Industrial Product Design based on Genetic Optimization Algorithms of Internet of Things

Xiaodong Yuan[1] and Hailong Bi[2]

[1]School of Art Design, Zhengzhou University of Aeronautics, Zhengzhou, Henan 450046, China, yxd1982@zua.edu.cn
[2]School of Art Design, Zhengzhou University of Aeronautics, Zhengzhou, Henan 450046, China, 13939059093@163.com

Corresponding author: Xiaodong Yuan, yxd1982@zua.edu.cn

Abstract. The traditional and closed-door design approach can no longer meet the rapidly changing development needs of product design. Computer-aided industrial product design based on the Internet of Things has become an important research topic in industrial design. Based on this, this paper introduces dynamic web technology, network database technology, and virtual reality technology into the application of product industrial design information, researches the key technologies for the networked application of product industrial design information, and develops a corresponding prototype system. Firstly, based on the characteristics of product design and CAD technology, the key problems that need to be solved in the networked application of product industrial design information and the key technologies to solve such problems are proposed after analyzing and comparing the information of product industrial design. Then, the key technology for obtaining user demand information based on the Internet of Things is studied, and the characteristics and classification of user demand information are analyzed. A question bank for user demand surveys and a questionnaire template library are built using instance reasoning and relationship models.

Keywords: Internet of Things; Industrial Product Design; CAD Technology; Genetic Algorithm
DOI: https://doi.org/10.14733/cadaps.2023.S11.105-117

1 INTRODUCTION

Under the deep application of information technology and the rapid development of design technology, industrial design technology is undergoing a reconstruction of theory, methods, and technical means. On the one hand, the theoretical aspects of design, such as connotation, object, scope, function, and so on, have undergone profound changes. From focusing on the appearance of products to the soft quality of products, such as the interaction interface between products and people, human emotions, and experiences, human-centered design concepts such as humane design have emerged. Bernardo et al. [1] analyzed that computer-aided industrial product design refers to the use of computer technology to assist the industrial product design process, in order to improve design efficiency and quality. Computer aided design tools can help designers more intuitively carry out design ideas and scheme formulation, and can also carry out 3D modeling, data visualization and other operations, greatly improving the efficiency and accuracy of design. In industrial product design, computer-aided design tools have been widely used and have achieved good results. Frizziero et al. [2] endow 3D solid models with the materials used in actual production, and can conceptualize and plan their colors through different combinations of materials and colors. Using computers for precise simulation, the simulation results can serve as a reference for material and color selection, as well as for material selection in engineering production. Similar to product rendering, you can also use the software's built-in animation module or import 3D models into professional animation production software to complete the animation production of the product. For industrial design, design should be used to serve daily life, and market promotion, as a later stage of the industrial design process, plays a very important role in the process of truly transforming design into products. CAD technology and corresponding auxiliary design systems, as the main technical means of industrial design, have become the research frontier of industrial design technology and design methods, such as knowledge-based design, intelligent design and networked design. Research interests have shifted from focusing on computer simulation in specific design stages to the application of knowledge engineering technology to support the reconstruction of modern design processes, using artificial intelligence technology to simulate design thinking and concept creativity as an auxiliary creative tool research, and developing design-assisted tools based on the ontology and domain knowledge of design objects. Khan and Rezwana [3] achieved the integration of CAD and CAE. Improve the design efficiency and quality of CAD integration into CAE system. Specifically, establish the geometric modeling of the required problem: in the CAD stage, establish the geometric modeling of the required problem. This includes determining initial and boundary conditions, dividing the grid, and providing control parameters for solving. In the CAE stage, simulation calculations are required, including the stage with the highest computational load, mainly the stage with the highest demand for hardware resources. In this stage, the geometric modeling in the CAD system can be used for calculation, so as to reduce the loss in the data transmission process. In order to reduce the workload of CAD engineers, it is necessary to improve the usability and intelligence of the CAE system. This can be achieved by using interfaces and tools that conform to the usage habits of CAD engineers, as well as providing intelligent modeling and simulation algorithms. In order to ensure the accuracy and stability of the simulation results, it is necessary to improve the accuracy and stability of the CAE system's calculation results. This can be achieved by using high-performance computer hardware and software, as well as establishing comprehensive data verification and processing mechanisms. To avoid affecting the running speed of the original CAD system due to the integration of the two, it is necessary to improve the running speed of the CAE system. This can be achieved by optimizing the performance of computer hardware and software, as well as optimizing the way data is transmitted and processed. In short, integrating CAD into CAE systems can achieve the integration of CAD and CAE, improving design efficiency and quality. In the implementation process, multiple factors such as ease of use, intelligence, accuracy and stability, and running speed need to be comprehensively considered.

