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Retraction

Retracted: Application of GA in Furniture Modeling Style Design

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] H. Yu and C. Liu, "Application of GA in Furniture Modeling Style Design," *Journal of Function Spaces*, vol. 2022, Article ID 5264185, 11 pages, 2022.

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Research Article

Application of GA in Furniture Modeling Style Design

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With the rapid development of the national economy, the construction industry is unprecedentedly active and has made great achievements. However, most traditional structural design is based on the personal experience of designers. In order to improve the production efficiency of furniture, it is necessary to optimize it. Since the evaluation criteria mainly depend on people's subjective thoughts, it is difficult to describe the individual's adaptive function. In this paper, an interactive innovation evolution system based on evolutionary algorithm is proposed. Taking full advantage of the evolution function of genetic algorithm and the modeling advantages of ACIS platform, a prototype innovation evolution system is developed based on ACIS/hoops platform with the genetic algorithm based on tree structure as the innovation support, which can help designers complete the innovation modeling design. The results show that the total processing time of the sorting scheme obtained by this algorithm is reduced by 2475.2 s, the production efficiency is increased by 20.6%, and the job waiting time is reduced by 15079.2 s. The results show that the algorithm is feasible and effective in solving the furniture production scheduling problem. The furniture production scheduling scheme solved by genetic algorithm can provide certain reference value for production personnel to formulate production scheduling scheme and improve production efficiency.

1. Introduction

With the changing consumption concept of the society, factors such as product innovation, artistic appearance, agreeableness, and environmental protection are paid more and more attention and occupy a prominent position in the market competition [1]. This trend urges enterprises to raise the design of product innovation, appearance modeling, human engineering, and other aspects to a new level when they start to carry out new product development, which also urgently requires further breakthroughs in the research of industrial design, so as to improve the corporate image, product design level, and market competitiveness [2]. Product modeling design is the creative design of the product's shape, color, surface decoration, and material, so as to give the product a new shape and new quality. In the process of actual development, enterprises need to continuously improve according to the development of the times, and only in this way can they ensure the quality of their own business development [3].

At present, most digital model design software adopts these two modeling methods. In this software, designers control the modeling changes of products through characteristic parameters [4]. The optimization of product modeling design is based on the perfect matching of each local detail. There are many design schemes for each local detail, and the final matching effect is endless. The parametric modeling method forces designers to spend energy and time on the parameter adjustment of product local modeling, instead of grasping and optimizing the overall modeling effect of the product [5]. However, when designing products, it is very difficult for designers to produce a reasonable scheme due to the limitations of knowledge, design experience, and design knowledge [6]. In addition, design is a group collaborative work project. The complexity of modern products makes it impossible for a single designer to be competent for complex design tasks. Therefore, the research of the new generation of computer-aided design must provide designers with design tools and support frameworks in a distributed environment to support enterprises to produce high-quality, high reliability, low-cost, creative, and competitive products [7]. The synthetic part of the design has the following characteristics: creativity, multiple solutions, approximation, incompleteness, and empirical synthesis. At present, the optimization design problem of product modeling scheme is mostly performed by humans, it is difficult to form an exact system product scheme, and it is more complicated when faced with a large scheme set, so it is necessary to find a suitable mathematical algorithm for intelligent optimization [8]. Computer-aided design technology has been developed for decades, and it is becoming more and more mature. It has been widely used in various fields such as machinery, automobiles, aviation, and architecture and has become an indispensable auxiliary tool for modern engineering design [9]. CAD technology promotes the renewal and transformation of traditional industries and disciplines, realizes design automation, and enhances the competitiveness of enterprises and their products in the market. This trend urges enterprises to raise the design of product-oriented innovation, appearance modeling, ergonomics, etc., to a new level when starting new product development, which also urgently requires further breakthroughs in the research of industrial design, so as to improve the corporate image product design level and market competitiveness [10].

Under the above background, this paper studies the optimization method of parameters in parametric product modeling design and builds a ladder solution method to make the human-computer interaction in the whole design process more organized, so as to make up for the current parameterization and characterization. The method proposed in this paper is used in the detailed design stage of product modeling. At this stage, the method proposed in this paper helps designers to adjust and optimize the parameters of product modeling.

2. Related Work

In recent years, personalized products are popular in the market, and consumers have higher and higher requirements for the appearance of products, which makes the products have to be constantly updated with the changes of users' needs. In addition, the design characteristics of sofa products and the size and shape of internal parts largely depend on the appearance of the products, and the design mainly depends on the shape of the products.

Fabisiak studied the generation of building plans using GA. The novel building plans can meet multiple fuzzy constraints and target management. They also showed how evolution can generate new buildings by learning from famous architectural styles [11]. Colim et al. use computer simulation technology to generate artworks, such as table lamps and sculptures. They successfully organized the International Conference on Generative Art in Milan, Italy, on the theoretical research and application of evolutionary computing in architectural design, industrial design, art design, and music creation. An in-depth study was done [12]. Umentani et al. developed a garment style-aided design system by using genetic programming technology, which encodes a series of related sizes of styles into chromosomes, and the system evolves styles according to users' choices, and others proposed interactive GA; that is, the fitness function is obtained through interaction with users, thus solving the evaluation problem of style fitness [13]. Soleimani and Kannan apply GA to computer-aided design and discuss the new progress of GA in computer-aided design system [14]. Jia et al. have done a lot of exploratory work in the description model and calculation model of innovation principle and innovation process and creatively solved the problems of knowledge expression and realization such as pattern composition, color, and description through intelligent technologies such as synthesis and analogy generation design [15]. Yao et al. improved the GA to optimize the truss structure and combined the multiplier method and the pseudoparallel GA to improve the premature phenomenon of the simple GA, and it was also quite effective for the optimization problems with complex constraints [16]. Sayed proposed a new hybrid algorithm, relative difference quotient-GA, and gave several examples in this paper. The calculated results show that the hybrid algorithm can significantly improve the computational efficiency and the ability to search the global optimal solution [17]. Smorkalov and Vorobeichik proposed to use GA in the optimization design of steel structures, discussed in detail the principle and implementation steps of GA, and put forward useful improvement suggestions for the advantages and disadvantages of GA, providing guidance for the application of GA in practical engineering [18]. Lotta et al. developed a clothing style-aided design system by using genetic programming technology, which encodes a series of relevant dimensions of styles into chromosomes, and the system evolves styles according to the user's choice. The fitness function is obtained to solve the evaluation problem of style fitness [19]. Sahu et al. optimize the furniture production line on the basis of GA, improve the running quality and running cost of the furniture production line, continuously improve the operating efficiency of furniture manufacturers, and promote the development of China's economy [20].

