Construction of Environment-friendly Electric Bicycle Styling Design System based on Consumers' Kansei Image

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Abstract. As an important transportation vehicle, electric bicycles have the characteristics of high convenience and low cost, which have the potential to alleviate urban traffic problems, have already gradually been widely adopted. However, the current electric bicycle styling designs tend to be homogenized accompanied by too sample improved design, and ignore the consumer's emotional preference demand for electric bicycle styling. Therefore, this article aims to dig deeper into the styling elements of consumers' emotional preference for electric bicycles, a Whale Optimization Algorithm (WOA) optimization algorithm is proposes to construct a product design system; simultaneously, in order to continuously and quantitatively describe the relationship between consumers' emotional response information and product form elements, the back propagation neural network (BP-NN) model is applied to train product form design data, and further, the combination of WOA algorithm and BP-NN makes up for the disadvantages between them, which can better construct the relationship between consumers and product design and design electric bicycle products that reflect consumers' emotional demands. In the experiment phase, firstly, the number of nodes in the input layer, the output layer and the hidden layer of the artificial neural network algorithm is obtained by morphological decomposition of the design elements of the electric bicycles. Secondly, a comparative analysis of the fitting results of the BP neural network in the training set before and after the optimization of WOA is carried out, and it is verified that the fitting results of the training set BP neural network after WOA optimization have a good fitting degree on the predicted output and expected output; At the same time, the fitting results of different test examples also show that for a large-scale BP neural network, the weights and offsets of the initial network should be selected reasonably so that the optimization does not fall into the local maximum during the gradient descent process. Finally, an electric bicycle styling design system is designed, which is mainly divided into two parts: BP neural network training and the fitting results of the BP neural network training set after WOA optimization It can be verified that the electric bicycle Whale Optimization Algorithm and back propagation neural network (WOA-BP) styling design system can effectively predict the optimal form combination results of different perceptual words. Therefore, the system designed in this study can be applied in the form design process of electric bicycle products.

Keywords: electric bicycle design; whale optimization algorithm; back propagation neural network
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1 INTRODUCTION

With more and more people living in cities, traffic pollution has become increasingly serious, which poses a threat to people's healthy life and sustainable development of society. Currently, there is an increasing trend to seek more sustainable transportation solutions. It can be found that electric bicycles have been playing an important role in large cities because of their economy, convenience and environmental advantages for urban traffic. However, the electric bicycle market has the problem of homogenization of styling design. The styling design of electric bicycles is either a simple modified design or an imitation of popular designs in the market. At present, the research on the shape design of electric bicycles has attracted the attention of researchers. For example, it is particularly important to study the emotional response of consumers to the product shape [1]. The majority of electric bicycle consumers not only pay attention to the performance and functions of electric bicycles, but also have a significant emotional preference for electric bicycles [2]. Some scholars have put forward some far-reaching product emotional design theories, expressed as "emotional engineering", "Kansei engineering" (KE) [3], "pleasure with products", etc. Norman [4] systematically expounds the emotional design theory and proposed three levels of emotional design. Desmet and Hekkert [5] believe that emotional feedback can reach three levels from the interaction between users and products, including the aesthetic level of sensory pleasure, the meaning level of product symbols and the emotional level induced by the product. Jordan [6] points out that products first meet functional needs, followed by usability, and finally emotional needs. Among the emotional measurement methods, subjective psychological evaluation is widely used, such as the semantic differential scale. Huang et al. [7] proposes a basic-emotion based semantic differential method to improve the traditional semantic differential method.

In the field of product design, many emotional design methods have emerged, and one of the more mature methods is Kansei Engineering [3], a consumer-oriented technology , which mainly studies which characteristics of product modeling can induce consumers' specific emotions, has been applied for emotional design of products [8]. For example, Shieh and Yeh [9] combine Kansei Engineering to design running shoes with consumer emotional response as a predictive system. Kittidecha et al. [10] study user emotions and optimal design parameters in the form of liquor glasses to obtain customer satisfaction. Llinares et al. [11] apply Kansei Engineering to analyze the emotional response of consumers in housing purchases decision. It is a notable fact that Kansei Engineering has been widely applied in the product design process, and most of the literature mainly uses mathematical statistics to establish a technical framework. With the rapid development of technologies such as brain neuroscience, machine learning, and data mining, intelligent emotional design based on computer aided design has gradually become a trend. For example, product color emotional experience has become an important factor for users to decide to buy and use products. In order to accurately obtain users' product color emotional demands and preferences, Ding and Bai [12] proposes a product color emotional design method based on support vector regression (SVR) that adapts to changes in product shape features.

Product shape design is an important factor that affects consumers' emotional preferences for products. Therefore, it is particularly significant to develop product shape designs that meet consumers' emotional demands. In view of that electric bicycles are commonly used in daily life, and the emotional experience of their users has not received enough attention. Kuo and Chang [13] evaluate the user emotional experience of bicycle design from a multi-sensory perspective. Wang and Zhou [14] uses the evaluation grid method and fuzzy KANO model to extract consumers' emotional preference factors for electric bicycle modeling, which improved the appearance appeal of electric bicycle and provided a new way to study the emotional relationship between consumers and electric bicycle. However, consumers' emotions are complex. In order to ensure the accuracy of electric bicycle styling design that meets consumer's emotional demands, this paper proposes a Whale Optimization Algorithm (WOA) to search for consumer's emotional preferences for electric bicycles. The research results can provide references for electric bicycle designers.

2 LITERATURE REVIEW

2.1 Kansei Engineering and Product Design

With the shift from a seller's market to a buyer's market, the market generally calls for products that focus on design style, especially the individual and customization demands of customers. There is no doubt that product designs need to follow the trend of the times and integrate customers' psychological perception into product design. Therefore, a large number of scholars have done a lot of research on how product design meets the individual demands of consumers. Among them, Kansei Engineering is the most significant application of engineering design in the design world. Shen et al. [15] construct a fuzzy Kansei Engineering method including association method, and applied it to the design process of audio products. At the same time, the article uses the artificial neural network method to process the corresponding relationship between product shape images and customer demands. The final results show that the above two-stage method can effectively improve consumer satisfaction by 11.7%. Ding et al. [16] build a mapping model based on the semantic difference and back propagation neural network between the users' color image perceptions and the elements of the product's color design to match the users' emotional image goal through the k-nearest neighbor algorithm. Liamd et al. [17] focus on a predictive case-based procedure to assists the user to elaborate a preliminary forecast about the perception of an object based on some of its features through the Kansei engineering approach. Lv et al. [18] establish a novel design method based on the error back propagation (BP) neural network to effectively design innovative patterns matching users' preferences.

The above-mentioned research aims to obtain the customer's evaluation and demand of product design elements through surveys or on-site surveys. With the rise and prosperity of e-commerce platforms and user-generated content platforms in recent years, a large amount of data has been accumulated on the platform resources, it become popular that extracting the online review data information of the product, and analyzing the real needs of customers for product design can benefit to help build resonance between customers and products [19-21]. Jiang et al. [22] indicate that a large number of previous studies that generally conducted customer surveys based on questionnaires and interviews to collect customers' views or preferences could be time-consuming and the survey data does not contain much sentiment expression. In the paper, a methodology for generating association rules for supporting affective design based on online customer reviews is proposed to address opinion mining of affective dimensions from online customer reviews and association rule mining based on multi-objective particle swarm optimization (PSO). Lin et al. [23] applies evolutionary neural networks into a robust product design to help designers search for an optimum combination of variable characteristic values for a given product design problem. In the design procedure, the data resulting from the experimental design in the Taguchi method are forwarded to the back-propagation network training process and genetic algorithm simulation to predict the most suitable combination of variable characteristic values. and the results showed that the proposed procedures could enhance the efficiency of product design efforts.

