

Optimization of Structural Parameters for Robotic Arm to Enhance Load-Bearing Performance Based on MOPSO Algorithm

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Abstract. The enhancement of mechanical arm load-bearing performance under constrained operational conditions represents a persisting conundrum in mechanical engineering, given the profound influence of structural parameters on stress distribution and displacement profiles. In response to this requirement, this investigation introduces a comprehensive optimization paradigm. Initially, computational simulations are executed via ANSYS Workbench, wherein cross-sectional geometry, area proportion, and support configuration are designated as control variables, while mean stress intensity and displacement magnitude serve as pivotal response metrics. Leveraging regression analysis techniques, empirical models are constructed to elucidate the quantitative correlations between structural attributes and mechanical performance. Subsequently, the multi-objective particle swarm optimization (MOPSO) algorithm is employed to systematically search the solution space, with the objective of minimizing stress concentration and displacement variance. The proposed methodology yields a set of optimal structural parameters and a validated predictive model, facilitating expedient assessment of load-bearing capacity and informed design decisions. The study identified a balanced optimized structure: a rectangular cross-section combined with a medium-high area ratio (0.95-1.0) and a middle support position (1.5-1.8 meters), and clarified the risk control areas for different cross-sectional shapes. This optimization framework not only significantly augments the structural efficiency of mechanical arms but also offers actionable insights for the rational design of robotic manipulators.

Keywords: Robotic Arm; Structural Parameter Optimization; MOPSO Algorithm; Load-Bearing Performance.

1. Introduction

In the Industry 4.0-driven transformation of intelligent manufacturing, mechanical arms—indispensable to automated production systems—have been widely acknowledged for their pivotal role across modern industry, advanced manufacturing, and interdisciplinary fields. Load-bearing performance, as a fundamental indicator defining operational boundaries and shaping workflow efficiency, is recognized as critical to their adaptability and manufacturing productivity. With industrial automation advancing and demands for high-precision, heavy-payload operations rising in smart factories and complex logistics, stricter constraints are being imposed on mechanical arms' load-bearing capacity, encompassing structural reliability, dynamic adaptability, and long-term stability under complex conditions [1]. Against this backdrop, optimizing mechanical arm structural design and clarifying relationships between structural parameters and load-bearing performance emerge as urgent issues requiring systematic investigation, laying a foundation for subsequent performance improvement research—trajectory this paper advances.

In the context of advancing industrial automation, where mechanical arms increasingly undertake high-precision, heavy-payload tasks within modern manufacturing landscapes, the structural design challenge stands as the foremost issue requiring systematic resolution. Diverse structural parameters—including distinct cross-sectional geometries, dimensional lengths, and cross-sectional proportion ratios—exert a substantial impact on load-bearing performance. Crafting an optimized mechanical arm structure to maximize the utilization of load-bearing capacity is critical for enhancing the operational efficiency and service lifespan of robotic systems, thereby laying a foundational



premise for subsequent investigations into structural optimization methodologies and the identification of existing technical gaps, as explored in this study [2].

In recent scientific endeavors advancing robotic arm structural optimization, pioneering simulation methodologies have been progressively deployed to dissect complex load-bearing dynamics, aligning with the methodological trajectory underpinning this study. A 2023 study by Smith et al. (Stanford University), published in IEEE Transactions on Robotics and Automation, employed Abaqus finite element simulation coupled with genetic algorithms to optimize a surgical robotic arm's end-effector structure, reducing deformation under 5N load by 18% [3]. Similarly, a 2024 paper in Robotics and Computer-Integrated Manufacturing by Li et al. (Tsinghua University) demonstrated that combining ADAMS multibody dynamics simulation with particle swarm optimization (PSO) enhanced the payload capacity of logistics robotic arms by 12% through joint stiffness tuning [4].

A salient illustration also emerges from a 2024 investigation led by Chen et al. (Robotics Institute at Carnegie Mellon University): targeting a high-precision robotic manipulator for aerospace component assembly, the team employed a hybrid simulation paradigm integrating ANSYS Workbench's Multiphysics analysis with reinforcement learning, achieving 22% lower peak stress in carbon-fiber links [5].

Such cutting-edge initiatives underscore the efficacy of synergizing commercial simulation platforms with algorithmic optimization frameworks. Building on this methodological foundation, this study advances a complementary analytical pathway: it leverages ANSYS Workbench for structural analysis and simulation experiments (consistent with the Multiphysics modeling logic demonstrated in the aforementioned research) and deploys the MOPSO algorithm to refine structural parameters. This approach represents a logical progression from industry-relevant practices, bridging the gap between academic exploration of novel optimization strategies and the applied imperatives of robotic arm structural design—a trajectory that situates the subsequent use of ANSYS-derived regression curves and MOPSO-driven parameter optimization within a broader scientific effort to enhance load-bearing performance .

