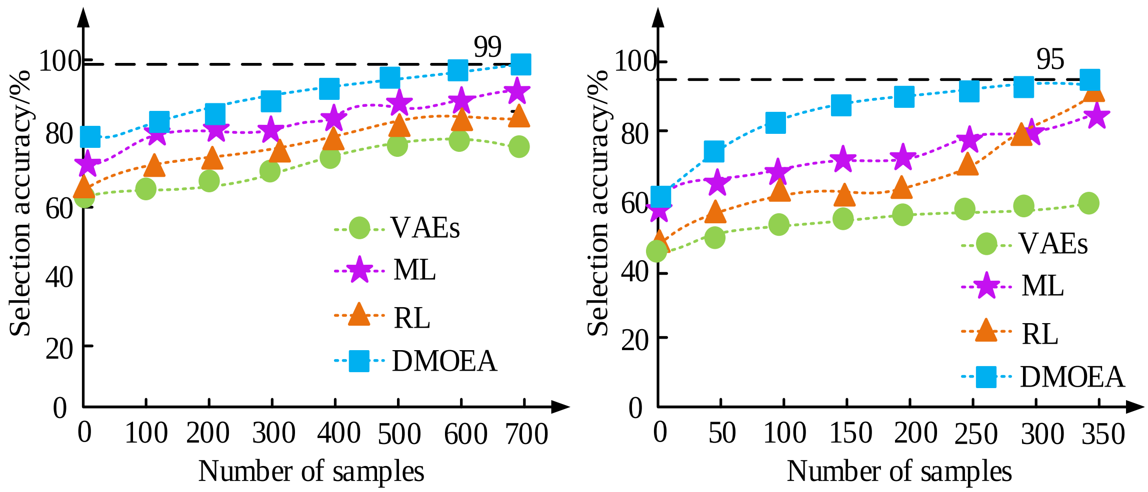
To verify the performance of the DMOEA selection model proposed in the study, the study first trains the same type of selection model with self-made data and determined the optimal algorithm parameters. Then, a comparison is made on the selection accuracy, success rate, and quality loss. In addition, a comparative test for DMOEA selection scheme is conducted using a four cylinder plunger pump valve as the simulation object.

A. Performance Testing of Selected Models

The system architecture of the browser combined with the server is used to simulate the generation of DMOEA models. 150 bearing seats of P215 and 150 outer spherical bearings of NA215 are subjected to selection testing. The inner diameter range of the bearing seat is φ120±0.02mm. The outer diameter range of the bearing is φ120±0.04mm. The range of bearing inner diameter is φ65-φ65.02mm. The range of journal diameter is φ65-φ65.03mm. The above four experimental materials are randomly combined. The combined results are divided into training and testing sets in an 8:2 ratio. At the same time, the training set data is sequentially input into popular deep learning selection algorithms of the same type for comparative testing. These algorithms include Reinforcement Learning (RL), Variational Autoencoders (VAEs), and Meta Learning (ML), with selection accuracy as the reference indicator. The test results are shown in Fig. 7.