2.2 Back Propagation Neural Networks (BP-NN)

In recent years, some studies have obtained excellent results in the research and application of artificial neural networks. Although it is rough to simulate the human brain through artificial neural networks, it can still be seen that it has many similar characteristics to the human brain. Some scholars apply neural networks to obtain sample knowledge, which provides a way to solve the "bottleneck" problem of knowledge acquisition in the development of artificial intelligence. In practical applications, neural networks have been applied in many important fields. And recently, artificial neural networks are being developed to a higher level that simulates human cognition, for example, combined with genetic algorithms, combined with intelligent algorithms such as artificial fish swarm algorithm, to form artificial intelligence. The artificial neural network can also be used to simulate the consumer's emotional response to the product, which is very consistent with the nonlinear perception process of the human brain neural network structure. At present, artificial neural network (ANN) has been successfully applied in the field of product modeling design. For example, Chen et al. [24] design an office chair design database based on the ANN algorithm, which provides product designers with the best combination of product form elements to illustrate the emotional image in office chair design. Through the analysis of the aesthetic, functional and environmentally friendly consumer emotional preferences represented by the emotional image vocabulary in the design of the office chair, the eco-product form design process is promoted to reflect the emotional needs of consumers. Diego-Mas et al. [25] analyze the consumer's emotional response to product form design based on the ANN model, and modeled the relationship between the consumer's emotional response and product design elements. Zheng et al. [26] develop a model based on ANN that can build a design decision support system for facilitating the vehicle form design process and matching specific needs with a case study of sand making machine, which can examine the design optimization on product elements and help designers do the best choice as they design a new vehicle product. Xu et al. [27] propose a new method based on gray theory and ANN to solve the problem that product morphological characteristics are difficult to quantitatively predict. Lin et al. [28] establish an ANN model through the research of mobile phone styling and consumer emotional response. Kang [29] uses grey relational analysis and ANN to establish an evaluation model for simulating consumers' emotional responses to product forms. Shieh et al. [30] apply morphological analysis and ANN to establish the relationship between the morphological characteristics of conceptual bicycles and consumer emotional responses.

As a widely used nonlinear fitting method, BP-NN has the characteristics of back propagation. Therefore, the combination of BP-NN and Kansei Engineering can effectively simulate the mapping relationship between consumers and product elements and realize the improvement of product modeling design efficiency. For example, Shen and Wang [31] use the combination of perceptual engineering and BP-NN to establish the relationship between the vocabulary and morphological characteristics representing consumer emotions, and combined the associative creative thinking process with Kansei Engineering to design product form that meet customer emotional preferences. Li et al. [32] combine BP neural network and genetic algorithm, taking teapot as a research case, and constructed a product form design method. Guo et al. [33] take the mobile phone model as an example and established a method of product model optimization design based on BP-NN. Besides, in order to accurately predict the key modeling feature of the products according to the emotional demands of a certain consumer. Li et al. [11] apply the BP neural network algorithm to the shoe design system process, and realize the combination optimization of shoe design elements. Therefore, comprehensively analyzing the application of the above-mentioned artificial neural network algorithm and Kansei Engineering, it can be concluded that BP-NN combined with Kansei Engineering proves to be very suitable for studying the relationship between product characteristics and consumer emotional response.

2.3 Whale Optimization Algorithm (WOA)

Whale Optimization Algorithm is a new heuristic search optimization algorithm developed by Mirjalili and Lewis [34] in 2016. The algorithm is inspired by the bubble net hunting strategy of humpback whales, which has the advantages of simple operation, few adjustment parameters, and easy to jump out of the local optimum, has been applied in engineering field to solve optimization problems. In view of the above-mentioned advantages of WOA, it has been widely used in various engineering optimization fields, such as: electrical engineering, civil engineering, clustering, image processing, mechanical engineering, control engineering, robot path, network, industrial engineering, mission planning and other engineering industries [35]. The specific idea and process of the WOA algorithm can be described as follows. The WOA simulates the whale's food search process, which specifically includes three steps.

(1) Encircling prey

$|A|$ decreases to 1 with the increase of the number of iterations, and the algorithm enters the phase of encircling prey. As the prey position is ambiguous at initial search, it is assumed in the WOA algorithm that the optimal solution of fitness value in whales at this time is the prey position or the position approaching the target prey, so other whales update the position according to the position information of the current optimal solution, approach the prey by gradually encircling and shrinking, and finally determine the target position. The mathematical model is as follows:

$$\vec{D}=\left|\vec{C}\cdot\vec{X}^{*}(t)-\vec{X}(t)\right| \tag{1}$$

$$\vec{X}(t+1)=\vec{X}(t)-\vec{A}\cdot\vec{D} \tag{2}$$

Where, t is the current number of iteration; $\vec{A}$ and $\vec{C}$ are coefficient vectors; $\vec{X}^{*}$ is the best spatial position of whales' individual currently obtained; $\vec{X}$ is the current spatial position of whales' individual; || refers to absolute value; • represents element-wise multiplication.

The calculation of coefficient vectors $\vec{A}$ and $\vec{C}$ is shown below:

$$\vec{A}=2\vec{a}\cdot\vec{r}-\vec{a} \tag{3}$$

$$\vec{C}=2\cdot\vec{r} \tag{4}$$

Where, $\vec{a}$ represents the linear decrease from 2 to 0 in the exploration and exploitation phase, expressed as $a=2-t/M$, M is the maximum number of iterations; $\vec{r}$ is a random number on the 0-1 interval.

(2) Bubble-net attacking method

The mathematical model was established based on humpback whale's bubble-net attacking behavior, which consists of the following two mechanisms:

Shrinking encircling mechanism: This behavior is realized by decreasing the $\vec{a}$ value in Equation (3). It should be noted that the variation range of $\vec{A}$ also shrinks as the $\vec{a}$ value decreases. In other words, $\vec{A}$ is a random number in the interval of $[-a,a]$ (where, $\vec{a}$ represents a linear decrease from 2 to 0 in the exploration and exploitation phase), and the current behavior of humpback whales can be judged by the module value of coefficient $\vec{A}$.

Spiral updating position: Whales have a unique hunting strategy. They swim upward in a spiral pattern while exhaling bubbles, and encircle while bringing the prey closer to the ocean surface to capture it in an optimal manner. The mathematical model for this rare hunting behavior is described below:

$$\vec{X}(t+1)=\vec{D}'\cdot e^{bl}\cdot\cos(2\pi l)+\vec{X}^{*}(t) \tag{5}$$

Where, $\vec{D}'=\left|\vec{X}^{*}(t)-\vec{X}(t)\right|$, represents the distance between the current optimal position of the ith whales' individual and the prey; b is the defined logarithmic spiral shape constant; l is the random number between $[-1,1]$; • represents element-wise multiplication.

