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Computer-Aided Design AND APPLICATIONS

Strategy of Sustainability Algorithm in Industrial Product Design Using Multi-Objective Genetic Algorithm

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Abstract. Due to the continuous growth of Computer aided design (CAD) technology, it has been widely used in the field of industrial product design. In order to improve the application effect of CAD in industrial design and practice the concept of sustainable growth of industrial product design, this article proposes an industrial process optimization algorithm of Computer aided industrial design (CAID) based on multi-objective Genetic algorithm (GA). In this algorithm, sustainability factors are included in the optimization objective, and the tradeoff and optimization among multiple objectives, such as cost, performance, resource utilization and environmental impact, are considered. By optimizing the product design process, the algorithm can help enterprises to achieve more efficient and environmentally friendly product design and improve the market competitiveness of products. The algorithm is described in detail in this article, and its effectiveness is verified by experiments. Experiments show that the multi-objective GA has fast convergence speed and good robustness and adaptability. Moreover, the multi-objective GA has a low RMSE value, only 0.514; the accuracy of the optimization results is high, and the optimal solution that meets the actual needs can be found with high accuracy.

Keywords: Computer Aided Design; Industrial Product Design; Multi-Objective Genetic Algorithm; Process Optimization; Sustainable Growth
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1 INTRODUCTION

In today's society, with the continuous progress of sci & tech and the rapid growth of global economy, industrial design plays an increasingly important role in various fields. With the rapid development of artificial intelligence technology, more and more industries are attempting to use AI to improve production efficiency and optimize product quality. Especially in the manufacturing industry, the application of AI can achieve comprehensive intelligence from product design to production manufacturing. As an important branch of artificial intelligence, digital dual drive supervised machine learning has broad prospects in the application of manufacturing. Alexopoulos et al. [1] introduces training in supervised learning. By training, an accurate prediction model can be obtained. Unsupervised learning lacks label information and mainly utilizes techniques such as clustering and dimensionality reduction to discover the structures in the data. Semi supervised learning combines the characteristics of supervised learning and unsupervised learning, utilizing partially labeled data and a large amount of unlabeled data for training. Reinforcement learning learns strategies through interaction with the environment, thereby achieving goals. Moreover, with the increasing awareness of environmental protection and the increasing shortage of resources and energy, the concept of sustainable growth of industrial product design has been paid more and more attention. With the continuous maturity of 5G technology, the development of intelligent automation and industry digitization has also entered a new stage. 5G technology, with its characteristics of high speed, low latency, and large capacity, provides strong support for the development of intelligent automation and industry digitization, leading the new trend of industry development. Attaran et al. [2] explored the impact of 5G on the development of intelligent automation and industry digitization, analyzed its advantages, disadvantages, and development prospects. Research was conducted on the application of 5G in the development of intelligent automation and industry digitization. 5G technology can monitor the allocation of energy in real-time, dynamically adjust according to demand, and improve energy utilization efficiency. For example, in the energy field, 5G technology can monitor power distribution and dynamically adjust according to demand to improve power utilization efficiency. Sustainable growth requires that environmental impact, resource utilization and social benefits should be considered in product design, so as to achieve the balance among economy, society and environment. With the rapid development of the global economy, supply chain networks are playing an increasingly important role in the operation of enterprises. However, traditional supply chain network optimization methods often only consider a single objective, such as the lowest cost or shortest delivery time, while ignoring other important factors, such as sustainability. Therefore, establishing a supply chain network optimization model that comprehensively considers multiple objectives and achieves sustainability has become an urgent demand. Ehtesham and Sohanian [3] encode parameters as chromosomes, each representing a possible solution. In the encoding process, we adopted real number encoding to better handle continuous parameters. In genetic algorithm, we adopt the following optimization strategies: selection, crossover, and mutation. The selection operation selects excellent individuals based on the fitness function. The crossover operation involves randomly selecting a portion of two individuals for exchange to generate a new individual; Mutation operations randomly alter a portion of an individual's genes to increase population diversity.

In industrial product design, CAD technology has been widely used. Gregory et al. [4] analyzed the role of artificial intelligence and data network effects in creating user value. The data network effect can help enterprises collect and analyze user data more effectively, thereby better understanding user needs and behaviors. Through data collection and analysis on social media and e-commerce platforms, enterprises can understand users' purchasing habits and preferences, thereby providing more accurate products and services. The data network effect can be analyzed by analyzing a large amount of user behavior data to identify potential user needs and pain points, thereby optimizing the design and functionality of products and services, and improving user experience. By analyzing user behavior data while using the app, enterprises can identify the problems and difficulties encountered by users, thereby improving the design and functionality of the app. AI and data network effects can promote each other and further improve user experience. At the same time, these optimized products and services will generate more user behavior data, further enriching the sources of data network effects. CAD technology can help designers to model, simulate and analyze products on computers, so as to speed up product design and improve design quality and reliability. Multi product production planning is a common problem. While meeting the needs of different products, enterprises also need to consider multiple goals such as production efficiency, resource utilization, and quality control. How to effectively solve the multi-objective aggregation production planning problem of multiple products has become a challenging problem. Genetic algorithm, as a commonly used optimization method, has been widely applied to solve various complex optimization problems., Traditional genetic algorithms often face problems such as large search space and low efficiency when dealing with multi product and multi-objective production planning problems. Therefore, Liu and Yang [5] proposed a genetic algorithm optimization method based on local search to solve the multi-objective aggregation production planning problem of multiple products. The experimental results show that the genetic algorithm optimization method based on local search has higher optimization efficiency and accuracy in solving multi-objective aggregation production planning problems for multiple products. Compared to traditional genetic algorithms, our proposed method can achieve better optimization results in most cases.