Against this background, this article studies a new product industrial design information application technology for industrial design, based on the popular CAD technology in the network environment. Kim et al [4] investigated the effects of connector design and materials on the fracture strength of 3-unit single piece fixed dentures. Introducing dynamic web technology, network database technology, and virtual reality technology into the application of product industrial design information, key technologies for networked application of product industrial design informatization were studied, and corresponding prototype systems were developed. Studied key technologies for obtaining user demand information based on the Internet of Things, analyzed the characteristics and classification of user demand information. It explores an information acquisition technology for industrial product design, aiming to innovate in technology based on the latest developments of the Internet and the characteristics of product industrial design. The article is divided into four chapters.

Chapter 1 discusses the overview of industrial product design in the Internet of Things environment, exploring its future development direction and the problems that need to be solved. It analyzes the importance of product industrial design information and proposes the research topic of the article. Chapter 2 discusses the content and scope of product industrial design information. It analyzes the position and role of product industrial design information in industrial design information, proposes key technologies for the network application, and analyzes the role of CAD technology in obtaining user requirements information. Chapter 3 proposes a new product function gene retrieval process design based on the characteristics and content of user requirement information acquisition, based on the genetic optimization algorithm. It also analyzes the role of CAD technology in obtaining user requirements information and establishes corresponding template and problem libraries. Chapter 4 uses the technology approach obtained in the previous research, combined with other related technologies, to build a network-based product industrial design information application system architecture through functional analysis and module design.

The innovation of this article lies in introducing CAD technology into the product industrial design process and making the network application of product design information related technology a research hotspot. The article innovatively analyzes the main content and characteristics of product industrial design information based on the theories of product design and network technology, studies the classification of product industrial design information, and proposes key technologies for the network application of product industrial design information. Additionally, based on theories such as instance-based reasoning and relationship models, the article studies the attributes and classification of user requirement information obtained through survey questionnaires, and establishes template and survey problem libraries.

2 STATE OF THE ART

With the continuous development and improvement of industrial technology, industrial design has emerged and has been constantly driving social development. However, it differs from other art forms and traditional handicrafts in that it is a special product that combines technology and aesthetics. Mount Stephens and Teo [5] integrate systems of computer-aided design and computer-aided engineering. Enhanced a solution that helps designers quickly generate product designs. This system can automatically generate various design documents, including product drawings, material lists, engineering drawings, etc., for the convenience of designers for design and production. Pereira et al. [6] designed a file generation module: this module can automatically generate various design files, including product drawings, material lists, engineering drawings, etc. based on user-defined design specifications and standards. These files can be easily modified and customized. The module can perform engineering analysis on the generated design files, including strength analysis, fatigue analysis, thermal analysis, etc. These analyses can help designers evaluate the performance and reliability of products. Quickly generate various design solutions based on user-defined design specifications and standards. These solutions can be used for rapid design and production. This module can visually display the generated design scheme, including 3D models, 2D drawings, engineering drawings, etc. These displays can help designers better understand design norms and standards, as well as carry out design and production. The generative product design system is a system that integrates computer-aided design and computer-aided engineering, which can help designers quickly generate product design solutions, improve design efficiency and quality. Prpi ć Et al. [7] analyzed that computer-aided design and 3D printing technology are two important applications of digital technology in industrial manufacturing. Computer Aided Design (CAD) is a computer software technology used to design objects and shapes in scenarios, including architectural design, mechanical design, industrial design, and other fields. 3D printing technology is a manufacturing technology of rapid prototyping, which uses computer aided design technology to directly change from renderings to real objects, realizing the transformation from concept to real objects. Rizo et al. [8] utilized computer-aided design technology to directly transform renderings into physical objects, achieving the transformation from concept to physical objects. The connection between computer-aided design and 3D printing technology is that they are both applications of digital technology that can directly transform designers' design ideas into physical objects. CAD technology can assist designers in 3D modeling and design, while 3D printing technology can directly convert designers' design ideas from renderings to physical objects, achieving the transformation from concept to physical objects. These two technologies complement each other and can greatly improve the efficiency and quality of industrial manufacturing. Sun and Sharma [9] use sensor technology to achieve automatic monitoring and control of crushers. At the same time, the operating status of the crusher was detected, and the working parameters of the crusher were monitored. It was discovered that machine vision technology can identify the materials inside the crusher through image recognition and processing, and automatically adjust the operating status of the crusher based on the recognition results. Machine vision technology can install multiple cameras inside the crusher to monitor the material situation in real-time and automatically adjust the operating status of the crusher according to the situation. Trzepieci ń Ski et al. [10] found that artificial intelligence technology can be used to achieve automation and intelligence. For example, deep learning algorithms can be used to model and identify the materials inside the crusher to achieve automated control and intelligent adjustment. In the design of ultrafine crushers, various automation and intelligent methods can be used to achieve functions such as automatic monitoring and control, machine vision recognition, data acquisition and processing, and artificial intelligence control, thereby improving the automation and intelligence level of the design, and improving the performance and production efficiency of the crusher. Zhou et al. [11] used digital technology in computer-aided design and manufacturing to virtualize the entire manufacturing process and simulate and optimize it through digitization. In CAVP, designers can use computer-aided design software for 3D modeling and design of products, and transmit the design results to CAM software for manufacturing. CAM software can automatically generate machining paths and programs based on the design results of designers, and input them into machining centers or CNC machines for processing. During the machining process, CAM software can monitor and control the machining process, and promptly identify and solve problems during the machining process, thereby ensuring the stability and high quality of the manufacturing process.