To simulate whales' hunting behavior of synchronous shrinking encircling and spiral bubble-net hunting, a random probability was set to select the position updating strategy. When the random probability is $p \geq 0.5$, the whales update the bubble-net spiral hunting position, and approach the prey by swimming in a spiral way while exhaling bubbles; When the random probability is $p < 0.5$, the whales update the encircling hunting position based on the position of current optimal solution. In the iterative process of continuously approaching the target, $|A|$ continues to decrease. When $|A| = 0$, WOA has the theoretical optimal solution. The overall hunting mechanism is described below:

$$\vec{X}(t+1) = \begin{cases} \vec{X}(t+1) = \vec{X}(t) - \vec{A} \cdot \vec{D} & p < 0.5 \\ \vec{D}' \cdot e^{bl} \cdot \cos(2\pi l) + \vec{X}^*(t) & p \geq 0.5 \end{cases} \tag{6}$$

(3) Search for prey (exploration phase)

In WOA, each whale in the hunt represents a feasible solution x. In the phase of search for prey, based on the random walk mechanism in whales hunting, whale individuals update the position of the next generation according to the position information of each other in the group, and random search realizes the global optimization performance of the algorithm. According to the tth search behavior, when $|A| > 1$, the whale updates the $t+1$th search behavior, expressed as follows:

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_{rand}(t) - \vec{X} \right| \tag{7}$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A} \cdot \vec{D} \tag{8}$$

Where, $\vec{X}_{rand}$ represents the position of random whale individual.

Therefore, in the WOA, the initial solution is randomly initialized in the initialization phase, and then the subsequent iteration and update strategy are used to achieve continuous update of the current solution during each iteration. Finally, algorithm stops the iteration process when the WOA algorithm meets certain iteration conditions and output the optimal result of the algorithm solution.

On the other hand, because simply using one algorithm may not be able to meet the increasingly complex engineering optimization needs, a hybrid optimization method composed of two algorithms is becoming a research trend in the field of engineering optimization. For example, the conventional neural network algorithm has the disadvantages of long iteration training time, large amount of calculation, slow training speed, poor generalization ability, which is easy to fall into local minima. To overcome these shortcomings, Hsiao et al. [35] combine genetic algorithm with BP neural network to predict the best emotional design of product modeling. Lai et al. [36] studied the method of combining the gray relational analysis method with the neural network model to provide the modeling design method for mobile phone product image recognition. Guo et al. [37] use genetic algorithm (GA) to integrate multiple emotional demand target values predicted by BP neural network (BPNN) into a single target value for optimization design, and develop a product emotional design based on Kansei Engineering method. Sai and Huajing [38] propose a combination of whale optimization algorithm (WOA) and support vector regression (SVR), and verified the effectiveness of the support vector regression and Whale Optimization Algorithm (SVR-WOA) method through experiments and engineering applications.

2.4 Literature Summary

Through review and analysis of the existing literature, it can be concluded that the use of BP-NN model for product form design can continuously and quantitatively describe the relationship between consumer emotional response information and product form elements. And in view of the good performance of BP-NN in the KANSEI evaluation, it has been proved to be very suitable for constructing the relationship model between product features and emotional response and user preferences. At present, WOA has been applied in various engineering optimization fields, and it shows that the WOA method is effective, but it has not been used to solve the product modeling design. The paper combines morphological analysis method [39], WOA and BP neural network (MAM -WOA-BPNN) to solve the optimization problem of product modeling design. Experiments show that this method has a higher convergence speed and higher accuracy. Due to this combination, the local minimum trap problem that affects the quality of the solution is completely reduced. In the proposed method, WOA explores widely solution space, and the backpropagation algorithm finds the global optimal solution.

3 AN ALGORITHM BASED ON WOA COMBINED WITH BP-NN

This study proposes a product morphology design decision-making method in an electric bicycles case driven by user Kansei image which can combine WOA with BP-NN. The established algorithm has been divided into three phases, which are stated as follows: 1)apply the morphological analysis method [40] to form deconstruction and coding of electric bicycles which allows consumers to evaluate product samples under a series of perceptual words; 2)then establish the mapping relationship between perceptual vocabulary and product form elements through BP neural network; 3)use WOA algorithm to optimize the initial weights and thresholds of the BP neural network, and select the optimal initial weights and thresholds of the BP neural network. Specifically, the algorithm flowchart is shown in Fig. 1.

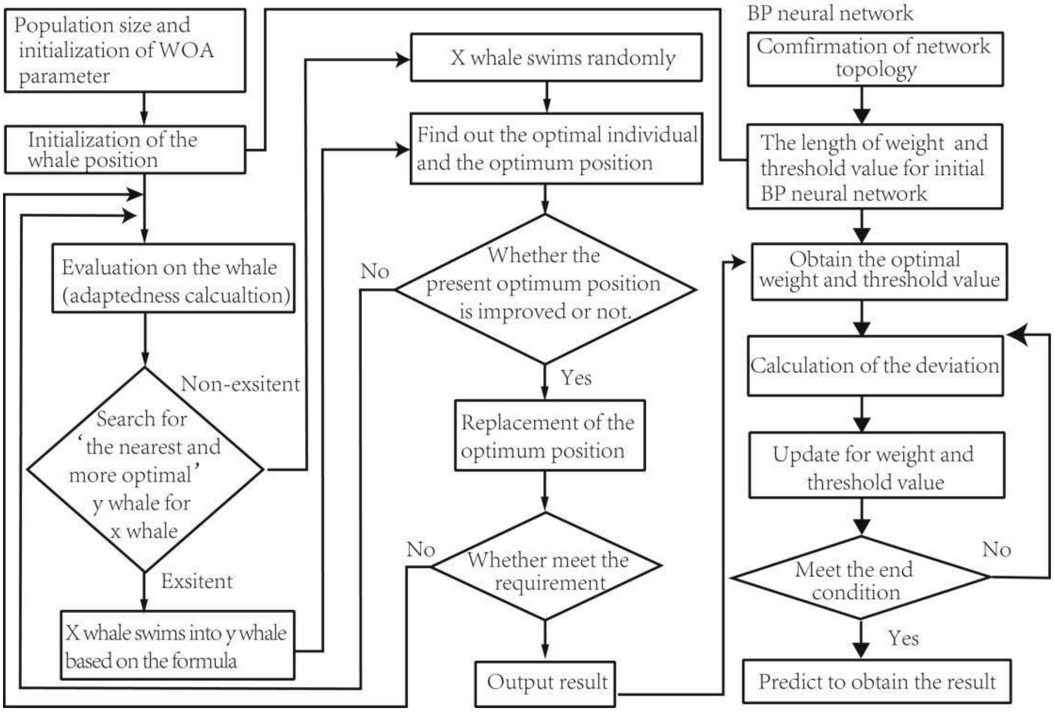


Figure 1: Algorithm flow chart.

3.1 Morphology Composition and Coding of Electric Bicycles

In order to obtain the morphological design elements of electric bicycles, this article first invites 60 students from the industrial design department to participate in the work of collecting and arranging data. Through various websites, e-magazines and sales stores, various styles of electric bicycles are collected and sorted. And after removing poorly recognized pictures, a total of 30 clearly visible electric bicycle samples were retained，as it is shown in Fig. 2. Then the pictures are processed with Adobe photoshop image processing software to extract the morphological elements of electric bicycles. At the same time, since this study is to evaluate the influence of the morphological characteristics of electric bicycles on user experience, it is necessary to remove brand information and product color potential. Subsequently, 10 people with more than 3 years of design experience compared the samples with a large degree of similarity based on the structure and morphology of the samples, and finally got 15 design image sample with large differences. This study uses the morphological analysis method in Kansei Engineering to deconstruct the morphological characteristics of the product. It first decomposes the morphological characteristics of the electric bicycle into several main components (items), and then examines each possible attribute (category) of each component. In this study, electric bicycles are broken down into 4 items (frame style, electric bicycle saddle, front and rear tire size, battery type), and the 4 component elements of electric bicycles have 4, 2, 4, 2 design element types respectively, a total of 12 design elements. As shown in Table 1, the 12 design elements are generated as below: the structure of an electric bicycle can be decomposed into four components: frame style, electric bicycle saddle, front and rear tire size, battery type. For example, the frame style of 30 electric bicycles can be divided into four types. See Table 1 for details of the four types: Type 1, Type 2, Type 3, and Type 4; By analogy, the saddle style of 30 electric bicycles can be divided into 2 types, the front and rear tire size can be divided into 4 specifications, and the battery type can be divided into 2 types. According to the classification results in Table 1, the morphological classification of 30 electric bicycles can be broken down into four items: frame style, electric bicycle saddle, front and rear tire size, battery type, each of which has 4, 2, 4, 2 design element types respectively, a total of 12 design elements. Since the design elements cannot be directly used as the input parameters of the BP neural network algorithm, it is necessary to encode the design elements of the electric bicycle. The number of bits of each sample code is the same as the total number of design elements, which is 12. The corresponding code of each design element of the experimental sample has only one digit as 1, and the rest are 0 . For example, the design element types of No. 1 sample under the 4 items are 1 (1, 0, 0, 0), 1 (1, 0), 1 (1, 0, 0, 0), 2 (0, 1) , The code of sample No. 1 is 100010100001, and other samples are coded in the same way. The specific encoding format is shown in Fig. 3 below.