However, the existing CAD technology still has some shortcomings in product design process optimization, which cannot fully meet the needs of sustainable growth. For example, designers often only give priority to the function and appearance of products, but ignore the sustainability of products. With the rapid development of technology, the application of optimized molecular and hybrid product design frameworks and tools in various industries is becoming increasingly widespread. This framework and tool can improve product performance and reduce costs by optimizing the design solutions of molecules and hybrid products, thereby meeting the constantly changing market demands. Liu et al. [6] provided a detailed introduction to the structure, functions, and application cases of this framework and tool, and analyzed its advantages and value. The molecular and hybrid product design framework based on optimization is a tool that integrates computer-aided engineering (CAE), computer-aided design (CAD), and optimization algorithms. This module is used to establish mathematical models of molecules and mixed products, including physical models, chemical reaction models, etc. This module is used to simulate the performance of molecules and mixed products, such as mechanical properties, chemical reactions, etc. In addition, traditional product design methods often only consider a single goal, such as cost and performance, while ignoring the trade-off and optimization among multiple goals. This makes a lot of resources and energy waste in the product design process. With the continuous development of virtual reality (VR) technology, more and more designers are starting to use this technology for product development. In virtual reality environments, conceptual modeling has become an important aspect of product development. Lorusso et al. [7] elaborated on the importance of conceptual modeling in virtual reality environments, introduced modeling methods and steps, and demonstrated its application value through case analysis. A conceptual model refers to a model formed by abstractly describing entities in the real world. In virtual reality environments, conceptual models are a key tool for designers in product design. It can quickly transform designers' creativity into virtual models, making it easy for designers to modify and improve. At the same time, conceptual models can also help designers communicate and collaborate effectively with team members during the development process.

In order to solve the above problems, this article proposes an industrial process optimization algorithm of CAID based on multi-objective GA. The algorithm uses the optimization principle of GA to optimize the design process of industrial products, so as to improve the design efficiency and quality and reduce the waste of resources and energy. Specifically, the algorithm takes sustainability factors into the optimization objective, and considers the tradeoff and optimization among multiple objectives, such as cost, performance, resource utilization and environmental impact. By optimizing the product design process, the algorithm can help enterprises to achieve more efficient and environmentally friendly product design and improve the market competitiveness of products. The innovation of this article is mainly reflected in the following aspects:

(1) Incorporate sustainability factors into optimization objectives: In the traditional industrial product design process, designers usually only give priority to single objectives such as product function, performance and cost, while ignoring product sustainability. In this article, an industrial process optimization algorithm of CAID based on multi-objective GA is proposed, which integrates sustainability factors into optimization objectives, such as resource utilization, energy consumption and environmental impact, so as to realize product design that meets the requirements of sustainable growth.

(2) Consider the tradeoff and optimization among multiple goals: Traditional product design methods often only consider a single goal, but ignore the tradeoff and optimization among multiple goals. The algorithm proposed in this article can not only optimize a single objective, but also comprehensively consider the tradeoff and optimization among multiple objectives, such as cost, performance, resource utilization and environmental impact. By optimizing the product design process, the algorithm can help enterprises to achieve more efficient and environmentally friendly product design and improve the market competitiveness of products.

(3) Optimize the design process of industrial products: The algorithm proposed in this article considers not only the design process of products, but also the whole process of product life cycle. By optimizing the product design process, the algorithm can reduce the waste of resources and energy, improve the design efficiency and quality, and reduce the product cost and environmental impact.

Firstly, this article introduces the background and significance of industrial product design with CAD, and expounds the application of multi-objective GA in industrial product design. Secondly, clarify the research purpose of this article and explain the significance and value of this research. Moreover, it introduces the research methods adopted in this article, including literature review, case analysis and experimental verification. Then, the application of multi-objective GA in industrial product design is introduced. Moreover, the experimental results and data analysis show the effectiveness and superiority of the algorithm. Finally, the main conclusions of this article are summarized and the advantages and applicability of multi-objective GA in industrial product design are expounded. Moreover, the future research direction and the application prospect of this algorithm in other fields are prospected.

2 RELATED WORK

With the rapid development of technology, Industrial Internet of Things (IIoT) and Artificial Intelligence (AI) have found widespread applications in many industries. By combining AI with IIoT, we can achieve more efficient and intelligent production methods, thereby improving efficiency, reducing costs, and improving product quality. However, this combination also brings new challenges, the most crucial of which is the issue of credibility. Lv et al. [8] explored how to ensure the credibility of industrial IoT systems based on artificial intelligence. By integrating AI with IIoT, we can achieve intelligent production and management. This integration can not only improve production efficiency and reduce costs, but also help enterprises make wiser decisions. By integrating AI with IIoT, we can achieve intelligent production and management. This integration can not only improve production efficiency and reduce costs, but also help enterprises make wiser decisions. With the increasingly serious global environmental issues, sustainable product growth has become a focus of attention for various industries. As an indispensable part of modern people's daily lives, tablet devices have also received widespread attention for their sustainable product growth. Manjunatheshwara and Vinodh [9] combine environmental awareness and use the QFD weighted decision matrix evaluation method to explore strategies for sustainable product growth of tablet devices. The QFD weighted decision matrix evaluation method is a combination of qualitative and quantitative decision analysis methods. It can decompose complex problems into multiple simple sub problems, and obtain the final decision result through weight assignment and matrix operation. In the field of sustainable product growth, the application of QFD weighted decision matrix evaluation method can help us better understand the environmental impact of products and provide optimization solutions for product design.

