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Improved dung beetle optimization algorithm and finite element analysis for spindle optimization

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ABSTRACT

This research introduces an integrated optimization methodology for spindle design, combining the improved dung beetle optimization (IDBO) algorithm with finite element analysis (FEA). The IDBO algorithm, enhanced in population initialization and convergence factors, minimizes total deformation and mass, addressing a multi-objective optimization model. The obtained optimal parameters guide the construction of a finite element model, considering additional factors like stiffness and maximum stress. The ensuing FEA produces a foundation for constructing a response surface, further optimized to refine the initial design. Through the combination of the IDBO algorithm and FEA method, the mass of the spindle is reduced from 46.582 kg obtained by the IDBO algorithm solution to 28.479 kg, a total reduction of 38.86%, while meeting design requirements such as maximum total deformation. Modal analysis up to the sixth order validates the design correctness reveals dynamic spindle behavior and guarantees the design requirements. The study demonstrates the reliability and effectiveness of the proposed IDBO algorithm in conjunction with FEA, providing a versatile framework for engineering optimization.

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1. INTRODUCTION

Optimization of machine tool components is a key aspect of modern manufacturing processes, aiming to improve efficiency, precision, and overall performance. The spindle plays a key role in determining the success of a machining operation. Achieving optimal spindle design is critical to minimizing energy consumption, improving machining accuracy, and extending the life of cutting tools. Current research areas emphasize using advanced optimization algorithms and analytical methods to enhance the design of machine components [1].

Subbaiyan *et al.* [2] used transient load data from spindle-level MBS to predict critical locations and component life. Greco *et al.* [3] proposed a simulation-based design of an ultrasonic-assisted air-bearing spindle for micromachining applications, including the arrangement of the journal and thrust air bearing, the drive turbine, and the mechanism to promote the movement of the vibrating tool. Yamato *et al.* [4] selected the optimal amplitude and frequency of sinusoidal spindle speed changes based on the chatter frequency and nominal spindle speed, and contributed to the design of intelligent spindles.

This study investigated the effects of spindle optimization. While earlier studies have explored the impact of structural design, material selection, processing technology, and intelligent diagnosis, they have not explicitly addressed its influence on adaptive design, vibration suppression, and smart design for spindle design. Recent research has shown a growing interest in integrating nature-inspired optimization algorithms, such as the dung beetle optimization (DBO) algorithm, into engineering applications. In addition, finite element analysis (FEA) has become the cornerstone for validating and improving structural design in various engineering disciplines. By combining these methods, this study strives to provide a comprehensive and innovative approach to optimizing spindle design, contributing to the broader precision engineering, and manufacturing fields.

The significance of this study lies in its potential to provide innovative insights into the design and optimization of spindles for machining applications. Using a simplified mathematical model based on hollow tubular structural steel profiles, design parameters can be systematically explored while considering the critical trade-off between structural integrity and weight reduction. Contents of this paper: section 2 introduces the spindle design modeling, the improved DBO algorithm, and the FEA technology involved in the research. Section 3 applies response surface optimization design to the spindle optimization calculation required by the case, and verifies the rationality of the design. Section 4 summarizes the results achieved in this study.

2. METHOD

Early work on spindle optimization mainly relied on traditional engineering principles and empirical methods. Researchers work to improve spindle performance through improved material selection, bearing technology, and geometric design. While these methods provide valuable insights, they often face limitations in resolving complex interactions within spindle structures [5]. FEA became the cornerstone for assessing the structural integrity of spindles and predicting performance under different operating conditions [6]. These models contribute to a more detailed understanding of the mechanical behavior of the spindle, but sometimes lack optimization efficiency. Recent trends in optimization research show a surge in applying nature-inspired algorithms to complex engineering problems. Various metaheuristic algorithms such as genetic algorithm, particle swarm optimization, and simulated annealing have been adapted for spindle optimization. These methods enhance the exploration of the design space and provide novel solutions for improving spindle performance [7]. The framework of this research is shown in Figure 1, which includes the integration of the improved DBO and FEA to solve practical engineering problems.

