Research on Brand Design based on Particle Swarm Optimization Algorithm Using Product Experience

Xiaodan Dai[1] and Xinqiang Cao[2]

[1]School of Art and Design, Shaanxi Fashion Engineering University, Shannxi 712046, China, daixiaodan520@126.com
[2]School of Design and Art, Shaanxi University of Science & Technology, Shaanxi 712100, China, caoxinqiang@sust.edu.cn

Corresponding author: Xinqiang Cao, caoxinqiang@sust.edu.cn

Abstract. Autocad as a brand design drawing software, provide brand design pattern drawing. Based on the unclear product experience attribute in brand design, this paper proposes a multi-level product modeling evaluation model from Autocad and experience perspective. This model fully considers the measurement of uncertainty, and combines it with mathematical decision method to form a brand design evaluation method from the perspective of product experience. Users often hesitate to describe their perceptual preferences accurately. The user evaluation matrix was optimized and consensus reached by particle swarm optimization algorithm (PSO) under non-consensus conditions. The product modeling scheme was ranked by the method of approximate ideal solution ranking, and the perceptual evaluation process of product modeling design based on HFLTSs and PSO was proposed. Taking the perceptual evaluation of brand modeling scheme as an example, it is verified that HFLTSs is helpful to solve the uncertainty of product experience cognition, and combined with PSO, it can improve the consistency of hesitant fuzzy language evaluation, so as to improve the perceptual evaluation quality of product modeling. Through the evaluation of product experience, the influencing factors will be fully taken into account in AutoCAD product design, so as to improve the quality of brand design.

Keywords: AutoCAD; Product Experience; Product Experience; Particle Swarm Optimization Algorithm
DOI: https://doi.org/10.14733/cadaps.2023.129-141

1 INTRODUCTION

With the increasingly fierce market competition, the continuous development and successful entry of new products into the market is the key for enterprises to win in the competition. New products are the result of innovation, and there are many problems that need to be solved at different stages of product innovation. Based on existing experience, some of these problems can be solved. But they cannot solve difficult or invention problems, and the accumulation of these problems leads to obstacles in the process of product innovation. After years of development, computer-aided innovation technology centered around TRIZ theory has become a way to assist designers in effectively solving innovation challenges. Computer assisted innovation technology is a new technology that has rapidly developed in the manufacturing field in recent years. Including scientific problem analysis and innovative thinking methods, principle of problem transformation and contradiction resolution, standard problem solving and invention problem solving algorithms, etc. The constantly maturing ontology technology provides important avenues for the expansion of innovative thinking and patent-based problem solving. And integrating theoretical methods such as value engineering, patent analysis, root cause analysis, and project management, the theoretical foundation of computer-aided innovation technology is gradually improving. This technology has been widely applied in the design phase of new product development, manufacturing engineering systems, and process optimization in enterprises, and has become an important tool for many enterprises in the process of product innovation design. It can effectively help enterprise R&D personnel eliminate obstacles in product or process innovation. This is an era in which all market trends are oriented towards consumers. Understanding consumers' consumption behavior and insight into consumers' consumption motivation have become new marketing themes in this era. With the advent of experience economy, experience factors play an increasingly significant role in determining the success of a company's products or services. Azman et al. [1] utilized computer technology and software tools to assist in product design and development. The development and application of CAD technology have fundamentally changed the content and methods of product design and manufacturing, and have become an important means for the manufacturing industry in modern industrialized countries to maintain competitive advantages and expand the market. Conduct product design and manufacturing engineering in a mutually considered manner. The design process includes conceptual design, material selection, and finally, the manufacturing of the design. To highlight the superiority of the selected surface mounted PMSM topology. Cote ţ Others [2] believe that the application of CAD technology in product design and manufacturing can significantly improve work efficiency and product quality. For example, using CAD technology can perform 3D modeling, facilitate surface design and simulation, and perform numerical control machining and product manufacturing simulation. The application of CAD technology can also improve the consistency and coordination of design and manufacturing, achieve rapid development and optimization of products, reduce production costs, and improve market competitiveness.

The innovation of the method in this paper lies in the full consideration of the uncertainty and fuzziness of the product experience group, and the fuzzy decision method is adopted to obtain the effective impression factors of brand design. Considering the difference of individuals and the uncertainty of evaluation, the term set theory of hesitation fuzzy language is used to integrate evaluation information. Based on its mathematical operator, the hesitant fuzzy language consensus model is constructed to measure the degree of user cognitive consistency. The optimization and consensus reaching of user evaluation matrix under non-consensus conditions are achieved by particle swarm optimization algorithm (PSO). The product modeling scheme is ranked by the ranking method of the approximation ideal solution. Based on HFLTSs and PSO, the perceptual evaluation process of product modeling design was proposed. The proposed model and method are combined with the brand design system of AutoCAD system to improve the quality of brand design.