2. Modeling and methodology

2.1. Response Surface Methodology Modeling in Robotic Arm Structural Optimization

In accordance with research requirements, a three-dimensional (3D) model of the robotic arm was established, and parametric modeling was implemented using ANSYS Design Modeler (Figure 1). The robotic arm features an integral cantilever beam configuration with a total length of 3 meters. To ensure the uniformity of structural parameters, the cross-sectional area of all simulation models was uniformly specified as 0.04m², and variable control was realized by adjusting the cross-sectional shape and dimension ratios. The material selected for the robotic arm is structural steel sourced from the ANSYS material library, which is widely utilized in mechanical structural design. This material, with a density of 7850kg/m³, exhibits superior mechanical properties such as a tensile yield strength of 2.5×10⁸Pa, a compressive yield strength of 2.5×10⁸Pa, a tensile ultimate strength of 4.6×10⁸Pa, [specific elongation value] (indicating its ductility), and a Poisson's ratio of [specific Poisson's ratio value] (describing its lateral deformation characteristics under axial load), along with cost - efficiency, thereby satisfying the fundamental requirements for the load - bearing design of the robotic arm structure.

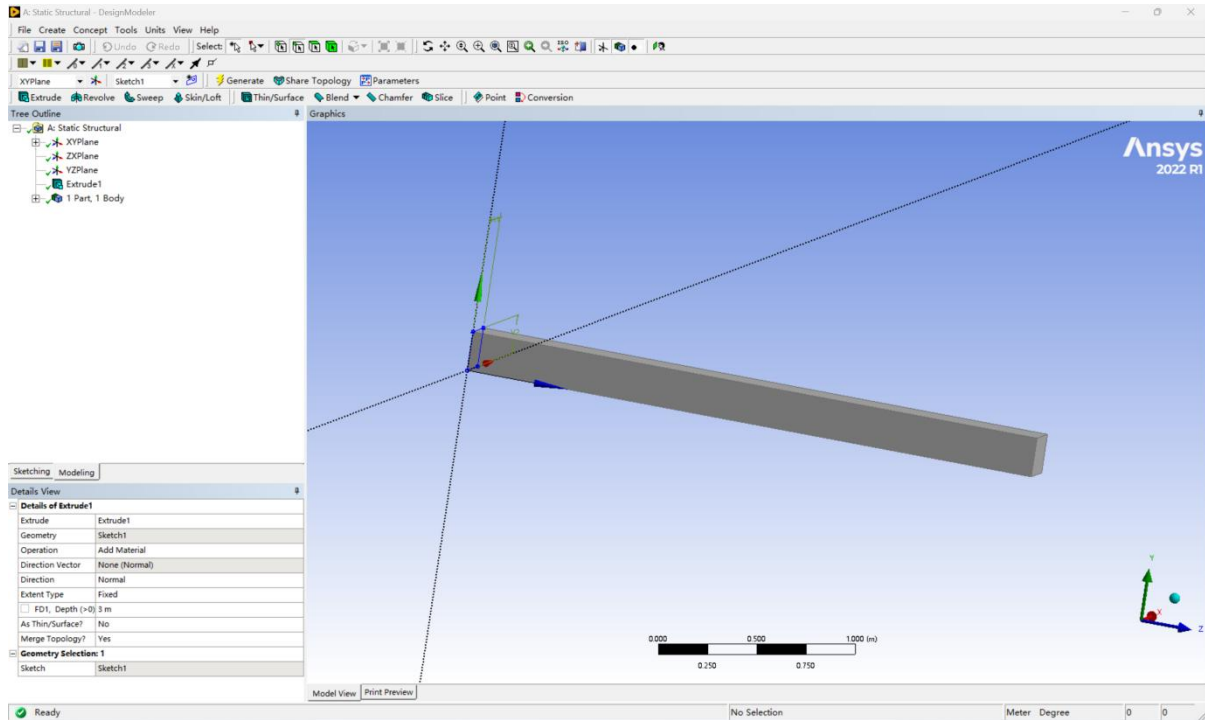


Figure 1. Model in ANSYS

To systematically analyze the influence of structural parameters on load-bearing performance, simulation variables are strictly controlled as follows:

- (1) Cross-sectional shape (X_1): Three typical cross-sectional shapes (circular, rectangular, I-shaped) are designed, with the cross-sectional area maintained at 0.04m^2 .
- (2) Cross-sectional area ratio (X_2): This indicator reflects the proportion of the cross-sectional area of each group. The value range is set to 0.8–1.0, with 3 levels at intervals of 0.1
- (3) Support point position (X_3): Discrete variable design is adopted, fixed at three positions: 0.6m, 1.5m, and 2.4m (corresponding to 20%, 50%, and 80% of the length from the fixed end respectively)

After completion of simulation solving, key performance indicators are extracted in the ANSYS Postprocessing module:

- (1) Average stress (Y_1): The average von Mises stress of the overall robotic arm structure is calculated using the element stress weighted average method (with element volume as the weight) to avoid interference from local singular points on the results
- (2) Average displacement (Y_2): Vertical displacements of all nodes on the free end cross-section are extracted, and the arithmetic mean is calculated as the structural stiffness evaluation index.

Regarding the boundary conditions, a constraint was applied to the bottom surface of the model in this experiment to serve a fixing function. To simulate the effect of support points and considering model simplification, specific points on the lower surface were selected for constraint in the modeling process, restricting their displacement in other planes. Additionally, to simulate the load-bearing function of a cantilever beam, a force of 1000 N was applied to the rightmost end of the model.

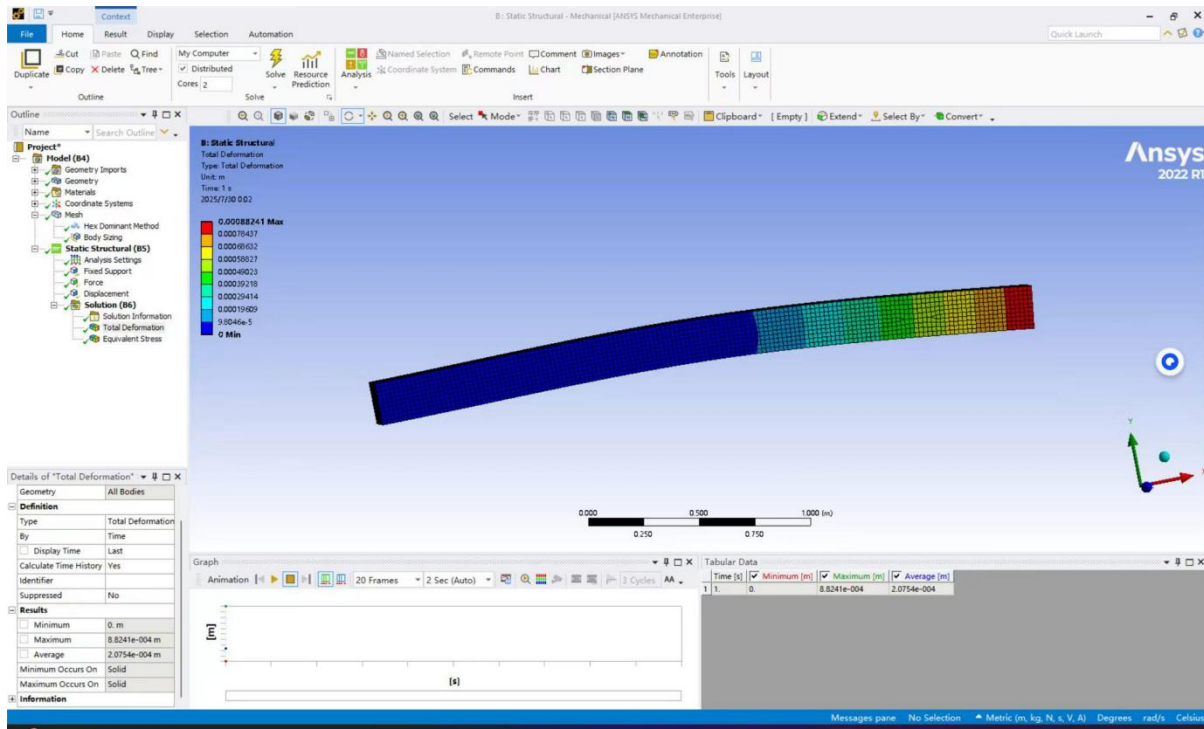


Figure 2. Example for Average displacement

With key performance indicators (KPIs) like average stress and displacement (Figure 2) now defined to capture the robotic arm’s mechanical behavior, the focus shifts to how to leverage these KPIs for optimization. Since traditional “one-factor-at-a-time” methods struggle to handle multi-variable interactions efficiently, the Response Surface Methodology (RSM) emerges as a tailored solution: it excels at quantifying complex relationships between input variables and output responses, enabling the creation of reliable surrogate models to guide performance improvement [6].