3.2 BP Neural Network Algorithm

BP-NN is a multi-layer feedforward neural network. The main feature of the network is that the signal can be forwarded back, and the error can be back propagated. In the forward transmission process, the input signal is processed by the input layer through the hidden layer to the output layer. The neuron state of each layer only affects the neuron state of the next layer. If the output layer cannot get the expected output, it will switch to back propagation, adjust the network weight and threshold according to the prediction error, so that the predicted output of the BP neural network will be close to the expected output. The topological structure of BP artificial neural network is shown in Fig. 4. Where $X_1, X_2, \ldots X_n$ is the input value of the BP neural network, $Y_1, Y_2, \ldots Y_P$ is the predicted value of the BP neural network, w_{ij} and w_{jk} is the weight of the BP neural network. This article takes the styling elements of electric bicycles as the input value of the neural network, and consumers' perceptual image of the product as the prediction value of the neural network. In order to speed up the learning efficiency of the network, it is generally necessary to normalize the input and output data of the original data. In order to speed up the learning efficiency of the network, it is generally necessary to normalize the input and output data of the original data to eliminate the order of magnitude difference between the data of each dimension, so as to avoid the large difference in the magnitude of the input and output data.

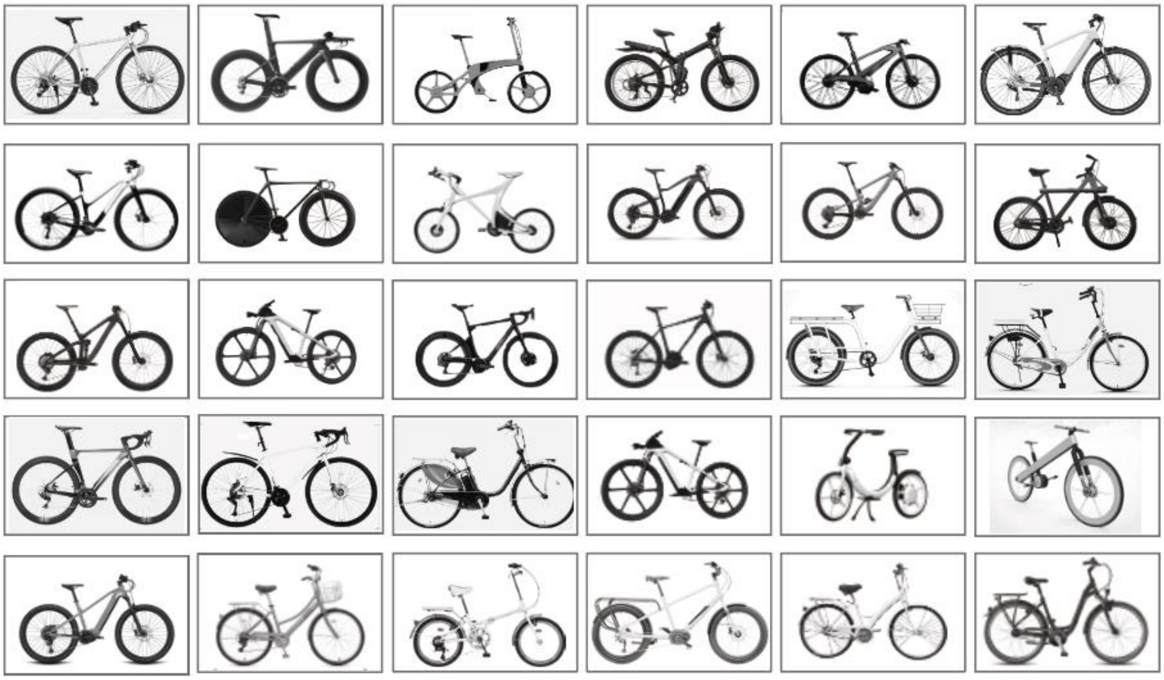


Figure 2: 30 typical bicycle samples.

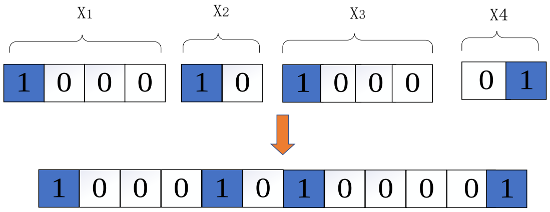


Figure 3: Sample coding form.

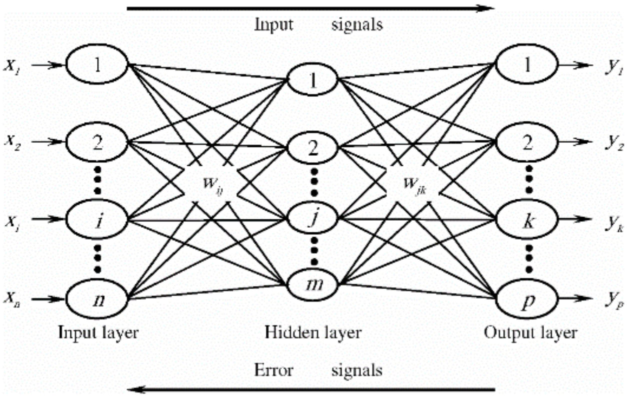


Figure 4: Schematic diagram of BP-NN.