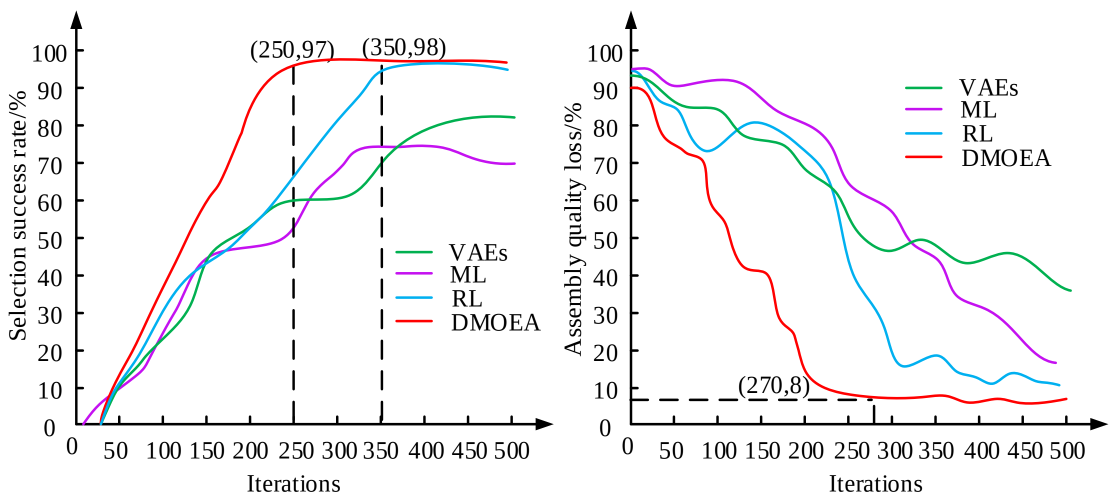
Fig. 7(a) shows the selection accuracy test results of four algorithms in the training set. Fig. 7(b) shows the selection accuracy test results of four algorithms in the test set. In Fig. 7, the VAEs model had the lowest average selection accuracy, followed by ML and RL. The DMOEA selection model had a selection accuracy of nearly 99% in the training set and nearly 95% in the testing set. This data illustrates that by optimizing the DMOEA's density Gann function, it will lead to a significant improvement in the selection accuracy of the whole model. In addition, to more accurately determine the optimal operational parameters of the optimization algorithm, the study takes the selection success rate and selection quality loss as reference indicators. Similarly, the training set data is input into four models for initial iteration parameter determination. Their respective operational iteration effects are compared. The test results are shown in Fig. 8.

Fig. 8(a) shows the comparison test results of the selection success rates for four models. Fig. 8(b) shows the comparison test results of the quality loss for four models. In Fig. 8, the optimal selection success rate of the RL was the highest at 98%, with 350 iterations. The success rate of the DMOEA proposed in the study was the highest at 97%, which was 1% lower, but the algorithm had 250 iterations at this time. In addition, the quality loss curve of the DMOEA decreased the fastest, reaching a minimum quality loss of nearly 8%, with approximately 270 iterations at this time. This data illustrates that the pruning approach has optimized the reproduction process of the DMOEA algorithm, which can significantly improve its computational speed and increase the diversity of strategies, thus improving the success rate of selection. In summary, for the convenience of subsequent testing, the study determined 260 iterations as the optimal iteration number for the MOEA. To verify the feasibility of the DMOEA, three fixed bearing combinations are randomly selected, namely bearing 3 with bearing seat 3, bearing 8 with bearing seat 8, and bearing 12 with bearing seat 12. The better performing DMOEA algorithms and the state-of-the-art three types of algorithms are tested in comparison with each other using absolute error, relative error and algorithm fitting credibility as the reference indexes. Such as Strength Pareto Evolutionary Algorithm (SPEA), Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) and ε-Multi-Objective Evolutionary Algorithm (ε-Epsilon-Multiobjective Evolutionary Algorithm, ε-MOEA), and the test results are shown in Table I.



(a) Training set (b) Test set

Fig. 7. Comparative testing of selection accuracy of different algorithms.



(a) Comparison test of selection success rate (b) Comparative testing of quality loss during selection

Fig. 8. Performance comparison testing of different algorithms.

TABLE I. ANALYSIS OF BEARING SELECTION RESULTS FOR TWO ALGORITHMS

Allocation model	Combination 3		Combination 8		Combination 12		Index		
/	Bearing 3	Bearing seat 3	Bearing 8	Bearing seat 8	Bearing 12	Bearing seat 12	Sum of absolute errors	Relative error sum	Fit credibility
SPEA optional diameter/mm	120.015	120.009	120.007	120.01	120.009	120.008	0.01	0.08%	96.90%
MOEA/D optional diameter/mm	120.017	120.012	120.005	120.002	120.009	120.008	0.006	0.01%	98.50%
ε-MOEA optional diameter/mm	120.0.16	120.013	120.006	120.004	120.008	120.007	0.005	0.03%	99.10%
DMOEA optional diameter/mm	120.017	120.015	120.008	120.008	120.006	120.006	0.002	0.01%	99.90%

As can be seen from Table I, after quantifying the data, it is found that for the three sets of bearing sets under the same conditions, the absolute error sum of the diameter of the bearings and housings selected by the SPEA selection model is 0.01 at the maximum, and the relative error sum is 0.08% at the maximum, and the algorithm fitting credibility is 96.9% at the maximum. The other three types of algorithms in the MOEA series perform significantly better than SPEA, especially the proposed DMOEA algorithm model of bearing and housing selection performs the best, with the maximum absolute error of diameter of 0.002, the maximum relative error and 0.01%, and the maximum algorithmic fitting confidence of 99.9%. In summary, the new allocation model proposed by the research can refine the control of product dimensions in the process of part selection, avoiding the product quality problems caused by dimensional errors.