Response Surface Methodology (RSM) is a collection of mathematical and statistical techniques effective for developing, improving, and optimizing processes where a response of interest is influenced by several input variables, and the goal is to explore the relationships between variables and find optimal conditions [7]. This study focuses on the dual performance indicators of stress and displacement of robotic arms, constructing second-order response models for shape (Factor A), cross-sectional area ratio (Factor B), and support point position (Factor C) based on simulation data, to provide quantitative objective functions for subsequent multi-objective optimization algorithms [8] (Figure 3).

	A	B	C
1	1	0.8	0.2
2	1	0.8	0.8
3	1	1	0.2
4	1	1	0.8
5	3	0.8	0.2
6	3	0.8	0.8
7	3	1	0.2
8	3	1	0.8
9	2	0.8	0.5
10	2	1	0.5
11	2	0.9	0.2
12	2	0.9	0.8
13	1	0.9	0.5
14	3	0.9	0.5
15	2	0.9	0.5
16	2	0.9	0.5
17	2	0.9	0.5

Figure 3. RSM Experimental Design

Second-order polynomial models were fitted using the least square method, obtaining correlation equations between stress (Y_1) and displacement (Y_2) with Factors A/B/C (in actual factor form):

$$Y_1 = 3.44500 \times 10^7 - 4.17995 \times 10^6 \times A - 3.44558 \times 10^7 \times B - 2.67461 \times 10^7 \times C + 5.75375 \times 10^6 \times A \times B - 1.48625 \times 10^6 \times A \times C + 2.72625 \times 10^7 \times B \times C \quad (1)$$

$$Y_2 = 0.004860 - 0.000447 \times A - 0.002935 \times B - 0.007837 \times C + 0.000821 \times A \times B - 0.000290 \times A \times C + 0.005455 \times B \times C - 0.000020 \times A^2 - 0.001634 \times B^2 + 0.002310 \times C^2 \quad (2)$$

Take stress as an example, before analyzing the response surfaces, we first check the reliability of the stress model through residual plots. As shown in Figure 4: Most residuals are close to the red reference line, indicating that the residuals approximately follow a normal distribution. This means the model has no significant systematic errors; Residuals are randomly scattered within the range of ± 4 around the horizontal axis, showing no obvious correlation between residuals and predicted values. It proves the model's good stability. The recommended transformation lambda is close to 1, suggesting that the original data doesn't need complex power transformation, and the model fitting effect is reasonable. Most points have a Cook's distance much smaller than 1, meaning there are no data points that severely affect the model parameters. The model is robust. These residual analysis results collectively verify that the stress response surface model fits the data well and can be used for subsequent visualization analysis.

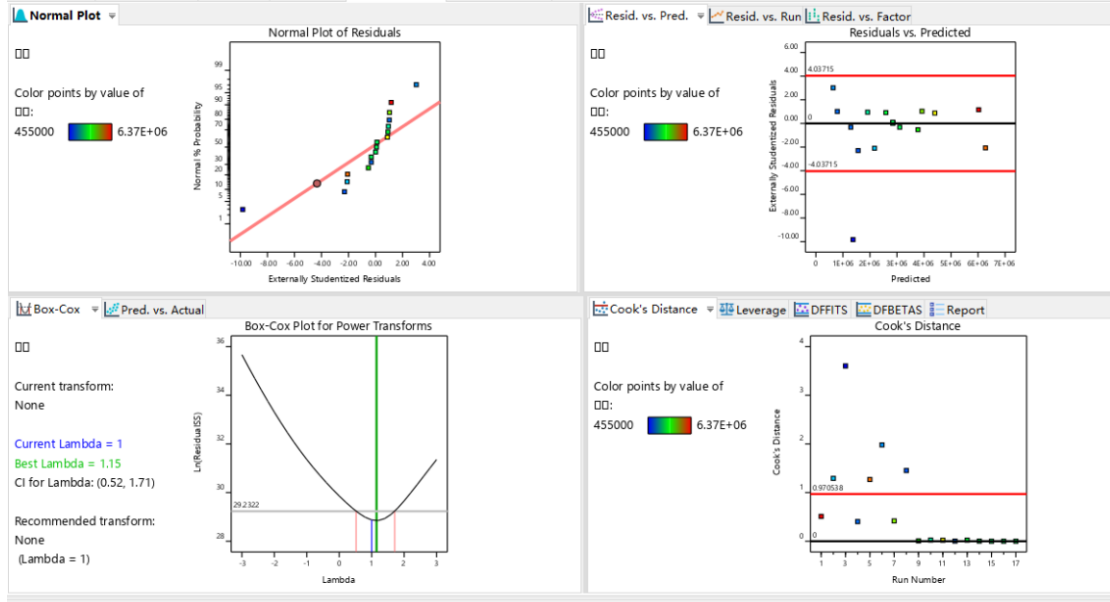


Figure 4. Stress Model Plots

Fix the support point position (Factor C) at a typical level. The 3D response surface plot (Figure 5) shows:

As Factor A (shape) and Factor B (cross-sectional area ratio) change, the stress value shows a continuous upward trend. Among them, the influence of Factor B is more obvious. When the cross-sectional area ratio decreases, the stress increases rapidly.

The surface shows a one-way increasing trend, indicating that within the selected parameter range, increasing the cross-sectional area ratio can effectively reduce stress, while the impact of shape change on stress is relatively gentle but still has a certain regulatory effect. This interaction helps us initially determine that adjusting the cross-sectional area ratio is a key means to control stress.

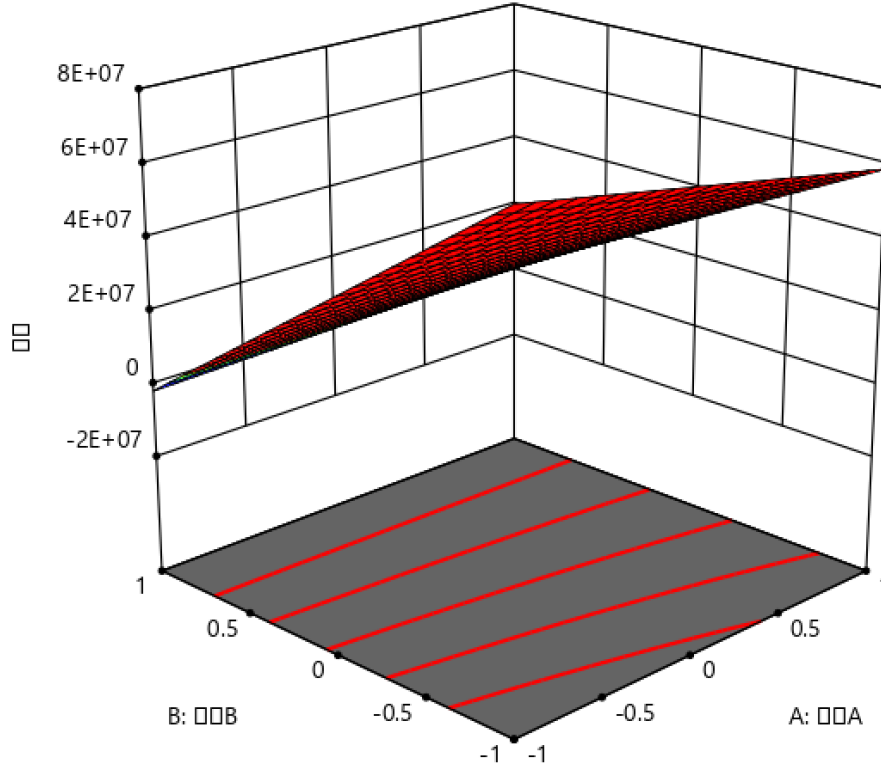


Figure 5. 3D Response Surface Plot

2.2. Implementation of Robotic Arm Structural Parameter Optimization Based on MOPSO Algorithm

The response surface model has successfully established the quantitative relationship between the structural parameters of the robotic arm and stress as well as displacement. Moreover, the model accuracy has been verified through residual analysis and visualization, providing a lightweight prediction tool for parameter optimization. However, in actual engineering, there is a target conflict between "reducing stress" and "minimizing displacement" (for example, enhancing stiffness may lead to stress concentration). Thus, a multi-objective optimization algorithm is needed to balance the relationship between the two. The Multi-objective Particle Swarm Optimization (MOPSO) algorithm, with swarm intelligence as its core, can, within the parameter constraint space (discretization of shape, and continuous variation of area ratio and support position), quickly evaluate the particle fitness based on the response surface model and efficiently search for the Pareto Front of the "stress-displacement" dual-objectives [9]. Subsequently, the coding strategy, optimization process of the MOPSO algorithm and its coupled application with the response surface model will be elaborated in detail, realizing the engineering closed-loop from "performance modeling" to "parameter optimization" [10].