The research content of this article is divided into five chapters. The first chapter first reviews the problems in brand design in CAD and the relevant background of considering the importance of product experience. Chapter 2 reviews the empirical evaluation methods of uncertainty and fuzziness, and summarizes the existing problems. In Chapter 3, the author first considers the evaluation factors of cognitive experience, emotional experience, and behavioral experience, and proposes an evaluation model for AutoCAD and brand design under product experience. Secondly, by considering user preferences for the scheme and due to the uncertainty and ambiguity of perception and cognition, an evaluation method for HFLTS was proposed, and the parameters of the model were evaluated using PSO. The experimental verification of the proposed model in Chapter 4 shows that HFLTS can help describe users' hesitation in perception evaluation of product modeling solutions and to some extent solve the uncertainty problem of users' perception and cognition. Meanwhile, consensus based on PSO algorithm can improve the consistency of hesitant fuzzy language evaluation and improve the quality of product modeling perception evaluation. In addition, the convergence and effectiveness of the algorithm were also verified. Finally, in Chapter 5, the main content of this article is summarized.

2 RELATED CONCEPTS

Computer assisted innovation is a new technology that has rapidly developed in recent years and has been widely applied in the design phase of new product development, manufacturing systems, and process optimization in enterprises. It has become an essential tool in the innovative design process of enterprises. CAI technology plays an important role in product or process development, effectively improving product design quality and efficiency. Assist designers in referencing effective methods and technologies from different disciplinary fields to construct scientifically ideal innovative design solutions and improve the efficiency of research and development work. Reduce repetitive work and resource waste in the research and development process. Computer assisted innovation technology starts from analyzing and solving different contradictions encountered in product and process innovation. Based on problem-solving theory and existing knowledge accumulation, promoting functional and principle innovation in the product and process design process of enterprises can greatly improve their technological innovation ability and efficiency. There are many definitions of brand. The American Marketing Association defines a brand as a name, term, mark, symbol or design, or a combination of them, which is used to identify a seller or a group of sellers' products or services and distinguish them from competitors' products or services. Han et al. [3] presented information in a graphical manner through visualization. Augmented/Virtual Reality (AR/VR) refers to the use of computer technology and software tools to simulate or enhance real-world experiences, enabling users to interact and interact in the virtual world. Therefore, combining visualization technology with augmented/virtual reality technology can enhance or virtualize the real world, thereby creating a richer and more vivid experience. He et al. [4] demonstrated the details and dynamic effects of virtual scenes and objects, which can also be used for real-time interaction and feedback. This combination can bring users a richer and more vivid experience, improving the attractiveness and user experience of virtual reality applications. Jones et al. [5] analyzed the interactive relationship between brand experience and brand attitude, which is influenced by various factors, including brand cognition, brand perception, brand behavior, and brand emotion. Nayeem et al. [6] refer to the feelings and experiences gained by users when using branded products or services. Brand experience includes aspects such as product or service quality, appearance, user experience, and service quality. Brand attitude refers to users' emotions and perceptions towards the brand. Brand attitude includes emotions such as trust, love, and loyalty towards the brand. Enhance users' emotions and cognition towards the brand, thereby improving their attitude towards the brand; On the other hand, users' attitude towards the brand can also affect their evaluation and experience of the brand experience, thereby affecting their emotions and behaviors towards the brand. Pess ô a and Becker [7] believe that the industrial revolution refers to the process of transitioning from manual labor to machine production, which has had a profound impact on the manufacturing system of enterprises. Before the Industrial Revolution, many manufacturing enterprises mainly relied on manual labor for production, which required a lot of manpower and time, while production efficiency was relatively low. However, with the invention and application of machines, the industrial revolution began. The speed, accuracy, and efficiency of machine production enable enterprises to produce more products faster and better control the production process. Raffaeli et al. [8] believe that AutoCAD can be used to draw various types of graphs and charts. In AutoCAD, brand experience can be defined as the feelings and experiences that users experience when using AutoCAD software.

Špelic [9] analyzed the crucial importance of the accuracy and precision of CAD software for the quality of design and manufacturing. Therefore, it is necessary to check the accuracy and precision of CAD software in terms of geometric shape, dimension annotation, text identification, etc., to ensure that the designed and manufactured products comply with specifications and standards. The maintainability of CAD software also has a significant impact on the production efficiency and product quality of enterprises. Therefore, it is necessary to check whether the operation interface of CAD software is simple and easy to understand, whether the operation process is concise and clear, and whether it has good maintainability and scalability [10]. Zhou et al. [11] examined whether the performance of CAD software is stable and reliable, whether it has good fault tolerance and fault tolerance ability, and whether it has good recoverability and recoverability. The cost-effectiveness of CAD software also has a significant impact on the production efficiency and product quality of enterprises. Therefore, it is necessary to check whether the price of CAD software is reasonable, whether it has good performance and cost-effectiveness, as well as whether it has good scalability and upgradability.