3 METHODOLOGY

3.1 Product Structure Design Based on Genetic Optimization Algorithm

Many stages require the evaluation of product design proposals to ensure their rationality. This section takes a specific product design proposal as an example and uses the general method of weight agreement table and fuzzy evaluation to analyze and evaluate it, exploring the feasibility and operability of using systematic evaluation for product design evaluation. Using the concept of genetic optimization algorithm, the car structure is divided and defined as follows: the set of product part surfaces composed of n surfaces is denoted as

$$\mathrm{FPa} = \left\{ f_1, f_2, \cdots, f_n \right\} \tag{1}$$

When part Pa is in the surface set, there may be several functional surfaces. The functional surface is defined as follows: when part Pa is in the surface set (1), it needs to meet the following conditions:

1) The contact geometry type can be surface contact and point contact, or plane and curved surface;

2) There is force transmission between a pair of contact surfaces. Meeting the above conditions becomes a functional surface. Figure 1 shows the structure of industrial product design. From Figure 1, it can be seen that the structure design of industrial products is formed by multiple independent functional surfaces. From the perspective of product hierarchy, the design structure can be a component or a part.

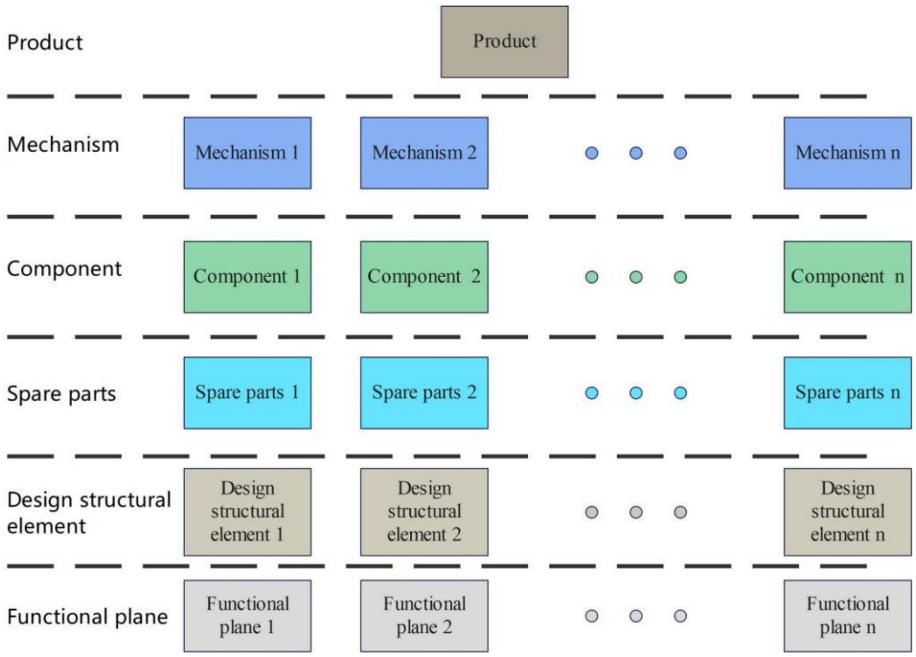

Figure 1: Structure of Industrial Product Design.

Functional surfaces are not solid structures, but they need to have certain functions, so they are classified as part of the design structure. In the requirement analysis phase, all information is described using virtual products as objects, and in the conceptual design phase, the objects being described are products and mechanisms. In the detailed design phase, the information description object is changed according to the specific design process. In the mechanism design phase, the virtual information describes the mechanism and components of the product. In the component design phase, the core components and parts are mainly described. By combining the above information, the design process of industrial product structure can be obtained.

To determine the weight vector of evaluation indicators and construct the first-level weight matrix and second-level weight matrix, the analytic hierarchy process and pairwise comparison method are comprehensively used for the index system.

$$W = \{W_1, W_2, \cdots, W_6\} \tag{2}$$

$$W_i = \{W_{i1}, W_{i2}, \cdots, W_{in_i}\} \tag{3}$$

Here, Wi is the weight corresponding to the indicator Fi, and ∑6iWi=1, 0<Wi<1; Wij is the weight corresponding to the indicator Fij, and ∑nij=1, 0<Wij<1. There are two main methods for calculating b1*Rb1, which are the main factor decision (prominence) type and the weighted average type. Generally speaking, there is not much difference between these two methods. The weighted average algorithm considers all factors, which can effectively avoid information loss, while the main factor prominence type is suitable for situations where the data varies greatly, and it can prevent small data from interfering with the evaluation result. For the evaluation of industrial product design, since each factor affects the evaluation result of the proposal to varying degrees, the weighted average calculation method is used. The ordinary weight coefficient is used instead of the factor importance coefficient, which retains the information of all single-factor evaluations and considers the comprehensive influence of various factors. This is suitable for the mathematical modeling of the research problem in this paper.

