J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 3719--3735

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

Research on industrial product design optimization based on simulation and genetic algorithm

Kanghui Ma[1,✉]

[1] *College of Art and Design, Xi'an Mingde Institute of Technology, Xi'an, Shaanxi, 710000, China*

ABSTRACT

In response to the rapidly developing market demand, this paper proposes the use of genetic algorithms in industrial product design optimization under simulation environment. Design the product base gene coding, use the fitness function to determine the fitness value of different individuals, the genetic operator to support the optimization of industrial product design, by clarifying the optimal individual in the population in order to determine the optimization of industrial product design to meet the conditions. Then build up the industrial product design system based on genetic algorithm, plan the functional modules such as product information collection and coding, genetic generation of product solutions, and formulate the system process and function realization method. Exploring the performance of this paper's industrial product design model in the simulation environment, this paper's model in the operation efficiency, convergence speed and other aspects of performance are better than its other comparison model, in the iteration to about 300 times to achieve convergence. In the application practice of this paper's design system, the R^2 values of this paper's system are close to 1, and the RMSE values of each design parameter are lower than 0.5, and the average product quality score reaches 0.157, which is excellent in real-world applications.

Keywords: analog simulation, genetic algorithm, fitness function, industrial product design

1. Introduction

How to make the product in the market for a long time to maintain a competitive advantage is the enterprise and industrial design companies in the product design level are to think about the problem, each product has its life cycle, the product sales time after a long period of time may appear function aging, appearance of the old and other problems, can not meet the current market trends and consumer demand, get rid of the dilemma of the way is to upgrade the product. Through upgrading and iteration, the product structure, appearance, functional innovation and other aspects of

✉ Corresponding author.
E-mail address: 13088995986@163.com (K. Ma).
Received 20 December 2024; Revised 05 February 2025; Accepted 25 March 2025; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-207

optimization and improvement. Product design is not a one-time job, but must be continuously optimized and upgraded [1-4].

Genetic algorithm, as one of the most widely used algorithms in process optimization at present, is a search algorithm with evolution and natural selection as the main model, which simulates the evolutionary process in nature to search for solutions by representing the genetic structure and fitness as a solution and a numerical function in the search space of the problem, respectively. Genetic algorithm has the advantages of self-adaptation, global search and good optimization effect, which can help enterprises to screen out the optimal combination of the many process parameters, and bring great advantages for enterprises to improve process and production efficiency. In terms of process optimization, genetic algorithms can significantly improve production efficiency by finding the optimal solution that can achieve specific parameters such as minimizing energy consumption, maximizing productivity, minimizing material loss, etc., and conducting simulation studies on it. In addition to genetic algorithms, analog simulation technology, as a new design method, has gradually become an indispensable tool for industrial product designers [5-8].

Literature [9] proposes a product design optimization method based on genetic algorithm (GA) and specific artificial intelligence techniques, which effectively improves the product design process with greater advantages than traditional techniques and has great potential in the product design paradigm. Literature [10] takes the shape design of UAV products as an example, optimizes the BP neural network using genetic algorithm and constructs a GA-BP hybrid model to effectively evaluate and screen out excellent design solutions, and reveals that the evaluation system shows effectiveness in evaluating design solutions. Literature [11] aims to solve the supplier selection problem in the context of integrated product design and employs a non-dominated sorting genetic algorithm (NSGA-II), which shows that NSGA-II is superior to the CPLEXMIP solver in terms of solution quality and computation time. Literature [12] describes the application model of interactive genetic algorithms based on composite fitness allocation strategy and hierarchical fitness allocation strategy and analyzes the parameters of the former, and evaluates the design results using full replacement and fuzzy evaluation methods. Literature [13] examined the transformation between product customization problems and expressions of genetic algorithms based on understanding genetic algorithms and modern industrial design systems, and pointed out that industrial product design centered on genetic algorithms has positive effects. Literature [14] highlights the use of generative design methods for the optimization of design parameters and generation of design solutions in the product design process, aiming at is the development of a system for the optimization of jewelry design parameters and shape changes, which utilizes genetic algorithms that can assist designers to avoid tedious design iterations, effectively saving the time and effort of the design, and reveals the applicability of the method in product design optimization. Literature [15] comprehensively describes the Genetic Algorithm (GA), the GA tool embedded in the MATLAB package, and the methodology for sustainable product design optimization carried out using GA, highlighting the methodology is demonstrated with a case study using an industrial gearbox. Literature [16] proposed an intelligent product design approach based on genetic algorithms to solve the problem of intelligent generation of batch design solutions, revealing that the approach is effective in mitigating the evaluation fatigue problem in evolutionary computation.

The above research describes the application of genetic algorithm in industrial product design optimization, and reveals the effectiveness of genetic algorithm in product design optimization by comparing it with traditional techniques and its application in modern industries such as unmanned aerial vehicles, whereas as another optimization method, relatively few researches analyze it from the perspective of simulation. Literature [17] outlines the relevant research and application of modeling and simulation techniques in manufacturing, and explores typical simulation techniques in manufacturing based on aspects such as manufacturing integration simulation and manufacturing intelligence simulation. Literature [18] explored simulation and its optimization and mechanical product development and design based on soft computing techniques such as finite element method and artificial neural network.

In this study, the principle of genetic algorithm is firstly discussed, and genetic algorithm is applied to the optimization of industrial product design by taking advantage of its high degree of parallelism and self-adaptability. The genetic coding of industrial products is designed, and the fitness function is utilized to evaluate the fitness value of individuals and determine the fitness of coded individuals. The genetic operator supports the evolution of the product modeling design scheme, and after meeting the conditions of artificial participation, the design scheme is evaluated by the human in the virtual reality environment until a user-satisfied scheme is generated. Based on the industrial product design model of this paper as the basis of function realization, the industrial product design system based on genetic algorithm is built. Product information collection and coding, genetic generation of product solutions, design expression and evaluation, management services and other functional modules. Based on the characteristics of genetic algorithm and product design, the key steps of system operation such as chromosome coding and decoding methods are formulated, and the structural characteristics of industrial products are transformed into the parameters required for design. Through simulation experiments, the performance of this paper's industrial product design model is examined in terms of operation efficiency, convergence speed and product gene matching. The industrial product design system of this paper is used to carry out the optimization design of pumped storage power station diversion steel fork pipe, carry out the practice of industrial product design optimization application, and explore the performance of the system of this paper in practical application.