B. Selection Model Simulation Testing

To verify the practical application effect of the DMOEA selection model, the SI6K-50 four cylinder plunger pump valve is studied as the test object. The selected parts mainly include the main piston, guide plate, pull rod, and small shell. The size range of the main piston is φ18±0.05mm. The fit clearance is 0.05-0.07mm. The optimal clearance is 0.06mm. The size range of the guide plate is φ18±0.02mm. The clearance and optimal clearance are the same as the main piston. The size range of the pull rod is φ7±0.04mm. The fit clearance is 0.05-0.07mm. The optimal clearance is 0.07mm. The size range of the small shell is φ7±0.03mm. The clearance and optimal clearance are the same as the tension rod. 60 different sizes of main pistons, guide plates, pull rods, and small shells are randomly selected, with 15 of each type. After random arrangement and combination, 15 schemes are selected for testing. The pre-selected parts for testing are shown in Table II.

From Table II, the diameter values of each group of parts in the 15 pre-selected configuration schemes had a small difference. The overall similarity of the schemes was higher after random combination. To distinguish and evaluate the practical application effectiveness of the DMOEA model, the success rate and quality loss of selection are used as reference indicators. At the same time, to more realistically compare the performance differences between the proposed selection model and the existing popular Generative Adversarial Network (GAN) selection model, the above 15 sets of pre-selection schemes are sequentially inputted into the DMOEA and GAN. The measured assembly success rate and assembly quality loss are checked. The specific test results are shown in Table III.

According to Table III, the 15 pre-selection schemes were inputted into the DMOEA and GAN, respectively. Quantitative data showed that the success rate of GAN selection in schemes 5, 8, and 12 was higher than the DMOEA proposed in the study. All other options showed that DMOEA was superior. In addition, the selection quality loss value of the DMOEA was all lower than that of the GAN. The highest selection success rate of the DMOEA was 0.99, the average selection success rate was 0.93, the lowest selection quality loss was 0.08, and the average selection quality loss was 0.26. In summary, the product selection model proposed in the study combined with DMOEA optimization model had higher performance. Compared to similar selection models, it was more feasible and stable. In addition, to more vividly demonstrate the selection effect of DMOEA and GAN, the study selects four schemes each with better assembly success rate and quality loss for the two models. The confusion matrices of the two models are plotted. The results are shown in Fig. 9.

TABLE II. PRE-SELECTION SCHEME

Assembly plan	Guide disc size/mm	Main piston size/mm	Rod size/mm	Small shell size/mm
1	φ18.02	φ18.01	φ7.01	φ7.03
2	φ18.04	φ18.02	φ6.96	φ6.97
3	φ18.03	φ18.04	φ6.97	φ6.99
4	φ18.00	φ18.03	φ7.04	φ7.02
5	φ17.96	φ17.96	φ6.99	φ6.97
6	φ17.99	φ17.96	φ6.98	φ7.00
7	φ18.05	φ18.04	φ7.03	φ7.01
8	φ18.02	φ18.05	φ6.98	φ6.99
9	φ18.04	φ17.98	φ7.02	φ7.02
10	φ18.03	φ17.99	φ7.00	φ7.03
11	φ18.01	φ18.04	φ7.03	φ6.98
12	φ17.97	φ17.99	φ7.04	φ7.01
13	φ18.02	φ17.96	φ7.05	φ6.98
14	φ17.95	φ18.02	φ6.96	φ6.99
15	φ17.98	φ18.04	φ7.00	φ7.00