The hybrid multi-objective evolutionary algorithm, as an advanced optimization technology, can be applied to sustainable distributed manufacturing systems to help enterprises achieve resource optimization, improve production efficiency, and reduce environmental pollution. Ramakurthi et al. [10] introduced the semantic foundation of hybrid multi-objective evolutionary algorithms in sustainable distributed manufacturing systems. The Semantic Web is an internet technology based on XML language, which can achieve semantic description and understanding of network information. In sustainable distributed manufacturing systems, semantic web can be used to describe information about manufacturing resources and production processes, enabling information sharing and interaction between different manufacturing units. The knowledge in the knowledge base can be applied to the actual manufacturing process through inference engines, providing support for system decision-making and optimization. At the same time, the knowledge base can continuously learn and accumulate new knowledge, achieving knowledge updates and optimization. With the rapid development of aerospace technology, the design and optimization of low thrust rocket engines are particularly important. The application of computer-aided design (CAD) and computer-aided engineering (CAE) systems provides new possibilities for the design of rocket engines. Ryzhkov et al. [11] explored how to use domain specific knowledge databases and CAE/CAD systems for computer-aided design of low thrust rocket engines. The types of databases available include knowledge databases, parameter databases, and simulation databases. The knowledge database stores a large amount of design knowledge, empirical data, and expert advice, providing valuable reference information for designers. The parameter database contains performance parameters of various materials, components, and systems, making it easy for designers to access and use. The simulation database stores a large amount of simulation result data, which helps designers evaluate and optimize design schemes. In the context of Industry 4.0, the development of sustainable industry and operational engineering faces many challenges and opportunities. Data driven analysis, as an effective means, can help enterprises better understand the energy consumption and emissions during the production process, and thus take targeted measures to improve. Through the Internet of Things technology, real-time collection of equipment operation data, environmental monitoring data, raw material data, etc. can be achieved, providing a foundation for subsequent data analysis. By using professional data analysis tools and methods, valuable information can be extracted from the collected data, such as the energy consumption of equipment and the optimization direction of production processes. Tseng et al. [12] conducted in-depth analysis on the collected and processed data to understand the energy consumption and emissions during the production process, in order to identify existing problems and improve space. Based on data analysis results, enterprises can make more scientific and reasonable decisions, such as adopting cleaner energy, improving production processes, etc., to achieve the goals of sustainable industrial and operational engineering.

Wang et al. [13] aim to study product primitive recognition in computer-aided brand product development systems, and provide effective support and guidance for brand product development by analyzing the concepts, methods, and applications of product primitive recognition. The research results indicate that product primitive recognition can effectively improve the efficiency and accuracy of brand product development, providing better auxiliary tools for designers and developers. With the intensification of market competition, brand product development has become an important means of survival and development for enterprises. However, traditional brand product development methods have problems such as long development cycles, high costs, and unstable quality. Product primitive recognition is an important component of computer-aided brand product development systems. It provides accurate product design and development support for designers and developers by identifying and understanding the original product information. With the rapid development of technology, the application of intelligent computer-aided design in various fields is becoming increasingly widespread. The appearance design of agricultural product packaging art style is no exception. With the help of intelligent computer technology, the innovation and efficiency of design can be improved. Zhao et al. [14] explored the current status, trends, and significance of intelligent computer-assisted artistic style appearance design for agricultural product packaging. The appearance design of agricultural product packaging art style includes multiple elements, and the selection and application of these elements directly affect the artistic effect of packaging. Firstly, the selection of packaging materials is crucial, as different materials bring different visual and tactile sensations to people. Next is the form design, including the shape, size, and structure of the packaging, which determines the overall image of the product. In addition, color matching is also a key aspect of exterior design, which can enhance the visual appeal of the product. Finally, the rendering of text cannot be ignored as it can convey relevant information about the product and enhance its recognition. In today's design field, collaboration and computer-aided design (CAD) have become industry standards. Designers not only need to handle various design issues in practice, but also need to communicate and collaborate effectively with team members. At the same time, the emotions of designers also play an important role in the design process. Zhou et al. [15] explored the methods and significance of analyzing designer emotions in collaborative and traditional computer-aided design. Through a questionnaire survey, designers can understand the opinions and feelings of team members towards design, thereby analyzing the impact of emotions on design. Based on the requirements analysis results, the designer and team members jointly develop a design plan and continuously optimize and improve it.

The existing research mainly focuses on the optimization of a single goal, ignoring the consideration of sustainability. Therefore, this article puts forward a multi-objective GA, which takes sustainability factors into the optimization goal to realize the product design stage that is more in line with the requirements of sustainable growth.

3 METHODOLOGY

3.1 Sustainable Growth of Industrial Products

Sustainable growth emphasizes the coordination and unity of economy, society and environment, and is a sustainable growth mode. Industrial products are indispensable items in people's daily life, so it is of great significance to realize the sustainable growth of industrial products. First of all, it can reduce the waste of resources and energy and improve the efficiency of resource utilization; Secondly, it can reduce environmental pollution and protect the ecological environment; Finally, it can improve the market competitiveness of products and promote economic development.

The design principles of sustainable growth of industrial products are as follows: ① Reduce resource consumption: In the stage of industrial product design, the consumption of resources and energy should be reduced as much as possible to improve resource utilization efficiency. For example, adopting renewable materials, optimizing product structure and reducing the number of parts and components. ② Reducing environmental impact: The design of industrial products should reduce the negative impact on the environment as much as possible, such as adopting environmental protection materials, optimizing production technology, reducing waste emissions and other measures. ③ Improving product performance: Industrial product design should improve product performance and quality, prolong product service life, and thus reduce the waste of environment and resources. ④ Promoting recycling: The design of products should consider the recycling and recycling of products, so as to reduce the waste of resources and energy. For example, measures such as adopting recyclable materials and designing detachable structures. ⑤ Optimized design scheme: Industrial product design should optimize the design scheme and consider the whole life cycle of the product, thus reducing the waste of environment and resources. For example, adopt life cycle assessment method, optimize maintenance and update scheme and other measures. Figure 1 shows the life cycle of products and its relationship with the environment.