2. Industrial product design model based on genetic algorithm

The industrial product design direction in the simulation environment is complicated and mostly operated by human beings, and the speed of obtaining the global optimal design results is not good, which is difficult to meet the rapid development of today's market demand. For this reason, this paper proposes the use of genetic algorithms in the optimization of industrial product design in the simulation environment, and constructs an industrial product design model based on genetic algorithms to improve the design efficiency and quality in the process of industrial product design [19].

2.1. Principles of Genetic Algorithm

In optimization problems, a population refers to a genetically coded collection of individuals, each of which can be considered as a chromosomal entity with characteristics. A chromosome consists of multiple genes whose internal genotype determines the external appearance and shape of an individual, such as skin and eye color. In the initial phase of the optimization problem, coding from expression to genotype is required, and binary coding is usually used to simplify the process. Once the initial population is obtained, the next step is to evolve the population generation by generation so that it gradually produces individuals close to the optimal solution. In each generation, individuals are selected by a fitness function and manipulated using genetic operators (e.g., crossover and mutation) to generate a new generation of individuals. Genetic algorithms start searching for optimal solutions from an initial population of many individuals, rather than from a single individual. In genetic algorithms, operations such as selection, crossover and mutation are performed to generate a new generation of populations, which contain much population information. Through the design of the fitness function, factors such as path smoothness can be introduced to make the generated path smoother and more reasonable, which is especially suitable for scenarios such as fire escape. The advantage of genetic algorithm is its parallelism and global search ability. Due to the simultaneous processing of multiple individuals, genetic algorithms can find the global optimal solution faster in the solution space without falling into the local optimal solution. In addition, genetic algorithms are able to be applied flexibly to a wide range of problems because they do not depend on the specific structure of the problem, which is dealt with through the encoding of genotypes.

Genetic algorithms also have some challenges and limitations, such as the population size, the choice of genetic operators and parameter settings will affect the performance and convergence speed of the algorithm. In practical application, it needs to be adjusted and optimized according to the characteristics of specific problems to obtain better optimization results.

In summary, genetic algorithm, as a powerful optimization algorithm, shows good results in solving complex problems and global optimization problems. Through reasonable design and parameter adjustment, genetic algorithm can play an important role in various fields and provide effective ways and methods for problem solving. The fitness function is shown in equation (1):

$$f_1 = \frac{1}{\sum_{i=1}^{n-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2}} \tag{1}$$

where, f_1 denotes the fitness function of the genetic algorithm, x_i and y_i denote the values of x and y coordinates the distance between two neighboring nodes and three neighboring nodes is calculated as in equation (2):

$$d_{1i} = \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2}, i \in (1, n-1) \tag{2}$$

where n is the total number of nodes in the total path and d_{1i} is the distance between any two neighboring nodes in the path:

$$d_{2i} = \sqrt{(x_{i+2} - x_i)^2 + (y_{i+2} - y_i)^2}, i \in (1, n-2) \tag{3}$$

where n is the total number of nodes in the total path and d_{2i} is the distance quotient between any three neighboring nodes in the path, respectively.

Firstly, determine the feasible solution domain and encoding method according to the specific problem, represent each feasible solution in the feasible solution domain in the form of a numerical string or a character string, and then construct a fitness function to measure each solution, which is a non-negative function, and finally determine the size of the population, the selection, the way of crossover and mutation, the probability of crossover and mutation, and judge the termination condition (which can be a certain threshold or the number of generations of specified evolutions). In this process, the crossover operation is the main operation of optimization, while the mutation operation can be viewed as a perturbation of the population. The fitness function is constructed according to the specific problem and the extremes are optimized (either for a maximum value or a minimum value).

Genetic algorithm is a path selection optimization method that simulates natural selection and genetic mechanisms. It makes individuals gradually converge to the optimal solution by simulating the phenomena of gene inheritance, crossover and mutation in the process of biological evolution, starting from a single initial population and optimizing sequentially through iterations. This algorithm is characterized by strong parallelism, wide range of application, and strong global search capability.

Genetic algorithm can deal with multiple design objectives at the same time, and obtain multiple satisfactory product design results in one industrial product design process. The use of genetic algorithm in industrial product design is based on the theory of evolution and the doctrine of heredity, coding each individual design element in product modeling, and then arranging and combining genes through selection, crossover, and mutation operators until generating a satisfactory new individual. After the evolutionary process meets certain conditions, it enters the artificial evaluation stage for program adjustment, and if the output result is not optimal, it then enters the natural stage of computer operation, forming a cycle until the optimal design program is generated. Since the computer can perform parallel search for multiple objectives at the same time, it can improve the design efficiency of product modeling.

2.2. *Designing the product genetic code*

In this section, product genetic coding will be designed by hierarchical product modeling structure [20]. In the genetic algorithm operation, the actual feasible solution variables are transformed into individual coding using floating-point coding method, which is able to represent more patterns in a population of definite size. In the initial population, the product form, color, etc. can be represented as specific hierarchical structure data, each functional unit corresponds to a structural feature parameter, and each chromosome contains a series of feature parameter sets. The feasible solution is transformed from the solution space to the search space, and the characteristic floating-point parameters are encoded into the product individuals through this hierarchical structure. The hierarchical chromosome structure is used to represent the product modeling elements.