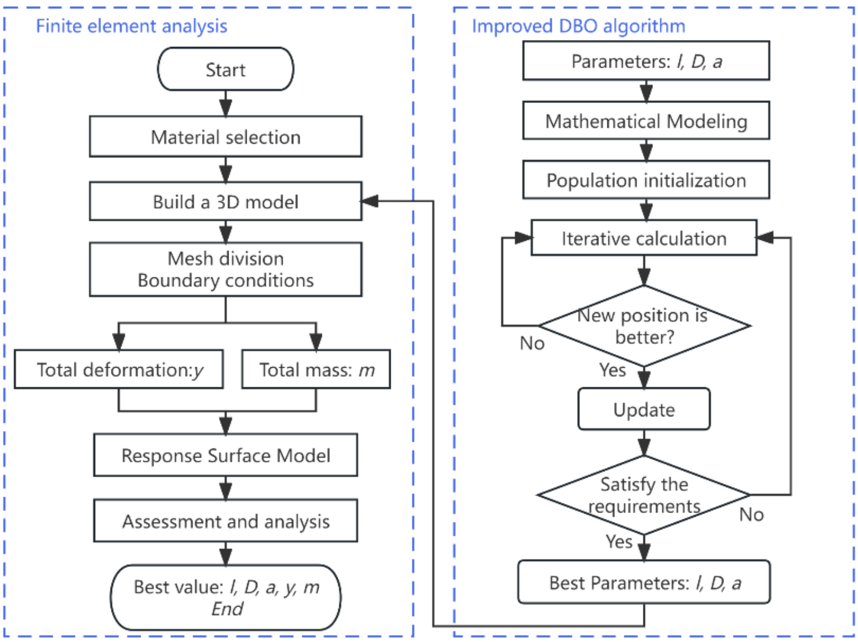


Figure 1. Flow chart of DBO algorithm and FEA

2.1. Spindle design modeling

Spindle design modeling involves creating a mathematical representation that captures a machine tool spindle's fundamental characteristics and behavior. Models are the basis for analyzing, optimizing, and predicting spindle performance in machining applications. The modeling machine tool spindle structure and stress analysis are shown in Figure 2. Such a simplified model helps optimize calculations. When designing, consider the deflection of point *C* at the spindle's extended end and the spindle's weight [8].

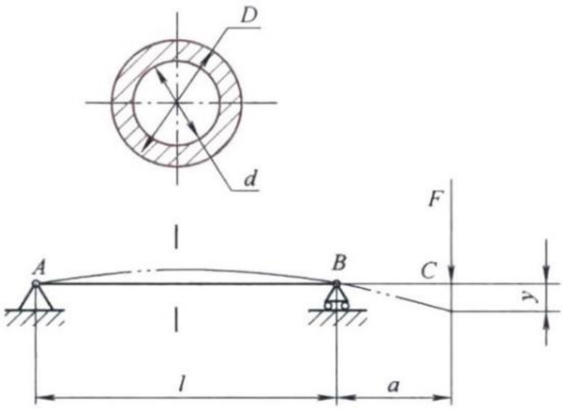


Figure 2. Schematic diagram of the structure and force of the spindle

The spindle is made of a tubular profile, the aperture *d* is a fixed value, and the outer diameter is *D*. When the material of the spindle is selected, the density of the material is expressed as ρ and young's modulus is *E*. The span of the spindle is *l*, and the length of the outer end is *a*. Design variables can be expressed as (1). $x= (x_1, x_2, x_3)^T= (l, D, a)^T$. The objective function of the optimization problem is (2).

$$x = (x_1, x_2, x_3)^T = (l, D, a)^T \tag{1}$$

$$f(x) = \frac{1}{4}\pi\rho(x_1 + x_1)(x_2^2 - d^2) \tag{2}$$

The spindle work requires that the deflection value *y* of point *C* cannot exceed the given value y_0. The deflection value *y* is calculated as (3). Based on this, constraint conditions are established such as (4).

$$\begin{aligned} I &= \frac{\pi}{64}(D^2 - d^2) \\ y &= \frac{Fa^2(l+a)}{3EI} \end{aligned} \tag{3}$$

$$g(x) = \frac{64Fx_3^2(x_1+x_3)}{3\pi E\left(x_2^4-d^4\right)} - y_0 \leq 0 \tag{4}$$

The boundary constraints of variables are as shown in (5).

$$\begin{cases} l_{min} \leq l \leq l_{max} \\ D_{min} \leq D \leq D_{max} \\ a_{min} \leq a \leq a_{max} \end{cases} \tag{5}$$

Combining all the above formulas, the mathematical model of spindle design can be expressed as (6).