The application of sustainability algorithm strategy in industrial product design can help designers achieve the goal of sustainable growth better. For example, the GA is used to optimize the design of industrial products, and the sustainability factors are included in the optimization objectives, and the trade-off and optimization among multiple objectives are considered. By optimizing the product design process, the algorithm can reduce the waste of resources and energy, improve the design efficiency and quality, and reduce the product cost and environmental impact. In addition, the sustainability algorithm strategy can be combined with other design methods to form a more efficient design process. For example, the combination of sustainability algorithm strategy and concurrent design method can speed up the design and improve the design quality.

3.2 Principle of Multi-Objective GA

Multi-objective GA is developed on the basis of GA. It is suitable for solving complex, nonlinear and MOO problems. MOO problem refers to the problem of optimizing multiple objective functions at the same time, so that multiple objective functions can reach the optimal solution.

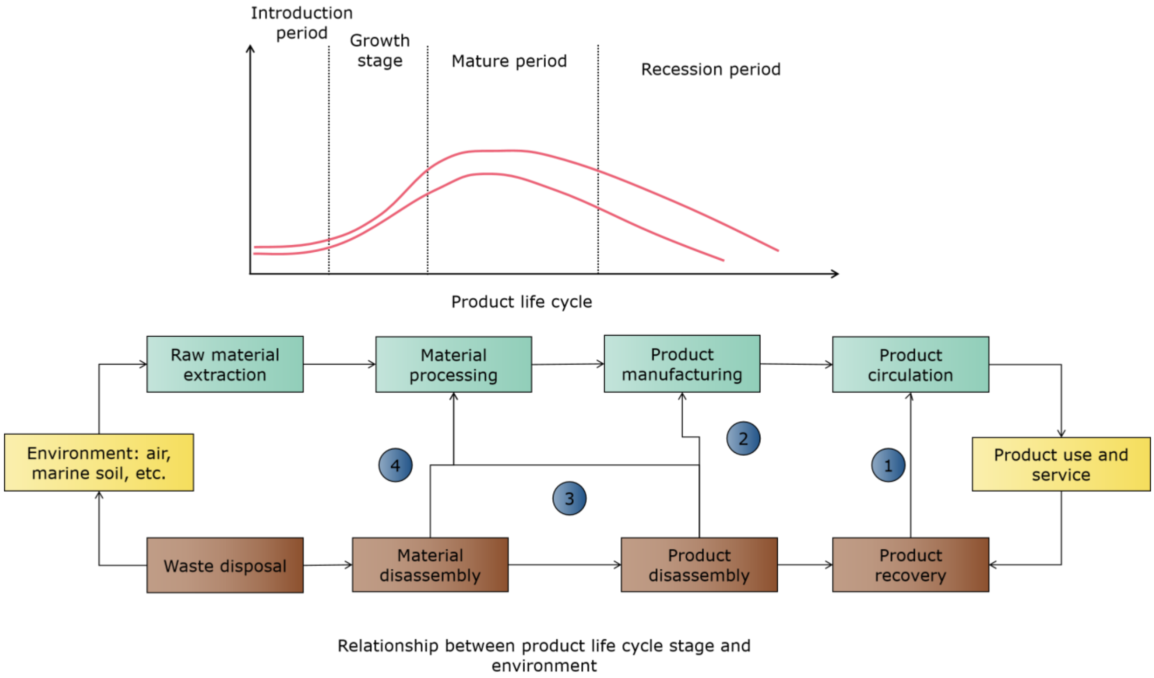

Figure 1: Life cycle of industrial products and its relationship with environment.

In the design of industrial products, MOO problems are often encountered, for example, in the process of product design, production, use and maintenance, many factors need to be considered at the same time, such as cost, performance, resource utilization and environmental impact. Multi-objective GA optimizes multiple objective functions at the same time by introducing MOO functions. MOO function combines multiple objective functions into an optimization objective function, and gradually searches for the optimal solution through operations such as chromosome selection, crossover and mutation. In multi-objective GA, each chromosome represents a possible solution, and each solution is a trade-off and optimization of multiple objective functions. Pareto optimal solution means that the solution of at least one goal can be improved without damaging any goal.

By introducing natural selection, crossover and mutation in the process of biological evolution, it can gradually search for the optimal solution and avoid falling into the trap of local optimal solution. In addition, it can be combined with other optimization methods to form a more efficient optimization algorithm. For example, this algorithm can be combined with heuristic algorithm, and the search efficiency of heuristic algorithm can be improved by using its fast search ability.

3.3 Realization of Industrial Process Optimization Algorithm Based on Multi-Objective GA

In industrial product design, the industrial process optimization algorithm based on multi-objective GA can realize more efficient and environmentally friendly product design. The algorithm optimizes the product design process, reduces the waste of resources and energy, improves the design efficiency, and reduces the product cost and environmental impact by considering the trade-off and optimization among multiple objectives. The realization process of industrial process optimization algorithm based on multi-objective GA includes the following steps: ⊖ Determine the optimization goal. ⊜ Coding. ⊛ Initialization. ④ Fitness function. ⑤ Select operation. ⑥ Cross operation. ⑦ Mutation operation. ⑧End conditions. Figure 2 shows the specific algorithm framework.