The gene position of the product chromosome is the chromosome of the functional unit, and the gene position of the chromosome of the functional unit is the chromosome of the feature parameter, and the functional feature parameter is defined by the floating point value. Setting the parameter coding of each product design element includes the name of the functional unit, quantity, shape characteristics, geometric size, product color, etc.

Before importing the coded parameters into the computer-aided software, the designer needs to extract the required data from the market and the conceptual design and code the data according to the above hierarchy. Different products correspond to different feature parameters, and this differentiation will affect the genetic algorithm to obtain an effective solution. Therefore, the floating-point values of the encoded data are forced to be mapped in the same effective range interval, so that each corresponding gene locus is in the range of [0,1], to solve the problem of parameters on different ranges.

2.3. *Determining coded individual fitness*

In the non-manual evaluation phase, which is the natural phase, the fitness function is obtained from the transformation of the objective function to evaluate the individual parallel fitness values. The fitness function is [21]:

$$F(x)=\begin{cases} C_{\max}-f(x) & f(x)<C_{\max} \\ 0 & f(x)\geq C_{\max} \end{cases} \tag{4}$$

where: $F(x)$ is the fitness function; $f(x)$ is the objective function; and $C_{\max}$ is a predetermined relatively large positive number to ensure that most solutions are positive. Set the population average fitness value is F_{Λ}.

Product design is a multi-objective optimization process, and the actual process contains a variety of feature parameters corresponding to different states of the product. Using the morphosyntactic weighting method, appropriate weight values are set according to the importance of the design elements in the design solution, linking the user semantics with the correspondence of the product feature descriptions, reflecting the degree of superiority of the design individual in multiple aspects. Each design element is investigated, and the arithmetic mean of the investigation results is taken to obtain the manual evaluation adaptation value F_E.

Randomly generate a string of N individual, where N individuals are used as the initial population size, the initial number of evolutionary generations is GEN, and the maximum number of non-artificial evolutionary generations is GEN.

2.4. Evolution of product design solutions

The evolution of the product design scheme is supported by three genetic operators. Starting from the initial population iteratively, after obtaining the average fitness of the initial population, the individuals with higher fitness are selected to be paired two by two, and then regenerated by the crossover and mutation operations in the genetic algorithms to obtain new individuals to be put into the new population, and the process is repeated until the new population is generated, and the new population generated after each generation of the algorithms will replace the old one [22]. Crossover operation is to randomly select two individuals in the population of the previous generation for crossover under the control of crossover probability P_e, and more genes will be provided by the individual with higher fitness value among the two individuals. The mutation operation first sets the initial mutation probability P_m, $P_m \in [0,1]$. After generating the next generation of population, the fitness values of the best individuals in the two generations of population are compared, and if the best individual of the new population is smaller than the fitness value of the best individual of the old population, the initial mutation probability P_m is increased by 0.05, otherwise, it is decreased by 0.05, but the mutation probability is always kept between the value of the initial mutation probability and 1. To ensure that the individual with the best fitness value is retained in the next generation of the population, the individual with the highest fitness value in the current population is used to directly replace the individual with the lowest fitness value resulting from the crossover and mutation genetic operations. At the same time, if the fitness value of the optimal individual in the previous generation population is higher than that of the optimal individual in the current population, the optimal individual in the previous generation population is used to replace the individual with the lowest fitness value in the current population. When the algorithm runs to generate a new product design scheme, and at the same time meets the artificial participation conditions, the decoding enters the virtual reality environment to participate in the artificial evaluation stage.

2.5. Manual evaluation of design options in an analog simulation environment

Simulation of the manual evaluation stage in the simulation environment, controlled by the computer host, through the four-dimensional form of the algorithmic content stored in the knowledge base and database is displayed in the virtual scene, the output of the final design results of the program, drawings or modeling to the customer.

It is evaluated manually whether the optimal solution is generated. Setting the design product evaluation objective as $u = (u_1, u_2, \cdots, u_n)$, the corresponding weights as q_i respectively, and expressed in a matrix as $Q = (q_1, q_2, \cdots, q_n)$, each evaluation objective of the product is scored:

$$B = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1n} \\ b_{21} & b_{22} & \cdots & b_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ b_{m1} & b_{m2} & \cdots & b_{mn} \end{bmatrix} \tag{5}$$

If a user-satisfied program is generated in the manual evaluation phase, then the algorithm is stopped, otherwise, it is transferred to the natural phase to continue running, and the program that does not meet the design requirements is eliminated.

This completes the design of genetic algorithm in industrial product design under simulation environment.

3. Industrial product design system based on genetic algorithm

In the previous chapter, this paper conducted an in-depth study on the principle of genetic algorithm and its method to support the optimization of industrial product design, and constructed an industrial product design model based on genetic algorithm. In this chapter, an industrial product design system based on genetic algorithm will be developed based on the industrial product design model proposed in this paper.

3.1. System implementation framework

The realization framework of the industrial product design system based on genetic algorithm is specifically shown in Fig. 1. The realization framework of the product form design system based on genetic algorithm includes the following steps.

1) Define the product to be designed.

2) Select product elements with development potential in the existing market and conceptual design to form an initial product population.

3) Divide the products into functional units according to their functions to form a tree structure of product functional units.

4) Establish the corresponding tree structure of product structural features according to this tree structure, which serves as the basic framework for 3D secondary development and the basis for coding product structural features.

5) Selecting a suitable coding method, the product elements in the initial population are coded according to the tree structure of structural features to form a coded chromosome population of products.

6) According to the coding method of genes, design the appropriate genetic operator, based on the evaluation of product programs, to ensure that programs with higher adaptability have a higher chance to participate in the genetic operation and be inherited into the next generation of the population.

7) Using a questionnaire, find out the connection between the satisfaction of the product's functional units to the user's needs, constitute a binary group of the user's needs and functional units, and utilize the weighting method to quantify the size of the satisfaction of the binary group as the fitness of the individual genes.