$$\begin{aligned} &x: \begin{cases} x_{1min} \leq x_1 \leq x_{1max} \\ x_{2min} \leq x_2 \leq x_{2max} \\ x_{3min} \leq x_3 \leq x_{3max} \end{cases} \\ &\min f(x) = \frac{1}{4}\pi\rho(x_1 + x_1)(x_2^2 - d^2) \\ &S.t.\, g(x) = \frac{64Fx_3^2(x_1+x_3)}{3\pi E\left(x_2^4-d^4\right)} - y_0 \leq 0 \end{aligned} \tag{6}$$

2.2. Improved DBO algorithm

The DBO algorithm, proposed in 2022 [9], is a nature-inspired meta-heuristic optimization technique inspired by the foraging and reproductive behavior of dung beetles. The DBO algorithm mimics the complex navigation mechanism of dung beetles, in which the beetles use solar signals, celestial patterns, and environmental features to determine their direction and navigate to their destination efficiently. This bionic motion is translated into solutions that explore the search space. This study applies the DBO algorithm to solve the optimization problem of the machine tool spindle [10], [11].

The DBO algorithm incorporates an adaptive mechanism to dynamically adjust its parameters during the optimization process. This adaptability enhances the robustness of the algorithm in dealing with different problem scenarios. There are four main roles in the DBO algorithm design: rolling dung beetles, egg balls (breeding dung beetles), small dung beetles, and stealing dung beetles. The original DBO algorithm converges quickly and easily into local optimality. This study proposes an improved DBO algorithm based on the original algorithm.

2.2.1. Mapping initialization

The original DBO algorithm population initialization is randomly generated and unstable. The proposed improved DBO (IDBO) algorithm logical chaos map population initialization, (7) shows the initialization process [12],

$$x_{n+1} = \mu x_n(1 - x_n) \tag{7}$$

where n represents the number of populations, and μ is the set parameter. Given an initial value $x_0 \in (0,1)$, u=4 initializes the population. During the population initialization process, it is necessary to determine whether the upper and lower limits are exceeded. This study is a 3-dimensional (3 variables) problem. The comparison of the original randomly generated population initialization and the logical chaotic population initialization drawn in three-dimensional space is shown in Figure 3.

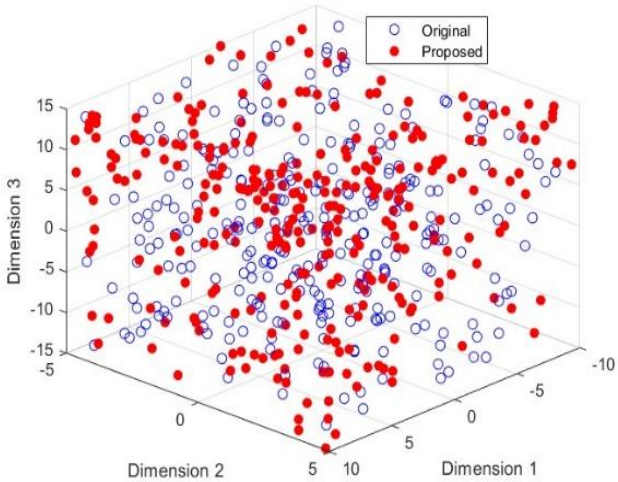


Figure 3. Population initialization comparison chart

2.2.2. Convergence factor

The original DBO algorithm has a linear convergence factor, and based on this, a nonlinear convergence factor is proposed such as (8), where r is the value of the convergence factor, t is the current number of iterations, T is the set total number of iterations, and k is the control parameter [13]. This convergence factor can converge slower at the beginning of the algorithm to satisfy a larger search range.

$$r = \frac{1}{2} + \frac{\sin\left(\frac{\pi}{2} + \pi\left(\frac{t}{T}\right)^k\right)}{2} \tag{8}$$

Figure 4 illustrates a comparison of the convergence factor curves. In this study, the value of k was 0.8. This convergence factor can make the convergence slower at the beginning of the algorithm to satisfy a larger search range, and slower at the end to make it easier to jump out of the local optimal solution and obtain a better solution [14].