3 METHODS

3.1 Brand Design Evaluation Model Under AutoCAD and Product Experience

In the era of technological economy, technology has become an important resource for economic and industrial development, but brand creative products are one of the products deeply influenced by it. Brand product design is recognized as a sunrise product in the 21st century, and it has amazed people with its unique charm and rapid growth rate, attracting global attention. Both developed and developing countries view branded products as a strategic product, and have now seen the vigorous development of branded products as a new economic growth point. With the development of brand product design and the rapid development of emerging network technologies worldwide, it has become one of the most advanced technologies and a core part of the development process of brand product design. Computers centered around IT and CAD technology are like engines for brand product design, greatly promoting the development of brand products. Compared with previous brand product designs, the involvement of computer-aided design, whether in manufacturing techniques or display, is significantly different from previous designs. Brand product design is not imagined out of thin air, but built with the help of computer programs. Computer aided design has a very wide range of applications in the field of design. When conducting computer-aided design, technology can be combined to create a more perfect product design. However, designers are also indispensable. Designers can utilize the current content on the internet to further improve and refine various aspects of design work and content. And applying it to product design will make the design of brand products more creative, which also brings about changes, and computer-aided design has also generated more interest.

With the progress of the information age, the rapid development of the internet and big data has accelerated the arrival of the 5G era. In the production mode of the 4G era, product design has made computer-aided design widely used, producing a variety of products, including computer-aided design. In the process of computer-aided design, product design has completely entered the process of digitization and informatization. Computer Aided Design (CAD) can transform product designers from traditional manual drawing to computer-aided design in product production and manufacturing. Computer-aided design can also help brand creative product designers complete work such as scheme comparison, design content retrieval, and drawing design review, greatly shortening the product design cycle. And it can improve the efficiency of product design, and also facilitate feedback on product structure analysis and production manufacturing related information after the completion of product design. For brand products, the "product experience" includes: the meaning (meaning experience) given to the product by the feelings generated by various senses (perceptual experience) and the emotions generated in the interaction between people and things (emotional experience). Nathan Crilly believes that users' acceptance of product design knowledge signals should be measured from three perspectives: cognitive emotional behavior. Bloch from the University of Missouri constructed the "Consumer Response Model for Product Modeling", in which he proposed that the psychological response triggered by product modeling can be divided into cognitive response and emotional response, in which emotional response can be divided into positive response and negative response, and behavioral response will occur on the basis of cognitive response and emotional response. Starting from aesthetic psychology, Leder et al. believed that the evaluation of art and design products should be thought from the cognitive state and emotional state, and the cognitive state emphasizes understanding, while the emotional state emphasizes satisfaction.

1) cognitive experience evaluation factors

First of all, cognition is the most important part of styling evaluation. The cognitive elements and levels of automobile form refer to the constituent elements of the overall brand form based on cognitive attributes and aesthetic attributes, and its hierarchical decomposition holds that there are three main cognitive elements, namely, volume, shape feature and figure, and that volume, shape surface and figure are divided into three levels to construct brand cognition. In the evaluation, the Likert scale will be scored for the design information that is expected to be passed to the user, and the amount of information obtained by the user will be examined. The scoring results were used as a series of positive emotions to calculate the evaluation matrix.

2) Evaluation factors of emotional experience

Human beings are emotional animals. Each design reflects its own specific feelings towards the design." With the addition of cognition, customers will form subjective cognitive evaluation of the product: whether it is beneficial or harmful to themselves, and generate associated emotions. Emotions are closely related to aesthetics, and there are many explanations for the classification of emotions. For example, Lzard proposed 10 basic emotions such as sadness, disgust and pleasure. Rosemary R Seva et al. positioned the emotion of subjective evaluation in amazed, hopeful, content, and encouraged when studying the emotion of mobile phone products. Emotion can be divided into positive emotion and negative emotion, among which positive emotion plays a positive and encouraging role in judging the quality of products. In this study, the Likert scale was used to investigate the positive emotions of users, and the Likert semantic scale was used to investigate the emotions, namely, seven points were scored for five positive emotions including surprise, calm, friendly and calm. The feedback of positive emotions was used to reflect the emotional experience effect of users on the car modeling. After the average scores of each user were obtained, the resulting scores were scored Results The evaluation matrix was used as a series of positive emotion.

3) Evaluation factors of behavioral experience

Subconscious behavior is closely related to the potential needs of the user." Because of the hidden and uncontrollable nature of behavior, many psychologists and other researchers believe that facial expressions are more accurate than words in reflecting customers' true feelings. The current behavior observation can be done through multiple channels, such as facial expressions, movement analysis, eye tracking, physical arousal index based on respiration and blood pressure, etc. By evaluation of quickness and ease operation requirement, here mainly by observing the facial expressions and behavior analysis for consideration. That is, a series of actions that reflect the current user's emotions, such as blinking and frowning, are defined first, and these actions are formed into a matching action library. Then, two high-definition multi-frame cameras are used to capture the user's facial expressions and behaviors during the user's evaluation, and ObserverXT behavior analysis software is used to capture and count the user's expressions and behaviors in the video. Finally, it is matched with the action and expression database, and the successful matched parameter results are included into the evaluation matrix as an evaluation sequence.