8) Decode the obtained satisfied product coding genes, isolate the parameters of each structural feature from them, and match the parameters with the corresponding structural units.

9) Utilize SolidworkZO03 as a platform to build a new 3D model of the product solution based on the parameters of the corresponding functional units.

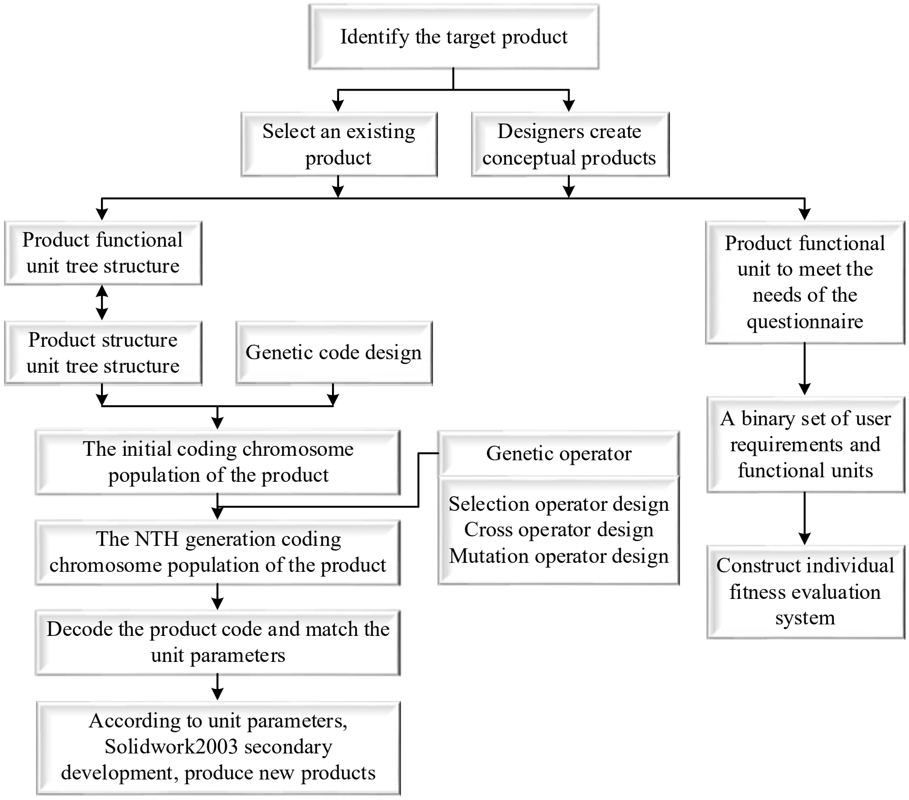

Fig. 1. The implementation process framework of industrial product design system

3.2. System Functional Modules

Genetic algorithm-based product form design system integrates product information resource collection and coding, product generation and product release, which can be categorized into product information collection and coding, genetic generation of product solutions, design expression and management service modules according to its functions.

1) Product information collection and coding module. This module is the pre-preparation module of the genetic algorithm, including the collection of existing and innovative product information and product information coding functions.

2) Genetic generation module of product program. This module is the core of the product form design system based on genetic algorithm. It mainly completes the function of product scheme development, which is the specific realization of the application of genetic algorithm in product form design. It includes components such as selection, mutation and cross transformation of product programs.

3) Design expression and evaluation module. This module mainly includes the three-dimensional drawing module of the product scheme and the weighted design evaluation form based on the questionnaire, which is the basis for determining the comprehensive adaptability of the product scheme.

4) Management Service Module. This module consists of a knowledge base that contains knowledge related to the design and manufacturing process of the product. The knowledge base realizes the collection, updating and utilization of knowledge of the whole system. It is the coding basis and evaluation support standard for the product form design system based on genetic algorithm.

3.3. System Process and Key Steps

Relative to traditional design, genetic algorithm-based product design adds the operation of genetic coding of products with development potential under the guidance of design knowledge in the design initialization stage, and the obtained genetic codes form the initial coding population of the product, and the design of functions, principles, shapes, layouts, and preliminary structures of the product in the conceptual design stage is implicitly included in the selection of the initial product in the initialization stage of the design in the design initialization stage. In the design development stage, it utilizes genetic operators to generate new design solutions rather than relying on manual generation and evaluation of possible solutions, reducing human intervention and increasing the degree of design automation.

According to the characteristics of genetic algorithm and product design, the key steps of product design system based on genetic algorithm are as follows.

The first step is to determine the design elements and their various constraints. That is, the representation of the individual product and the solution space of the problem are determined.

The second step is to establish an optimization model, that is, to determine the type of objective function or objective system. For product morphology design, it is difficult to evaluate product adaptation with a single objective function, and it is necessary to establish an objective evaluation system to quantify the adaptation of product individuals.

In the third step, the chromosome coding method for representing feasible product individuals is determined, i.e., the genotypes of product individuals and the search space of the genetic algorithm are identified.

In the fourth step, the decoding method is determined, i.e., the correspondence or conversion method between the individual genotype and the individual phenotype of the product is determined.

In the fifth step, the quantitative evaluation method of individual fitness is determined, i.e., the conversion rule from target value to individual fitness is determined.

The sixth step is to design the genetic algorithm, i.e., to determine the specific operation methods of the genetic algorithms such as selection operation, crossover operation, mutation operation, and so on.

The seventh step is to determine the operational parameters related to the genetic algorithm, i.e., to determine the population size, the number of generations of terminated evolution, the crossover probability and the mutation probability of the genetic algorithm.

Feasible coding methods, the design of genetic operators are the two main issues to be considered when constructing genetic algorithms, they are closely related to the specific problems sought, and are the key to the success of the application of genetic algorithms.