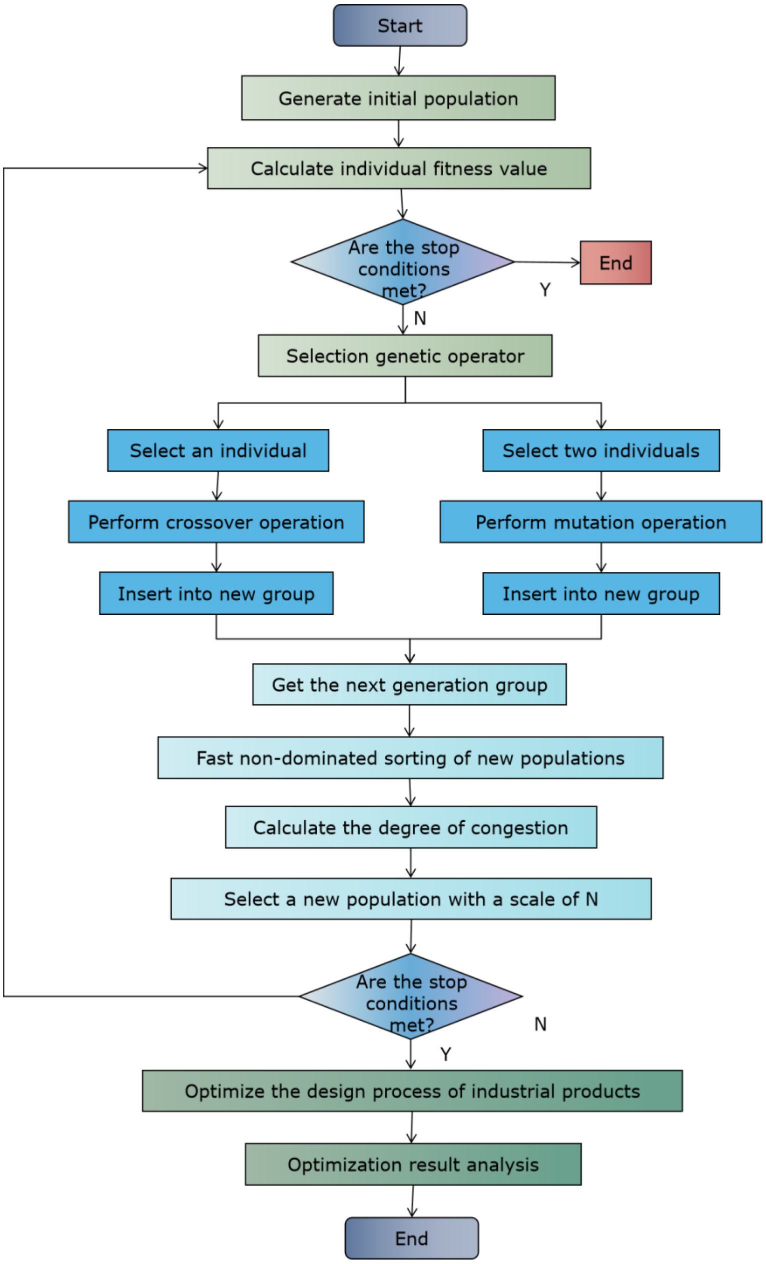

Figure 2: Algorithm frame diagram.

Industrial process optimization is a MOO problem, and the objective function and constraints can be established into an unconstrained optimization objective function by using the penalty function method. Industrial process optimization can be expressed as:

$$\min\ f(X)\quad x_{i_{\min}} \le x_i \le x_{i_{\max}} \tag{1}$$

$$s.t.\ h_j(X)=0 \quad g_k(X)\le 0 \tag{2}$$

$$i=1,2,3,\ldots,n \quad j=1,2,3,\ldots,p \quad k=1,2,3,\ldots,q \tag{3}$$

The objective function is constructed as follows:

$$\min F(X)=f(x)+c\left\{\sum_{j=1}^{p}\left|h_j(X)\right|+\sum_{k=1}^{q}\max\left[0,g_k(X)\right]\right\} \quad c>0 \tag{4}$$

Where c is the penalty function; $F(X)$ can take one or a combination of several evaluation criteria.

An actual case is used to illustrate the application of industrial process optimization algorithm based on multi-objective GA. Suppose a manufacturing enterprise needs to design a new industrial product, which needs to meet a variety of performance indicators, and at the same time needs to consider production costs, resource utilization and environmental impact. The enterprise can use this algorithm to design products, get a set of Pareto optimal solutions by optimizing multiple objective functions, and choose the most suitable solution as the final design scheme. Specifically, you can follow the following steps:

⊖ Determination of design requirements: According to the requirements of product performance index, production cost, resource utilization and environmental impact, determine the objective function to be optimized. These objective functions can be multiple, in this article, including performance index, manufacturing cost, resource utilization and environmental impact. It is assumed that each industrial component has a fixed development time and cost. The cost and time of re-growth of each component will be different with different communication impact. The objective function of defining the development time, development cost, environmental impact and change risk of each change propagation path is:

$$T=\sum_{i=1}^{n} i_{i-1,i}\times T_i \tag{5}$$

$$C=\sum_{i=1}^{n} i_{i-1,i}\times C_i \tag{6}$$

$$R=\sum_{i=1}^{n} i_{i-1,i}\times l_{i-1,i} \tag{7}$$

$$F(x)=\left\{\min\sum_{i=1}^{n} i_{i-1,i}\times T_i,\min\sum_{i=1}^{n} i_{i-1,i}\times C_i,\min\sum_{i=1}^{n} i_{i-1,i}\times l_{i-1,i}\right\} \tag{8}$$

Where T is the total development time of all parts on the change propagation path; C is the total development cost; R is the total change risk; T_i is the development time of part i; C_i is the development cost of part i. The optimization model of complex product design change communication needs to meet the following constraints:

$$C\le C_m, T\le T_m \tag{9}$$

Where C_m is the maximum development cost that can be accepted by the design change of the product; T_m is the longest product delivery time that can be accepted by the design change of this product.

⊜ Coding: coding the design scheme into the form of chromosome. Each chromosome represents a possible design scheme. In this article, the coding method of chromosomes adopts binary form.

⊛ Initialization: randomly generate a set of chromosomes as the initial solution. The number of initial solutions can be determined according to the scale and complexity of the problem, and a certain number of random solutions are generally used for initialization.