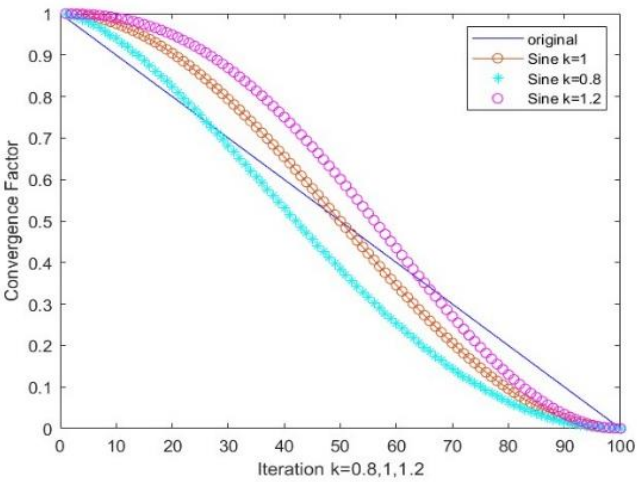


Figure 4. Convergence factor curves

2.3. Finite element analysis

In this study, FEA is used to evaluate the mechanical integrity and performance of the spindle structure, providing valuable insights into deformation, stress distribution, and overall stability under various operating conditions [15], [16]. The main content involves the three-dimensional geometric model of the spindle structure, accurate definition of material properties, finite element meshing, definition of boundary conditions, solver configuration, result analysis, and optimization. The FEA method further optimizes the calculation of stiffness, and vibration that are not involved in mathematical modeling, and more comprehensively guides and improves the reliability and performance of the main design.

3. RESULTS AND ANALYSIS

In this section, the specific parameters of the spindle are set, the proposed IDBO algorithm is used to find the optimal solution, and the obtained results are optimized and verified through FEA. Additionally, response surface optimization is conducted to refine the design further, enhancing performance metrics. Modal analysis is also performed to assess the dynamic characteristics of the spindle, ensuring its stability, and reliability under operational conditions.

3.1. Optimization calculation

The spindle is made of structural steel, with Young's modulus of 2×10^5 MPa, density of 7850 kg/m^3, Poisson's ratio of 0.3, Bulk modulus of 1.667×10^5 MPa, and Shear modulus of 7.5923×10^4 MPa. According to the established optimization mathematical model formula (6), given value y_0=0.05, F=15,000 N, the lower limit of variable x is lb= [300, 50, 90], and the upper limit is ub= [650, 140, 150]. The penalty function method [17] is used to construct the fitness function as shown in formula (9).

$$fitness(x, r) = f(x) + r \sum_{j=1}^{m} \max\left[0, g_j(x)\right] \quad (9)$$

Where r is the penalty factor, the value here can be r=100. The proposed IDBO algorithm is used to calculate the fitness function (9). The convergence curve is shown in Figure 5. The value of the variable when obtaining the optimal solution is x= [300, 64.1155, 90]. The total length of the shaft under this solution is 390 mm, the volume reaches 5.934×10^6 mm^3, the total mass is 46.582 kg, and the maximum deformation is 0.0062278 mm (less than y_0=0.05), which meets the design requirements. The results prove that the proposed IDBO algorithm can solve this engineering problem efficiently.

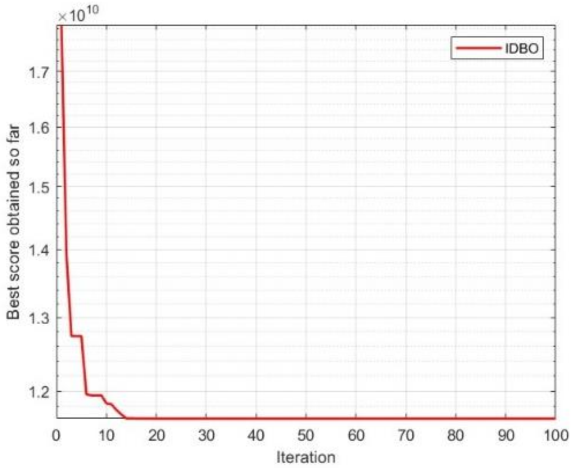


Figure 5. Convergence curve

3.2. Response surface optimization

To verify the correctness of the spindle design example, FEA was used to analyze the project to consider aspects not covered more comprehensively in mathematical modeling. Use the value model solved by the IDBO algorithm, that is, x= [300, 64.1155, 90], and set the material to structural steel. The mesh size is 5 mm. Set the length and outer diameter of the spindle as input parameters and set the maximum value of total deformation and total mass as output parameters [18]. Figure 6 shows the solved total shear moment diagram, matching the force case in Figure 2.

