Research on Reliability Evaluation of Scissor Lifting Structure Based on BP Neural Network

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Abstract. In order to solve the problem that the reliability of scissor lift lifting mechanism is difficult to evaluate under large load, a method based on neural network for reliability evaluation of scissor lift mechanism is verified. Based on the static analysis of the scissor lift mechanism, three kinds of variable parameters, such as geometric parameters, material parameters and external loads, which affect the reliability of the scissor lift mechanism are determined. The response surface fitting is used to obtain the maximum deformation of some design variables. The influence trend, combined with the probability analysis method to control the influence of random variables on the maximum deformation of the lifting mechanism, obtain the reliability of the lifting mechanism of 45 sets of design variables under different values, and finally use BP-neural network to fit the design variables and reliability. The functional relationship between the two, establishes the reliability evaluation model of the scissor lift mechanism, and calculates the reliability of the scissor lift mechanism. The calculation results show that the maximum relative error of the reliability calculation result of the scissor lift mechanism is 2.1%, and the minimum error is 0.9%. It proves the feasibility of the neural network applied to the reliability evaluation of the scissor lift mechanism, and provides a new method and idea for the reliability evaluation of the scissor lift mechanism.

1. Introduction

The scissor support lifting mechanism is an important mechanism for carrying large-scale pressure vessel non-destructive testing robots and supporting X-ray detectors for efficient and safe inspection of welds. Since the detection position is on the high-altitude wall of the pressure vessel, the robot moves to the wall to move and turn during the operation, and the detection instrument is large in volume and heavy in weight. Therefore, the reliability of the static stiffness of the scissor-supporting lifting mechanism directly affects the quality of the flaw detection film and the accuracy of the detection. It affects the detection of defects in the inspection site and even affects the safety of the robot. Therefore, the reliability of the scissor lift mechanism is put forward.

At present, many scholars have combined the finite element method to analyze the reliability of mechanical structures, and provided many reliability analysis methods and ideas. Among them, the literature [1-2] combined with the finite element analysis method to analyze the reliability of the
hydraulic struts, and obtained the reliability model of the hydraulic struts. Literature [3-6] combines the finite element analysis method to analyze the reliability of different structures, which provides different ideas for structural reliability analysis. Literature [7-8] combined with finite element analysis has obtained material properties and dimensional parameters that have a great influence on structural reliability. On the basis of the construction of the index system, Yang J H established the BP neural network prediction model, and used the actual data and simulation data of the national grid of Jiangxi Province to conduct empirical experiments, showing the validity of the model [9]. Although these research work has achieved good results in the reliability evaluation of individual components, it is computationally intensive and cumbersome to evaluate the reliability of the mechanism. Therefore, a simple and efficient method for structural reliability assessment is needed.

Based on the static analysis, the geometric parameters, material parameters and external load parameters affecting the reliability of the scissor lift mechanism are determined. Through the response surface fitting, the influence trend of some design variables on the maximum deformation is obtained. The probabilistic analysis method controls the influence of random variables on the maximum deformation of the lifting mechanism, and obtains the reliability of the scissors lifting mechanism under different parameters. Then the BP neural network method is used to establish the reliability evaluation model of the scissor lifting mechanism, which realizes the lifting and lowering of the scissors. Agency reliability assessment. The method has high calculation precision, simple and high efficiency, and overcomes the shortcomings of traditional reliability calculation and cumbersome process.

2. Analysis of the system of scissors support lifting mechanism

The scissor support lifting mechanism is mainly composed of a clamping support, a chute, a telescopic rod, a cylindrical strut, a rack and pinion assembly, a lifting drive motor and the like. The organization and working principle are shown in Figure 1. The labels indicate: 1. ray instrument 2. clamping support 3. chute 4. telescopic rod 5. cylindrical struts 6. lifting drive motor 7. rack and pinion assembly.