In the above formula (1): $X_{\min}$ is the smallest number in the data sequence; $X_{\max}$ is the largest number in the data sequence. Then input the normalized data into the hidden layer for calculation. According to the input variables X, the connection weights w_{ij} and w_{jk} between the input layer and the hidden layer and the hidden layer threshold a, the hidden layer output Y is calculated.

$$H_j = f(\sum_{i=1}^{n} \omega_{ij} x_i - a_j), j = 1, 2, ...m \tag{10}$$

In the above formula: i is the nodes number of hidden layer; f is the activation function of hidden layer, which has a variety of expressions. The function selected in this designed algorithm is as following Eq. (11):

$$f(x) = \frac{1}{1+e^{-cx}} \tag{11}$$

According to the output value of the hidden layer H, connecting the weight w_{jk} and the threshold b to calculate the predicted output of the BP neural network as formula (12):

$$O_k = \sum_{j=1}^{l} H_j \omega_{jk} - b_k, k = 1, 2, ...m \tag{12}$$

According to the predicted output O and expected output Y, we could calculate the network prediction error e:

$$e_k = Y_k - O_k, \quad k = 1, 2, ..., m \tag{13}$$

And update the network connection weights w_{ij} and w_{jk} through the network prediction error e:

$$\omega_{ij} = \omega_{jk} + \eta H_j \left(1 - H_j\right) x\left(i\right) \sum_{k=1}^{m} \omega_{jk} e_k \tag{14}$$

$$\omega_{jk} = \omega_{jk} + \eta H_j e_k \tag{15}$$

In the above formula: i=1,2, …, n; j=1,2, …, l; k=1,2, …, m represents the learning rate, and then update the network threshold a, b according to the network prediction error e.

$$a_{ij} = a_{jk} + \eta H_j \left(1 - H_j\right) \sum_{k=1}^{m} \omega_{jk} e_k \tag{16}$$

$$b_k = b_k + e_k \tag{17}$$

3.3 WOA Optimize BP Neural Network

The basic idea that the WOA optimizes the BP neural network is to use the WOA to optimize the initial weights and thresholds of the BP neural network. The specific process is: 1) Initializing the BP neural network to determine the input and output structure and initial connection weights and threshold value; 2) encoding the initial value of the WOA according to the initial connection weight and threshold of the BP neural network; 3) using the BP neural network training error as the fitness value for selection, crossover, mutation, bubble net predation until a specific termination condition is reached; 4) obtaining the optimal weight and threshold; 5) calculating the error update weight and threshold; 6) output the error result. In order to develop the whale swarm algorithm to solve the function optimization problem, we made some assumptions about the behavior of whales. At the same time, in order to improve the solution efficiency and accuracy of the WOA algorithm, this article assumes some behaviors of whales, which can be summarized as the following four idealized rules:1) all whales communicate through ultrasound in the search area; 2) each whale can calculate the distance between itself and other whales; 3) each whale uses the fitness value to evaluate the pros and cons of the current solution; 4) the whale can guide the whale closest to it to continuously achieve food quality.

The pseudo code of established WOA is shown in Fig. 5. Among them, $|\Omega|$ in the 6th row represents the number of individuals in the whale group Ω, that is the population size; Ω_i in the 7th row is the i-th whale in Ω. It can be seen from Fig. 5 that, similar to most other meta-heuristic algorithms, the steps of WOA before iterative calculation are some initialization steps, including the initialization configuration of parameters, the location of the initialization individual, and the evaluation of each individual. Here, the positions of all individual whales are initialized randomly. The key step of WOA is that, during the movement of whales (lines 5-13), each whale moves to a better position by cooperating with other whales in the group. First, the whale needs to determine its "better and nearest" whale (line 7). If its "better and nearest" whale exists, then it will move to its "better and nearest" whale according to Eq. 2 (line 9); otherwise, it will stay in place. The pseudo code for finding the "better and closest" whale is shown in Fig. 4, where $f(\Omega_i)$ represents the fitness value of the whale Ω_i, and $dist(\Omega_i,\Omega_u)$ represents the distance between Ω_i and Ω_u.

WOA pseudo code

Input: Fitness function, whale group Ω.

Output: Global optimal solution.

1: Begin
2: Initialize parameters
3: Initialize the whale position;
4: Evaluate the quality of the food found by the whale (calculate its fitness value);
5: **while** termination condition is not satisfied **do**
6:   **for** *i*=1 **to** **|Ω|** **do**
7:     Look for the "better and nearest" whale Y of Ω_i;
8:     **if** Y exists **then**
9:       Ω_i moves according to formula (2) under the guidance of Y;
10:       Evaluate Ω_i;
11:     **end if**
12:   **end for**
13: **end while**
14: **Return** the global optimal solution;
15: **End**

Figure 5: The overall framework of WOA.

According to the pseudo code in Fig. 6, the solution steps of the whale swarm algorithm are organized:

1.The parameter initialization setting of the whale swarm algorithm, here $\rho_0 = 2$, $d_{\max} = \sqrt{\sum_{i=1}^{n}(x_i^U - x_i^L)^2}$, x_i^L 与 x_i^U indicate the lower limit and upper limit of the i-th variable respectively. And then bring the value of $d_{\max}$ into $\eta = -20 \cdot \ln(0.25)/d_{\max}$, finally, we can get the value of η, and then we can solve it.

2.The population of the whale swarm algorithm is randomly initialized, for example, the initial population size can be set as 10;

3.Calculate the fitness value corresponding to each individual, which is the value of the objective function, and retain the optimal individual X*;

4.Determine whether the algorithm termination condition is met, for example, when the maximum number of iterations is reached, if it is not met, step 5 is executed; if it is met, step 6 is executed;

5.Perform the iterative operation of the whale swarm algorithm on the remaining 9 individuals;

6.Output the optimal X* and the corresponding optimal objective function value.

```
Pseudo-code looking for "better and closest" whales
Input: Whales group Ω, whale Ω_u.
Output: The "better and nearest" whale of whale Ω_u.
Begin
Define an integer (int) variable v and initialize it to 0;
Define floating-point (float) variable temp and initialize it to
+∞;
for i=1 to |Ω| do
if f(Ω_i)<f(Ω_u) then
if dist(Ω_i, Ω_u)<temp then
v=i;
temp=dist(Ω_i, Ω_u);
end if
end if
end for
Return Ω_v;
End
```

Figure 6: Pseudo-code for finding "better and nearest" whales.

4 CONCLUSION AND DISCUSSION

4.1 The Construction of the BP-NN Neuron

The construction of BP network model is used to establish the relationship between product perceptual image and design elements. The decomposition of electric bicycle styling elements mainly uses morphological analysis model. As shown in Tab. 1, the styling characteristics of electric bicycles can be decomposed into 4 morphological elements by analyzing the shape of electric bicycles, which are the style of X1 frame, the saddle of X2 electric bicycle, the size of X3 front and rear tires, and the type of X4 battery. The 4 morphological characteristic elements are divided into several types. For example, the frame style of the X1 electric bicycle is divided into 4 types (X11-X14), and then these 15 samples are coded according to the coding rules as shown in Tab. 2.

According to the above analysis, each electric bicycle has 4 styling feature elements (X1-X4), and the coding of each styling feature element is combined in order, with a total of 12 digits. The coding of 15 electric bicycle morphological feature elements is used as the input into input layer, that is, the input layer has 15 learning samples, and each sample is composed of 15 neurons. By collecting and filtering perceptual vocabulary, the six factors of "concise, unique, smooth, technological, fashionable, and light" in the shape design of the electric bicycle in this case are determined as multiple goals. Taking the evaluation values of perceptual words of 15 samples as the target output value, the output layer has 6 neurons. In this paper, the number of input layer nodes is the type of 15 electric bicycle morphological design elements, and the number of output layer nodes is the number of perceptual words 6. Lin et al. [28] points out that, when the number of neurons in the hidden layer equals the half of the sum of the number of neurons in the input layer and the output layer, the mean square error of the output value of the neural network algorithm is small. Therefore, this research sets the number of neurons in the hidden layer as 9.

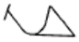
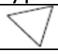
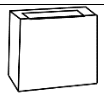
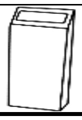
Item	Type1	Type2	Type3	Type4	Definition
Frame					X1
Saddle					X2
Front and rear tires	Mountain bike tires are mostly 26 inches	Most road bikes are 28 inches wide and 20mm wide.	Ordinary tire, 20-26 inch	Small tires are mostly 8-20 inches	X3
Battery type					X4

Table 1: Electric bicycle design element composition.