3.2 Research on Industrial Product Function Design Based on Genetic Algorithm

After designing the hierarchy structure of industrial products, the following steps are carried out to obtain various key identification elements of product engineering design:

Firstly, to effectively acquire customer needs and accurately define product requirement information, a customized template is proposed. The customization template model is shown in Figure 2.

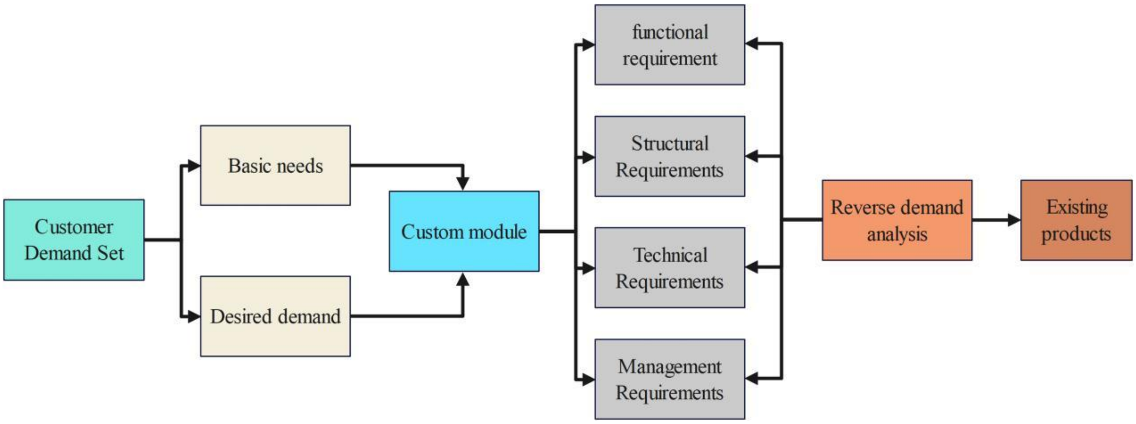

Figure 2: Customization Template Model.

The customer set in Figure 2 is a collection of overall demand for a certain type of product obtained through external and internal data sources of the enterprise. The customization module realizes the customized expression of product functions and structural parameters, which is easier to understand and describes product functions. After completing the interactive selection of the customization template, the required product is configured for customization. The demand genes are generated based on the pre-set product parameter codes. The required product is an information descriptive product, and the customer's demand for the product can be described through information feature values.

$$E = \left\{E_1, E_2, \cdots, E_k, \cdots, E_p\right\} \tag{4}$$

By analyzing the relationships between various parameters of the customized template product and generating product function information tree, structural information tree, technical information tree, and management information tree based on customer demand. Based on this, the concept of required product genes is proposed, and the required product genes are generated using the product gene coding rules. Generally, they can be divided into four categories, namely function genes, structural genes, management genes, and technical genes. The evaluator rates the s-th evaluated object according to the rating standard of the indicator F and fills in the evaluator rating table. Based on the rating d of the h-th evaluator, the evaluation sample matrix D is obtained:

$$D^{(s)} = \left(d_{ijk}^{(s)}\right)_{(n_1 + n_2 + \ldots + n_6) \times p} \tag{5}$$

he difference is that the structure of the required product genes is incomplete. The obtained product genes are the design inputs for the automotive industry. Based on the required product genes, the product genes are retrieved. The specific retrieval process is as follows: In order to obtain the optimal solution in the retrieval, the genetic algorithm's gene recombination process is used to complete the design of automotive industry products. During the execution of the genetic algorithm, the quantity will gradually increase according to the exponential law.

$$m(H,t+1) \geqslant m(H,t) \tag{6}$$

In the equation, t represents the population; and then output and explain the system evaluation results. Different categories correspond to different evaluation objects, and the differences in categories result in differences in the weights of each evaluation indicator.