TABLE III. TEST RESULTS OF 15 PRE-SELECTED FORMULA CASES IN 2 MODELS

Scheme number	Algorithm model	Assembly success rate	Assembly quality loss
1	DMOEA	0.95	0.34
	GAN	0.83	0.52
2	DMOEA	0.99	0.27
	GAN	0.94	0.43
3	DMOEA	0.98	0.14
	GAN	0.92	0.27
4	DMOEA	0.96	0.11
	GAN	0.94	0.28
5	DMOEA	0.95	0.15
	GAN	0.96	0.19
6	DMOEA	0.97	0.14
	GAN	0.96	0.19
7	DMOEA	0.98	0.08
	GAN	0.89	0.18
8	DMOEA	0.91	0.25
	GAN	0.93	0.34
9	DMOEA	0.92	0.24
	GAN	0.92	0.28
10	DMOEA	0.94	0.34
	GAN	0.81	0.41
11	DMOEA	0.87	0.43
	GAN	0.86	0.56
12	DMOEA	0.89	0.37
	GAN	0.91	0.41
13	DMOEA	0.92	0.32
	GAN	0.90	0.41
14	DMOEA	0.86	0.50
	GAN	0.85	0.67
15	DMOEA	0.91	0.24
	GAN	0.89	0.38
Average value	DMOEA	0.93	0.26
	GAN	0.90	0.37

Fig. 9(a) shows the confusion matrix of the selection success rate for the DMOEA. Fig. 9(b) shows the confusion matrix of the selection success rate for the GAN. Fig. 9(c) shows the confusion matrix of the selected quality loss for the DMOEA. Fig. 9(d) shows the confusion matrix of the selected quality loss for the GAN model. From Fig. 9, in the comparison test of the confusion matrix for the selection success rate, the schemes of DMOEA model can smoothly perform allocation prediction. The highest confusion prediction score is 60. In the confusion matrix of the GAN, scheme 4 and scheme 5 were easily confused, while scheme 5 and scheme 2 were easily confused. In addition, in the comparison test of the confusion matrix for quality loss selection, the DMOEA model had a high accuracy in predicting allocation, with only schemes 3 and 6 being prone to confusion. In summary, the DMOEA model proposed in the study is more suitable for product task allocation. It has certain feasibility and stability. The overall performance is relatively good.

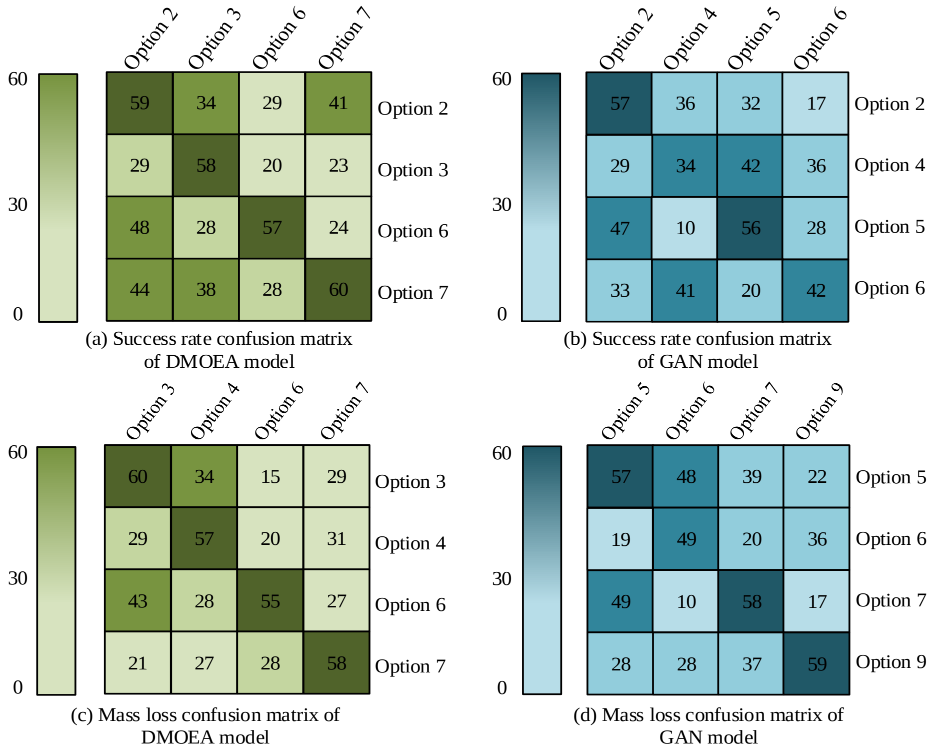


Fig. 9. The confusion matrix results of the two models.