Sample No.	X 1				X 2		X 3				X 4	
	X 11	X12	X 13	X 14	X 21	X 22	X 31	X 32	X 33	X 34	X 41	X 42
1	0	0	0	1	1	0	0	0	0	1	1	0
2	0	1	0	0	0	1	0	1	0	0	0	1
3	0	0	0	1	1	0	0	0	0	1	1	0
4	0	0	1	0	0	0	0	0	1	0	0	1
5	0	1	0	0	0	1	0	1	0	0	1	0
6	1	0	0	0	0	0	1	0	0	0	0	1
7	0	0	0	1	0	0	0	0	0	1	1	0
8	0	0	0	1	0	0	0	0	0	1	0	1
…	…	…	…	…	…	…	…	…	…	…	…	…
15	0	0	0	1	0	1	0	0	0	1	1	0

Table 2: Fifteen training samples corresponding coding.

4.2 BP-NN Model Establishment and Testing

After the above construction of the artificial neural network training model, the input data is trained, and the fitting results of the BP neural network training set shown in Fig. 7 and Fig. 8 are obtained.

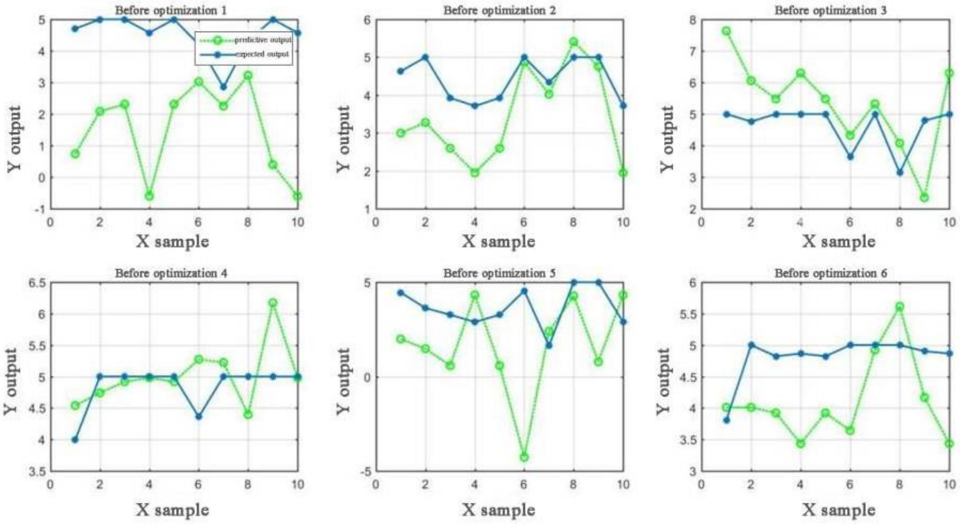


Figure 7: Fitting results of BP-NN training set before optimization.

	MSE	RMSE	R^2	MAE	MAPE	RPD
[Optimized][Testset][Output 1]	14.28100469	3.779021657	-2.665161753	5.957656178	104.2364584	0.180235067
[Optimized][Testset][Output 2]	3.361963939	1.833565908	-0.163790352	3.370492403	91.80505336	0.310260876
[Optimized][Testset][Output 3]	0.720036056	0.848549383	0.823388489	1.896296211	51.3337798	0.967599326
[Optimized][Testset][Output 4]	3.789382259	1.916633571	-2.293273379	3.023093084	84.94098461	0.308096333
[Optimized][Testset][Output 5]	3.697920741	1.922997853	-0.650066224	5.343382346	143.6885587	0.411725386
[Optimized][Testset][Output 6]	17.29692515	4.158957219	-13.84765159	6.268358285	86.58590409	0.330451659

Table 3: Regression index of training set before optimization.

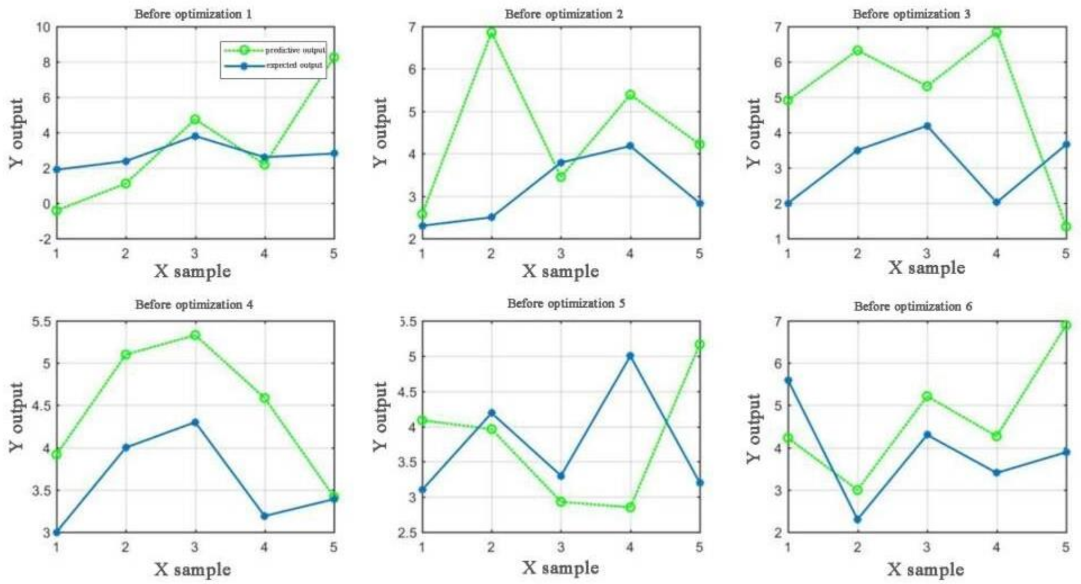


Figure 8: Fitting results of BP neural network test set before optimization.

	MSE	RMSE	R^2	MAE	MAPE	RPD
[Optimized] [Test set][Output 1]	15.55624679	3.944140817	-1.99404545	7.320059387	170.1015043	0.366012579
[Optimized] [Test set][Output 2]	1.269019185	1.126507517	0.517915304	1.895623243	40.53157995	0.615592623
[Optimized] [Test set][Output 3]	6.227011431	2.495398051	-1.182062941	3.926494078	191.2103262	0.573265815
[Optimized] [Test set][Output 4]	2.794365658	1.671635624	-0.742584783	2.170809293	68.4044107	0.552165229
[Optimized] [Test set][Output 5]	3.548851206	1.883839485	-0.445049472	3.500014946	78.46702572	0.1449386488
[Optimized] [Test set][Output 6]	6.979886871	2.641947553	-432.4295926	4.033974721	61.72777957	0.404508424

Table 4: Test set regression indicators before optimization.

As shown above, Fig. 7 shows the fitting result of the BP neural network in the training set before optimization, and Fig. 8 shows the fitting result of the BP neural network in the test set before optimization. Since the variables are classified into types, the samples are all coded with one-hot. The total number of samples is 15, the first 10 samples are used as the training set, and the last 5 samples are used as the test set. The input layer of the BP neural network is 12, the hidden layer is 9, and the output layer is 6. It can be seen from Fig. 7 and Fig. 8 that the training set and the test set have not achieved good fitting results, which shows that the BP neural network is not suitable for multiple inputs and multiple outputs when the initial weights and offsets are randomly selected. And, Tab. 3 and Tab. 4 further analyze the regression indicators of the training set and test set before optimization. It can be seen that all the R^2 indicators of the training set and the test set are far away from 1, which all illustrates the necessity of optimizing the initial weight and offset of the BP network.

