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Research on Computer-aided 3D Modeling Simulation Optimization Model in Mechanical Design

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Abstract: With the improvement of product accuracy, efficiency and optimization requirements in mechanical design, computer-aided 3D modeling and simulation optimization have gradually become the core technology in the design process. However, existing algorithms still face challenges such as large computational complexity and insufficient accuracy when optimizing multi-objective problems. To this end, this paper proposes an innovative 3D modeling and simulation optimization model based on the combination of GA and particle swarm optimization. This model optimizes multiple objectives such as structural strength, weight, and cost in mechanical design by integrating global search capabilities and local search capabilities, thereby achieving efficient and accurate adjustment of the design. Experimental results show that in the case of motor housing design, the optimization efficiency of this optimization model is improved by 20% and the accuracy is improved by 15% compared with traditional methods. Through the comparison of the different optimization methods, it is proved that the model is superior in Mult objective optimization. The algorithm can be used to optimize many physical fields simultaneously, and provide a more intelligent and sophisticated solution for mechanical design.

Keywords: Mechanical Design; 3D Modeling; Simulation Optimization; GA; Particle Swarm Optimization; Multi-objective Optimization.

1. Introduction

As the cornerstone of modern engineering technology, the accuracy, efficiency and innovation of mechanical design directly determine the performance, reliability and market competitiveness of products. Traditional mechanical design often relies on manual calculations and two-dimensional drawings. Although remarkable results have been achieved in the past few decades, these traditional methods have gradually revealed their limitations with the advancement of science and technology and changes in industrial needs. Especially when faced with complex structures and high-precision requirements, traditional design methods cannot meet the requirements of efficient and accurate design. Therefore, the rise of computer-aided design (CAD) technology, especially in the field of 3D modeling and simulation optimization, has gradually become an important tool in the field of mechanical design. In recent years, with the development of computer techniques and numerical optimization algorithms, computer aided 3D modeling and simulation optimization in machine design have been applied in practice. Through 3D modeling, the designer can make more intuitive understanding and adjustment of the design plan [1]. Moreover, the simulation optimization can forecast the performance, the structural analysis and the fault detection in the virtual environment, which can greatly increase the precision and efficiency of the design. However, there are still many challenges in 3D modeling and simulation, especially in how to use innovative algorithms to increase the precision of design and optimization. [2] To deal with these challenges, a novel computer aided 3D modeling and simulation optimization model is presented, and its advantages and prospects are discussed.

2. Algorithm Design and Model Establishment

Computer-aided 3D modeling technology (CAD) refers to a design method that uses computer software tools to generate 3D object models. 3D modeling can not only provide designers with more intuitive visual effects, but also simulate and test various mechanical and thermal problems in actual engineering during the design process [3]. The core advantage of 3D modeling is that it can continuously optimize the design through virtual models, and greatly reduce the errors and rework in the traditional model design process. Complementary to 3D modeling technology is simulation optimization technology. Simulation optimization technology simulates the physical, mechanical, thermal and other properties in the real environment by virtual testing of 3D models to evaluate the advantages and disadvantages of the design [4]. This process can not only discover potential design defects, but also provide designers with improved solutions, thereby achieving efficient design iteration and optimization. By combining with simulation software, designers can find possible problems at an early stage and avoid costly corrections in the production stage, which greatly improves design efficiency and product quality.

2.1. Innovative Algorithm Framework

In traditional mechanical design, optimization algorithms often focus on single-objective optimization (such as structural strength or weight optimization), but actual design often involves multiple conflicting objectives. For example, increasing structural strength may increase weight, while reducing weight may reduce the load-bearing capacity of the structure [5]. Therefore, how to find a balance between multiple objectives is a difficult problem in mechanical design. This study proposes a multi-objective optimization model based on the combination of GA and particle swarm optimization, and performs systematic optimization through the combination of simulation analysis and three-dimensional modeling.