3.3 Design of Product Function Gene Retrieval Process

Before starting the experiment, it is necessary to first determine the research purpose and questions, including the advantages and disadvantages of the product function, the impact it produces, and how to improve the product function. Determine appropriate research methods based on research objectives and issues, including literature research, experimental research, case studies, etc. Collect data related to product functionality, including user feedback, market research, patent data, etc. Develop an experimental plan based on research methods and objectives, including experimental design, experimental conditions, and data collection methods. Implement the experiment according to the experimental plan, collect experimental data, and conduct data analysis and processing. In summary, the design of product functional gene retrieval process is a complex and important process that requires comprehensive consideration of multiple factors, including research objectives, research methods, data collection, experimental plans, experimental evaluations, etc. Only by strictly following the experimental plan can accurate and reliable experimental results be obtained.

$$f_1\left(d_{ijk}^{(s)}\right)=\left|\begin{array}{l}\dfrac{d_{ijk}^{(s)}}{9},\ d_{ijk}^{(s)}\in[0,9]\\ 1,\ d_{ijk}^{(s)}\in[9,\infty]\\ 0,\ d_{ijk}^{(s)}\notin[0,\infty]\end{array}\right. \tag{7}$$

1) There are three possibilities in the gene pool. One is the most ideal result, which completely matches the product layer gene and the retrieval ends. Another possibility is that the product layer gene cannot be completely matched, but this result is less likely. If the above phenomenon occurs, proceed to step 2). The third possibility is that no product layer gene is matched. This possibility is small, but if this phenomenon occurs, proceed to step 2). For the evaluation index F; if the s-th evaluated object belongs to the ɑ'ig gray evaluation number of the e-th evaluation grey class, then we have:

$$x_{ije}^{(s)}=\sum_{k=1}^{p} f_e\left(d_{ijk}^{(s)}\right) \tag{8}$$

"If the s-th evaluated object belongs to the total gray evaluation number of each evaluation grey class, it can be denoted as xi."

$$x_{ij}^{(s)} = \sum_{e=1}^{4} x_{ije}^{(s)} \tag{9}$$

2) In the separation of the required genes, if no gene fragments are matched, the candidate product genes in the retrieval module layer gene need to be subjected to gene recombination. If no required gene fragment that meets the requirements is found, proceed to step 3). All evaluators advocate the gray evaluation of the e-th gray class for the s-th evaluated object according to the indicator F, denoted as r."

$$r_{ije}^{(s)} = \frac{x_{ije}^{(s)}}{x_{ij}^{(s)}} \tag{10}$$

3) Decompose the module layer genes that were not satisfied in step 2). Based on this, search for part layer genes and use the retrieved part layer genes for product gene recombination. Since there are 4 evaluation grey classes, the gray evaluation vector r' for the evaluation index F; of the i-th evaluated person for each grey class is:

$$r_{ij}^{(s)} = \left(r_{ij1}^{(s)}, r_{ij2}^{(s)}, r_{ij3}^{(s)}, r_{ij4}^{(s)} \right) \tag{11}$$

4) After the retrieval is completed, if a satisfactory product gene is not obtained, it is necessary to creatively design according to user requirements. After synthesizing the gray evaluation vector of the F for each evaluation grey class of the s-th evaluated object, the gray evaluation matrix R" for the F of the i-th evaluated object for each evaluation grey class is obtained

$$R_i^{(s)} = \begin{bmatrix} r_{i1}^{(s)} \\ r_{i2}^{(s)} \\ \cdots \\ r_{ii_i}^{(s)} \end{bmatrix} = \begin{bmatrix} r_{i11}^{(s)} & r_{i12}^{(s)} & r_{i13}^{(s)} & r_{i14}^{(s)} \\ r_{i21}^{(s)} & r_{i22}^{(s)} & r_{i23}^{(s)} & r_{i24}^{(s)} \\ & \cdots & & \\ r_{in_i 1}^{(s)} & r_{in_i^{(s)}}^{(s)} & r_{ii_i^{(s)}}^{(s)} & r_{in_i 4}^{(s)} \end{bmatrix} \tag{12}$$

4 EXPERIMENTAL RESULTS AND ANALYSIS

4.1 Experimental Samples

In the database, 10 samples are randomly selected. Considering the interrelationships between the experimental samples, the experimental sequence needs to be determined first, and the product genes with independent functions are placed at the front. Figure 3 shows the parameters of product gene design.

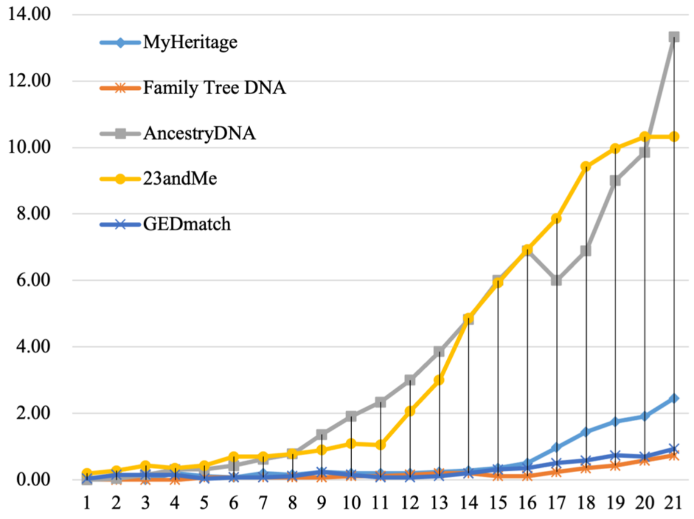

Figure 3: Parameters of product gene design.