4.3 Apply WOA to Optimize BP-NN

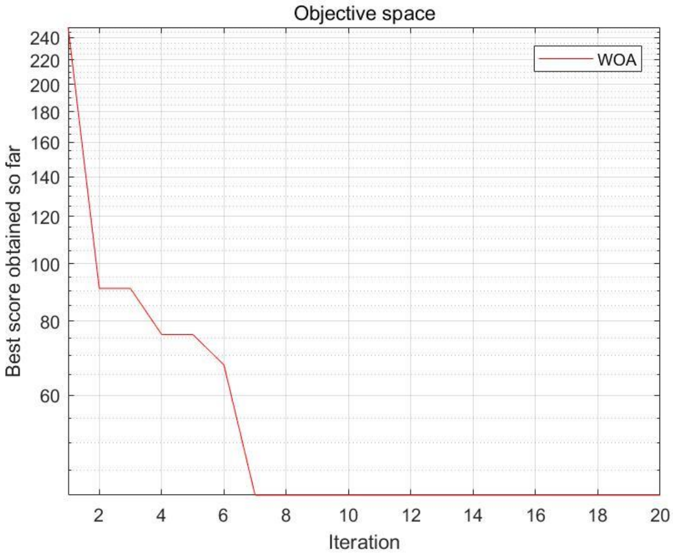


Figure 9: Convergence graph of BP-NN optimized by WOA.

Fig. 9 shows the convergence curve of WOA optimization. Here, the BP-NN structure adopts the previous structure and takes the MSE of the BP neural network test set as the optimization target. The optimized variables are the initial weight and offset of the BP neural network. The nodes of the input layer is 12, the nodes of the hidden layer is 9, and the nodes of the output layer is 6. For hidden layer w1, the number of optimizations is 108; for hidden layer offset b1, the number of optimizations is 9, and for output layer w1, the number of optimization variables is 54; for output layer offset b2, the number of optimization variables is 6. The optimized WOA parameters are set as follows: the whale population is 20, the number of iterations is 20, and the range of the initial weight and offset of the BP neural network is [-5,5]. It can be seen from the convergence graph that when the number of iterations is 7, a better convergence effect is achieved. This shows that WOA has a strong optimization ability.

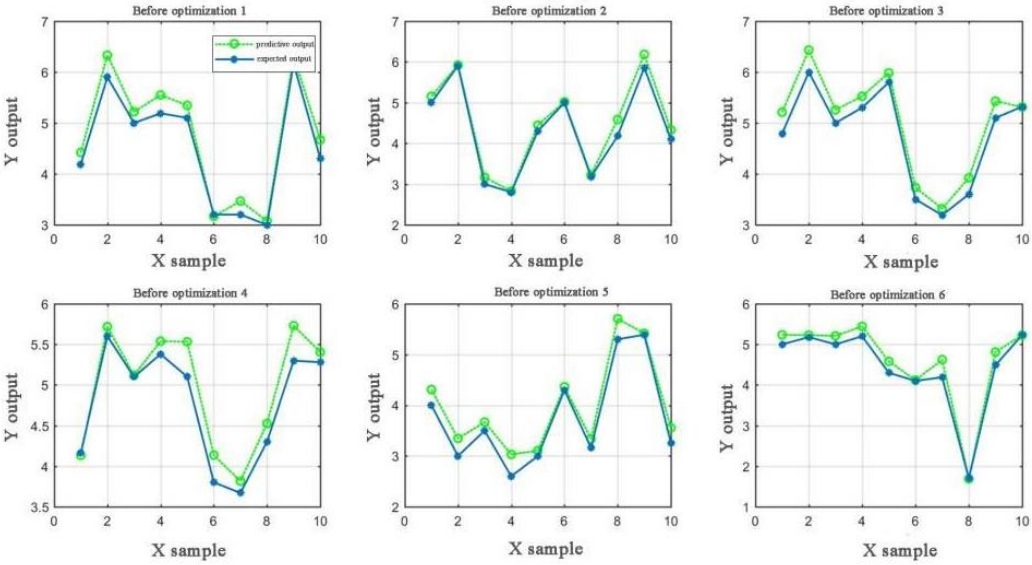


Figure 10: Fitting results of BP-NN training set after optimization.

	MSE	RMSE	R^2	MAE	MAPE	RPD
[Optimized] [Test set][Output 1]	0.711345459	0.843412983	0.938649878	2.366922852	48.5147856	1.436742057
[Optimized] [Test set][Output 2]	0.400474556	0.63283059	0.964382031	1.530079615	33.8738854	1.808965923
[Optimized] [Test set][Output 3]	0.799968982	0.894409851	0.909059298	2.540627873	51.36893926	1.135894087
[Optimized] [Test set][Output 4]	0.61231376	0.782504779	0.865829239	2.014854954	40.44498452	0.944672646
[Optimized] [Test set][Output 5]	0.727572198	0.852978428	0.914956454	2.325281063	62.30427582	1.109597616
[Optimized] [Test set][Output 6]	0.531707221	0.72918257	0.947273708	1.08543575	37.30413534	1.517805627

Table 5: Regression index of training set after optimization.

Fig. 10 shows the fitting results of the BP neural network training set after WOA optimization, and Fig. 11 shows the fitting results of the BP neural network test set after WOA optimization. It can be seen that, for both the training set and the test set, the predicted output and expected output have achieved a good degree of fit. And then, Tab. 5 and Tab. 6 further analyze the regression indicators after WOA optimization. For the training set, except for output 4, the R^2 of each output is above 0.9; for the test set, the R^2 of variable 4 is about 0.75, and the rest are all above 0.85. Compared with the unoptimized BP neural network, the training results of the WOA optimized BP neural network have made a qualitative leap in the fitting effect of multiple input and multiple output problems, which shows that for a BP neural network with a larger fitting scale, the weights and offsets of the initial network should be selected reasonably so that the optimization does not fall into the local optimum during the gradient descent process.

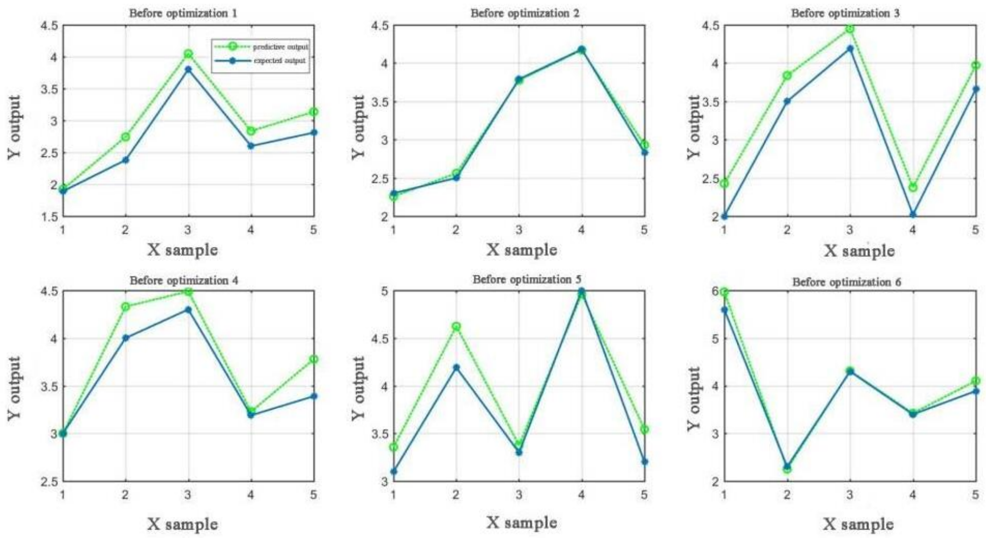


Figure 11: Fitting results of BP neural network test set after optimization.