3.4. Functional realization methods and processes

After determining the industrial product to be developed and designed, the system will decompose the functional units of the product and transform the structural features of the product into a parametric representation based on the industrial product design model in this paper.

1) Functional unit decomposition of the product. Functional unit decomposition of industrial product form design should pay attention to several issues, the first is to consider the rationality of functional decomposition. That is, it is emphasized that the causal logical relationship between each functional unit should be reasonable. The logical relationship between a functional unit and other functional units is often one-to-many. That is, a function is often and more than one other function has a causal relationship, and often change over time, resulting in the difficulty of functional decomposition; Second, is to consider the realization of the product structure, that is, the reasonable description of the functionality of the product into a description of specific shapes, sizes, and interrelationships between

the parts that can achieve these functions. A product tree hierarchical decomposition structure is formed for the industrial product to be designed.

2) Parametric representation of product structure features. Based on the functional decomposition of industrial products, this paper proposes a hierarchical framework to support genetic algorithms. In this framework, three layers are included, i.e. product layer, functional unit layer and structural feature layer. From the perspective of genetic algorithm, the individuals in the upper layer are obtained by combining one or several individuals in the lower layer. For each layer, the initial population of individuals is iterated through many genetic operations to obtain a satisfactory solution population for that layer, and then some suitable individuals can be selected from this solution population to form the initial population of individuals in the upper level.

4. Industrial product design optimization simulation experiment

In this chapter, simulation experiments will be designed to compare the performance of the genetic algorithm-based industrial product design model proposed in this paper in a simulation environment. The comparison models selected for this simulation experiment are the traditional Apriori-based industrial product design model ("Apriori model"), the traditional SVM-based industrial product design model ("SVM model"), the traditional Random Forest-based industrial product design model ("Random Forest model"), and the traditional Random Forest-based industrial product design model ("Random Forest model"), and the traditional Random Forest-based industrial product design model ("Random Forest model"). ("SVM model"), and the traditional random forest-based industrial product design model ("random forest model").

The data used in this simulation experiment comes from the engine design assembly data of an engine manufacturing plant. Before formally carrying out industrial product design simulation simulation experiments, the model of this paper to run the parameter adjustment and settings, specific as shown in Table 1.

Table 1. Operating parameter settings

Operating parameters	Parameter value
Population	10~300
Number of iterations	10~900
Maximum crossover probability	0.8
Minimum crossover probability	0.07
Maximum mutation probability	1
Minimum mutation probability	0.05

4.1. Comparative analysis of operational efficiency

The comparison results of the operation efficiency of different industrial product design models under different data sizes are specifically shown in Fig. 2. Where,the horizontal axis represents the data size, and the vertical axis represents the algorithm elapsed time. The results show that the computational time consumption of each algorithm increases with the increase of data size. In this comparison, the Apriori model consumes the most time, and with the increase of data size, its time consumption increases significantly, and the time consumption reaches 1767 s. In contrast, the time consumption of the model in this paper is always lower than that of the other comparative models, and the increase in time consumption is relatively stable. When the data size reaches 10000, the computation time of this paper's model increases by 716s compared to the data size of 1000, which is the lowest among all models. Obviously, the model in this paper has achieved significant improvement in operational efficiency.

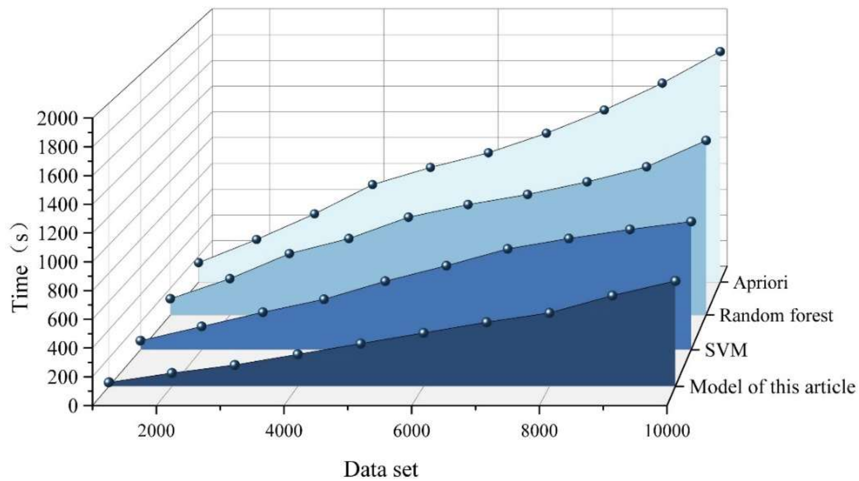

Fig. 2. Comparison of algorithm efficiency

4.2. *Comparative analysis of convergence speed*

The convergence speed of each industrial product design model in generating optimal industrial product design results is specifically shown in Figure 3. As can be seen from the figure, the conventional Apriori model, SVM model, and random forest model converge after about 860, 430, and 740 iterations, respectively, when generating the optimal industrial product design results. In contrast, the genetic algorithm-based industrial product design model in this paper achieves the exact convergence of the global optimal solution in about 300 iterations. This indicates that the model in this paper has the fastest convergence speed to generate the optimal industrial product design results, and the industrial product design efficiency is excellent.