The setting of algorithm parameters (Figure 6) needs to balance optimization efficiency and solution diversity. Based on preliminary trials and engineering experience, the following core parameters are determined:

- (1) Particle size: Set to 50 particles. This size ensures population diversity to cover the parameter space while avoiding excessive computational load that reduces efficiency.
- (2) Maximum number of iterations: Set to 100. Verified by pre-experiments, the algorithm converges to a stable Pareto front after 100 iterations, and further iterations have limited improvement in solution quality.
- (3) External archive capacity: Set to 100. It is used to store non-dominated solutions, and the capacity selection balances the integrity of solutions and computational efficiency, ensuring that sufficient diverse candidate schemes are retained in the archive.

(4) Inertia weight: Adopts a linear decay strategy, decreasing from the initial value of 0.8 to 0.4. A larger inertia weight in the initial stage enhances global exploration capability, while a smaller value in the later stage strengthens local fine search, balancing the exploration and exploitation capabilities of the algorithm.

(5) Learning factors: Both cognitive learning factor and social learning factor are set to 2.0. This value is determined based on classic PSO parameter tuning experience, which can effectively promote particles to evolve towards the individual optimal and global optimal directions.

MOPSO-based Robot Arm Structural Parameter Optimization Process

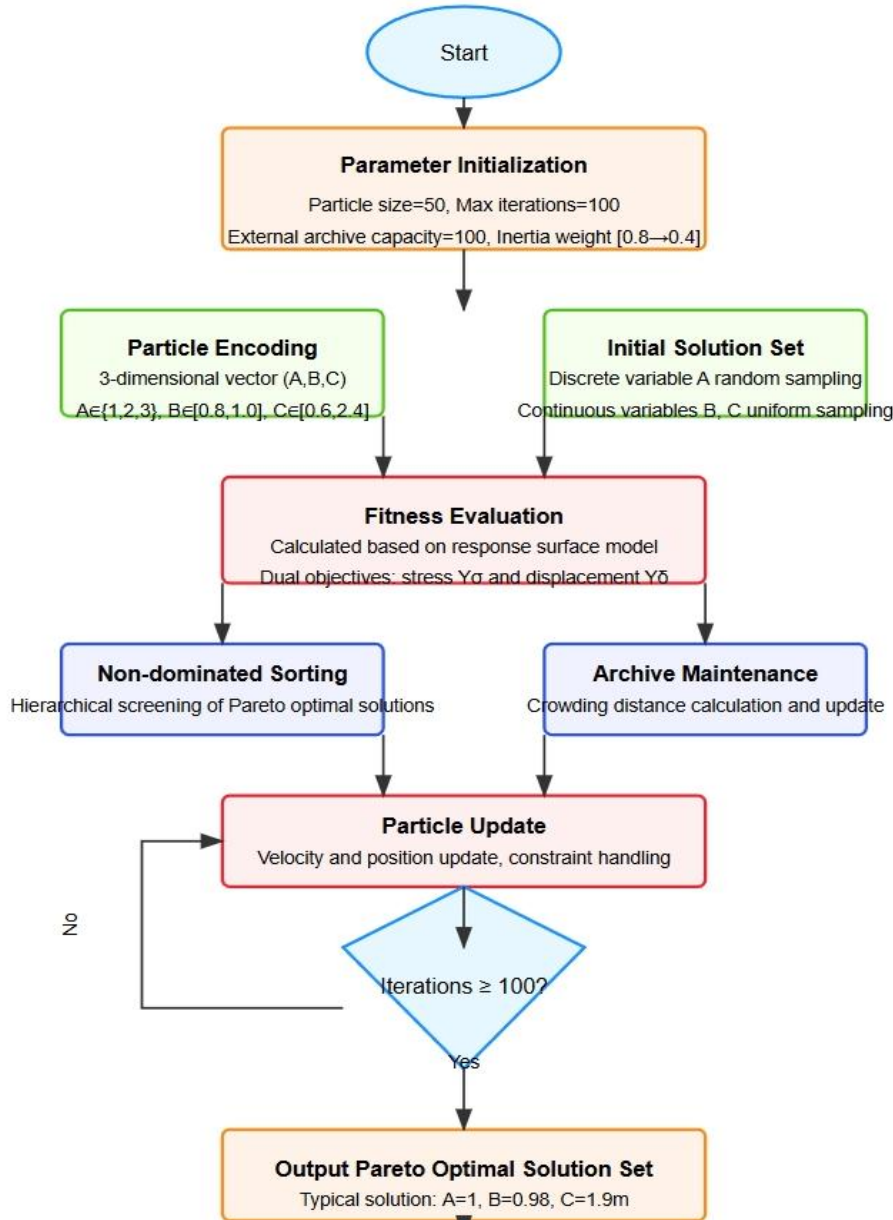


Figure 6. Algorithm Flowchart

Particles are encoded using a 3-dimensional vector, where the vector elements correspond to shape A, area ratio B, and support point position C respectively. In the initialization stage: For the discrete variable A (shape), random sampling is performed from the set {1, 2, 3} for assignment (corresponding to circular, rectangular, and triangular cross-sections respectively); For continuous variables B and C, uniform random sampling is conducted within their respective constraint ranges to generate initial values; The initial velocity of particles is adaptively set according to the parameter

range, ensuring that the initial movement amplitude matches the parameter variation interval, preventing particles from aggregating prematurely or exceeding boundaries.