	MSE	RMSE	R^2	MAE	MAPE	RPD
[Optimized] [Test set][Output 1]	0.357259522	0.597711906	0.820519501	1.205248773	39.69992717	1.284969532
[Optimized] [Test set][Output 2]	0.015588238	0.124852865	0.99425509	0.223973552	8.160184186	6.489500099
[Optimized] [Test set][Output 3]	0.58537355	0.765097085	0.854915942	1.68885759	54.9561167	1.243181331
[Optimized] [Test set][Output 4]	0.296851193	0.54484052	0.756543653	0.946493898	23.320506	1.202929388
[Optimized] [Test set][Output 5]	0.378494525	0.615219087	0.858943336	1.148182723	29.72457598	1.23778839
[Optimized] [Test set][Output 6]	0.183968443	0.428915415	0.968606498	0.661616193	14.3344628	3.163737634

Table 6: Test set regression indicators after optimization.

4.4 Construction of Electric Bicycle Modeling Design System Based on WOA-BP Model

As an important transportation equipment, the design of electric bicycles is very important. Therefore, in order to simplify the actual operation of electric bicycle design, this research designs an electric bicycle model design system, which mainly includes two parts: BP neural network training and WOA optimized BP neural network training set fitting results. The specific steps are as follows:

1. Click the BP neural network training button;
2. Select WOA-BPNN parameters;
3. Click the WOA-BPNN button to optimize model.

The electric bicycle shape is disassembled into 4 parts, and each part has 4, 2, 4, 2 types to choose from. Therefore, it can be seen that, there are 4×2×4×2=64 combinations of the basic shape of the electric bicycle. By encoding all combinations and importing them into the BP neural network model as input layer parameters, and then optimizing the fitting results of the BP neural network training set through WOA, the perceptual evaluation value corresponding to each combination is calculated. After algorithm optimization and calculation, 6 groups of perceptual vocabulary can be obtained including innovative, streamlined, dynamic, modern, mellow, and mature where the combination of styling elements are 4132, 3241, 1112, 3242, 2122, and 4112. Therefore, the optimal combination of design elements under each perceptual vocabulary can be judged. As shown in Fig. 12, the electric bicycle WOA-BP styling design system predicts the optimal form combination results of different perceptual words, and it can be used as a guiding direction for the form design of electric bicycle products. In terms of electric bicycles of innovative style, the styling combination 4132 can give consumers a "sense of innovation". Then, based on Table 1, the designer converts the styling elements corresponding to 4132. The product styling features of a certain style are optimized by the calculation of Kansei engineering, which can guide designers to form a certain style of bicycle styling. However, product design includes other elements besides styling, and further creative thinking is needed in the design of the eco-friendly electric bicycle. The design scheme is shown in Figure 13. The bicycle structure design is inspired by the bamboo structure, and the saddle design comes from the bamboo weaving culture. Bamboo is a natural, organic and eco-friendly material, but it lacks the hardness and strength of modern materials such as metal at the joints of bicycle structures. In addition, the bamboo structure is handmade, with relatively low production efficiency, and it is not suitable for mass production. Therefore, innovation is imperative for the bicycle structure based on the eco-friendly design concept, so the metal structure is used to connect the bamboo tube, which is an inheritance and modern innovation of traditional bamboo structure.

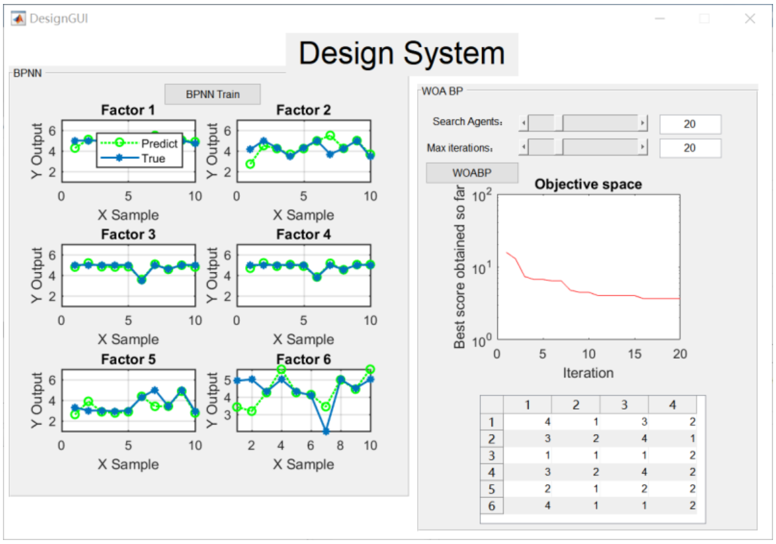


Figure 12: Optimal results of WOA-BP modeling design system for electric bicycles.

5 CONCLUSION

In the context of urban traffic pollution and traffic congestion, this article seeks more sustainable transportation solutions through the electric bicycles, which help to alleviate urban traffic problems and become an economic and environment-friendly choice of urban traffic congestion and pollution problems. However, the electric bicycle market has a set of problem such as homogenization of styling design.

Figure 13: Styling design for electric bicycles based on consumers' sense of innovation.

The styling design of electric bicycles is either a simple improved design or an imitation of popular designs in the market. Especially, as consumers' requirements for product styling continue to increase, consumers not only pay attention to the performance and functions of electric bicycles, but also have a significant emotional preference for the shape of electric bicycles. Consumers' emotional response to product design can not only improve the product's market competitiveness, but also benefit the links of urban traffic pollution problems. To this end, this article proposes a optimization algorithm based WOA to search for the styling elements of consumers' emotional preference for electric bicycles. The research results can provide references for electric bicycle designers. At the same time, the BP-NN model is used for product form design to achieve a continuous quantitative description of the relationship between consumer emotional response information and product form elements.

In the construction process of the neural network algorithm, this paper draws the fitting results of the training set BP neural network before optimization. The total number of samples is 15, the first 10 samples are used as the training set, and the last 5 samples are used as the test set. The input layer of the BP neural network is 12, the hidden layer is 20, and the output layer is 6. The results of the study found that before optimization, the training set and the test set did not achieve good fitting results. This indicates that the BP neural network does not have the ability to multi-input and multi-output when the initial weights and offsets are randomly selected. Through further analysis of the regression indicators of the training set and test set before optimization, it can be found that basically all R^2 indicators of the training set and test set are far away from 1, which shows the necessity to optimize the initial weight and offset of the BP-NN.

However, by analyzing the fitting results of the BP neural network training set optimized by WOA, it can be clearly found that for both the training set and the test set, the predicted output and expected output have achieved a good degree of fit. We further analyzed the regression index value after WOA optimization, and finds that for the training set, only one output value has an R^2 value of 4, and each of the remaining outputs has an R^2 value above 0.9; for the test set, there is only one output value R^2 at around 0.75, the R^2 of the remaining output values are all above 0.85. Through the above algorithm results, it can be found that the algorithm designed in this paper has higher convergence speed and higher accuracy. The combined algorithm of WOA and BP-NN significantly reduces the local minimum trap problem that affects the quality of the solution. Through the method proposed in this article, WOA optimization can develop new solutions in the solution space while the BP-NN helps to find the global optimal solution. With the combination of the above two algorithms, it is possible to design a more satisfactory product design plan for consumers, which not only considers the combination of product design elements and functional requirements, but also pays full attention to consumers' emotional appeals to product design. It can be said with certainty that the designed algorithm can be widely applied to similar product design optimization problems.

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