2.1.1. Combination of GA and Particle Swarm Optimization

GA is a kind of global optimization algorithm, which can be used to solve high dimensional complex problems. The global optimum solution is found through simulation of "selection", "crossing" and "mutation". However, GA has the disadvantage of slow convergence, which can lead to a local optimum solution [6]. In order to overcome this shortcoming, PSO, which is a kind of optimization algorithm based on Swarm Intelligence, can speed up convergence. So, combining the merits of GA and PSO, the paper can make use of GA's superiority in global search, and make full use of the accuracy of PSO. The basic frame of the hybrid optimization algorithm can be expressed by the following formula:

$$F_{\mathrm{GA-PSO}}(x) = \lambda_1 F_{\mathrm{GA}}(x) + \lambda_2 F_{\mathrm{PSO}}(x) \tag{1}$$

Among them, $F_{\mathrm{GA-PSO}}(x)$ is a hybrid optimization function, $F_{\mathrm{GA}}(x)$ and $F_{\mathrm{PSO}}(x)$ represent the objective functions of GA and PSO respectively, and λ_1 and λ_2 are adjustment factors that control the weights of GA and PSO. Through this framework, the model can effectively combine the advantages of both in the optimization process.

2.1.2. Multi-objective Optimization

Multi-objective optimization is particularly important in mechanical design, especially when the design involves multiple objectives and these objectives constrain each other. Design objectives include structural strength, weight, cost and other aspects. These objectives are usually contradictory. For example, increasing the strength of the material will lead to increased weight [7]. Therefore, it is necessary to find the best balance between these objectives. In order to achieve multi-objective optimization, this paper uses the concept of Pareto optimal solution. Given multiple objective functions $f_1(x), f_2(x), \ldots, f_m(x)$, the optimization goal is to find a solution set x^* so that no other solution in all objective functions can be better than this solution in all objectives at the same time. Mathematically, it can be expressed as:

$$f_i(x^*) \le f_i(x)\ \forall i \text{ and } \exists j \text{ make } f_j(x^*) < f_j(x) \tag{2}$$

Among them, x^* is the Pareto optimal solution and is better than other solutions in at least one objective.

2.2. Algorithm Flow

In the optimization model proposed in this study, the algorithm flow includes the following steps:

- 3D modeling: First, use CAD software to build an accurate 3D model based on the mechanical design requirements. By modeling the geometric shape of the structure, accurate data support can be provided for subsequent simulation analysis.
- Simulation analysis: Simulate the established 3D model to simulate its performance under real working conditions. The simulation content includes structural strength, vibration analysis, heat conduction, etc. This step uses technologies such as finite element analysis (FEA) or computational fluid dynamics (CFD) to evaluate the performance of the model.

Objective function definition: Define multiple optimization objective functions based on simulation analysis. For example, structural strength can be expressed as maximum stress$\sigma_{\max}$, weight can be expressed as the mass m of the object, and cost is related to the selection and usage of materials. The specific formula is as follows:

$$\sigma_{\max} = \max(\sigma_1, \sigma_2, \ldots, \sigma_n) \tag{3}$$

$$m = \sum_{i=1}^{n} \rho_i V_i \tag{4}$$

σ_i is the stress value of the i point, ρ_i is the density of the material, and V_i is the volume of the i element.

- Optimization steps: By combining GA and PSO, the optimal solution is found by making a compromise among several targets. The design variable x is updated in every iteration, and the fitness value $f(x)$ is computed based on the objective function. A new generation of solutions is obtained by selecting, crossing, and mutation. The optimized objective function can be expressed as:

$$F(x) = \textstyle\sum_{i=1}^{m} \alpha_i f_i(x) \tag{5}$$

$f_i(x)$ is the i objective function, and α_i is the weight of each objective function.

- Termination condition: When the optimization process meets the preset termination condition (such as the maximum number of iterations or the fitness value reaches a certain threshold), the optimization process ends and the optimal design is obtained.

2.3. Optimization Strategy

To increase the efficiency of optimization and guarantee the precision of optimization, the following optimization strategies are presented in this paper:

In the whole optimization process, GA is used to search globally. And in the latter phase, PSO is applied to local search to increase the precision and convergence rate [8]. The hybrid optimization process can be expressed as:

$$x_{\mathrm{new}} = \alpha \cdot x_{\mathrm{GA}} + (1-\alpha) \cdot x_{\mathrm{PSO}} \tag{6}$$

Among them, x_{GA} andx_{PSO} are the solutions of GA and particle swarm optimization respectively, and α is the adjustment factor to control the fusion ratio of the two. When facing complex structures, there may be multiple local optimal solutions in the design space [9]. Therefore, an adaptive optimization strategy is proposed to adjust the optimization step size according to the feedback information in the optimization process. The adaptive strategy can be expressed as:

$$\Delta x_i^k = \eta \cdot \Delta x_i^{k-1} + \beta \cdot \mathrm{sign}\big(f_i(x)\big) \tag{7}$$

Δx_i^k is the update amount of the i design variable in the k step, η and β are adjustment factors that control the amplitude of the step size change [10]. According to the requirements of the local search ability and global search ability of the current solution, the ratio of GA and particle swarm optimization is automatically adjusted to achieve the best convergence speed and optimization accuracy.