![Figure1. Scissor lift lifting mechanism.](image)

The scissor lift is fixed on the quick installation slot of the detection robot frame, and the radiometer is fixed by the clamp support, the fixed end is at the rear, and the movable end is at the front. A high torque geared motor with a pinion is mounted on the moving end to slide in the track and engage with a rack fixed to the frame. In order to enhance its stability, the hinges of the left and right pairs of scissor mechanisms are connected by crossbars without affecting the movement of the mechanism and the radiation, so that the platform is kept synchronized while the two motors are simultaneously driven to drive the gears, which drives the two sides. The moving end of the rod lifts the platform.
3. Finite Element Analysis of Scissor Lifting Mechanism

3.1. Parametric modeling of scissor lift mechanism

The size parameter of the scissor lift mechanism is the key to reliability analysis. It is necessary to establish a corresponding parametric model to facilitate static and reliability analysis of the model. Due to the complex model of the scissor lift mechanism, it is difficult to establish directly through the Design Modeler module in the ANSYS Workbench software. Therefore, this paper uses UG to carry out three-dimensional parametric modeling, in which the lifting drive motor and the rack and pinion assembly are omitted, and the geometric parameter model is shown in Figure 2.

![Figure 2](image)

Figure 2. Geometric parameter model.

Some initial mechanism parameters of the lifting mechanism are as follows: cylindrical struts diameter D3 (diameter taken 8mm), telescopic rod width D16 (width is 12mm), telescopic rod thickness FD1 (thickness 4mm), parameter settings are shown in Table 1:

| Serial number | name | Numerical value | unit |
|---------------|------|-----------------|------|
| 1             | D3   | 8               | mm   |
| 2             | D16  | 12              | mm   |
| 3             | FD1  | 4               | mm   |

3.2. Static Analysis of Scissor Lifting Mechanism

In order to prevent parameterized data loss, the parameterized model is established directly in UG. It is directly imported into ANSYS Workbench through the ANSYS Workbench channel in the UG menu bar. The Workbench main interface automatically generates the Geometry module, and the new Static Structural module is created on the Geometry module. Meta-analysis platform for related settings:

1. The material property is set to the default mechanical steel with a modulus of elasticity of 200 GPa and a Poisson's ratio of 0.3;

2. For the meshing of the model, the mechanism selects Automatic intelligent meshing mode, the size of Element size is set as the default distribution, the number of cells generating the mesh is 5661, and the number of nodes is 12639;

3. Boundary condition setting: According to the working condition and posture of the lifting frame, the corresponding boundary condition is set, the lifting mechanism is subjected to the pressure in the positive direction of the X-axis, the size is 80N, and the fixed constraint is set at the bottom end of the telescopic rod.
(4) Set the solution target to the total deformation and equivalent stress values. The final result is shown in Figure 3 and Figure 4:

3.3. Determining design variables
According to the results of the finite element analysis and the force analysis of the scissor lift mechanism, the parameters of the width of the scissors, the thickness of the scissor and the diameter of the cylindrical strut, and the parameters of the cylindrical strut have an influence on the stress
distribution of the scissor support. Affect the reliability of the scissors. According to related research, the Poisson's ratio and elastic modulus of load and steel are also design variables that affect the reliability of the scissor support. Therefore, the design variables related to the reliability of the scissor support are: the load \( F \), the Poisson's ratio \( v \), the elastic modulus \( E \), the width \( D_{16} \) of the zoom bar, the thickness \( F_D \) of the zoom bar, and the diameter \( D_3 \) of the cylindrical strut. The range of values for the design variables is: \( F = 70 \sim 90 \text{N} \), \( v = 0.25 \sim 0.35 \), \( E = 170 \sim 230 \text{GPa} \), \( D_3 = 6 \sim 10 \text{mm} \), \( D_{16} = 10 \sim 14 \text{mm} \), \( F_D = 3 \sim 5 \text{mm} \).