④ Fitness function: According to the design requirements and objective function, the fitness function is defined to evaluate the quality of chromosomes. Fitness function should be able to reflect the performance of each chromosome in many aspects, such as performance index, manufacturing cost, resource utilization rate and environmental impact. This article weights or combines them according to the actual situation.

⑤ Selection operation: select chromosomes according to fitness function, and select chromosomes with better fitness for subsequent crossover and mutation operation. In this article, roulette wheel selection, sorting selection, optimal individual preservation, random league selection and other methods are adopted.

⑥ Crossover operation: two chromosomes are randomly selected for crossover operation to produce new chromosomes. This article chooses according to the actual situation.

⑦ Mutation operation: mutation operation is performed on chromosomes to increase the diversity of chromosomes.

⑧ Termination condition: judge whether the optimal solution is reached according to the set termination condition; if it is, output the result; otherwise, return to step 3 to continue the search.

⑨ Result analysis: Analyze and evaluate the output results, and choose the most suitable solution as the final design scheme. The results analysis should consider the performance of each solution on multiple objective functions, and weigh and choose according to the actual situation.

Through the above steps, the industrial process optimization algorithm based on multi-objective GA can realize the optimization of multiple objective functions, get a set of Pareto optimal solutions, and choose the most suitable solution as the final design scheme. The algorithm has good generalization ability and adaptability, and can complete the optimization process automatically and intelligently, reduce manual intervention and cost, and improve design efficiency and accuracy.

4 CASE ANALYSIS

This section selects a manufacturing enterprise as the research object to optimize its product design process. Firstly, collect the product design data and resource utilization data of the enterprise; Secondly, the product design process model and resource utilization model are established according to the collected data; Then, the sustainability factor is included in the optimization goal, and the product design stage is optimized by multi-objective GA. Finally, the optimized product design stage is verified by experiments, and the effects before and after optimization are compared. Figure 3 shows the convergence speed of the algorithm.

The convergence speed of the multi-objective GA shown in Figure 3 can be understood as the speed at which the algorithm finds the approximate optimal solution in the iterative process. Through many experiments, it can be observed that the multi-objective GA has a fast convergence speed, which means that the algorithm can find the satisfactory results with fewer iterations. Specifically, the multi-objective GA uses the genetic principle in biological evolution to gradually search for the optimal solution through operations such as selection, crossover and mutation. In each iteration, the algorithm will evaluate the advantages and disadvantages of chromosomes according to fitness function, and select chromosomes with better fitness for subsequent crossover and mutation operations. This process can quickly eliminate a large number of invalid solutions and focus on the better solution, so it has a faster convergence speed.

Because the multi-objective GA adopts randomized search method, it can avoid falling into the trap of local optimal solution and find a group of Pareto optimal solutions. This set of solutions contains trade-offs and optimizations among multiple objective functions, which can meet various needs in practical applications. Figure 4 shows the accuracy of the optimization results of the algorithm.

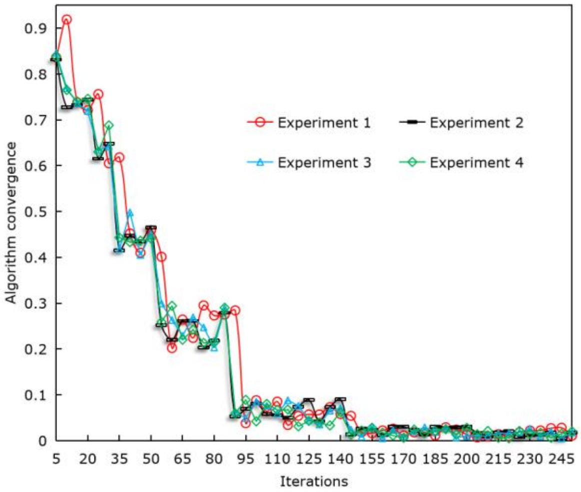

Figure 3: Convergence rate of the algorithm.

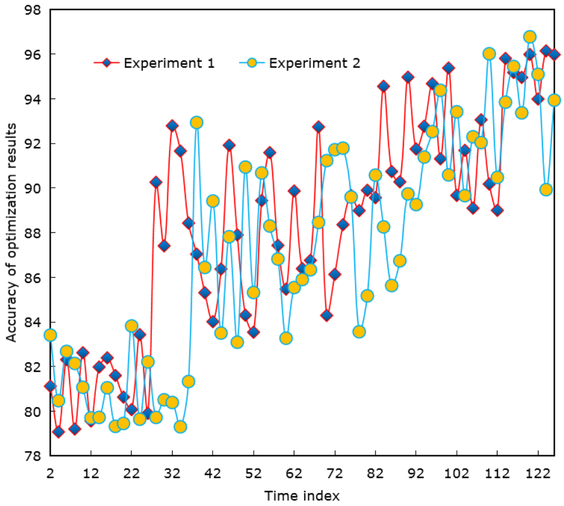

Figure 4: Accuracy of optimization results of the algorithm.

The accuracy of the optimization results of the multi-objective GA shown in Figure 4 shows that the algorithm can find the optimal solution to meet the actual needs with high accuracy. The accuracy of the optimization results can reach 96.78%, which means that the algorithm can give quite accurate results in most cases. This advantage makes this algorithm become an effective method of sustainability algorithm strategy in industrial product design.

RMSE is a commonly used error measurement index. Lower RMSE value means that the prediction result of the algorithm is more accurate and reliable. Figure 5 shows the RMSE of the algorithm. The RMSE of the multi-objective GA shown in Figure 5 is low, only 0.514. This means that the prediction results of the algorithm are more accurate and reliable.

In the process of product design, we often encounter MOO problems, such as meeting the performance indicators, taking into account manufacturing costs, resource utilization and environmental impact. Traditional product design methods are often difficult to optimize multiple objectives at the same time, resulting in low design efficiency. Table 1 shows the comparison of a manufacturing enterprise before and after using the algorithm proposed in this article to optimize the product design process.