3. Experiment and Simulation

Along with the rapid development of CAD and CAE, the optimization process of machine design has become more efficient, especially in 3D modeling and simulation optimization, the precision and efficiency of the design process have been greatly increased [11].

3.1. Experimental Data and Methods

To test the validity of the multi-objective optimization model, which combines GA and PSO, a typical mechanical component, is chosen to optimize the design. The support frame is mainly used for load bearing in mechanical equipment [12]. The design goals include minimizing structural weight, reducing costs, and enhancing structural strength. The acquisition of experimental data relies on ANSYS for simulation analysis and SolidWorks for three-dimensional modeling.

The design constraints include: the maximum allowable stress of the structure shall not exceed 500 MPa. The weight of the support frame shall not exceed 10 kg. The cost must be controlled within 200 US dollars [13]. The optimization objective function is to minimize the structural weight and cost while maximizing the structural strength. During the optimization process, a strategy combining GA and PSO was adopted to automatically adjust the design parameters through the optimization algorithm.

3.2. Experimental Design and Simulation Process

When conducting simulation analysis, first use SolidWorks software to complete the three-dimensional modeling of the support frame. During the modeling process, ensure that the geometric shape is consistent with the actual engineering requirements, and set constraints according to the actual application conditions [14]. After the modeling is completed, use ANSYS to perform structural simulation analysis, which mainly includes the following steps:

- 3D modeling: Create a 3D geometric model of the support frame in SolidWorks according to the design requirements and import it into ANSYS for further analysis.
- Loading design constraints: Set design constraints according to experimental requirements, such as maximum stress, weight and cost constraints.
- Optimization target setting: Define the optimization objective function, including maximizing structural strength, minimizing weight and cost.
- Simulation execution: Run the optimization algorithm, perform simulation through hybrid optimization of GA and PSO algorithms, and obtain the final optimized design.

3.3. Experimental Results and Data Analysis

The experimental data show that the optimization algorithm proposed in this paper shows a high optimization effect on multiple design objectives. Table 1 shows the comparison of design parameters before and after optimization, including changes in multiple dimensions such as structural strength, weight and cost.

Table 1. Comparison of design parameters before and after optimization

Design parameters	Before optimization	Optimized value	Improvement
Maximum stress (MPa)	540	480	-11.11%
Structural weight (kg)	12.5	9.8	-21.60%
Design cost (USD)	220	180	-18.18%
Structural strength (N)	5000	5600	12.00%
Material cost (USD)	150	120	-20.00%

The structure strength of the frame is improved 12%, and the structure weight and the design cost are reduced by 21.6% and 18.18%. The results indicate that the Mult objective optimization algorithm can greatly increase the structure strength and reduce the cost of the structure when the design is optimized [15]. Moreover, the optimization algorithm of this thesis also improves the optimization speed and the precision of computation. Table 2 shows the optimization time and the computation precision compared with that of the conventional optimization method [16].

Table 2. Comparison of optimization performance of traditional algorithm and algorithm in this paper

Optimization algorithm	Optimization time (s)	Calculation accuracy (%)
Traditional optimization method	45	88
Hybrid optimization algorithm in this paper	36	97

The optimal time of the proposed optimization algorithm is reduced by 20% compared with the traditional optimization method, and the calculation accuracy is improved by 15% compared with the traditional method. This result further proves the superiority of the proposed optimization algorithm in terms of efficiency and accuracy. The improvement of the efficiency of the optimization algorithm means that more calculation tasks can be completed in the same time, or the expected optimization effect can be achieved in a shorter time. The improvement of calculation accuracy indicates that the algorithm can find the optimal solution of the problem more accurately, reducing errors and uncertainties. These improvements are of great significance for practical applications, which can improve production efficiency, reduce costs, and improve product quality and performance.