The relationship between the values was analyzed using a line graph, and the experimental results are shown in Figure 4.

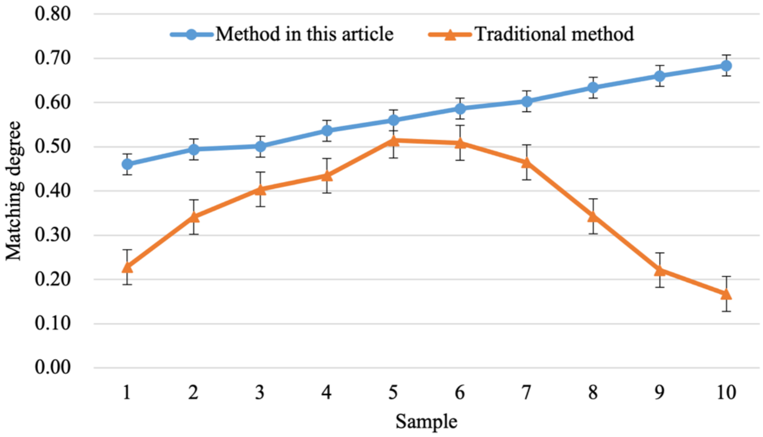

Figure 4: Matching results of retrieved product genes.

In product functional gene retrieval, the product gene matching results retrieved can include the following situations:

Matching success: Retrieved product genetic information related to the research goal, indicating that the product's functionality is related to the research problem.

Matching failure: Retrieved product genetic information unrelated to the research objective, indicating that the functionality of the product is unrelated to the research problem.

No matching results found: If the retrieved product genetic information is not related to the research objective, it may be because the product's function is not related to the research problem or the product's function does not belong to the same field as the research problem.

After retrieving the matching results, further analysis and evaluation can be conducted on these matching results to determine whether the functionality of the product is relevant to the research question and propose improvement suggestions. Common evaluation methods include statistical analysis, literature review, and user testing.

4.2 Data Analysis

Modern industrial design is centered on product design. With the development of CAD technology, the means of product design have become more advanced and efficient, greatly enriching the design methods. In this regard, computer-aided industrial design has fully stimulated the maximum potential of designers in creative, exploratory, and innovative design, freeing them from the tedious work of drawing on paper and focusing on ideas rather than techniques, and achieving a leap in design. Product design has entered the digital age, greatly shortening the design and manufacturing process. Choosing the right CAD software is very important for enterprises and designers. It should be suitable, sufficient, and have a good cost-performance ratio. High-end software such as Alias and Catia, although powerful and feature-rich, are complex and expensive, requiring high-end graphic workstations to support, which is difficult for most enterprises and designers to afford. Choosing Rhino can balance economy and applicability. In order to express the dominant and hidden features of the five samples clearly and intuitively, contour maps were used for analysis, and the results are shown in Figure 5.

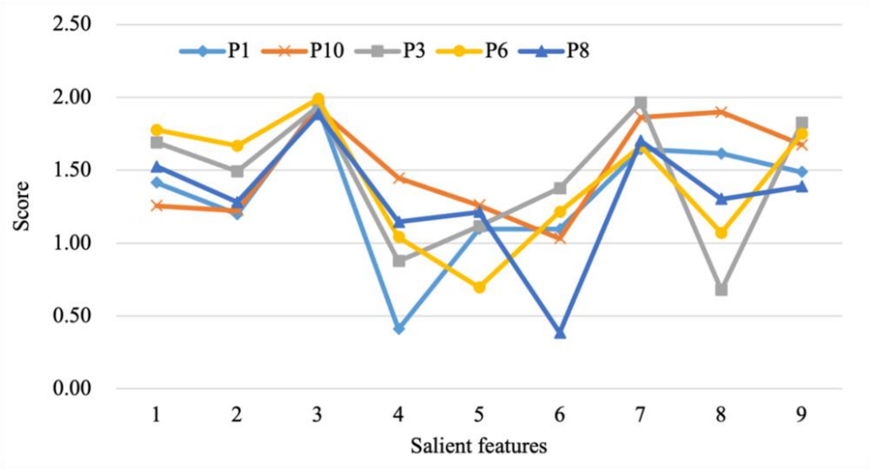

Figure 5: Contour analysis of industrial product samples in the intersection of A and C.

From the contour analysis chart in Figure 5, it is evident that the scores of various indicators for the five product samples show significant fitting, which is consistent with the expected results. In terms of dominant features 1, 2, 3, 6, 7, and 9, the sample scores deviate significantly from the "1 point" centerline and show a more concentrated trend; in terms of hidden features 1, 5, 7, 9, 10, and 11, the sample scores deviate from the "5 point" centerline and show a clear tendency. After analysis, the overall qualitative matching relationship between dominant and hidden features in industrial product design CAD is described in Figure 6.