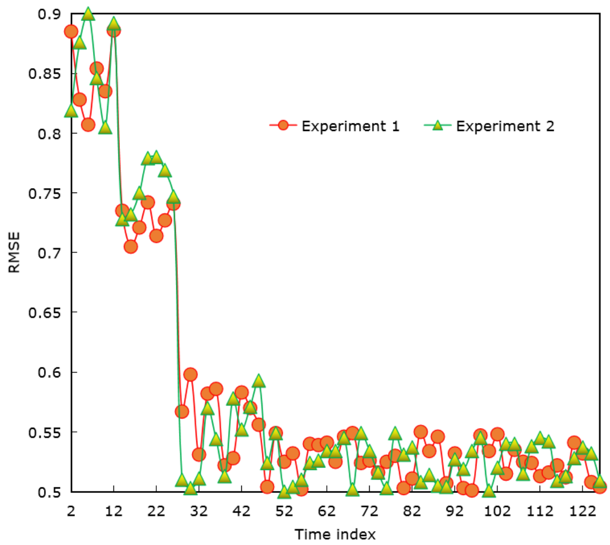

Figure 5: RMSE of the algorithm.

Optimization aspect	*Optimization effect (Before optimization)*	*Optimization effect (After optimization)*	*Optimal difference*
Resource utilization	100 unit material usage	80 unit material usage	-20%
Energy consumption	100 unit energy consumption	80 unit energy consumption	-20%
Design efficiency	100 units of design time	80 unit design time	-20%
Product costs	100 unit manufacturing cost	90 unit manufacturing cost	-10%
Environmental effect	100 units of environmental impact value	80 units of environmental impact value	-20%

Table 1: Comparison before and after optimizing product design process.

Through the display of the above table, it can be clearly seen that after optimizing the product design process, the waste of resources and energy is reduced, the design efficiency and quality are improved, and the product cost and environmental impact are also reduced compared with before optimization. The specific numerical differences of these optimization effects can explain the advantages and values of the algorithm more intuitively.

The following shows the efficiency of product design after algorithm optimization in the form of data graph. The product design efficiency before and after multi-objective GA optimization is shown in Figure 6.

The efficiency of product design before optimization is low, but the efficiency of product design after optimization by multi-objective GA is obviously improved. On the one hand, this is because the algorithm has found a better design scheme, which makes the product perform better in multiple objective functions; On the other hand, because the algorithm reduces the number of iterations and search space in the design process, the design efficiency is improved. This result verifies the conjecture that CAID's industrial process optimization algorithm based on multi-objective GA can effectively improve the efficiency of product design process.

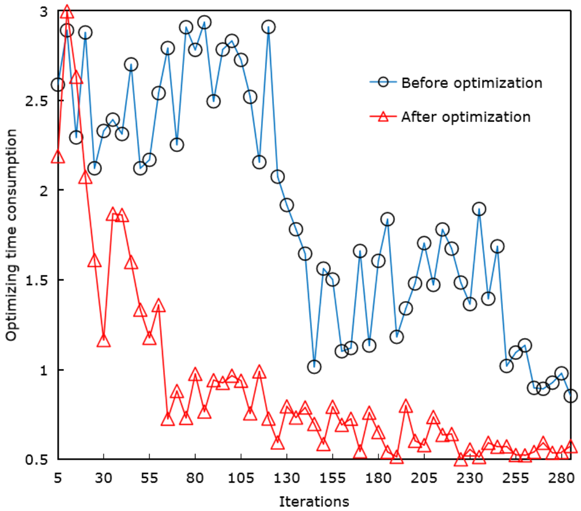

Figure 6: Comparison of product design efficiency before and after optimization.

In industrial product design, product quality is a very important factor. Traditional design methods are often based on experience and personal judgment, and it is difficult to ensure the stability and reliability of product quality. As an advanced optimization algorithm, multi-objective GA can comprehensively consider multiple objective functions, including performance index, manufacturing cost, resource utilization rate and environmental impact, so as to get the optimal solution. The quality of product design before and after algorithm optimization is shown in Figure 7.

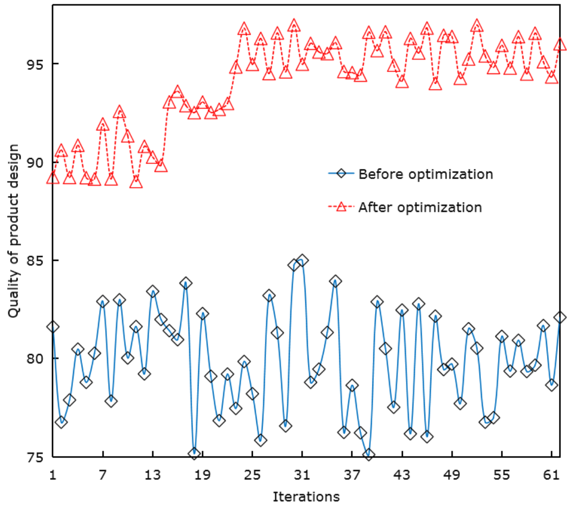

Figure 7: Quality comparison of product design before and after optimization.

The quality of product design after multi-objective GA optimization has been significantly improved compared with that before optimization. The industrial process optimization algorithm of CAID based on multi-objective GA can effectively improve the quality of product design. By applying this algorithm, enterprises can design and optimize products more efficiently, improve product quality and competitiveness, and meet the requirements of sustainable growth.

This section has been verified by experiments, and the optimized product design process has obviously improved the efficiency, while reducing the waste of resources and energy. The results show that the industrial process optimization algorithm of CAID based on multi-objective GA can effectively improve the efficiency and sustainability of product design process.