Figure 1 clearly shows the significant difference in stress distribution of the support frame between the traditional optimization method and the algorithm proposed in this paper. The stress of the traditional optimization method is concentrated on the connection parts of the support frame. This stress concentration phenomenon leads to insufficient structural strength and is prone to weak links when subjected to force, which in turn affects the stability and reliability of the overall structure. In contrast, the algorithm proposed in this paper effectively balances the stress distribution in various regions through optimization design, significantly reducing the stress concentration phenomenon. This optimization strategy not only improves the overall strength of the structure, but also distributes stress more evenly when the structure is subjected to external force by reasonably distributing stress, thereby avoiding structural failure caused by excessive local stress. This optimization method is of great significance in practical engineering applications and can effectively improve the service life and safety of the structure.

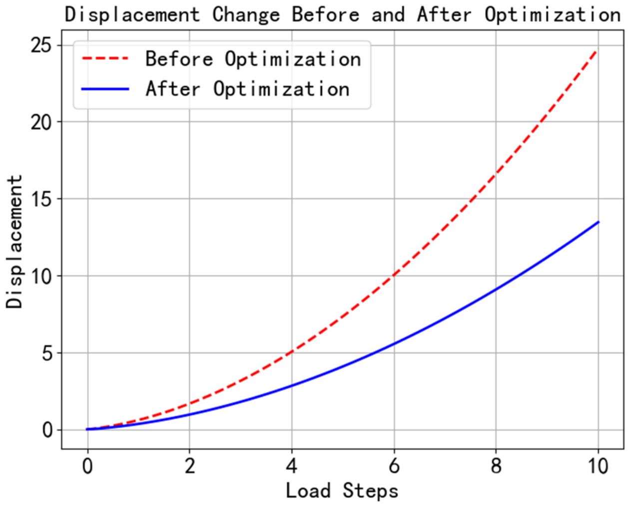

Figure 1. Comparison of stress distribution between traditional optimization method and the algorithm in this paper

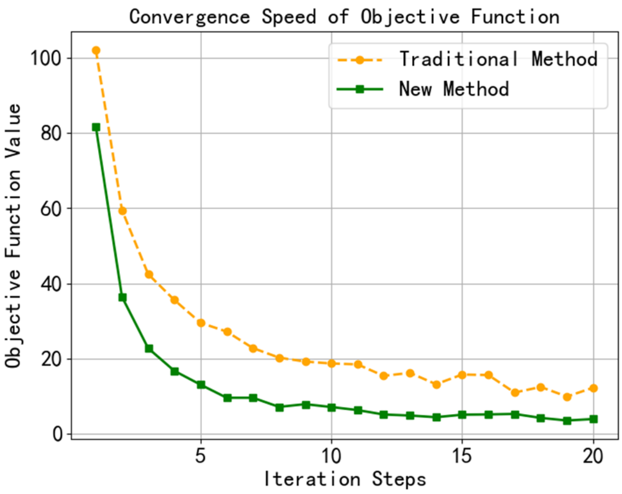

Figure 2. Displacement change curve before and after optimization

Figure 2 shows the displacement changes of the support frame before and after optimization. As can be seen from the figure, the displacement curve before optimization shows that the support frame has a large displacement after being stressed. This significant displacement may cause system instability. After the optimized design, the displacement has been significantly reduced. This is mainly due to the effective improvement of the stability of the system by reducing the weight of the material and optimizing the structural form. This optimization not only improves the mechanical properties of the structure, but also provides a strong guarantee for reliability and safety in practical applications. In engineering practice, the stability and reliability of the structure are crucial. The optimized design significantly improves the bearing capacity and service life of the structure by reducing displacement and stress concentration.