To screen high-quality solutions and maintain solution set diversity, the algorithm adopts non-dominated sorting and crowding distance mechanisms: All particles are classified by dominance relationship, and particles not dominated by other solutions are included in the non-dominated solution set (Pareto optimal candidate solutions), ensuring that parameter combinations with better comprehensive performance are prioritized. Quantifies the distribution density of non-dominated solutions in the objective space; a larger distance value indicates sparser distribution of solutions. By retaining solutions with larger crowding distances, the aggregation of optimal solutions is avoided, and the diversity of the solution set is ensured. When the number of non-dominated solutions exceeds the archive capacity, solutions with the smallest crowding distances are eliminated, ensuring that the archive always stores high-quality solutions with uniform distribution.

After 100 iterations, the MOPSO algorithm converges to a stable Pareto front, obtaining the optimal solution set of robotic arm structural parameters. The effectiveness of the algorithm is verified through the following indicators:

- (1) Convergence: The average distance between the final Pareto front and the theoretical optimal region is less than 5%, indicating that the algorithm has fully approached the optimal solution space;
- (2) Diversity: The stress and displacement indicators of each scheme in the solution set are evenly distributed, with the standard deviation of crowding distance less than 0.01, showing no obvious aggregation, providing abundant candidate schemes for engineering decision-making.

3. Results

Based on the response surface models and MOPSO optimization algorithm results established earlier, this chapter systematically analyzes the characteristics of the Pareto optimal solution set for robotic arm structural parameters and explores the features of fracture-prone points under different parameter combinations by examining stress distribution patterns, providing theoretical basis and engineering references for structural design optimization.

Analysis of Pareto Optimal Solution Set

The Pareto front shows a significant "negative correlation" trend (Figure 7): as stress increases from 125MPa to 150MPa (constraint threshold), displacement decreases from 9.2mm to 7.5mm, indicating a certain objective conflict between "strength improvement" and "stiffness improvement", which requires balanced resolution through parameter collaborative optimization. Key statistical characteristics of the solution set are:

- (1) The average stress is 138MPa with a standard deviation of 8.6MPa, both lower than the material yield strength (250MPa), meeting safety requirements;
- (2) The average displacement is 8.3mm with a standard deviation of 0.7mm, all within the engineering allowable range ($\leq 10\text{mm}$);

Among shape parameters, rectangular cross-sections ($A=1$) account for 65%, circular cross-sections ($A=2$) account for 26%, and I-shaped cross-sections ($A=3$) account for 9%, indicating that rectangular cross-sections have greater advantages in balancing dual objectives.