3.2 Mathematical Method of Multi-Attribute Decision Making

Multi attribute decision-making is an important component of modern decision-making science. Its theory and methods have extensive applications in various fields such as engineering design, economics, management, and military. For example, investment decision-making, project evaluation, maintenance services, weapon system performance evaluation, factory site selection, bidding, industrial sector development ranking, and comprehensive economic benefit evaluation. For multi-attribute decision-making problems, they can be said to be ubiquitous, including investment decision-making, project evaluation, scheme optimization, and application preferences. Due to the complexity, uncertainty, and fuzziness of human cognition in practical decision-making problems, the measurement or evaluation results of attribute values in multi-attribute decision-making problems are different. It can be exact numbers, interval numbers, language words, fuzzy numbers, and random variables. In view of the above evaluation matrix composed of evaluation attribute parameters, the multi-attribute decision mathematical method can be used to deal with it. RHastie, a famous American expert on decision research, pointed out that emotion is one of the 16 problems that need to be solved in the future in the field of decision making. TOPSIS method is a mathematical method of multi-attribute decision making to measure the distance between evaluation scheme and target scheme. This method mainly constructs positive ideal solution and negative ideal solution of multi-attribute decision making problem, calculates the distance between each scheme and positive ideal solution and negative ideal solution, and takes the two bases of close to positive ideal solution and far away from negative ideal solution as the evaluation basis to determine the ranking of schemes.

Firstly, the weight coefficient vector is defined as:

$$W=\{W_1,W_2,\ldots,W_n\} \tag{1}$$

The evaluation elements are normalized, namely:

$$C_{ij}=c_{ij}\,/\sqrt{\sum_{i=1}^{n}c_{ij}^{2}} \tag{2}$$

According to the normalization matrix, the semantic frequency vector of modeling image of the optimal scheme and the worst scheme is calculated:

$$C^{+}=(C_1^{+},C_2^{+},C_3^{+},..,C_j^{+},) \tag{3}$$

$$C^{-}=(C_1^{-},C_2^{-},C_3^{-},..,C_j^{-},) \tag{4}$$

Calculate the Euclidean distance corresponding to the semantic frequency vector of the modeling image of the judged vehicle, the optimal force case and the worst vector:

$$D_{\mathrm{i}}^{+}=\sqrt{\sum_{j=1}^{n}\left[W_j\left(C_{ij}-C_j^{+}\right)^2\right]} \tag{5}$$

$$\mathrm{D}_{\mathrm{i}}^{-}=\sqrt{\sum_{j=1}^{n}\left[W_j\left(C_{ij}-C_j^{-}\right)^2\right]} \tag{6}$$

Then, the closeness between the semantic vector of the judged brand and the semantic vector of the optimal vehicle is calculated as follows:

$$D_{\mathrm{i}}=\frac{D_{\mathrm{i}}^{-}}{D_{\mathrm{i}}^{-}+D_{\mathrm{i}}^{+}} \tag{7}$$

HFLTSs was proposed by RODRIGUEZ in 2012 to describe the indecisiveness of decision makers in the context of language. In the perceptual evaluation of product modeling, users often use perceptual terms to describe their preferences for the scheme, and because of the uncertainty and fuzziness of perceptual cognition, users often hesitate to express accurately. For example, when using the five-level scale (very poor, poor, average, good, very good) to describe the feature of "modern sense" of product modeling, the user's perception is "above average", corresponding to the "good" and "very good" in the five-level scale, but it cannot be accurately described. At this time, the user perception shows hesitation. Therefore, HFLTSs is introduced to solve this problem.

Order:

$$S=\{s_a \mid \alpha \in \{-\tau,...,0,....\tau\}\} \tag{8}$$

Is a set of symmetric language terms, it is easy to know that s≤s≤, and Neg(s)=s if there is a negative operator. When N*, S is the discrete language term set. In order to facilitate operation, S can be extended to the continuous language term set S by further setting R+.

Let S={s2: very poor, s1: poor, s0: average, s1: good, s2: very good}, HS(1)={s1: poor, s0: average}, HS(2)={s0: average, s1: good, s2: very good} in 2 HFLTSs, then the calculation rules are as follows

(1) Upper bound HS+ and lower bound HS are

$$\begin{cases} H_{s+}=\max\{s_i \mid s_i \in H_s\} \\ H_{s-}=\min\{s_i \mid s_i \in H_s\} \end{cases} \tag{9}$$

(2) Package operator env(HS) is

$$env(H_s)=[H_s^-,H_s^+] \tag{10}$$

3.3 Particle Swarm Optimization Algorithm

Due to different knowledge background, experience, social experience, etc., users have different perceptual cognition of product modeling, which makes it difficult for the emotional evaluation of user groups to reach complete consistency (consensus degree is 1). A threshold value can be set to judge the consensus level of users. When CON≥, it is considered that user evaluation has good consistency, which can be used as the basis for scheme selection; otherwise, further judgment is needed. Because the perceptual evaluation of product modeling reflects the first intuitive perception of users when they see the product, when the consensus degree is not reached, the user is asked to carry out the perceptual evaluation again, the boundary effect will decrease due to the repeated stimulation of the same object (such as liking the new and liking the old), and the perceptual judgment may be distorted. Therefore, this paper introduces the PSO algorithm to optimize the perceptual evaluation matrix, and uses its characteristics of easy execution, fast convergence and stability to achieve the adjustment of the perceptual evaluation matrix and reach consensus.