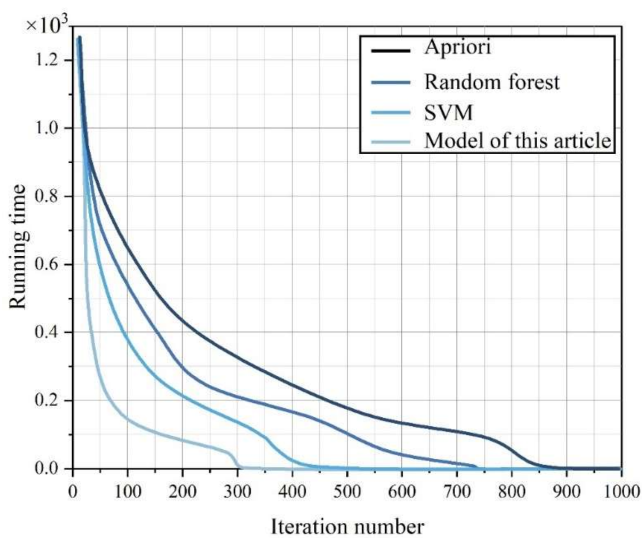

Fig. 3. Convergence curve

4.3. *Comparative analysis of product gene matching results*

Ten samples are randomly selected in the database, and the gene design parameters of industrial products are specifically shown in Table 2. In the table, DP1~DP5 represent gene design parameters such as length, width, thickness, curvature and material type in industrial product design in turn. Considering the interrelationship between the experimental samples in the experiment, the order of the experiment should be determined first, and the functionally independent product genes should be placed in the front.

Table 2. Product gene design parameters

Number of the products	DP1	DP2	DP3	DP4	DP5
1	0	0	1	0	0
2	1	1	0	0	0
3	0	0	0	0	0
4	0	0	1	0	0
5	0	0	1	1	0
6	1	1	1	0	0
7	0	0	0	0	1
8	1	0	0	1	1
9	0	1	0	0	1
10	0	0	0	0	1

The experimental steps in this section are summarized as follows.

1) Input the product genes and set the number of assignments to the initial randomly generated population of product genes to zero.

2) Calculate the fitness function value for each product gene.

3) Obtain the optimal product genes.

4) Establish an evaluation index set for evaluating the quality of the two methods for selecting product genes.

5) Using fuzzy evaluation method, compare the matching degree of product genes between traditional Apriori model, SVM model, random forest model and this paper's industrial product design model based on genetic algorithm.

The product gene matching results of each model are specifically shown in Figure 4. From the experimental results in the figure, it can be seen that compared with other models, the product gene matching degree of this paper's model is higher, with a matching degree as low as 46.27% and as high as 68.76%. The product gene matching degree of traditional Apriori model, SVM model and random forest model is lower, always lower than the model in this paper, and there is an obvious deficiency in the optimal solution acquisition of industrial product design results.

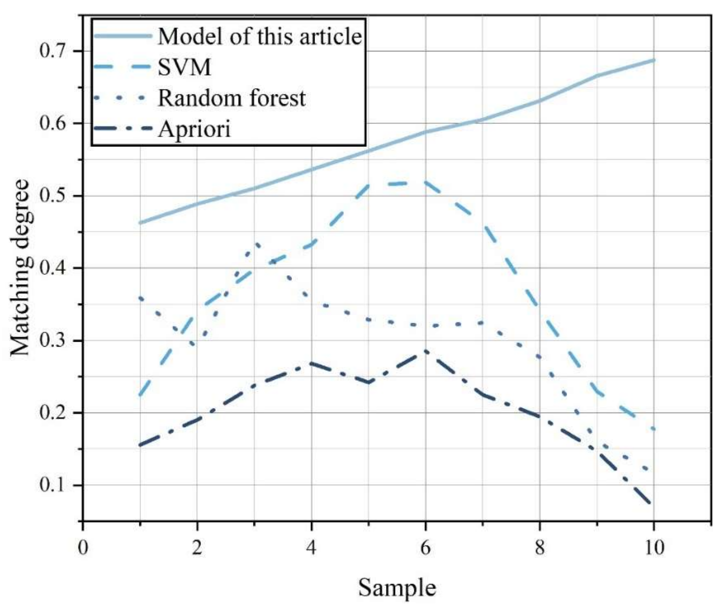

Fig. 4. Matching results of product genes

5. Practical application of industrial product design systems

The performance of the industrial product design model based on genetic algorithm proposed in this paper is verified above by carrying out industrial product design optimization simulation experiments, while the effectiveness of the industrial product design system designed based on this paper's industrial product design model remains to be verified. In order to ensure the effectiveness of the industrial product design system based on genetic algorithm designed in this paper, this chapter will focus on the application practice of industrial product design system, using this paper's system for the optimization of pumped storage power station diversion steel fork pipe design, compared with the traditional industrial product design system (referred to as the "traditional system") to explore the performance of this paper's system in the reality of industrial product design. The system is compared with the traditional industrial product design system ("traditional system") to discuss the performance of the system in the real industrial product design.

5.1. Industrial product design accuracy

The main design parameters of the bifurcation pipe are 7, which are the maximum Mises stress on the outer surface of the shell ($P1$), the maximum Mises stress on the middle surface of the shell ($P2$), the maximum Mises stress on the inner surface of the shell ($P3$), the integral membrane stress at point K ($P4$), the overall membrane stress at point L ($P5$), the Mises stress at point M of the rib plate ($P6$) and the total volume of the bifurcation pipe ($P7$).

The goodness of fit (R^2) and root mean square error (RMSE) are introduced to evaluate the parameters of the forked pipe design to explore the industrial product design accuracy of this paper's system and the traditional industrial product design system. The value of R^2 ranges from 0 to 1. The closer the value of R^2 is to 1, the better the prediction is. Similarly, the smaller the value of RMSE, the better the prediction effect, i.e., the better the industrial product design accuracy.

The results of the goodness of fit and root mean square error for each system on different design parameters are specifically shown in Table 3. It can be seen that the value of R^2 of the traditional system is generally lower than 0.9, and the lowest value is 0.001. The RMSE values are also generally high, except for $P2$, the RMSE values of other design parameters are all higher than 0.5. In comparison, the value of R^2 of the system in this paper is close to 1, and the RMSE values of the design parameters are lower than 0.5, and all of them are lower than the RMSE values of the traditional system. It can be clearly seen that the system in this paper performs better than the traditional system in industrial product design accuracy.