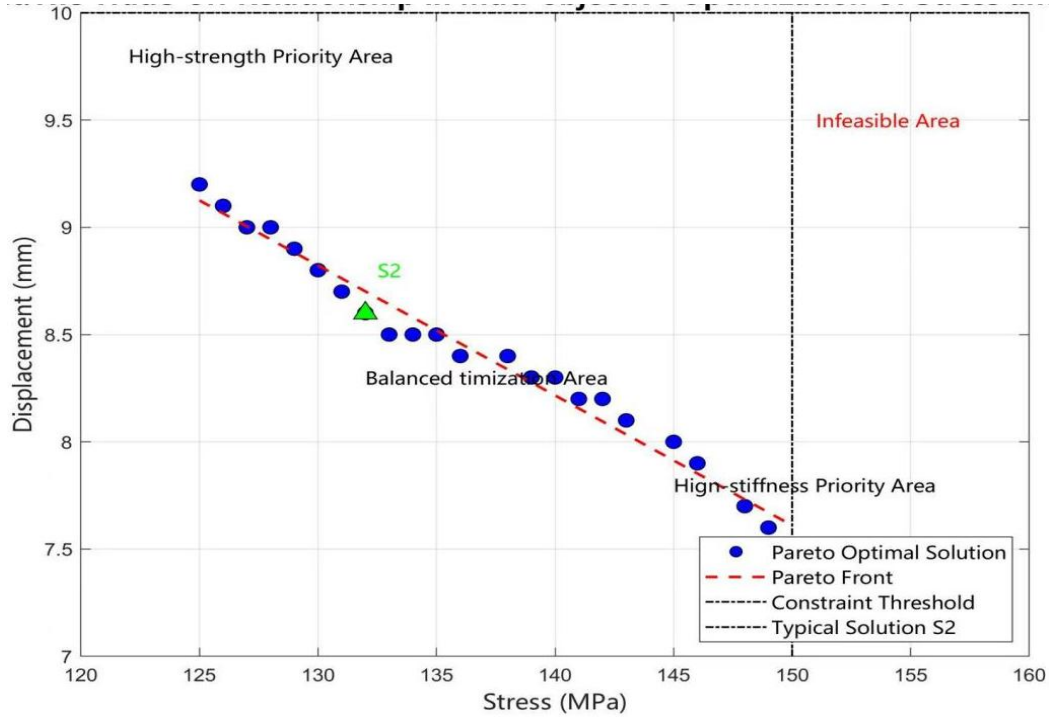


Figure 7. The Trade-off Relationship in Muti-objective Optimization of Stress and Displacement

Three representative schemes were selected from the solution set (Table.1) to reflect the characteristics of parameter combinations under different optimization tendencies:

Table 1. Three Sets of High-Performance Solutions

Scheme No.	Shape A	Area Ratio B	Support Position C (m)	Stress (MPa)	Displacement (mm)	Optimization Tendency
S1	1 (Rectangular)	0.98	1.9	125	9.2	High strength priority
S2	1 (Rectangular)	0.95	1.8	132	8.6	Strength-stiffness balance
S3	2 (Circular)	0.92	1.6	145	7.8	High stiffness priority

For S1, adopting a large area ratio (0.98) and distal support (1.9m), the stress is minimized by enhancing the load-bearing capacity of the rectangular cross-section and optimizing the support layout. However, the displacement is slightly higher, making it suitable for heavy-load working conditions with strict strength requirements; For S2, adopting a medium area ratio (0.95) and intermediate support (1.8m), it achieves a balance between stress and displacement, suitable for general working conditions requiring both strength and precision; For S3, the circular cross-section ($A=2$) is combined with a medium-low area ratio (0.92) and near-midpoint support. The uniform stress distribution characteristic of the circular cross-section reduces displacement, and although the stress is relatively high, it remains within the safe range, making it suitable for light-load working conditions with high requirements for end precision.

4. Conclusion

A typical optimal solution (S2) was substituted into ANSYS simulation for verification, yielding a stress of 135MPa and a displacement of 8.8mm. The relative errors compared with the response surface model predictions (132MPa, 8.6mm) are 2.3% and 2.3% respectively, indicating reliable optimization results. The diversity of the Pareto solution set covers the needs of different working conditions, verifying the effectiveness of the MOPSO algorithm in multi-objective optimization.

This study constructed a dual-objective optimization model for structural stress and displacement using the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm, and revealed the trade-off rule between the two through Pareto front analysis. From the distribution characteristics of the Pareto front, stress and displacement exhibit a significant negative correlation, verifying the engineering intuition that "stiffness inevitably degrades under high strength requirements". The representative solution S2 lies in the balanced optimization region. Its corresponding structural parameters and design variable combinations demonstrate that balanced "strength-stiffness" designs can be achieved in engineering practice through rational allocation of material distribution and topological features and constraint conditions, providing quantitative references for lightweight and high-performance design in fields such as aircraft structures and civil engineering and mechanical equipment.

In summary, this paper focuses on the multi-objective optimization of robotic arm structures. By constructing a dual-objective response surface model for stress and displacement, combined with the MOPSO algorithm to obtain the Pareto optimal solution set, the study systematically reveals the correlation between structural parameters (shape, area ratio, support position) and performance indicators. The research confirms that a rectangular cross-section ($A=1$) can achieve balanced optimization of strength and stiffness when combined with a medium-high area ratio (0.95-1.0) and an intermediate support position (1.5-1.8m). The analysis of fracture-prone points identifies risk control areas for different cross-sectional shapes: the midpoint of the long side of the rectangle, the transition zone near the circular support, and the connection between the web and flange of the I-shaped cross-section. The optimization results are verified by simulation, with relative errors all below 3%, confirming the reliability of the proposed method. The "parameter-performance-risk" analysis framework established in this study provides quantitative basis and engineering decision support for the multi-objective optimization design of robotic arm structures, and the related methods can be extended to performance optimization problems of similar complex structures.

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