3.4. Reliability analysis and calculation

In this paper, the Six Sigma Analysis module in ANSYS Workbench is used to analyze the reliability of the mechanism, and based on the static analysis, the reliability analysis is set. The module joint diagram is shown in Figure 5:

![Module joint diagram](image)

**Figure 5. Module joint diagram.**

3.5. Distribution of design variables

Considering the characteristics of materials, load distribution and manufacturing precision, the design variables are non-deterministic random variables and obey a certain distribution law. The initial design variable distribution function and parameter characteristics of the scissor lift mechanism are shown in Table 1. After the parameter setting is completed, the reliability simulation analysis is performed.

| Random variable                  | Distributed Types     | Variable Mean | Standard difference |
|----------------------------------|-----------------------|---------------|---------------------|
| Load                             | Normal distribution   | 80            | 4                   |
| Poisson's ratio                  | Normal distribution   | 0.3           | 0.018               |
| Elastic Modulus                  | Normal distribution   | 200           | 10                  |
| Cylindrical strut diameter       | Normal distribution   | 8             | 0.4                 |
| Telescopic rod width             | Normal distribution   | 12            | 0.6                 |
| Thickness of the lifting rod     | Normal distribution   | 4             | 0.2                 |
3.6. Generation of random samples

Table 3. Random samples.

| Serial number | D3  | D16 | ... | Poisson's ratio | Deformation |
|---------------|-----|-----|-----|----------------|-------------|
| 1             | 8   | 12  | ... | 0.3            | 8.57        |
| 2             | 6.76| 12  | ... | 0.3            | 11.21       |
| 3             | 9.24| 12  | ... | 0.3            | 7.24        |
| ...           | ... | ... | ... | ...            | ...         |
| 43            | 8.71| 10.93| ... | 0.27           | 7.35        |
| 44            | 7.28| 13.07| ... | 0.27           | 8.42        |
| 45            | 8.71| 13.07| ... | 0.33           | 6.36        |

Random samples are also the key to reliability design. They are the process of generating a series of experimental design points based on the floating range of design variables and target variables. The choice of test design parameters is related to whether the fitted response surface is accurate. The design point samples of different types of test designs, the operation time, and the accuracy of the fitted response surface will be different. In this paper, the design type selection center combination design (CCD) of the experimental design method is completed. After the solution is completed, 45 sets of experimental parameters are automatically generated by updating the design points, and the corresponding output results are obtained, which are presented in the form of a list. Some of the data are shown in Table 3.

3.7. Sensitivity of design variables to output results

Sensitivity analysis of parameters is an indispensable step in reliability analysis. It is mainly used to analyze and study the sensitivity of relevant input parameters in the model to target parameters and changes in surrounding conditions. The sensitivity analysis table generated in the experimental design, as shown in Fig. 6, can visually see that the width D16 of the lifting and lowering rod has a small influence on the target variable, and the thickness of the lifting and lowering rod FD1 and the diameter of the cylindrical strut D3 has a relatively large impact on the target variable.

![Figure 6. Sensitivity analysis.](image-url)
3.8. The influence of the corresponding variable model of the design variable on the output parameters

The 3D response surface optimization can directly observe the influence of the design variable on the output variable. Actually, it is a function. The input parameter is the function variable, and the output parameter is the function value. Response surface types include standard response surfaces, Kriging interpolation, nonparametric regression, neural networks, sparse grids, and more. The standard response surface is essentially regressively fitted using a quadratic polynomial algorithm. After testing, the response surface model fitted with the standard response surface type is closest to the real model, so the standard response surface type is selected.

The 45 sets of design points obtained from the experimental design were fitted with response surfaces, and the influence trend of some design variables on the target parameters was obtained. From the sensitivity analysis of the design variables, the effect of the wide D16 of the zoom bars on the target variables was relatively small. The thickness FD1 of the lifting and lowering rod and the diameter D3 of the cylindrical strut has a relatively large influence on the target variable. Therefore, the thickness FD1 of the lifting and lowering rod, the diameter D3 of the cylindrical strut, and the 3D response surface of the target deformation amount to the output variable are given here. As shown in Figure 7 and Figure 8.