This paper closely combines the innovative research of conceptual design with computer technology and develops an environment to support the innovative design of sofa products by using computational models and computer tools, using the high information storage capacity and visualization means of computers. In this paper, GA is introduced into computer-aided design, which makes the innovative design of sofa products more intelligent and makes the generated images more creative. We are combining technologies such as machine learning, GA, and artificial neural network to develop an environment with independent intellectual property rights that supports innovative product design.

3. Methodology

3.1. Design Theory of Furniture Modeling Style Based on GA. The operating efficiency of furniture production line directly determines the production efficiency and production cost of furniture. In order to improve the production efficiency of furniture, it is necessary to optimize it. Based on this, this paper will first introduce the operation status of furniture production line. Secondly, the balance of furniture production line is analyzed. Finally, the optimization measures of furniture production line based on genetic algorithm are analyzed. Finally, the furniture production line is optimized effectively. Since the object of this furniture production line optimization is mainly time and designated production elements, it is necessary to calculate the corresponding production beat according to the production output. Ensure that each production process is carried out independently, and the operation elements can only correspond to one workstation. In the process of allocating workstation time, the corresponding constraints must be met. The production time of each workstation cannot be greater than the constraints. On this basis, the furniture modeling style design based on genetic algorithm is determined. Modeling gene is a product modeling element determined according to the modeling characteristics of product semantic description, and it is the basic design element to express modeling style. The coding mode of product modeling genes is determined according to the modeling characteristics of modeling genes. For specific product modeling design, it is only necessary to distinguish the modeling characteristics of product modeling elements, and it is not necessary to accurately express their modeling characteristics. Therefore, fuzzy semantic quantification method is generally used to express the modeling feature information of product modeling elements. The modeling evolutionary design model of product semantic constraints is shown in Figure 1.

It includes two main parts: (1) the transformation between modeling design space and evolutionary design space and (2) shape evolution design. Semantic quantitative description is applied to realize the transformation from modeling design space to evolutionary design space, including the determination of modeling design elements, the coding of modeling genes, and the semantic quantitative description of target product modeling. In the process of actual product modeling design, in order to avoid the extreme value caused by the big difference with the actual design target, the modeling gene is set to be [0.1, 0.9] and encoded in the form of real numbers. In the modeling design of product semantic constraints, a modeling gene string corresponds to a possible modeling design scheme, that is, a solution. The length of the gene string is the same as the number of product modeling elements, and one genetic gene represents one modeling element, and it corresponds one-to-one. Genetic genes use numerical values [0.1, 0.9] to represent the level of modeling elements, so that a genetic gene type can specifically represent the modeling or structure type of a product modeling element. Taking the board desk as an example, its modeling genes and judgment criteria are shown in Table 1.

In Table 1, the judgment criteria of morphological elements are 0 and 1, respectively, indicating the straightness and curvature of the line. The judgment standard of color is 0 and 1, which, respectively, represent the cold and warm, simple, and gorgeous of 128 colors. The judgment standard of the connection is chosen. “independent 0” means that there is no common part between two parts, “crossing 0.5” means that one part is embedded in another part, and “containing 1” means that one part contains another part.

The furniture production line studied in this paper mainly produces sofas. In the actual production process, the sofas are composed of left three positions and right three positions and pedals, and two pillows are installed on the left three positions. The production process of the whole sofa requires a total of 24 processes. In the process of actual research, time measurement is carried out for each process, and a total of 6 times are measured for a process, so as to ensure the accuracy of time detection. The average value is calculated according to the measurement results of 6 times, which is taken as the actual working time. The assembly drawing of sofa is shown in Figure 2.

In the actual process of sofa making, 24 processes can be divided into 10 parts. First, take the wooden frame, and second, nail white gauze, install springs, nail nets, and install elastic belts Third, spray water, paste three position cotton, and install foot steps. Fourth, set adhesive cloth. Fifth, nail the cloth. Sixth, nail the feet, and install the hardware frame. Seventh, install the headrest, and install the coat. Eighth, put the glue, put the bag; ninth, inspection; and tenth, packaging. The above steps are the general process of sofa making. In the process of studying the optimization of furniture production line, we need to take the above steps as the main object and use GA to study it.

The interactive GA in which the designer participates can solve this problem. The designer’s personal concept is added to the process of optimization, and the evaluation and selection based on the fitness function are replaced by the designer’s choice. In this way, the advantage of the search breadth of the GA is used, and the final solution of the design scheme can be matched with the designer’s original design concept. At the same time, the designer’s participation also brings some limitations to the GA: (1) the limitation of population size. Because of the limited perception ability of human beings, there are not too many candidate solutions (individuals) participating in the search and solution, and the population size cannot be too large. (2) Designers, as human beings, cannot bear too much work, so the whole search process cannot be like the original GA, where the selected parent crosses and mutates to produce offspring, and then, it takes hundreds of cycles for reproduction to converge. (3) The product modeling scheme (individual) must be expressed in perceptual physical form to ensure the rationality of the designer’s choice, but not in abstract coding (chromosome).