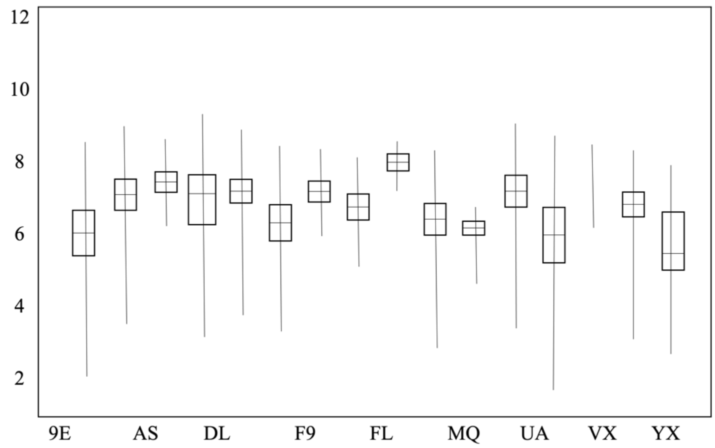

Figure 6: Fitting degree of matching relationship curve.

Through contour analysis, it can be seen that the score curves of the four industrial product samples still have a high degree of fitting. Moreover, the fitting degree of the curve of hidden features is higher than that of dominant features, indicating that even if the products have different styling features and combinations, relatively similar image features can still be obtained. Among these industrial product design samples, P11 and P12 belong to the third generation of products, while P13 and P15 belong to the fourth generation of products. With the advancement of technology, large touch screens have replaced traditional buttons. As shown in Figure 6, the scores of the four samples tend to be consistent in dominant features 1, 2, 3, 5, 7, and 9, among which the scores of dominant features 1, 3, 5, and 9 are significantly higher than the "1 point" centerline, while the score of dominant feature 7 is significantly lower and tends towards 0. In terms of hidden features, the evaluation factors are biased towards the positive side, the activity factors show a neutral performance, and the potential factors are clearly biased towards "power feeling". Based on the CAD statistical results, the development and trend of the 13 major styling features of the fourth-generation industrial products were depicted in a graph (as shown in Figure 7).

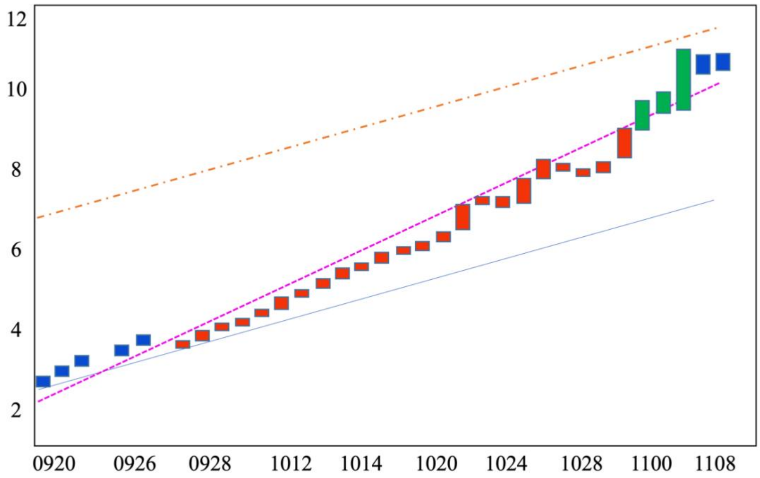

Figure 7: Development trend of industrial product design.

From Figure 7, it can be seen clearly and intuitively that: Feature 1 shows a relatively even and strong performance in all generations of products; Feature 2 (the overall form is a combination of a square and a large circular arc) and Feature 4 (the antenna is closely integrated with the body) show significant characteristics in the first and second generations of industrial products, but become weaker in the third and fourth generations; Feature 3 (symmetrical design) generally shows a strong performance and this trend continues to strengthen in the third and fourth generations of mobile phones; Feature 5 shows a steady strengthening trend in the first to fourth generations of products, which is closely related to technological advances. The pattern of Feature 6 is not clear; Feature 7 (the corners of the display screen are small arcs) shows a stronger performance in the first generation of products, weaker in the second generation, strongest in the third generation, and weaker in the fourth generation, but still relatively strong overall; Feature 8 (the keys are elliptical or flat oval) and Feature 9 are stronger in the first and second generations, but weaker in the third and fourth generations, with Feature 8 showing a particularly obvious trend. Feature 10 (metal texture of the navigation key) shows a stronger performance in the second and third generations, weaker in the first and fourth generations, and presents a "strong in the middle, weak at both ends" situation; Feature 11 and Feature 12 (other parts with decorative lines) are generally weak and show no significant changes in all generations; Feature 13 (prominent and prominent logo) is generally strong.