V. DISCUSSION

The study conducted various tests and analyses of the proposed DMOEA algorithmic model to investigate its superiority and feasibility. First, in order to verify the superiority of DMOEA, the study conducted training tests on the DMOEA model with the selection accuracy, and compared DMOEA with the same type of algorithmic models using the selection success rate and the loss of selection quality as indicators. It was found that the matching success rate of DMOEA was as high as 97%, and the matching accuracy was close to 95%, which was significantly better than the traditional matching model. This achievement is attributed to the high efficiency and accuracy of the DMOEA algorithm in dealing with multi-objective selection problems, especially the improvement in optimizing the density function and reproduction process of the calculation. In the experiments, the absolute error of the bearing and housing selection diameters of DMOEA is up to 0.002 and the relative error is only 0.01%, and this accuracy significantly improves the quality and reliability of the products. This result is consistent with Zhang H et al. who used big data analysis to optimize the selection efficiency of mechanical products [19]. Secondly, in order to verify the effective feasibility of the DMOEA model, the study took a four-cylinder piston pump valve as the test object, and the selected parts mainly included the main piston, guide disk, tie rod and small housing, while other models were introduced for comparison. The highest matching success rate of the DMOEA model is found to be 0.99, and the lowest matching quality loss is found to be 0.08, which is greatly improved compared with the GAN model, and also verifies the effectiveness and stability of DMOEA in dealing with industrial matching problems in complex environments. This result reaffirms that the DMOEA algorithmic model is more suitable for product allocation tasks compared to GAN, and is consistent with the result that the generalized growth remanufacturing model proposed by Yıldız et al. improves the utilization of retired products [20].

Despite the strong performance demonstrated by the DMOEA model in this study, there are still limitations. On the one hand, the model mainly focuses on the multi-objective optimization of part sizes and does not fully consider the performance metrics and cost factors of the parts, which may affect the practical application results of the selection scheme. On the other hand, the computational complexity of the DMOEA algorithm is relatively high, and further research is needed to improve its computational efficiency. Future research can refine the product selection model, and in addition to dimensional accuracy, product performance, cost and supply chain factors should also be considered to achieve more comprehensive selection optimization. In addition, we can try to combine artificial intelligence and machine learning technology to further improve the intelligence level of the selection model, for example, by automatically adjusting the algorithm parameters to adapt to different selection scenarios.

VI. CONCLUSION

The industrial machinery product selection is a complex optimization problem that involves multiple attributes and constraints. Traditional optimization methods have low efficiency or inability to effectively explore the design space when dealing with such problems. In view of this, after analyzing and summarizing the existing multi-objective problem of product selection, a new mechanical product selection model is proposed by introducing the DMOEA for improvement. The experimental results showed that the selection accuracy of the DMOEA in the training set was close to 99%, and the selection accuracy in the testing set was close to 95%. When the algorithm iterations were 250, the highest success rate of DMOEA was 97%. Although it was 1% lower than the RL model, the number of iterations decreased by nearly 100 times. In addition, the maximum absolute error sum of the selected diameters for bearings and bearing seats in the DMOEA was 0.002, and the maximum relative error sum was 0.01%. The highest fitting reliability of the algorithm was 99.9%. Compared to the RL, there was a significant decrease in error indicators and a significant improvement in credibility. Simulation tests showed that the highest selection success rate of the DMOEA was 0.99, the average selection success rate was 0.93, the lowest selection quality loss was 0.08, and the average selection quality loss was 0.26. At the same time, the DMOEA could smoothly perform allocation prediction. The confusion matrix had a maximum score of 60 points. In summary, the DMOEA model has certain practicality and feasibility, providing a new approach and method for solving complex selection problems. However, the actual product selection problem is too complex. This study only considers the size chain relationship, without considering the performance indicators and cost supply of the parts. Subsequent research can continue to increase these considerations to enhance the credibility and comprehensiveness of the study.

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