Table 3. R^2 and RSME

Design parameter	System of this article		Traditional system	
	R^2	RSME	R2	RSME
$P1$	0.998	4.075	0.842	6.456
$P2$	0.999	5.525	0.752	5.741
$P3$	0.997	3.162	0.884	6.166
$P4$	1	0.271	0.863	5.995
$P5$	1	0.235	0.752	8.146
$P6$	0.999	4.441	0.876	7.491
P7	1	0.001	0.755	7.924

5.2. Quality of industrial product design

Using the industrial product design system based on genetic algorithm designed in this paper and the traditional industrial product design system, six pumped storage power station diversion steel fork pipe design experiments were carried out respectively, and the product quality parameters and revised parameters in the design are specifically shown in Table 4.

Table 4. Parameters

Number of experiments	Product quality parameters	Revised parameters
1	500	10/7
2	600	10/9
3	700	10/9
4	800	20/13
5	900	20/13
6	1000	25/17

The product quality scores of the industrial products designed by this paper's system and the traditional system - pumped storage power station diversion steel forked pipe are specifically shown in Fig. 5. As can be seen from the figure, the product quality scores of this paper's system in six experiments are higher than the traditional system, and the average product quality score reaches 0.157, while the average product quality score of the traditional system is only 0.085, which is much lower than this paper's system.

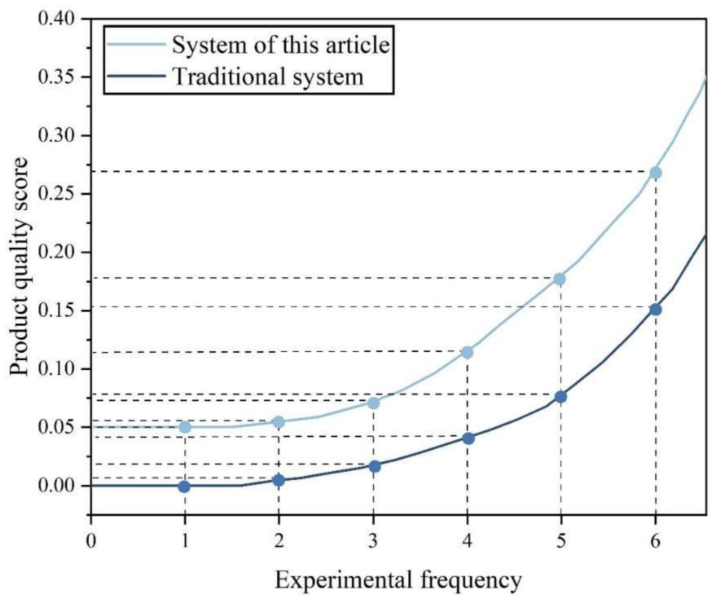

Fig. 5. Product quality score

In six experiments, the discrete degree of process indexes of this paper's system and the traditional system in the forked pipe is specifically shown in Fig. 6. It can be seen that the process indexes of this paper's system in the forked pipe design are floating in the interval of [-1,1], and the dispersion degree of process indexes is low. The fluctuation of the process indicators of the traditional system is obvious, fluctuating significantly in the interval of [-4,4], and the degree of dispersion is significantly higher than that of the system in this paper. This indicates that compared with the traditional system, the system in this paper can better and more accurately complete the design of process indicators, and has better performance in process product design.

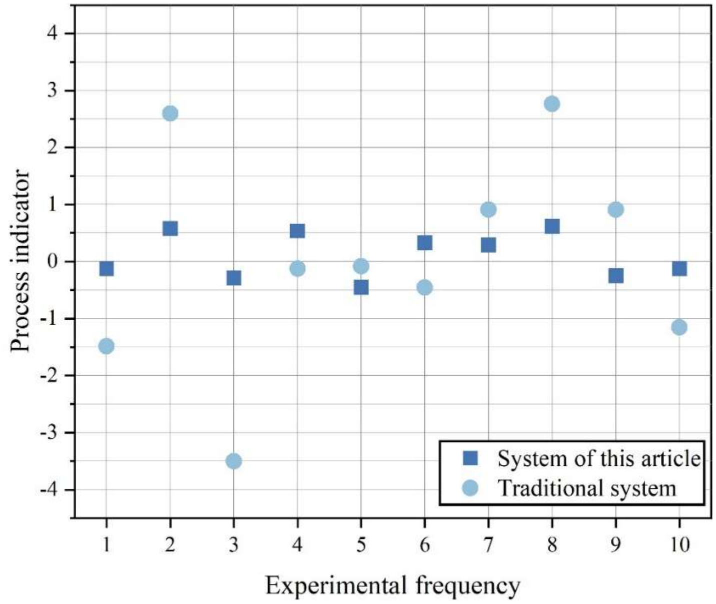

Fig. 6. Dispersion degree

6. Conclusion

In this paper, an industrial product design optimization model based on genetic algorithm is constructed, and a corresponding industrial product design system is built to carry out an in-depth study on the design optimization of industrial products. The performance of the industrial product design model in this paper is verified through simulation experiments of industrial product design optimization. In terms of operation efficiency, the time consumption of this paper's model is always lower than that of other comparative models such as Apriori, SVM, random forest, etc., and the increase in time consumption is relatively stable, with the increase in computation time when the data size grows from 1,000 to 10,000 being only a minimum of 716 s. In terms of the convergence speed, the Apriori model, the SVM model, and the random forest model are about 860, 430, and 740 iterations, respectively, After 740 iterations, the adequate product design results generated by Apriori model, SVM model, and random forest model converge. The model in this paper, on the other hand, realizes the exact convergence of the global optimal solution only when it is iterated for 300 times, which has the fastest convergence speed. In addition, the lowest and highest product gene matching degrees of this paper's model are 46.27% and 68.76%, respectively, which are also consistently higher than the other compared models. It can be seen that the industrial industrial design model based on genetic algorithm proposed in this paper has good performance.