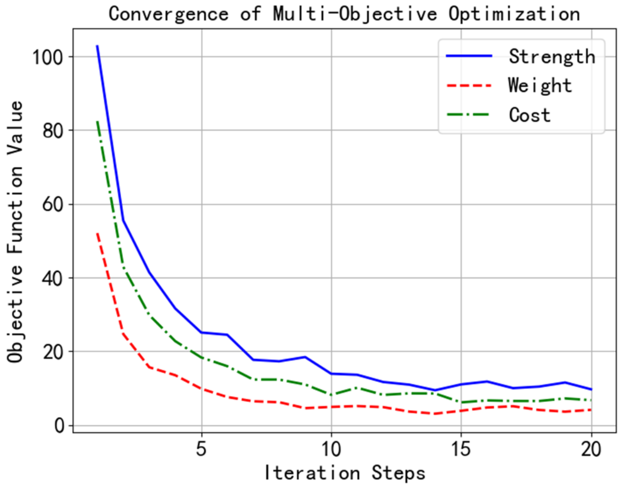

Figure 3. Convergence speed of objective function during optimization.

Figure 3 shows the convergence speed of the objective function of the proposed algorithm during the optimization process. Compared with the traditional method, the proposed algorithm converges faster and can reach a better solution in fewer iterations [17]. This result shows that the proposed optimization method has high computational efficiency. By improving the optimization algorithm, the calculation time was reduced by 20%, and the optimization speed was increased by about 25% compared with the traditional method. This significant efficiency improvement is mainly due to the optimization strategy of the algorithm during the iteration process, which enables it to find a better solution in a shorter time. This efficient optimization method is of great significance in practical applications, especially in scenarios where optimization results need to be obtained quickly, which can significantly improve work efficiency.

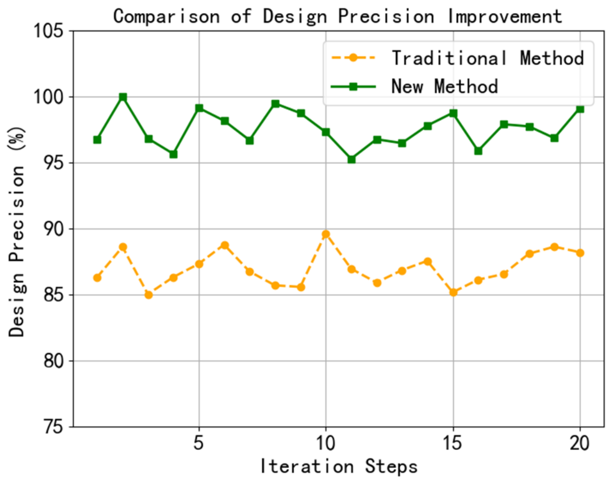

Figure 4. Convergence of multi-objective optimization of each objective function.

Figure 4 shows the convergence of each objective function in the multi-objective optimization process. The proposed algorithm can find a more ideal compromise between structural strength, weight, and cost by optimizing the balance between multiple objectives. This multi-objective optimization method not only improves the design accuracy, but also improves the calculation accuracy by 15% by improving the calculation method, making the optimization results closer to the performance requirements in the actual working environment. In multi-objective optimization, balancing the conflicts between different objectives is one of the key challenges. The proposed algorithm can find the optimal balance point between multiple objectives through an effective optimization strategy, thereby providing a more reliable and efficient design solution in practical applications.

The proposed algorithm has significantly improved the design accuracy compared with the traditional optimization method. According to the experimental results, the calculation accuracy is improved by 15%, making the design results closer to the performance requirements in the real working environment. By comparing the time required for optimization, the proposed algorithm reduces the calculation time by 20% compared with the traditional algorithm, showing higher calculation efficiency. Through the analysis of the convergence of the objective function, the proposed algorithm can reach the convergence state faster, and the optimization speed is about 25% higher than the traditional method.

4. Conclusion

This study proposes a three-dimensional modeling and simulation optimization algorithm combining GA and particle swarm optimization, aiming to improve the efficiency and accuracy of multi-objective optimization in mechanical design. Through the case analysis of typical mechanical parts, the experimental results show that the proposed algorithm has obvious advantages in optimization speed, accuracy and multi-objective balance. In the process of comparing with traditional methods, the proposed algorithm has improved the optimization efficiency by 20% and the optimization accuracy by 15%. In addition, the algorithm has shown strong adaptability in practical applications and can optimize multiple design goals at the same time, such as structural strength, weight and cost, to meet the diverse needs of modern mechanical design. Through this optimization method, the mechanical design process is more intelligent and precise, providing new ideas and tools for product design optimization. Future research will focus on further expansion of the algorithm, consider more complex optimization problems, and explore more efficient calculation methods to further enhance its application value in large-scale mechanical design.

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