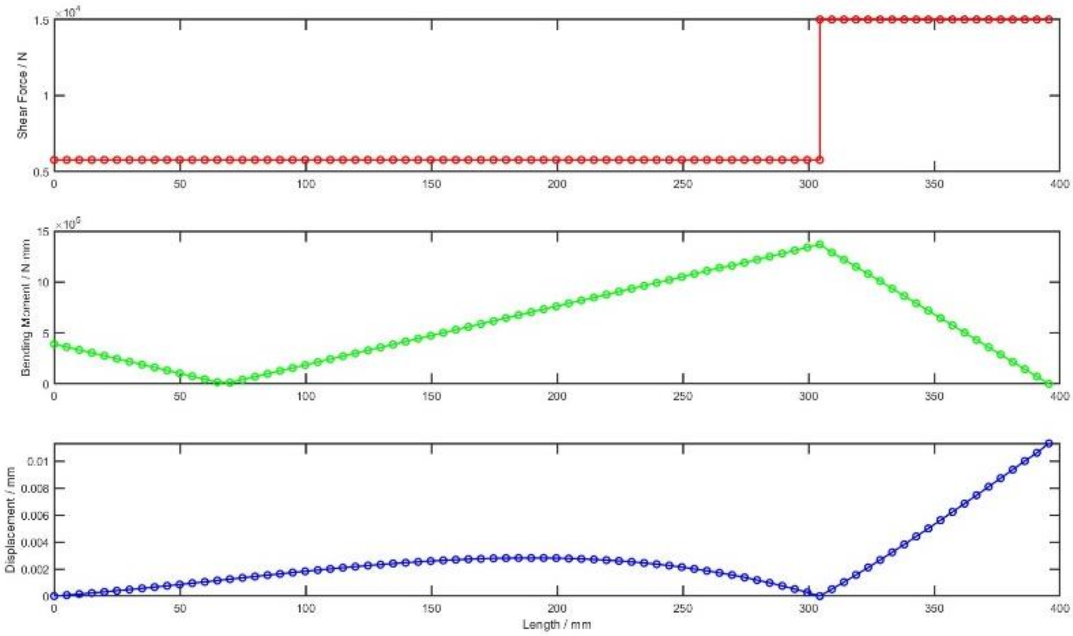
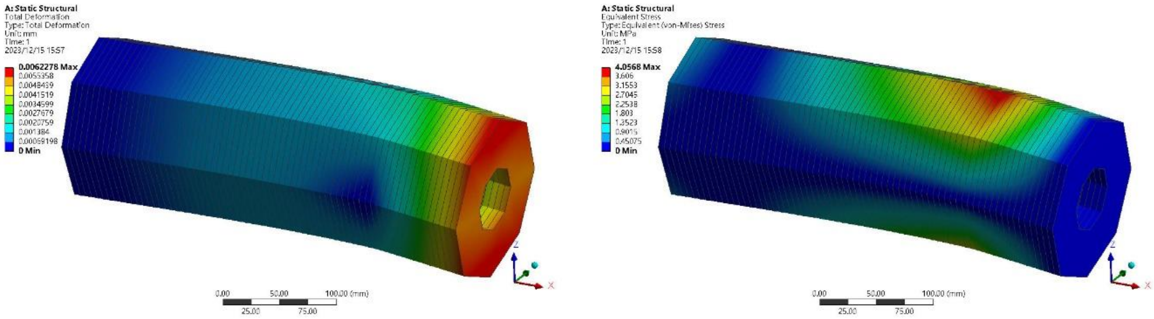


Figure 6. Total shear-moment diagram

The mechanical performance of the spindle design obtained through numerical optimization is illustrated in Figure 7. Figure 7(a) shows the total deformation cloud diagram, which has the largest deformation relative to position *C* in Figure 2. Figure 7(b) shows the equivalent stress cloud diagram, which has the largest stress relative to position *B* in Figure 2. Further narrow the range for the design parameters *l*, *D*, and *a*, with the lower limit *lb*= [300, 60, 90], limit *ub*= [350, 80, 100]. Central composite design (CCD) [19] was used to generate 15 groups of sampling points and calculated separately.