3.2. Furniture Design Model Based on GA. The algorithm design in the optimization process of furniture production line mainly includes the following contents. First is coding. This process needs to be carried out using the sequence of job elements. The job elements are allocated according to the actual situation of the workstation, and the corresponding serial numbers are arranged into chromosomes. Second is coding translation. Only the sequence of job elements can be displayed in the above chromosomes. Therefore, in the process of translation and coding, chromosomes need to be allocated to corresponding workstations. The third is

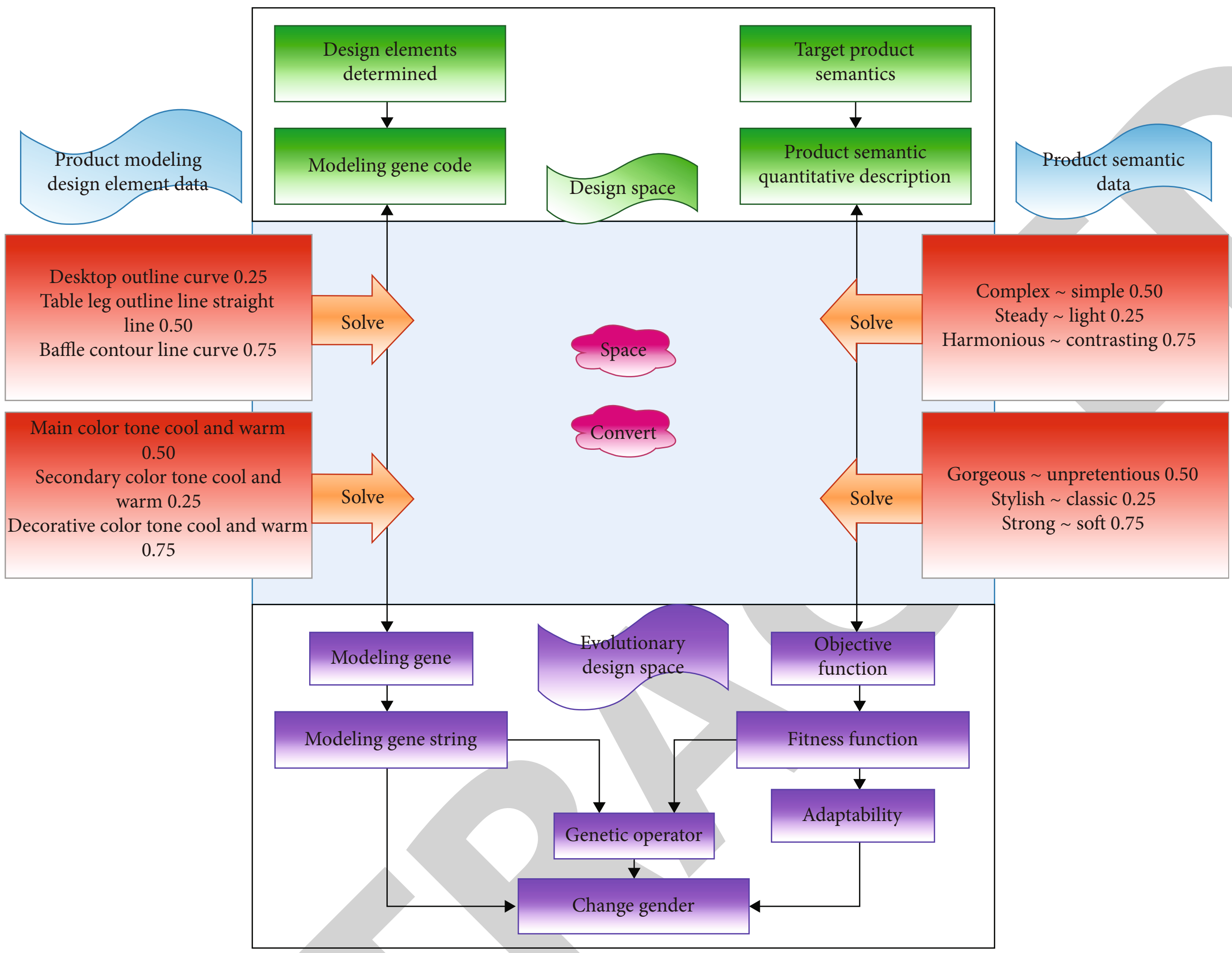

Figure 1: Modeling evolutionary design model with product semantic constraints.

Table 1: Modeling genes and judgment criteria of panel desks.

Shape feature category	Category number	Modeling gene	Judgment standard (value) 0	1
Morphological elements	1	Table top outline shape	Straight	Song
	2	Desktop bottom outline shape	Straight	Song
	3	Outline shape on both sides of the desktop	Straight	Song
	10	Desktop main color	Cold	Warm
	11	Desktop secondary color	Cold	Warm
	12	Desktop decoration color	Rustic	Gorgeous
Link relationship	19	Link form of table top and table legs	Cross 0.5	Contains 1
	20	Link form of table legs and baffles	Cross 0.5	Contains 1
	21	Link form between bezel and desktop	Cross 0.5	Contains 1

the selection operator. The fourth is the crossover operator. In this process, we need to use the crossover probability. The standard GA adopts fixed length binary coding. The advantages of this method are fine gene expression and long problem coding, which is conducive to solving combinatorial optimization problems. However, this method is not flexible enough, and it needs to map from coding domain to problem domain. For the problems that the coding domain is consistent with the problem domain and the coding length changes greatly, the representation method of tree structure is more flexible. There are two ways to initialize the population: the first method is to manually enter the expression by the designer or user. The system provides designers with a floating panel for manual parameter input. This