Suppose there are M particles in PSO flying at a certain speed in the n-dimensional space to search for the optimal solution, Aj=(A1j,A2j,⋯,Amj)T and v=(v1j,v2j,⋯,vmj) represent the position and velocity of the particles, and update according to the following formula

$$\begin{cases} v_{ab}(t+1)=\omega v_{ab}(t)+c_1 r_1(t)(pbset_{ab}(t)-x_{ab}(t))+\omega v_{ab}(t)+c_2 r_2(t)(pbset_b(t)-x_{ab}(t)) \\ A_{ab}(t+1)=A_{ab}(t)+v_{ab}(t+1) \end{cases} \tag{11}$$

Where, t is the number of iterations; vαβ(t) and Aαβ(t) are velocity and position of the particle in dimensional space, respectively. pbestαβ(t) is the current optimal position of the particle; gbestβ is the global optimal solution reached by all particles. r1β(t) and r2β(t) are random numbers between [0,1]; c1 and c2 are constants, usually c1=c2=2; ω is the inertia factor, and equation (10) can ensure the convergence of the algorithm.

$$\omega=\omega_{\max}-\frac{\omega_{\max}-\omega_{\min}}{t\_\max}\times t \tag{12}$$

Where, t_max is the maximum number of iterations; ωmax and ωmin are respectively the maximum and minimum values of the inertia factor, ω gradually decreasing from 0.9 to 0.4.

In order to avoid the large deviation between the optimized hesitancy language evaluation matrix and the original matrix, the upper bound of the optimization interval of any HS(k) is defined as

$$s_{i+0.5}(s_i=H_{s+})(i+0.5\le\tau) \tag{13}$$

The lower bound is

$$s_{i-0.5}(s_i = H_{s+})(-\tau \le i - 0.5) \tag{14}$$

If

$$H_{s-} = s_{-\rho} \tag{15}$$

Then the lower bound of the optimization interval is set as s−τ. There are two scenarios to consider:

(1) If the solution set of hesitation perceptual language evaluation matrix satisfying the consensus requirement is found within the limited interval, the perceptual evaluation matrix with the minimum deviation from the original matrix is selected as the basis for scheme ranking.

(2) If the group consensus requirements cannot be satisfied after optimization within the limited interval, the number of users should be expanded and more users should be introduced to make emotional evaluation on the product styling design scheme. If a consensus cannot be reached after a large number of user evaluations, it indicates that users' cognition of the product modeling scheme is quite different, which cannot meet users' emotional needs, and further design of the scheme is needed.

3.4 Perceptual Evaluation Process of Brand Product Styling Design

Based on the above research, the perceptual evaluation process of brand product modeling design based on HFLTSs and PSO is proposed, as shown in Figure 1. Specific description is as follows:

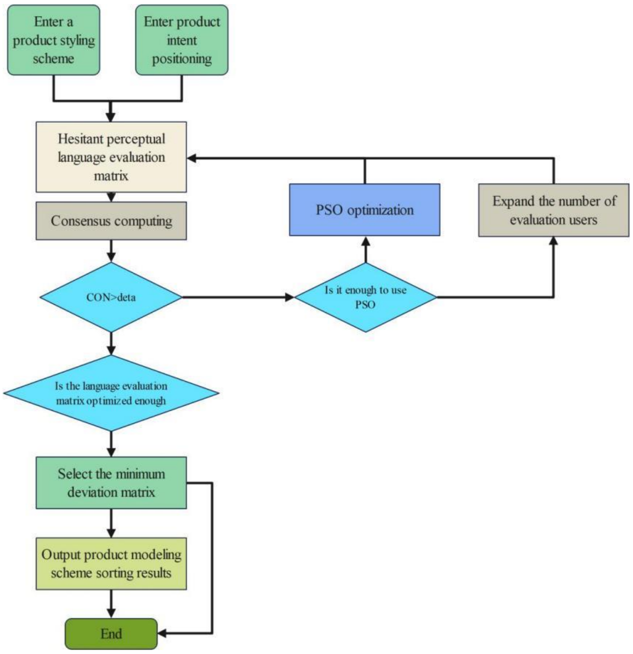

Figure 1: Perceptual evaluation process of brand product modeling design.

Step 1. Based on product image positioning and combined with HFLTSs, collect users' perceptual language evaluation of product styling design schemes;

Step 2. Calculate the consensus degree of user hesitancy language evaluation matrix;

Step 3. Check whether the user consensus reaches the consensus threshold. If yes, go to Step 4.

Step 4. Determine whether to use PSO to optimize the user hesitation language evaluation matrix. If yes, use PSO to optimize; otherwise, expand the number of user evaluations and transfer to Step 2;

Step 5. Judge whether the language evaluation matrix is optimized. If yes, go to step 6; otherwise, go to step 7;

Step 6. Select the minimum deviation matrix that meets the consensus requirements after PSO optimization;

Step 7. Use TOPSIS to sort the product shape design scheme and output the sorting result.