(a) (b)

Figure 7. Mechanical performance of optimized design parameters (a) total deformation and (b) equivalent stress

CCD are constructed within an experimental design framework, systematically combining factor points, pivot points, and center points to form a strategically chosen set of sampling points. This process enables the identification of configurations that meet the required performance criteria while minimizing computational effort. This method can provide an in-depth understanding of complex relationships within the design space in spindle design, thereby promoting the optimization of system performance. The results are shown in Table 1.

Table 1. Design points of CCD

No.	P1-x1-l (mm)	P2-x3-d (mm)	P3-x2-D (mm)	P4-Mass (kg)	P5-MaxDef (mm)
1	325	95	70	41.429	0.0090802
2	300	95	70	38.963	0.0088856
3	350	95	70	43.895	0.0092818
4	325	90	70	40.936	0.0082832
5	325	100	70	41.922	0.0099202
6	325	95	60	27.965	0.015598
7	325	95	80	56.965	0.0058264
8	304.67	90.935	61.87	28.564	0.012691
9	345.33	90.935	61.87	31.499	0.013191
10	304.67	99.065	61.87	29.151	0.014755
11	345.33	99.065	61.87	32.086	0.015334
12	304.67	90.935	78.13	50.773	0.005781
13	345.33	90.935	78.13	55.99	0.0059504
14	304.67	99.065	78.13	51.816	0.0066434
15	304.33	99.065	78.13	57.033	0.0068645

In this study, the response surface type chosen is genetic aggregation, which is a general technique for optimization and modeling. Genetic aggregation represents an innovative approach to capturing and modeling complex relationships within a design space, especially in scenarios where the interactions between variables are complex and nonlinear [20]. The response surface in Figure 8 shows the relationship between *l*, *D*, and the maximum total deformation. The X-axis represents l, the Y-axis represents *D*, and the Z-axis represents the maximum value of the total deformation. The response surface relationship between *l*, and *D* with total mass is shown in Figure 9. The X-axis represents *l*, the Y-axis represents *D*, and the Z-axis represents the total mass.

Spindle design from response surface analysis, using insights gained from experiments on system design and subsequent response surface modeling, determines the optimal set of parameters to achieve the expected minimum total deformation and total quality target [21]. The result is the identification of optimal parameters that significantly enhance the performance of the studied system. The final recommended optimal result is x= [304.5, 61.8, 91.1]. The model was updated again according to the optimal plan and FEA was performed again. Figure 10 presents the changes in mechanical properties after response surface optimization. The updated maximum total deformation is shown in Figure 10(a), and the maximum stress is shown in Figure 10(b). The total length of the shaft under this solution is 395.6 mm, the volume reaches 3.6279×10^6 mm^3, the total mass is 28.479 kg, and the maximum deformation is 0.01278 mm (less than $y0$=0.05), which meets the design requirements.