5 CONCLUSION

The purpose of this article is to discuss the effect of visual design optimization of industrial products based on CAD algorithm. Through the research of this article, the effectiveness and superiority of visual design optimization of industrial products based on CAD algorithm are verified. Experiments show that the multi-objective GA has fast convergence speed and good robustness and adaptability. Moreover, the multi-objective GA has a low RMSE value, only 0.514; Moreover, the accuracy of the optimization results is high, and the optimal solution that meets the actual needs can be found with high accuracy. These results show that the algorithm can complete the optimization process automatically and intelligently, and improve the design efficiency and accuracy. In this article, the industrial process optimization algorithm of CAID based on multi-objective GA is studied, which can realize more efficient product design process and reduce the waste of resources and energy. This will not only contribute to the sustainable growth of enterprises, but also improve their market competitiveness.

Generally speaking, the industrial process optimization algorithm of CAID based on multi-objective GA can improve the sustainability of products to some extent. This provides a new solution for enterprises to achieve sustainable growth. However, there are still limitations in this study. For example, the experimental object is only a manufacturing enterprise, and the future research can be further extended to other industries and fields. In addition, in the future, more sustainable factors can be included in the optimization objectives, such as carbon emissions and recycling, to achieve more comprehensive sustainable growth; Research more intelligent optimization algorithm to improve optimization efficiency and accuracy; The optimization algorithm is combined with other design methods to form a more efficient design process.

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REFERENCES

[1] Alexopoulos, K.; Nikolakis, N.; Chryssolouris, G.: Digital twin-driven supervised machine learning for the development of artificial intelligence applications in manufacturing, International Journal of Computer Integrated Manufacturing, 33(5), 2020, 429-439. https://doi.org/10.1080/0951192X.2020.1747642

[2] Attaran, M.: The impact of 5G on the evolution of intelligent automation and industry digitization, Journal of Ambient Intelligence and Humanized Computing, 14(5), 2023, 5977-5993. https://doi.org/10.1007/s12652-020-02521-x

[3] Ehtesham, R.-R.; Sohanian, M.: A multi-objective optimization model for sustainable supply chain network with using genetic algorithm, Journal of Modelling in Management, 16(2), 2021, 714-727. https://doi.org/10.1108/JM2-06-2020-0150

[4] Gregory, R.-W.; Henfridsson, O.; Kaganer, E.; Kyriakou, H.: The role of artificial intelligence and data network effects for creating user value, Academy of Management Review, 46(3), 2021, 534-551. https://doi.org/10.5465/amr.2019.0178

[5] Liu, L.-F.; Yang, X.-F.: Multi-objective aggregate production planning for multiple products: A local search-based genetic algorithm optimization approach, International Journal of Computational Intelligence Systems, 14(1), 2021, 1-16. https://doi.org/10.1007/s44196-021-00012-1
[6] Liu, Q.; Zhang, L.; Liu, L.: OptCAMD: An Optimization-based framework and tool for molecular and mixture product design, Computers & Chemical Engineering, 124(5), 2019, 285-301. https://doi.org/10.1016/j.compchemeng.2019.01.006
[7] Lorusso, M.; Rossoni, M.; Colombo, G.: Conceptual modeling in product design within virtual reality environments, Computer-Aided Design and Applications, 18(2), 2020 383-398. https://doi.org/10.14733/cadaps.2021.383-398
[8] Lv, Z.; Han, Y.; Singh, A.-K.; Manogaran, G.; Lv, H.: Trustworthiness in industrial IoT systems based on artificial intelligence, IEEE Transactions on Industrial Informatics, 17(2), 2020, 1496-1504. https://doi.org/10.1109/TII.2020.2994747
[9] Manjunatheshwara, K.-J.; Vinodh, S.: Sustainable product growth of tablet device using environmental conscious QFD - weighted decision matrix evaluation: a case study, International Journal of Services and Operations Management, 39(3), 2021, 415-437. https://doi.org/10.1504/IJSOM.2021.116104
[10] Ramakurthi, V.-B.; Manupati, V.-K.; Machado, J.; Varela, L.: A hybrid multi-objective evolutionary algorithm-based semantic foundation for sustainable distributed manufacturing systems, Applied Sciences, 11(14), 2021, 6314. https://doi.org/10.3390/app11146314
[11] Ryzhkov, V.-V.; Morozov, I.-I.; Lapshin, E.-A.: Computer-aided design of low-thrust rocket engines using the domain-specific knowledge database and CAE / CAD systems, VESTNIK of Samara University Aerospace and Mechanical Engineering, 18(4), 2019, 106-116. https://doi.org/10.18287/2541-7533-2019-18-4-106-116
[12] Tseng, M.-L.; Tran, T.-P.-T.; Ha, H.-M.; Bui, T.-D.; Lim, M.-K.: Sustainable industrial and operation engineering trends and challenges Toward Industry 4.0: A data driven analysis, Journal of Industrial and Production Engineering, 38(8), 2021, 581-598. https://doi.org/10.1080/21681015.2021.1950227
[13] Wang, W.; Su, J.; Zhang, X.: Research on product primitives recognition in a computer-aided brand product development system, Computer-Aided Design and Applications, 18(6), 2021, 1146-1166. https://doi.org/10.14733/cadaps.2021.1146-1166
[14] Zhao, Z.; Zheng, H.; Liu, Y.: The appearance design of agricultural product packaging art style under the intelligent computer aid, Computer-Aided Design and Applications, 19(S3), 2021, 164-173. https://doi.org/10.14733/cadaps.2022.S3.164-173
[15] Zhou, J.-J.; Phadnis, V.; Olechowski, A.: Analysis of designer emotions in collaborative and traditional computer-aided design, Journal of Mechanical Design, 143(2), 2020, 1-10. https://doi.org/10.1115/1.4047685