4 RESULTS AND ANALYSIS

4.1 Experimental Data

In the actual project, the listed model of a certain brand is taken as the ideal model, and 4 cars of the same type of other brands are selected as the evaluated models to form the shape evaluation group together with them. Fifteen ordinary users were randomly selected to evaluate the target vehicle and the evaluated vehicle in turn according to the evaluation model and conduct behavior analysis, and record the behavior data and final parameters to form the evaluation matrix. In the early stage, the designer designed the design scheme. The perceptual image of the product modeling is positioned as: technical, dynamic, modern and trendy, and the weight of the four perceptual image indicators is the same. Eighteen consumers were randomly selected to make an emotional judgment on the scheme through the language term set S={s3: very poor, s2: poor, s1: poor, s0: average, s1: good, s2: good, s3: very good}.

4.2 Result Analysis

The enterprise requires the user evaluation consensus threshold of 0.9 to meet the requirement of preference consistency, but the overall consensus degree of 18 users' evaluation is 0.8623, which needs to be optimized by PSO to promote consensus reaching.

When the number of groups N=125130, Figure 2 and Figure 3 show that in Sphere function, PSO-N performs better as the number of groups N increases. This is because the function is a simple unimodal function. In Rastrigin's and Schwefel's functions, PSO-N performs better than PSO1 and PSO-30 when the group numbers N=25 and 10. This is because their "step" is between PSO-1 and PSO-30, which can be faster in the advance of PSO-1 and strong resistance in the late evolution of PSO30 Strike a good balance between proficiency; On Rosenbrock's function, the value of N has no obvious rule on the algorithm performance. This is because the function is a unimodal function which is difficult to optimize, and its property is similar to multimodal function to some extent.

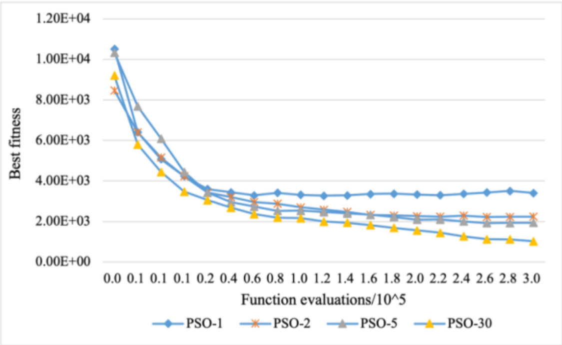

Figure 2: Fitness evolution curve of Schwefel's reference function.

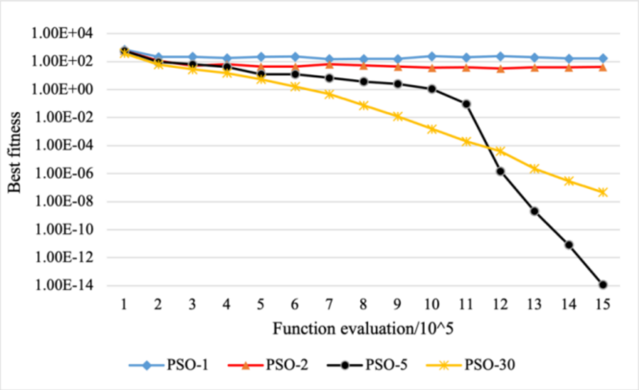

Figure 3: Fitness evolution curve of Rastrigin's reference function.

The fitness curve during operation can also be seen that the predicted result of PSO tends to be in a stable state, as shown in Figure 4 and Figure 5. The measure of user consensus in product modeling perceptual hesitation language evaluation reflects the cognitive consistency of user groups participating in program evaluation and is helpful to ensure the quality of product design. When user consensus cannot be met, both PSO optimization and increasing the number of user groups participating in the evaluation can promote the reaching of consensus. However, two problems need to be noted:

㊀The search interval of PSO optimization should be set correctly. In this paper, the optimization interval is limited to [smini0.5,smaxi+0.5], which may deviate from the original opinions of users when it exceeds the interval. If there is no hesitation language matrix that meets the consensus requirement, the number of users participating in the evaluation should be increased;

㊁If the number of users participating in the evaluation is increased and the consensus requirements still cannot be met after PSO optimization, it indicates that users have different perceptual cognition of the product modeling design scheme. Therefore, user opinions should be further investigated and the scheme should be refined before evaluation.