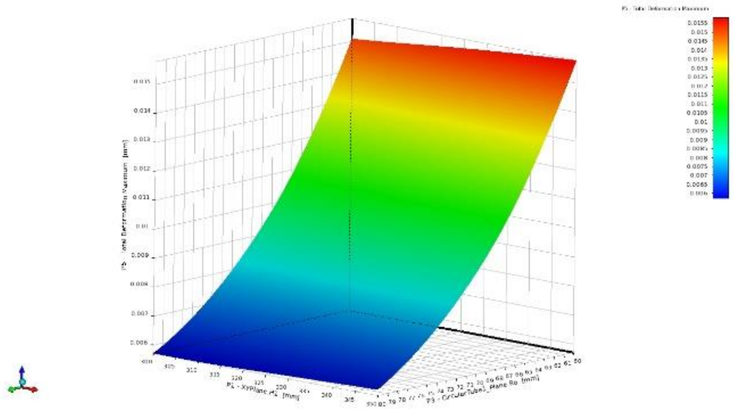


Figure 8. Response surface for maximum total deformation

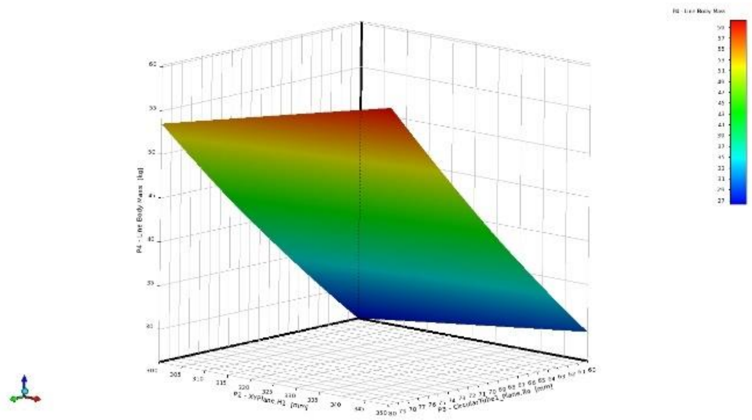
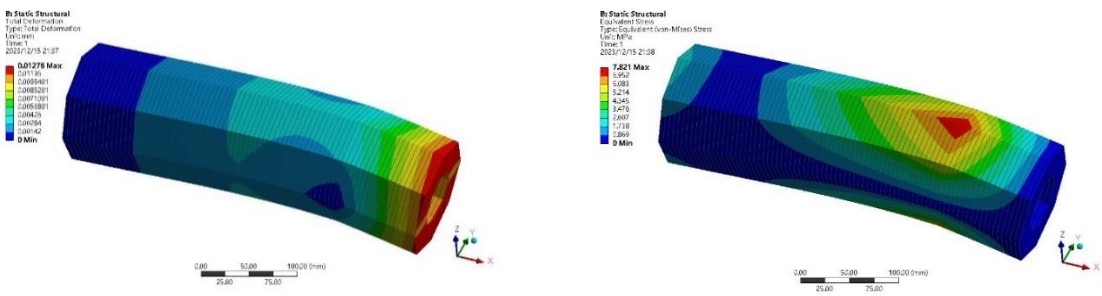


Figure 9. response surface for the total mass



(a) (b)

Figure 10. Mechanical performance after response surface optimization (a) updated maximum total deformation and (b) equivalent stress

Comparing the design solution obtained by the numerical solution of the IDBO algorithm, the mass of this solution was reduced from the original 46.582 kg to 28.479 kg, a total reduction of 38.86%. Although the maximum deformation point increased from 0.00623 mm to 0.01278 mm, they all reached the design requirement of 0.05 mm. Modal analysis [22], [23] is a key step in the verification and refinement process of optimized spindle designs. The natural frequency, mode shape, and dynamic characteristics of the spindle structure are studied through modal analysis. Help identify potential resonances and ensure designs meet structural integrity and performance standards. In this study, the 6th-order mode shape was completed, and the results are shown in Table 2. The sixth-order modal analysis results in Table 2 help to comprehensively evaluate the dynamic performance of the spindle and prove that the designed spindle exhibits robust behavior under a wide range of vibration conditions. This high-level analysis enhances the understanding of spindle vibration behavior and supports further refinement and validation to ensure the design is reliable and optimally performs in real-world applications [24], [25].

Table 2. Results for the 6th-order mode shape

Mode	1	2	3
Frequency (Hz)	1,978.2	2,564.2	2,564.2
Deformation (mm)	0.0027825	0.0097475	0.0097475
Mode	4	5	6
Frequency (Hz)	3,189.8	4,258.5	4,258.5
Deformation (mm)	0.083832	0.15551	0.15551

4. CONCLUSION

This study proposes an integrated optimization framework that combines the IDBO algorithm with FEA for the design of spindle systems. The IDBO algorithm is enhanced in terms of population initialization and convergence factors. A multi-objective optimization model is established to minimize the total deformation and mass.

This study explored a comprehensive finite element model with initial values provided by the IDBO algorithm. However, further and in-depth studies may be needed to consider factors such as stiffness and maximum stress, especially regarding that are not explicitly addressed in the mathematical model. The response surface obtained using FEA technology was used for further optimization. We found that the mass was reduced from 46.582 kg obtained by the IDBO algorithm solution to 28.479 kg correlates with a total reduction of 38.86%. Although the maximum deformation point increased from 0.00623 mm to 0.01278 mm, they all reached the design requirement of 0.05 mm.

Additionally, sixth-order modal analysis verified the correctness of the design and provided insights into the dynamic behavior of the spindle system. This integration of heuristic optimization with numerical simulation provides a versatile and efficient approach to solving complex engineering challenges, providing a valuable framework for industry practitioners and researchers. Future studies may explore the application of artificial intelligence to engineering problems with feasible ways of producing more efficient and comprehensive methods.

ACKNOWLEDGEMENTS

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