Further industrial product design system application practice is carried out to explore the effectiveness of this paper's system in actual industrial product design. In the design of pumped storage power station diversion steel fork pipe, the value of R^2 of the traditional system is generally lower than 0.9, and the RMSE values of other design parameters except $P2$ are all greater than 0.5. In contrast, the value of R^2 of this paper's system is close to 1, and the RMSE values of the design parameters are lower than 0.5, the RMSE values are much lower than that of the traditional system, which is excellent in the design accuracy of industrial products. As for the design quality of industrial products, the average product quality score of the system in this paper reaches 0.157, which is higher than the average product quality score of 0.085 of the traditional system. Moreover, the process index of the system always floats in the interval of [-1, 1], and the dispersion of the process index is lower than that of the traditional system which fluctuates significantly in the interval of [-4,4]. Overall, the industrial product design system built on the basis of the industrial product design model in this paper is excellent in the accuracy and quality of industrial product design, and can provide positive assistance to people in the real industrial product design work.

References

[1] Xiang, Z., Jinghao, X., & Nazarov, Y. (2023). Application of computer-aided design method to optimize the modeling and design stages for industrial products. Revista Gestão & Tecnologia, 23, 38-52.

[2] Ulrich, K. T., & Eppinger, S. D. (2016). Product design and development. McGraw-hill.

[3] Mahendra, I. D. M. Y. (2022). THE ROLE OF PRODUCT UPDATE ON THE PERFORMANCE OF MARKETING (CASE STUDY OF BANG HASYIM ARJASA FURNITURE). Jurnal Ekonomi, 11(02), 1629-1632.

[4] Huang, Z., Jowers, C., Kent, D., Dehghan-Manshadi, A., & Dargusch, M. S. (2022). The implementation of Industry 4.0 in manufacturing: from lean manufacturing to product design. The International Journal of Advanced Manufacturing Technology, 121(5), 3351-3367.

[5] Ding, M., Bai, Z., Zhang, J., & Huang, X. (2020). Dynamic color design for multimodal industrial products based on genetic algorithm. Journal of Intelligent & Fuzzy Systems, 38(1), 293-302.

[6] Liu, Y., & Kim, K. (2023). An artificial-intelligence-driven product design framework with a synergistic combination of Genetic Algorithm and Particle Swarm Optimization. Soft Computing, 27(23), 17621-17638.

[7] Rostami, A., Paydar, M. M., & Asadi-Gangraj, E. (2020). A hybrid genetic algorithm for integrating virtual cellular manufacturing with supply chain management considering new product development. Computers & Industrial Engineering, 145, 106565.

[8] de Paula Ferreira, W., Armellini, F., & De Santa-Eulalia, L. A. (2020). Simulation in industry 4.0: A state-of-the-art review. Computers & Industrial Engineering, 149, 106868.

[9] Han, S., & Sun, X. (2024). Optimizing Product Design using Genetic Algorithms and Artificial Intelligence Techniques. IEEE Access.

[10] Han, J. X., Ma, M. Y., & Wang, K. (2021). Product modeling design based on genetic algorithm and BP neural network. Neural Computing and Applications, 33, 4111-4117.

[11] Labbi, O., Ahmadi, A., Ouzizi, L., & Douimi, M. (2020). A non-dominant sorting genetic algorithm for optimization of a product design and selection of its suppliers. Journal of Advanced Manufacturing Systems, 19(01), 167-188.

[12] Xue, S. (2019). Intelligent system for products personalization and design using genetic algorithm. Journal of Intelligent & Fuzzy Systems, 37(1), 63-70.

[13] Liu, C., & Pei, K. (2022, December). Research on Personalized Product Design of Industrial Design Based on Genetic Algorithm. In 2022 International Conference on Information Technology, Communication Ecosystem and Management (ITCEM) (pp. 116-119). IEEE.

[14] Kielarova, S. W., & Pradujphongphet, P. (2023, July). Genetic algorithm for product design optimization: An industrial case study of halo setting for jewelry design. In International Conference on Swarm Intelligence (pp. 219-228). Cham: Springer Nature Switzerland.

[15] Ren, Z., & Su, D. (2020). Genetic Algorithm for Sustainable Product Design Optimisation. Sustainable Product Development: Tools, Methods and Examples, 167-190.

[16] Yang, C., & Kong, L. (2020, July). Research on Product Style Design Based on Genetic Algorithm. In 2020 IEEE 5th International Conference on Image, Vision and Computing (ICIVC) (pp. 317-321). IEEE.

[17] Zhang, L., Zhou, L., Ren, L., & Laili, Y. (2019). Modeling and simulation in intelligent manufacturing. Computers in Industry, 112, 103123.

[18] Shunmugam, M. S., & Kanthababu, M. (Eds.). (2019). Advances in Simulation, Product Design and Development: Proceedings of AIMTDR 2018. Springer Nature.

[19] Li Chongyuan & Yang Mengmeng. (2022). Text Knowledge Acquisition Method of Collaborative Product Design Based on Genetic Algorithm. Journal of Mathematics.

[20] Lariza Laura de Oliveira,Alex A. Freitas & Renato Tinós. (2018). Multi-objective genetic algorithms in the study of the genetic code's adaptability. Information Sciences48-61.

[21] Kubiński Wojciech,Darnowski Piotr & Chęć Kamil. (2021). Optimization of the loading pattern of the PWR core using genetic algorithms and multi-purpose fitness function. Nukleonika(4),147-151.

[22] Liu Haoran,Cai Yanbin,Shi Qianrui,Wang Niantai,Zhang Liyue,Li Sheng & Cui Shaopeng. (2023). An improved Harris Hawks optimization for Bayesian network structure learning via genetic operators. Soft Computing(20),14659-14672.