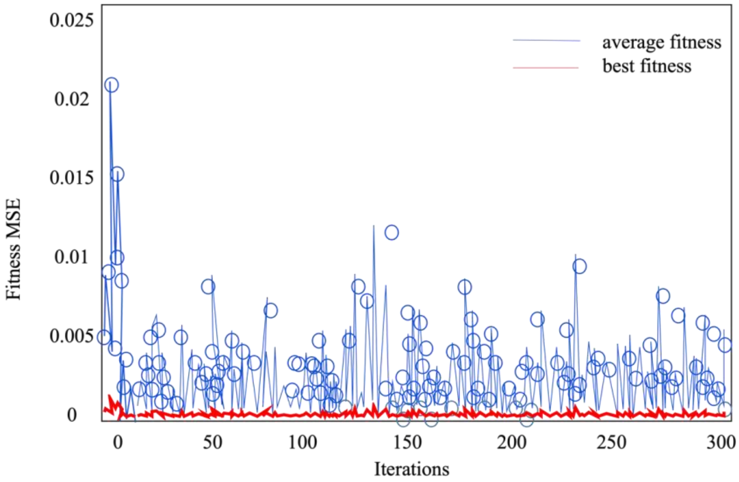

Figure 4: Fitness curve of PSO algorithm.

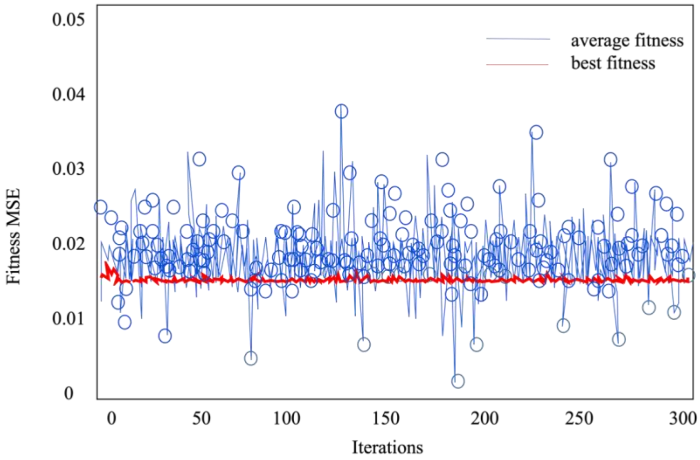

Figure 5: Convergence curve of PSO algorithm when consensus degree is maximum.

Suppose the number of particles is 10, c1=c2=2, and the maximum number of iterations t_max is 500. According to user opinions, the language preference adjustment interval is [-0.5,0.5]. The constraint range of the overall language interval is [-3,3], and a total of 432 parameters need to be adjusted. After 100 optimization calculations by PSO algorithm, the optimal consensus degree value distribution of each optimization is obtained. Wherein, the maximum consensus degree value is 0.9132, and the convergence curve of PSO when the maximum consensus degree is taken is shown in Figure 6. The hesitation language matrix that meets the consensus requirement (consensus degree 0.9066) and has the smallest deviation from the original matrix (deviation 0.2765) is selected as the optimized user evaluation matrix.

Since the perceptual evaluation of product modeling relies on the intuitive image perception of users, the aggregation of perceptual evaluation information based on language terms is helpful to cater to user habits. At the same time, when the user preference consensus degree of evaluation information aggregation based on hesitation fuzzy language cannot be reached, the boundary effect decline caused by multiple user evaluations can be avoided by using optimization algorithm for preference adjustment without increasing the number of evaluation users (the specific decline degree will be further studied in the next step), so as to improve the efficiency of reaching consensus. The fuzzy mathematics comprehensive evaluation method was adopted to convert the five-dimensional sensory evaluation results of the aesthetic feeling of the designed brand samples, and finally get the comprehensive sensory score of each sample, as shown in Figure 7. As can be seen from the figure, when the brand is a well-known brand, no matter how the shape and color are combined, consumers believe that their brand experience comes from the well-known brand. When the brand's unknown shape is simple, no matter the color is black or silver, consumers believe that their brand experience comes from the shape.

5 CONCLUSION

In his experience aesthetics, Dewey said: the interaction between people and products is a subjective aesthetic experience, and this experience is multi-level. Aiming at the multi-level product-user experience characteristics, this paper proposes a multi-level evaluation model of automobile modeling from the perspective of user experience, and uses mathematical decision method to obtain parametric decision results for this model, thus forming a brand design evaluation method from the perspective of product experience and finally conducting experimental verification.

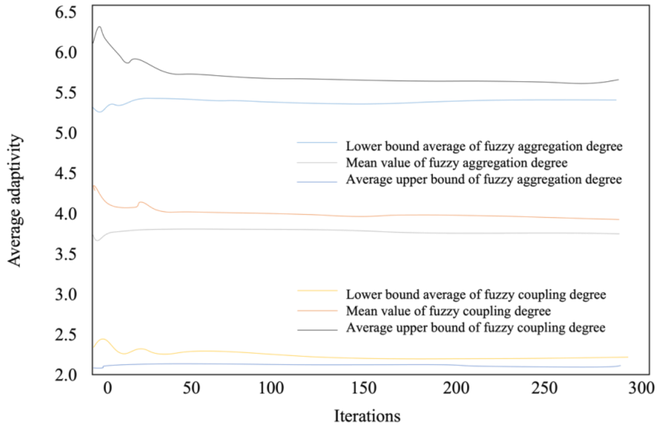

Figure 6: Variation curve of fitness mean value of fuzzy evaluation with the number of iterations.