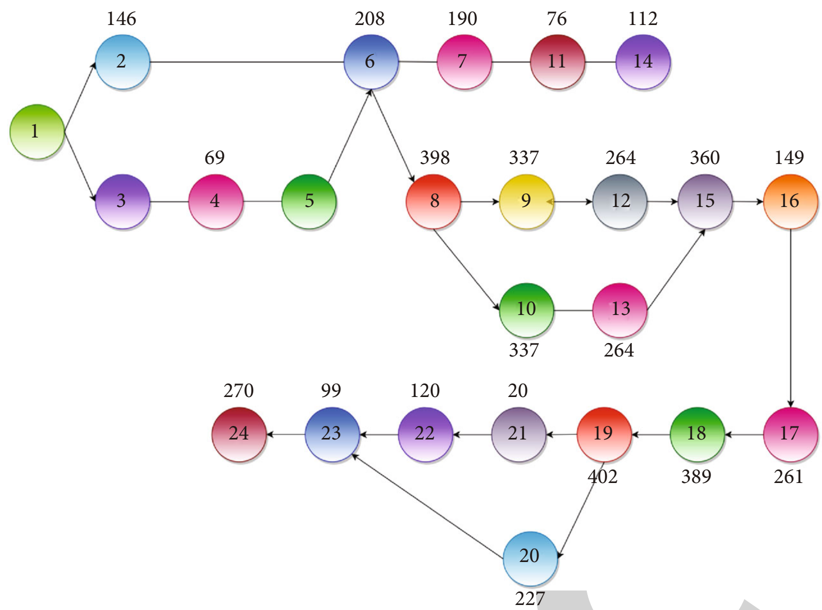

Figure 2: Sofa assembly.

method is suitable for designers and users with a certain mathematical foundation and requires a general understanding of the properties of the manipulated functions; the second is the random combination method. Each individual is actually a chromosomally characteristic entity. As the main carrier of genetic material, chromosome is a collection of multiple genes, and its internal expression, namely, genotype, is a combination of genes, which determines the external expression of individual shape. Therefore, at the beginning, we need to realize the mapping from phenotype to genotype, that is, coding. GA adopts natural evolution model, such as selection, crossover, mutation, and migration, and shows the process of GA. That is, the population is initialized randomly, and the fitness function of each individual is calculated. The fitness function refers to the function introduced to measure each chromosome in the problem in order to reflect the adaptability of chromosomes. All offspring mutate according to a certain probability. Then, the fitness function of the offspring will be recalculated, and the offspring will be inserted into the population, and the parent will replace it to form a new generation of offspring. This process will be executed circularly until the optimization criteria are met, as shown in Figure 3.

Adaptive crossover and adaptive mutation need to design formulas of adaptive crossover probability and adaptive mutation probability, which are closely related to individual fitness, according to the characteristics of GA, so as to effectively improve GA. The algorithm has a good adjustment effect for the problem that requires a small adjustment of the probability of crossover and mutation in the problem, but for the problem that requires a large range of adjustment of the probability of crossover and mutation, the optimization effect is not ideal. For example, in the early stage of evolution, too small variation range of crossover and mutation probability will make the excellent individuals basically unchanged, leading to the stagnation of optimization and falling into local optimal solution. In this paper, the adaptive GA is effectively improved. The formula is as follows:

$$
\begin{aligned}
P_c &= \begin{cases} P_{co} \times \log_2 \dfrac{f_m - f'}{f_m - f_a} + 1 & f' \geq f_{avg}, \\ P_{co} & f' < f_{avg}, \end{cases} \\
P_m &= \begin{cases} P_{mo} \times \log \dfrac{f_m - f'}{f_m - f_a} + 1 & f \geq f_{avg}, \\ P_{mo} & f < f_{avg}. \end{cases}
\end{aligned}
\tag{1}
$$

For optimization problems, the situation is often very complex, and there are many types of objective functions and constraints. Before optimization, it is necessary to establish a mathematical programming model for the problem to be optimized. For a solving function minimization problem, the mathematical programming model is as follows:

$$
\begin{aligned}
\min \quad & f(X) \\
\text{s.t.} \quad & X \in R \\
& R \subseteq U.
\end{aligned}
\tag{2}
$$

If the function $h \in L2(Rn)$ is radial, there is a function $\phi \in L2(R)$. For $h(x) = \phi(\|x\|)$, the following formula holds, where $\|x\|$ represents the Euclidean norm of x and its Fourier transform is also radial. A general expression of radial basis function is

$$
h(x) = \phi\left((x-c) \overset{T-1}{E} (x-c) \right), \tag{3}
$$

where φ represents the radial basis function, C represents the central vector of the function, and E is a transformation matrix, usually Euclidean matrix. It is a measure of the distance between the input vector x and the center C in the sense of the definition of matrix E.