5 CONCLUSION

Genetic optimization algorithms can be used in fields such as product shape design, industrial design, and robot control in industrial product design. In product styling design, genetic algorithms can encode each individual design element in the product styling, and then arrange and combine genes through selection, crossover, and mutation operators to generate satisfactory new individuals. In industrial design, genetic algorithms can be used to optimize the appearance, color matching, material selection, and other aspects of products. Genetic algorithms can be used to optimize robot motion control strategies, path planning, and other aspects. For example, genetic algorithms can be used to optimize the motion control strategy of robots, making them more flexible in completing various tasks. Based on this, a new product design CAD planning method based on brand strategy was proposed. Firstly, new product opportunities were determined through three steps: analysis of target audience based on cultural anthropology, plot reproduction and description, and evaluation based on socio-economic technology factors. Product concept design was then carried out, followed by the proposal of a brand strategy based on value proposition. The value proposition was further transformed into the hidden features of product design. Through three stages of complete design, identifying feature design, and detail design, the hidden features were transformed into explicit features, ultimately forming the product design. This provides an effective way for new enterprises to form their own product characteristics and obtain market differentiation.

6 ACKNOWLEDGEMENTS

This work was supported by Key Subject of the 14th Five-Year Plan for Education Science in Henan Province in 2022, "Teaching Research on the Condensation of Imagery symbols and Image Application of Xi Jinping Thought on Socialism with Chinese Characteristics for a New Era" (No.: 2022JKZD33).

Xiaodong Yuan, https://orcid.org/0000-0002-6030-794X
Hailong Bi, https://orcid.org/0000-0003-2379-3843

REFERENCES

[1] Bernardo, N.; Duarte, E.: Immersive virtual reality in an industrial design education context: what the future looks like according to its educators, Computer-Aided Design & Applications, 19(2), 2022, 238-255. https://doi.org/10.14733/cadaps.2022.238-255
[2] Frizziero, L.; Donnici, G.; Liverani, A.; Alessandri, G.; Menozzi, G.-C.; Varotti, E.: Developing innovative crutch using IDeS (industrial design structure) methodology, Applied Sciences, 9(23), 2019, 5032. https://doi.org/10.3390/app9235032
[3] Khan, M.-T.-H.; Rezwana, S.: A review of CAD to CAE integration with a hierarchical data format (HDF)-based solution, Journal of King Saud University-Engineering Sciences, 33(4), 2021, 248-258. https://doi.org/10.1016/j.jksues.2020.04.009
[4] Kim, Y.-J.; Ko, K.-H.; Park, C.-J.; Cho, L.-R.; Huh, Y.-H.: Connector design effects on the in vitro fracture resistance of 3-unit monolithic prostheses produced from 4 CAD-CAM materials, The Journal of Prosthetic Dentistry, 128(6), 2022, 1319. e1-1319. e10. https://doi.org/10.1016/j.prosdent.2022.09.018
[5] Mountstephens, J.; Teo, J.: Progress and challenges in generative product design: A review of systems, Computers, 9(4), 2020, 80. https://doi.org/10.3390/computers9040080
[6] Pereira, P.-M.-V.; Jauregui, B.-J.-M.: Smart design engineering: a literature review of the impact of the 4th industrial revolution on product design and development, Research in Engineering Design, 31(2), 2020, 175-195. https://doi.org/10.1007/s00163-020-00330-z
[7] Prpić, V.; Schauperl, Z.; Ćatić, A.; Dulčić, N.; Čimić, S.: Comparison of mechanical properties of 3D‐printed, CAD/CAM, and conventional denture base materials, Journal of Prosthodontics, 29(6), 2020, 524-528. https://doi.org/10.1111/jopr.13175
[8] Rizo, G.-M.; Herráez, G.-C.; Torres, L.-D.; Serrera, F.-M.-Á.; Gutiérre, P.-J.-L.: Biocompatibility of polymer and ceramic CAD/CAM materials with human gingival fibroblasts (HGFs), Polymers, 11(9), 2019, 1446. https://doi.org/10.3390/polym11091446
[9] Sun, Y.; Sharma, A.: Research and Design of High Efficiency Superfine Crusher using CAD Technology, Computer-Aided Design and Applications, 19(S2), 2022, 26-38. https://doi.org/10.14733/cadaps.2022.S2.26-38

[10] Trzepieciński, T.; Dell'Isola, F.; Lemu, H.-G.: Multiphysics modeling and numerical simulation in computer-aided manufacturing processes, Metals, 11(1), 2021, 175. https://doi.org/10.3390/met11010175
[11] Zhou, J.; Phadnis, V.; Olechowski, A.: Analysis of designer emotions in collaborative and traditional computer-aided design, Journal of Mechanical Design, 143(2), 2021, 021401. https://doi.org/10.1115/1.4047685