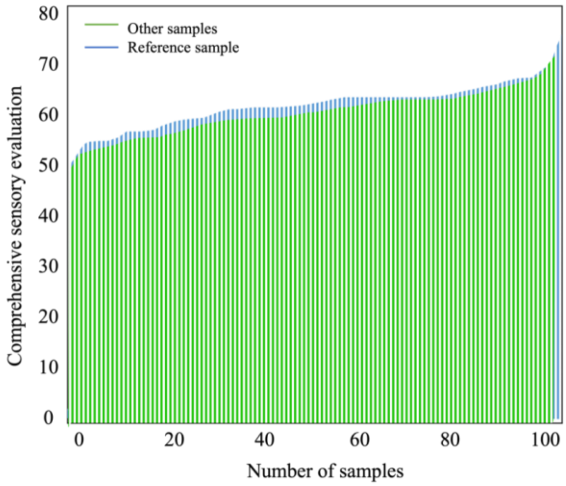

Figure 7: Aesthetic sense comprehensive score of brand samples.

This method has been applied to the computer-aided generation of automobile modeling based on evolutionary algorithm, and some results have been obtained. This method can also be independently applied to the modeling evaluation of other industrial design products. Product modeling perceptual evaluation is a process of aggregating and processing users' perception and preference information. This process has fuzziness and uncertainty, which makes users hesitate to make accurate judgments. To solve this problem, this paper introduced HFLTSs to describe users' image perception of product modeling schemes, built a user evaluation consensus degree model based on its operation rules, promoted non-consensus to reach by PSO algorithm, used the idea of TOPSIS method to realize the pros and cons of schemes, and put forward a product modeling design perceptual evaluation process based on HFLTSs and PSO. Examples show that HFLTSs is helpful to describe users' hesitation in perceptual evaluation of product modeling schemes, and to solve the uncertain problem of users' perceptual cognition to some extent. At the same time, consensus reaching based on PSO algorithm can improve the consistency of hesitant fuzzy language evaluation and improve the quality of product modeling perceptual evaluation. The next research will build an interactive system of user hesitation fuzzy language evaluation on this basis to improve the application efficiency of the algorithm.

Xiaodan Dai, https://orcid.org/0009-0002-0132-5918
Xinqiang Cao, https://orcid.org/0009-0003-2954-9910

REFERENCES

[1] Azman, M.-A.; Asyraf, M.-R.-M.; Khalina, A.; Petrů, M.; Ruzaidi, C.-M.; Sapuan, S.-M.; Suriani, M.-J.: Natural fiber reinforced composite material for product design: A short review, Polymers, 13(12), 2021, 1917. https://doi.org/10.3390/polym13121917
[2] Coteţ, F.-A.; Văscan, I.; Szabó, L.: On the Usefulness of Employing ANSYS Motor-CAD Software in Designing Permanent Magnet Synchronous Machines, Designs, 7(1), 2023, 1-22. https://doi.org/10.3390/designs7010007
[3] Han, Y.-S.; Lee, J.; Lee, J.; Lee, W.; Lee, K.: 3D CAD data extraction and conversion for application of augmented/virtual reality to the construction of ships and offshore structures, International Journal of Computer Integrated Manufacturing, 32(7), 2019, 658-668. https://doi.org/10.1080/0951192X.2019.1599440
[4] He, B.; Li, F.; Cao, X.; Li, T.: Product sustainable design: a review from the environmental, economic, and social aspects, Journal of Computing and Information Science in Engineering, 20(4), 2020, 040801. https://doi.org/10.1115/1.4045408
[5] Jones, B.; Hildreth, D.; Chen, D.; Baran, I.; Kim, V.-G.; Schulz, A.: Automate: A dataset and learning approach for automatic mating of cad assemblies, ACM Transactions on Graphics (TOG), 40(6), 2021, 1-18. https://doi.org/10.1145/3478513.3480562
[6] Nayeem, T.; Murshed, F.; Dwivedi, A.: Brand experience and brand attitude: examining a credibility-based mechanism, Marketing Intelligence & Planning, 37(7), 2019, 821-836. https://doi.org/10.1108/MIP-11-2018-0544
[7] Pessôa, M.-V.-P.; Becker, J.-M.-J.: 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
[8] Raffaeli, R.; Lettori, J.; Schmidt, J.; Peruzzini, M.; Pellicciari, M.: A systematic approach for evaluating the adoption of additive manufacturing in the product design process, Applied Sciences, 11(3), 2021, 1210. https://doi.org/10.3390/app11031210
[9] špelic, I.: The current status on 3D scanning and CAD/CAM applications in textile research, International Journal of Clothing Science and Technology, 32(6), 2020, 891-907. https://doi.org/10.1108/IJCST-07-2018-0094
[10] Yoo, S.; Lee, S.; Kim, S.; Hwang, K.-H.; Park, J.-H.; Kang, N.: Integrating deep learning into CAD/CAE system: generative design and evaluation of 3D conceptual wheel, Structural and multidisciplinary optimization, 64(4), 2021, 2725-2747. https://doi.org/10.1007/s00158-021-02953-9
[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, 1-10. https://doi.org/10.1115/1.4047685