![Figure 7. Response surface for maximum deformation.](image1)

![Figure 8. Response surface for mass.](image2)
3.9. Analysis of institutional reliability results
Six-sigma reliability analysis is a method based on probability and statistics to calculate the probability distribution of output parameters, indicating that there are only 35,000 pieces of unqualified probability of 1 million products. According to the sensitivity analysis, the thickness FD1 of the lifting rod and the diameter D3 of the cylindrical strut are the most sensitive to the target deformation. The reliability analysis is carried out by sampling 10000 times with the super-cubic Latin sampling (LHS). The sampled histogram is close to the distribution curve, indicating that the number of simulations is appropriate. For the type of equipment, the reliability of the mechanism is greater than 95% to meet the reliability requirements, so the model of the scissor lift mechanism has high reliability.

(1) Cumulative distribution function
Figure 9 is the cumulative distribution function of the maximum deformation of the spindle component. The black line in the figure shows the distribution function with probability from 0% to 100%. As can be seen from the figure, the maximum deformation is exponentially distributed and concentrated between 6 and 13mm. The distribution probability of this interval reaches 99.993%.

(2) Parameter probability list
As shown in Table 4 below, the probability map of the partial maximum deformation is listed, and the probability of 28 sets of data and their corresponding reliability is shown. You can directly query the reliability of any maximum deformation amount.

| Serial number | Maximum deformation | Reliability |
|---------------|---------------------|-------------|
| 1             | 5.6857              | 0.5069      |
| 2             | 6.0213              | 0.6202      |
| 3             | 6.3568              | 0.7139      |
| …             | …                   | …           |
| 26            | 13.0669             | 0.9994      |
| 27            | 13.4025             | 0.9996      |
| 28            | 13.738              | 0.9999      |

Figure 9. Cumulative distribution function of the maximum deformation.
4. Neural network reliability prediction

4.1. Neural network model features
When the reliability calculation of the scissors support is performed using the ANSYS Workbench module, the amount of calculation is large and the operation is cumbersome. In order to solve the shortcomings of the traditional reliability calculation, the neural network can be used to analyze the reliability of the scissors support. The neural network is based on modern neuroscience research and simulates the theory of human brain information processing mechanism. It has the characteristics of self-adaptation, self-organization and self-learning. BP neural network has the advantages of simple mechanism, fast learning convergence, and ability to fit arbitrary nonlinear functions. It is widely used in pattern recognition and image processing. In this paper, the reliability prediction model of scissors support mechanism based on BP neural network is established, and the nonlinear function relationship between different design variables and reliability is fitted, and the reliability prediction calculation of scissors support mechanism is carried out [10].

4.2. Principle of BP neural network
BP neural network is a three-layer forward neural network composed of input layer, hidden layer and output layer. The mechanism of the neural network is shown in Figure 10.

![Figure 10. Mechanism diagram of the neural network.](image)

The artificial neural network does not need to determine the mathematical equation of the mapping relationship between input and output in advance, and only learns some rules through its own training, and obtains the result closest to the expected output value when given the input value. As an intelligent information processing system, the core of the artificial neural network to achieve its function is the algorithm. BP neural network is a multi-layer feedforward network trained by error back propagation (referred to as error back propagation). Its algorithm is called BP algorithm. Its basic idea is gradient descent method, which uses gradient search technology to make the network the error mean square error between the actual output value and the desired output value is minimal.

4.3. BP neural network data sample
The reliability neural network model of the scissors lift mechanism requires data training to establish a nonlinear relationship between design variables and reliability. The random sample in the Six-sigma module is generated by the Latin hypercube sampling technique, which can sample better samples than the direct Monte Carlo sampling technique because the Latin hypercube sampling technique has sample memory function and will not be repeated. Sampling, with good uniformity and orthogonality, can achieve good input distribution with fewer iterations of sampling. