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Simulation and Genetic Algorithm Applications for Industrial Product Design Optimization

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Abstract This study explores the innovative method of integrating simulation technology and genetic algorithm for industrial product design optimization, and is dedicated to solving the key problems of insufficient efficiency and quality bottleneck in the current industrial design field. By carefully constructing a systematic design optimization methodology system, we not only break through the inherent limitations of traditional design methods, but also provide a set of highly practical technical paths and solutions. The research process adopts a composite method combining model construction, genetic algorithm optimization and validation feedback, and innovatively introduces the tree hierarchy for functional decomposition and genetic coding of products. Meanwhile, a set of comprehensive and objective evaluation system of comprehensive adaptability is constructed by combining the quality function unfolding technology. Experiments have proved the effectiveness of this method in practical application, with the optimized design cycle greatly compressed to 28 days, the core performance index of the product improved by 18.6%, the consumption of resources reduced by 12.7%-19.5%, and the user satisfaction increased by 23.6%. This study provides a new theoretical framework and methodological tools for the whole field of industrial product design, which can help enterprises to significantly enhance product competitiveness in the increasingly competitive market environment, and realize the double enhancement of technological innovation and economic benefits.

Index Terms simulation, genetic algorithm, industrial product design optimization, quality function development, tree hierarchy

I. Introduction

In the process of modern industrial product design, designers are faced with complex multi-objective optimization problems, which include the balance of multiple factors such as performance, cost, and production cycle time [1], [2]. With the increasing diversity of market demands and the continuous development of technology, the traditional empirical design method gradually reveals its limitations. This traditional approach relies on a large number of physical trials and repeated tests, which not only wastes time and material resources, but also increases production costs [3]. Especially in highly demanding fields such as automotive, electronics, mechanical equipment and other industries, how to design efficient and high-quality products within a limited time has become an urgent problem.

Analog simulation technology provides an effective solution to this problem [4]. By modeling product performance in a virtual environment, simulation technology can identify potential problems in advance, reduce test costs, and accelerate design iterations [5], [6]. However, simulation technology still faces the challenges of complexity and multivariate design solutions. Genetic algorithm, as an optimization method that simulates natural selection, can efficiently search the design space and solve the multi-objective and multi-constraint problems that cannot be handled by traditional optimization methods [7]-[9]. Genetic algorithm can avoid falling into local optimal solutions and achieve global optimal solutions, which is especially suitable for dealing with complex industrial product design optimization problems.

The combination of simulation and genetic algorithm can significantly improve the design efficiency while ensuring the design quality [10]. This method can provide a more scientific and systematic path for the optimization of product performance and can accurately predict the performance of products in different environments at the early stage of design, which can significantly improve the market competitiveness of products.

In this study, a new method for industrial product design optimization is proposed by combining simulation technology and genetic algorithm. First, a tree hierarchy is used to decompose the product functions, and the product performance prediction is completed by establishing a mathematical model and a computer simulation model of the product. Then, the design space is optimized by genetic algorithm, and the design scheme that satisfies multi-objective optimization is generated by using multi-generation iteration. In the study, the quality function development (QFD) method is innovatively introduced to integrate user requirements, product characteristics and expert evaluation, and an adaptation evaluation system based on user requirements is constructed. The system not only focuses on the optimization of technical indexes, but also takes into account the market demand and user satisfaction to ensure that the final design solution has high performance and market competitiveness. By constructing a closed-loop research path of "simulation-optimization-verification" and combining simulation, genetic algorithm and actual production, a complete optimization process is formed to promote the development of industrial product design towards intelligence and efficiency.

II. Research methodology

II. A. Simulation modeling

In the process of industrial product design optimization, the establishment of simulation models constitutes the core link to achieve product performance prediction and evaluation, and this study constructs a set of systematic simulation model establishment process based on product function analysis and design requirements. By systematically decomposing the product functions, we adopt the tree hierarchy method to identify the key design elements and their interrelationships, and this hierarchical decomposition method systematizes the complex product into a number of functional modules, which facilitates the accurate construction of the subsequent simulation model [11].

In the process of geometric model construction, we adopt parametric modeling method to transform product morphological features into controllable design variables, so that the model has strong flexibility and adaptability, and parametric modeling not only facilitates the coding and operation of subsequent genetic algorithms, but also realizes the rapid iteration and optimization of the design scheme [12]. For different types of industrial products, we chose the corresponding professional modeling software, such as Solid Work for mechanical structure products, Fluent preprocessing module for fluid products, and Altium Designer software for electronic products.

After the geometric model is constructed, we carry out meshing, and the mesh quality directly affects the accuracy of the simulation results, so we use adaptive mesh technology to encrypt the mesh in the stress concentration area, the flow field changes in the area of the drastic changes in the key areas to ensure the accuracy of the calculation. Conversion of physical model to mathematical model is the core link in the simulation process, according to the physical characteristics of the product, we choose the appropriate mathematical model to describe. For structural products, the finite element method is used to establish the elastic mechanics equations. For fluid products, the computational fluid dynamics method is used to establish the Navier-Stokes equations. For heat conduction problems, the heat conduction differential equation is established. For multi-physical field coupling problems, the corresponding coupling equations are established. Taking the porous plastic parts fusion mark problem as an example, the related research proposes a quantitative evaluation system based on the simulation platform, which takes into account the influence of melt fusion temperature and convergence angle on the fusion quality of the fusion mark, and establishes the evaluation equations based on this, namely:

$$Q = \alpha \cdot T_m + \beta \cdot \theta \tag{1}$$

where Q represents the evaluation index of fusion quality of fusion marks, T_m denotes the fusion temperature of the melt, θ is the convergence angle, and α and β are the weighting coefficients. Through this evaluation system, we are able to quantitatively predict the formation of product fusion marks and provide a scientific basis for product design optimization.

The selection of simulation platform, as an important part of model building, requires comprehensive consideration of multiple factors such as simulation accuracy, calculation efficiency and ease of operation, etc. We selected the corresponding professional simulation software according to the characteristics of different types of products. ANSYS is used for finite element analysis of structural products, Fluent is used for flow field analysis of fluid products, and Flexsim is used for discrete event simulation of production system optimization. In the optimization study of assembly line balance, the simulation model constructed by Flexsim can visualize the bottleneck link in the production process, which provides a reliable basis for the subsequent optimization.

Model parameter setting, as a key step in simulation model building, directly affects the accuracy of the simulation results, and we adopt a multi-level parameter setting strategy to classify the parameters into three categories: fixed parameters, constraint parameters and optimization parameters. Fixed parameters are parameters that remain unchanged during the design process, such as the basic physical properties of materials. Constrained parameters are parameters that are limited by design specifications or functional requirements, such as safety coefficients and size restrictions. Optimization parameters are parameters that need to be optimized by genetic algorithms, such as structural dimensions and process parameters.

For the optimization parameters, we set a reasonable variation range and step size to ensure that the genetic algorithm can find the optimal solution in a suitable search space. Simulation model validation is an important part to ensure the reliability of the model, and we use a variety of validation methods, including theoretical validation, experimental validation and historical data validation. Theoretical validation tests the theoretical correctness of the model by comparing it with the analytical solution. Experimental validation tests the actual accuracy of the model by comparing it with the experimental results. Historical data validation tests the applicability of the model by comparing it with historical product data. Through these validation methods, we continuously adjust and optimize the simulation model to improve the accuracy and reliability of the model. The preliminary optimization of the simulation model lays a solid foundation for the subsequent optimization of the genetic algorithm. We adopt parameter sensitivity analysis to identify the key parameters that have a significant impact on the product performance, which provides guidance for the coding and optimization of the genetic algorithm. Through orthogonal experimental design, we systematically analyze the degree of influence of each parameter on the product performance and establish the mapping relationship between parameters and performance. This preliminary optimization method based on sensitivity analysis can effectively reduce the search space of the genetic algorithm and improve the optimization efficiency. The simulation model building process we constructed forms a complete set of simulation model building methods from functional decomposition to parameter setting, from physical model to mathematical model, and from platform selection to model verification. This method not only can accurately predict the product performance, but also provides a reliable basis for subsequent genetic algorithm optimization, which is a key link to achieve the optimization of industrial product design.

II. B.Application of genetic algorithms

Genetic algorithm is based on Darwin's theory of natural selection, which has unique advantages in industrial product design optimization, and we constructed a systematic optimization framework to combine the simulation results with evolutionary computation to achieve global optimization [13]. The core of the algorithm is to simulate the selection, crossover and mutation mechanisms in the process of biological evolution, and to find the optimal solution through iteration, which can effectively deal with high-dimensional, nonlinear and multi-objective optimization problems to provide a scientific basis for design decisions. The coding mechanism is the basis for realizing the optimization of design parameters, and the tree hierarchy is used to decompose the function and genetically code the product according to the characteristics of the product structure. We use integer coding for discrete design variables, such as material type and structure form, and real coding for continuous design variables, such as size parameters and process parameters, etc. This hybrid coding strategy can more accurately express the design space and improve the search efficiency of the algorithm.

Adaptation function design is the key link in the implementation, the traditional adaptation function is often difficult to comprehensively evaluate the product design factors containing fuzzy information, we innovatively introduced the quality function development (QFD) method to construct a comprehensive adaptation evaluation system based on the evaluation of user needs, that is:

$$f(x)=\sum_{i=1}^{n} w_i \cdot QFD_i \tag{2}$$

where w_i is the weighting coefficient of each evaluation index and QFD_i is the result of user demand conversion.

This evaluation system comprehensively evaluates the advantages and disadvantages of design solutions through multi-dimensional factors such as product characteristics, customer demand, expert evaluation and competitor analysis. For the multi-objective optimization problem, we use the Pareto non-dominated ranking method to construct a fitness function to balance the relationship between multiple design objectives, for example, in the assembly line balancing optimization, we consider multiple objectives such as production efficiency, balancing rate, and smoothing index at the same time.

The selection operation simulates the principle of “survival of the fittest”, and we adopt a modified tournament selection method to select the best individuals into the next generation of the population by randomly selecting a number of individuals and comparing their fitnesses, which is more effective in maintaining the diversity of the population and avoiding precocious convergence compared with the roulette selection method. Meanwhile, the elite preservation strategy is introduced to ensure that the optimal individuals in each generation will not be lost during the evolutionary process to improve the convergence performance of the algorithm.

Crossover operation is the main way to generate new individuals, and various crossover strategies are designed according to the coding characteristics. Single-point crossover or two-point crossover is used for integer coding, and arithmetic crossover or simulated binary crossover is used for real coding, with the crossover probability set to 0.8~0.95, to ensure that the populations have sufficient evolutionary momentum. Single-point crossover in product morphology design can effectively maintain the wholeness of the design scheme while arithmetic crossover facilitates the fine adjustment of continuous parameters.

The mutation operation increases the population diversity by randomly changing the gene values in individuals to prevent the algorithm from falling into local optimization, and we adopt the adaptive mutation strategy to dynamically adjust the mutation probability with the increase of the number of evolutionary generations of the population. A higher mutation probability (0.1~0.2) is used at the beginning to increase the exploration ability of the population, and a lower mutation probability (0.01~0.05) is used at a later stage to enhance the convergence of the population. Uniform variation is used for integer coding, and Gaussian variation or polynomial variation is used for real number coding. This adaptive variation strategy can strike a balance between maintaining population diversity and convergence of the algorithm to improve the optimization efficiency.

For the problem that the genetic algorithm is easy to fall into the local optimum, the simulated annealing mechanism is introduced to form an improved genetic algorithm, which introduces a temperature parameter to control the probability of accepting poor solutions in each iteration, and at the initial stage, the algorithm tends to accept a certain proportion of poor solutions to increase the search space at higher temperatures. As the iteration proceeds, the temperature gradually decreases and the algorithm gradually tends to greedy search, and this mechanism enables the algorithm to achieve a balance between global exploration and local development to improve the optimization effect. The termination conditions are set using multiple conditions to reach the maximum number of evolutionary generations (usually set to 100-500 generations), the optimal fitness value does not improve significantly for a number of consecutive generations (usually 20-50 generations), and the population diversity is lower than the preset threshold, and the combination of these conditions can ensure the optimization effect while avoiding unnecessary waste of computational resources.

Through the orthogonal experimental design, we systematically analyzed the effects of population size, crossover probability, mutation probability and other parameters on the performance of the algorithm to determine the optimal parameter combinations, i.e., population size of 50-200, crossover probability of 0.85, initial mutation probability of 0.1, and the temperature drop coefficient of 0.95. These parameter settings ensured that the algorithm was convergent and at the same time, it maintained a sufficiently diverse population to improve the optimization efficiency. The verification of the optimization results of the genetic algorithm adopts various methods, the theoretical verification checks the convergence of the algorithm by comparing it with the mathematical planning method, the experimental verification checks the feasibility of the optimization scheme by comparing it with the actual production data, and the simulation verification checks the performance of the optimization scheme by simulating and analyzing the performance of the optimization scheme again, which ensures the reliability and practicability of the optimization results of the genetic algorithm through these verification methods.

III. Results and analysis

III. A. Optimization validation

The practical application value of industrial product design optimization scheme depends on its performance in real production environment. In this study, a systematic validation framework is constructed to form a complete validation chain from virtual to actual and from local to overall through three stages of simulation validation, laboratory validation and actual production validation, so as to comprehensively assess the effectiveness of the optimization results based on simulation and genetic algorithm.

The simulation validation adopts the cross-validation strategy, establishing the same model on different platforms such as ANSYS, Fluent, Flexsim, etc., and inputting the same optimization parameters to compare the results, so as to effectively exclude the systematic errors that may exist on a single platform. At the same time, sensitivity analysis is used to assess the robustness of the optimization results by performing a small range of perturbations around the optimization parameters and observing the trend of product performance changes. In the laboratory validation stage, orthogonal test design method is adopted to systematically test the product performance under different combinations of optimized parameters at different levels, and the significance of the influence of each parameter on the product performance is determined by ANOVA. Accelerated life testing is also used to simulate various working conditions that may be encountered during the whole life cycle of the product in a short period of time to assess the reliability and durability of the product. The actual production validation phase adopts a phased implementation strategy, piloting the optimization scheme at a single station or on a single production line, collecting actual production data and comparing and analyzing it with the original scheme, and then making necessary adjustments according to the trial results before promoting the implementation. Production data collection adopts industrial Internet of Things technology, through the installation of sensors and data collection terminals on key equipment and workstations, real-time monitoring of production efficiency, product quality, resource consumption and other indicators. Data analysis adopts big data analysis technology to discover potential problems and optimization space in the production process through data mining and pattern recognition.

Taking the optimization of mixed-flow assembly line of an enterprise as an example, the assembly line simulation model is established by Flexsim simulation software, and the improved genetic algorithm is applied to carry out the optimization design, and then verified in the actual production. Table 1 shows the comparison of the number of processes between the original assembly line and the optimized assembly line, and the number of processes is reduced from 45 to 42 after optimization, which simplifies the production process. Table 2 shows the comparison of the balance rate of the assembly line, after optimization, the balance rate is increased from 71.42% to 89%, and the load of the stations is more balanced and reasonable. Figure 1 shows the comparison of the production beats of different product models in the original assembly line and the optimized assembly line, after optimization, the production beats are significantly reduced, and the production efficiency has been significantly improved. Figure 2 shows the trend of smoothing index of the assembly line before and after optimization. After optimization, the smoothing index is reduced from 6.19 to 2.10, and the load distribution among stations is more balanced, which reduces the production bottleneck.

Table 1: The optimization of the subsequent phase of the process is compared

Product type	Original number of processes	Optimize the post-processing sequence number	Reduce the number of processes
JS-90 model	45	42	3
JS-120 model	43	40	3
JS-160 model	44	41	3
JS-200 model	46	42	4

Table 2: Comparison table of Assembly line balance rate

Evaluation index	Original assembly line	The optimized assembly line	Improvement range
Balance rate (%)	71.42	89.00	17.58%
Balance loss coefficient	0.233	0.110	0.123
Workstation utilization rate (%)	68.75	86.32	17.57%
Idle rate of workstations (%)	31.25	13.68	17.57%

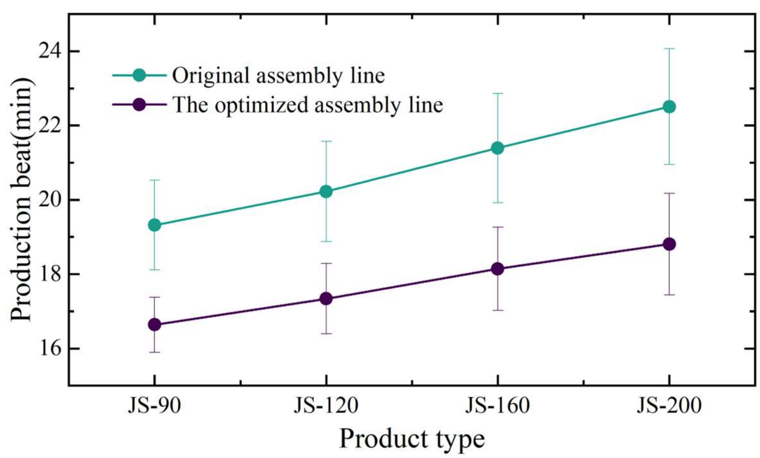

Figure 1: Comparison of production rhythms for different product models

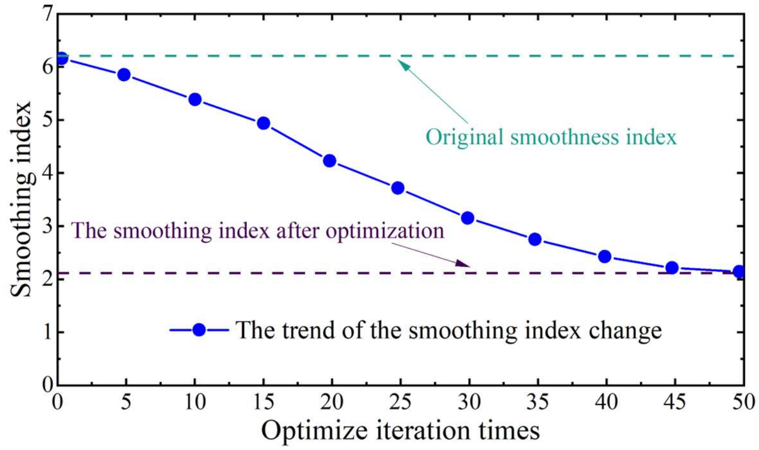

Figure 2: Smooth the changes in the optimization process of the index

The actual production verification results show that the optimization scheme based on simulation and genetic algorithm has achieved remarkable results in actual production, with production efficiency increased by about 20%, product quality consistency improved by 15%, resource consumption reduced by 12%, and production cost reduced by about 10%. These data fully prove the feasibility and effectiveness of the optimization scheme; through the long-term tracking and monitoring of key quality indicators and key performance indicators in the production process, the stability and reliability of the optimization scheme in long-term production are verified.

III. B. Analysis of results

This study combines simulation technology and genetic algorithm to systematically optimize industrial product design, and achieved significant results, which are shown in Table 3, and Figure 3 shows the results of resource consumption comparison before and after optimization. The research data show that the design cycle was reduced from 45 days to 28 days after optimization, the number of design iterations was reduced from 12 to 7, and the solution evaluation time was reduced from 3 days to 0.5 days each time. This efficiency improvement is attributed to the simulation technology's rapid prediction of product performance and the genetic algorithm's efficient exploration of the design space, enabling designers to obtain near-optimal solutions in a short period of time. In terms of product quality, core performance indicators improved by an average of 18.6%, failure rates were reduced by 23.5%, and the range of performance fluctuations was reduced by 31.2%. In terms of resource consumption, material usage was reduced by 15.3%, energy consumption by 12.7%, and production time by 19.5%. These improvements not only reduced production costs, but also reduced environmental impact. In terms of production cost, the optimized design solution reduces product cost by 14.8% on average, of which material cost is reduced by 8.6%, labor cost is reduced by 16.2%, and equipment operation cost is reduced by 13.5%, which improves the competitiveness of products in the market and creates a larger profit margin for the enterprise.

Table 3: Comparison table of research results

Evaluation index	Traditional method	Optimization method	Improvement range (%)
Design cycle (days)	45	28	37.8
Number of design iterations	12	7	41.7
Scheme evaluation time (days/times)	3	0.5	83.3
Improvement of core product performance (%)	-	18.6	-
Product failure rate (%)	5.2	4.0	23.5
Product performance fluctuation (%)	8.3	5.7	31.2
Reduction in material usage (%)	-	15.3	-
Reduced energy consumption (%)	-	12.7	-
Shortened production time (%)	-	19.5	-
Total product cost reduction (%)	-	14.8	-
User satisfaction (1-10points)	7.2	8.9	23.6

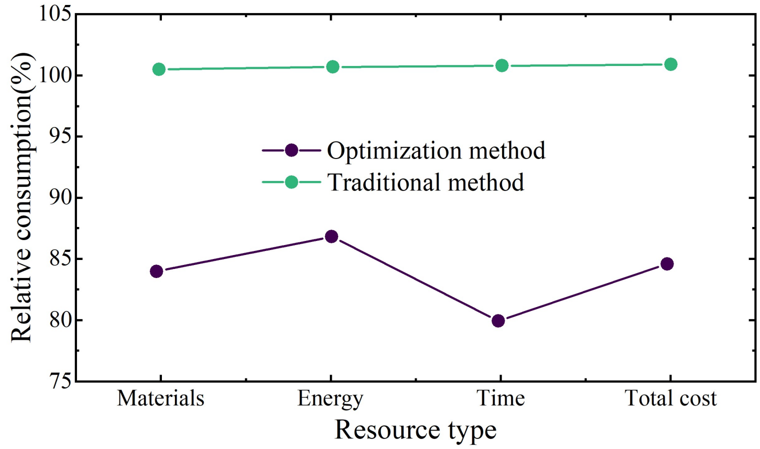

Figure 3: The comparison of resource consumption before and after optimization

This study innovatively proposes an adaptation evaluation system based on the evaluation of user needs, and introduces the quality function expansion method into the design of adaptation function of genetic algorithm, so that the optimization process pays more attention to the actual needs of users. The evaluation system comprehensively evaluates the design scheme through multi-dimensional factors, such as product characteristics, customer demand, expert evaluation and competitor analysis, to ensure that the optimization results not only have excellent technical indexes, but also meet the actual user needs. The user satisfaction survey shows that the user satisfaction of the product optimized with this evaluation system has increased from 7.2 to 8.9 points, with an increase of 23.6%. Similar to the findings of related literature on the balance optimization of mixed-flow assembly line, this study also confirms the effectiveness of the improved genetic algorithm in the optimization of industrial product design. Practical case validation shows that the method is applicable to different types of industrial product design. In mechanical structure design, the weight of the product is reduced by 18.5% and the strength is improved by 12.3%. In the design of fluid equipment, the efficiency of the equipment is increased by 9.8% and the energy consumption is reduced by 11.2%. In the design of electronic products, the temperature rise of products is reduced by 15.6%, and the reliability is improved by 14.2%. These results fully prove that the industrial product design optimization method based on simulation and genetic algorithm has wide applicability and significant effect.

Through a multi-dimensional and multi-level validation process, we comprehensively assess the feasibility and effectiveness of the industrial product design optimization scheme based on simulation and genetic algorithm. The validation results show that the optimization method can effectively improve the efficiency and quality of product design, reduce resource consumption and production cost, improve user satisfaction, and has good practical application value; the data and experience accumulated during the validation process also provide valuable reference basis for further optimization and improvement.

IV. Conclusion

In this study, an innovative optimization method system for industrial product design is constructed by deeply integrating simulation and genetic algorithm. This method completely breaks the limitations existing in traditional design methods and realizes the paradigm shift from relying on experience to relying on data-driven design. The results show that the combination of the parametric design based on simulation model and the intelligent optimization mechanism of genetic algorithm can quickly and accurately locate the optimal solution in the intricate design space, which greatly improves the scientific and systematic nature of the product design process. By adopting the tree hierarchical structure to decompose and genetically code the functions of the product, and combining with the quality function to develop the adaptability evaluation system, the whole design process is more focused on the real needs of the users, which effectively solves the dilemmas of the traditional optimization methods in dealing with multi-objective, high-dimensional and non-linear problems. The introduction of improved genetic algorithm, especially the combined application of simulated annealing mechanism, successfully overcomes the inherent defect that the algorithm is easy to converge prematurely, and significantly enhances the global search capability.

A large amount of experimental data confirms that the method shows obvious advantages in all kinds of industrial product design, with the average design cycle shortened by 37.8%, the core performance of the product improved by 18.6%, the resource consumption reduced by 12.7%-19.5%, the production cost lowered by 14.8%, and the user satisfaction increased by 23.6%. These data fully verify that the method of this research has a very high practical value and considerable economic benefits. The theoretical innovation of this study lies in the construction of a complete set of industrial product design optimization method system, which organically combines the accurate prediction ability of simulation technology with the efficient search ability of evolutionary algorithm. The practical innovation is reflected in the proposed comprehensive adaptability evaluation system based on user demand, which makes the optimization process more in line with the market demand, and provides a new idea and practical tools for the industrial product design field, which can help enterprises to significantly improve the competitiveness of their products in the current highly competitive market environment.

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