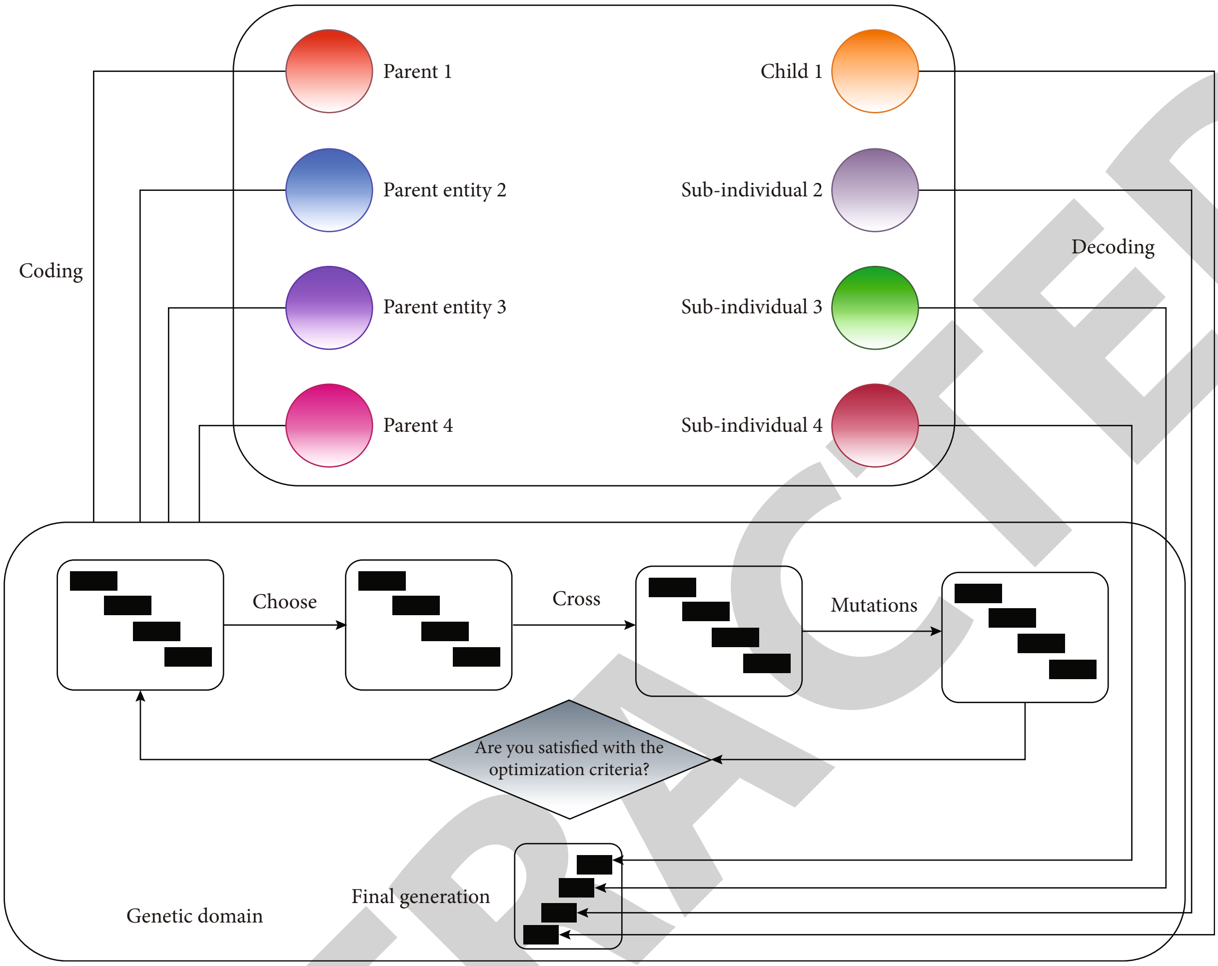

FIGURE 3: The process of GA.

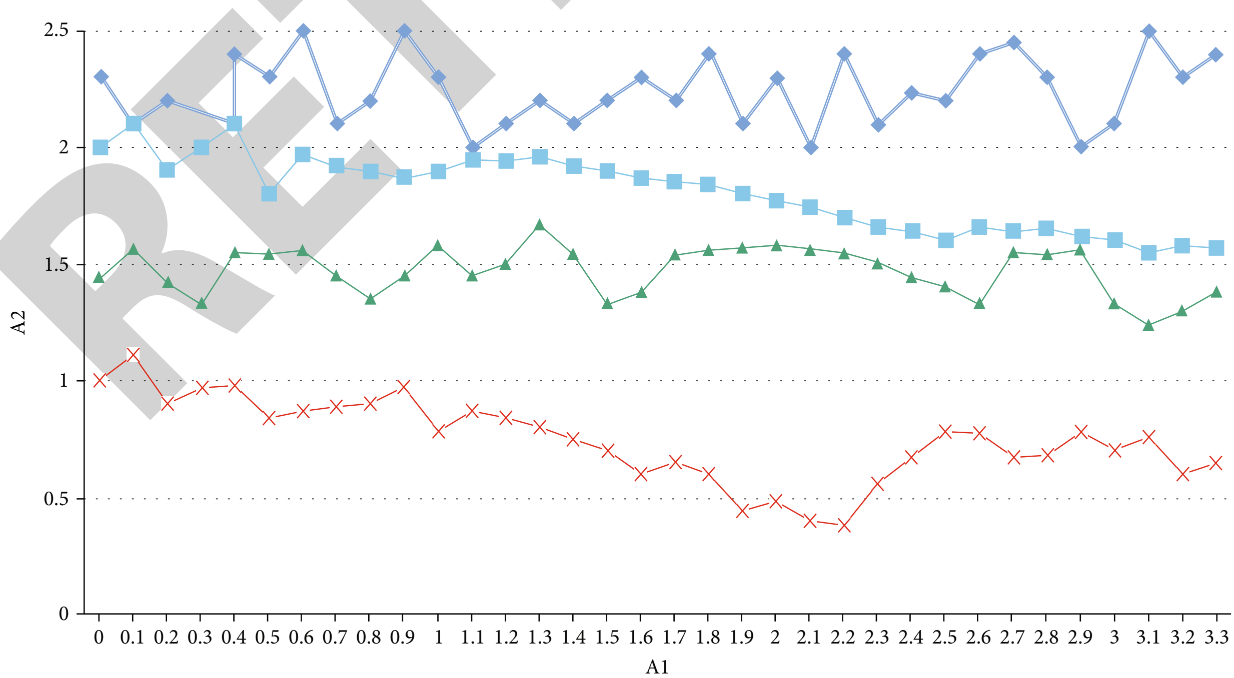

FIGURE 4: Test function T1.

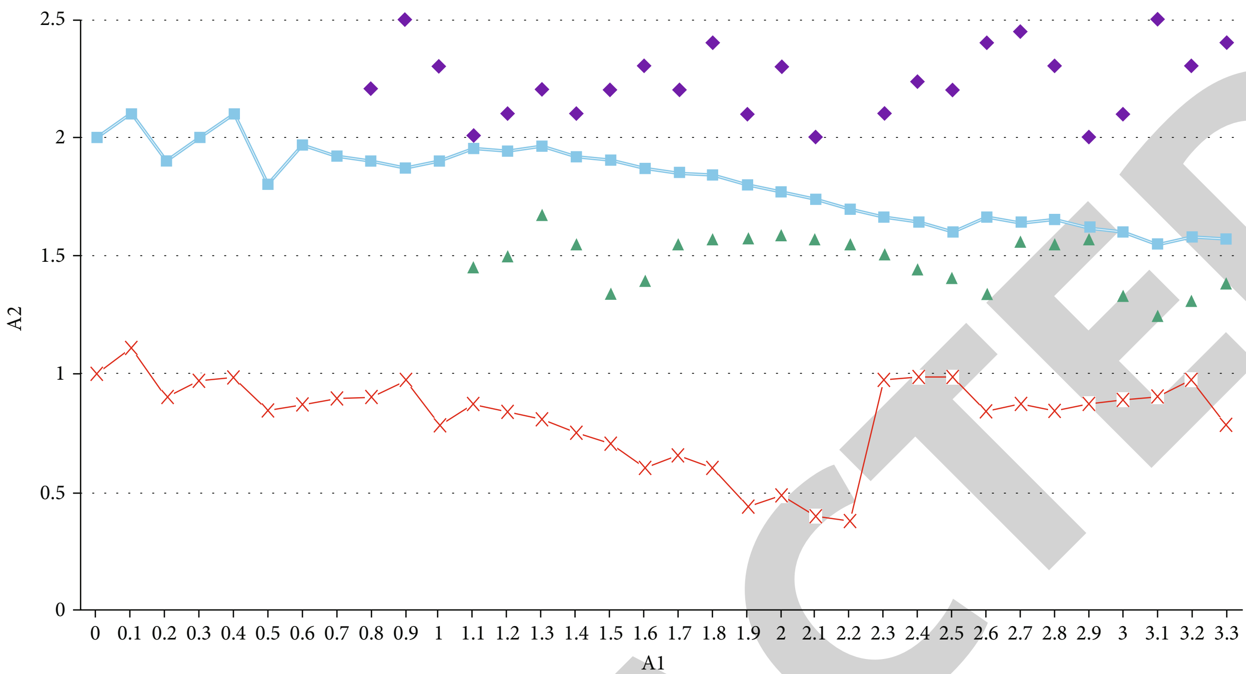

Figure 5: Test function T2.

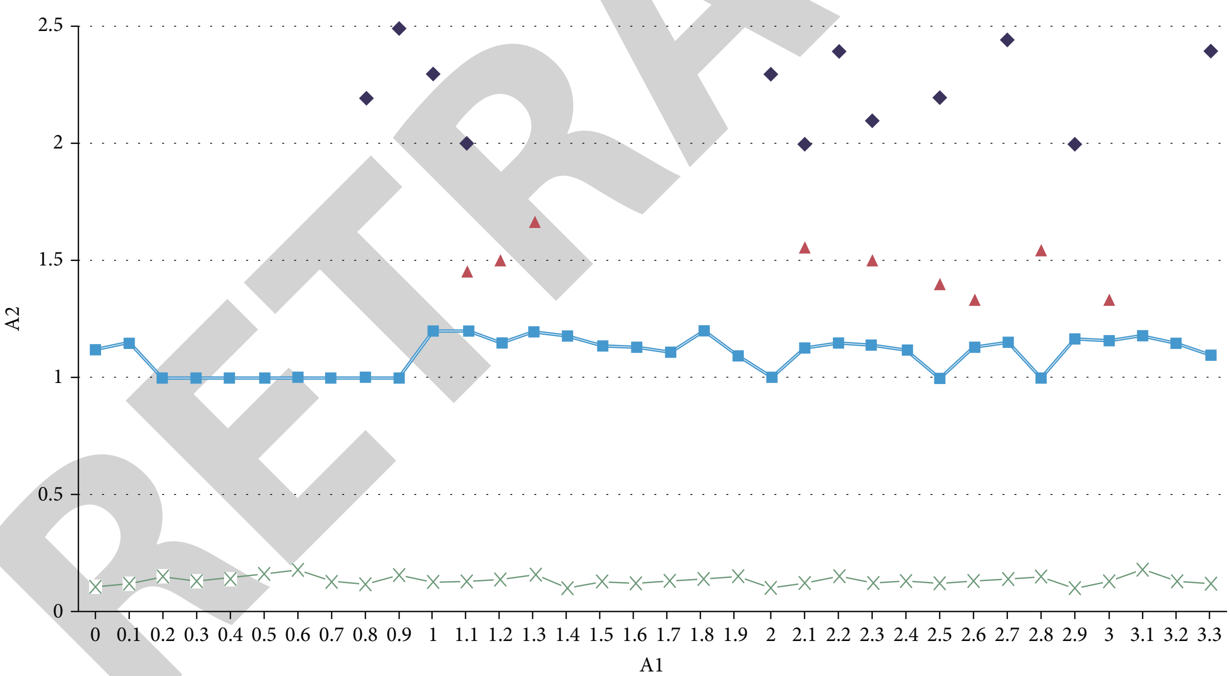

Figure 6: Test function T3.

If e represents a Euclidean matrix, in this case, $e = r^2$ 1. R is the radius of radial basis function; then, the above formula is simplified as

$$h(x) = \varphi\left[\frac{(x-c)^T(x-c)}{r^2}\right],$$
$$h(x) = \varphi\left[\frac{\|x-c\|^2}{r^2}\right]. \tag{4}$$

The standard is a three-layer structure, multi-input and multioutput feedforward network composed of input layer, nonlinear hidden layer radial base layer, and linear output layer. The number of neurons in the input layer is the same as the dimension of the input vector. The number is the same as the output vector dimension.

The function of the hidden layer is to perform nonlinear transformation on the input vector, and its activation function is defined as a radial basis function with symmetrical

Table 2: Internal forces of conventional design method columns.

Column number	Bending moment (KN m)	Shear force (KN)	Axial force (KN)	Axial pressure ratio
1	50.23	16.55	163.45	0.190
2	72.54	32.53	560.46	0.135
3	12.45	26.45	465.45	0.129
4	63.87	13.78	1323.748	0.1654
5	56.52	24.18	1658.46	0.096
6	45.53	28.73	586.75	0.377
7	83.55	46.53	178.74	0.319

Table 3: Internal forces after column optimization.

Column number	Bending moment (KN m)	Shear force (KN)	Axial force (KN)	Axial pressure ratio
1	44.23	14.90	535.41	0.291
2	45.45	34.12	1095.52	0.132
3	78.42	38.56	658.13	0.093
4	59.53	28.33	371.52	0.452
5	67.95	22.11	331.05	0.196
6	48.75	22.41	253.044	0.047
7	86.49	41.52	456.154	0.175

properties. The Gaussian function is used as an example to illustrate the structure.

Gaussian function:

$$\phi_1(x)\ \exp\left\{-\frac{\|x-c_t\|^2}{\sigma_t^2}\right\}. \tag{5}$$

Because of the special properties of radial basis function, it has the selective response ability to a certain range of input variables (i.e., the receptive field of hidden unit), resulting in the local tuning ability. The output activation function of the layer is a linear function, and the output of the hidden layer node is currently weighted. Its jth output node has the following form:

$$y_j = \sum_{t=1}^{k} w_{ij}\phi_t(x). \tag{6}$$

To a minimum, where $\xi_s(F)$ is the standard error term, which can be expressed as

$$\xi_s(F) = \frac{1}{2}\sum_{i=1}^{N}\left(y_i - \widehat{y}_i\right)^2 = \frac{1}{2}\sum_{i=1}^{N}\left[y_i F(x_i)\right]^2 \tag{7}$$

No matter how complex the mathematical function is, it is formed by some mathematical operators, operands, and mathematical functions through composition. The initial population can be generated by random selection in the set of effective operators and operands.

4. Result Analysis and Discussion

In order to compare the performance differences among the improved genetic algorithm, the basic genetic algorithm, and the immune genetic algorithm in this paper, we use the test function to evaluate them. These test functions have different typical characteristics: nonconvex, continuous/discrete noninferior optimal target domain, multipeak, and biased search space. These characteristics make it difficult for the algorithm to converge to the noninferior optimal solution domain and maintain the diversity of noninferior optimal solutions.

In this paper, three evolutionary algorithms are used to run each optimization test function 60 times. Among them, the same values are selected for the same parameters in the algorithm, such as the number of iterations, 300; population size, 80; cross probability, 0.75; and variation probability, 0.02. The function values are averaged, and the simulation results are shown in Figures 4–6.

In the figure, $*$ indicates the improved GA in this paper, + indicates the immune GA, o indicates that the curve near the bottom of the basic GA is the noninferior optimal target domain, and the other is the comparison curve. According to the evaluation criteria of the algorithm, the improved GA in this paper is superior to the basic GA and the immune GA. The design results obtained by the conventional design method and the design results optimized by the improved GA are listed in Tables 2 and 3, respectively.

The overall cost change curve is shown in Figure 7.

The change curve of the cost of board and sofa fabric is shown in Figure 8.

Through the data before and after optimization, it can be seen that the total cost before optimization is 11778.51 yuan, and the total cost after optimization is 8706.20 yuan, saving 3072.31 yuan. Compared with the total cost before optimization, the total cost is reduced by 26.08%, and the optimization effect is remarkable. Among them, the plate cost changes greatly in the early stage of optimization, the reduction range is large and tends to be stable in the late stage of optimization, the cloth increases in the early stage of optimization, and the change tends to be flat in the late stage of optimization. The reduction of plate consumption will lead to the increase of steel consumption, which is in line with the objective reality. It can be proved that the design of this program and the design of improved GA can realize the optimization of the frame structure. The initial parameters given by the user are used as the approximate design intention of the bottle body shape. On the basis of these parameters, the program changes the parameters in the original solution space according to a certain probability factor and obtains the initial solution group. The generated 600 bottle shape design schemes are in the form of 3D model files for users to interactively select to calculate their weight coefficients, and design practice has achieved good results. The determination and ordering of the ladder levels are determined by the interactive choices of the tested users, which provide a specific design direction for the designer's design. After the optimization, the operation benefit of the furniture production line has been effectively improved. In terms of

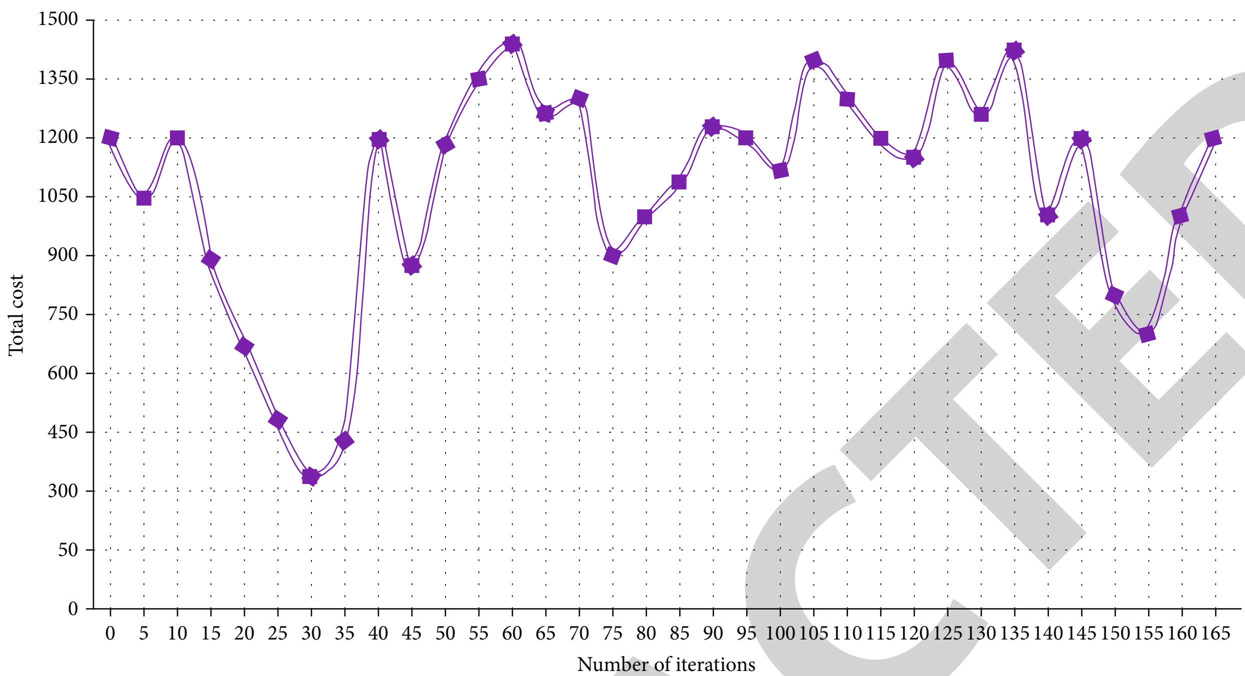

Figure 7: Total cost change curve.

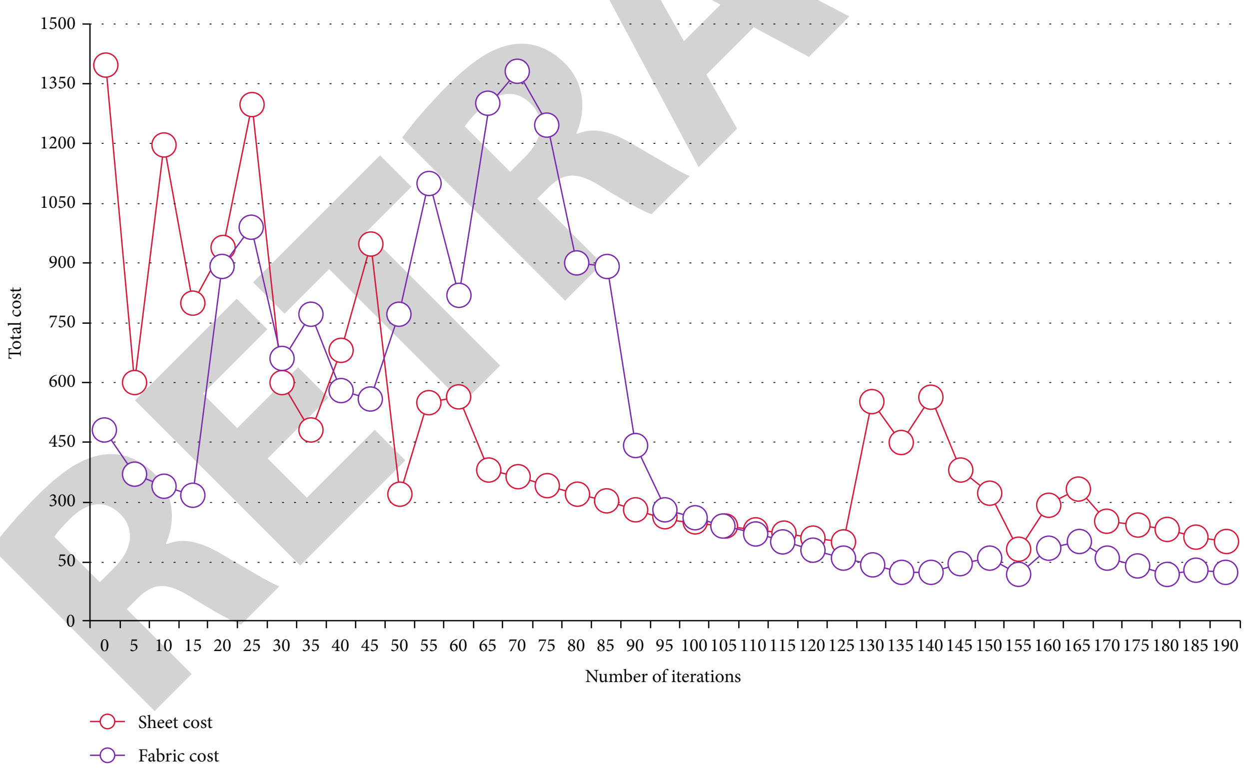

Figure 8: Subitem cost change curves.

economy, the benefit of the optimization of the furniture production line is $29.4\% \times 14 \times 3500 \times 12 = 172{,}930$ yuan (the number of benefits improved × the number of workers × the monthly salary per capita × the number of working months per year). It can be seen from this that the optimization of furniture production line by GA has achieved remarkable research results, both in economic benefits and in labor costs, which has made a very obvious improvement, promoted the efficient operation of furniture production line, continuously improved the economic benefits of enterprises, and promoted the stable development of China's economy. As people pay more and more attention to the furniture production line, how to improve the operation efficiency of the furniture production line has become a key issue concerned by relevant personnel. This paper studies the optimization measures of furniture production line based on genetic algorithm and finds that the research can greatly improve the production quality of furniture production line. Promote the development of genetic algorithm in furniture production line optimization in the future.

5. Conclusions

To sum up, as people's attention to furniture production lines gradually increases, and how to improve the operation efficiency of furniture production lines has become a key issue for relevant personnel. On the basis of the existing product scheme modeling, according to the semantic constraints, the rapid and intelligent drive between product semantics and product modeling scheme is realized, an optimized design scheme is generated, and the agile and intelligent product modeling design is realized. At the same time, taking the minimization of processing flow time as the objective function, a mathematical model of the scheduling problem of furniture assembly line production is built, and the GA is designed, and the solution program is programmed. In the workshop, the production sequencing experiment of six kinds of furniture products in the solid wood machining section is carried out as a comparative experiment of GA simulation experiment, and the processing hours of each process are measured to provide simulation data for the simulation experiment. The sorting results obtained from the simulation experiment are compared with the sorting scheme obtained from the production experiment. The results show that the total processing time of the sorting scheme obtained by the algorithm is reduced by 2475.2 s, the production efficiency is increased by 20.6%, and the job waiting time is reduced by 15079.2 s. It shows that the algorithm is feasible and effective in solving the furniture production job sorting problem. The furniture production sequencing scheme solved by GA can provide a certain reference value for the production personnel to formulate the production sequencing scheme and improve the production efficiency.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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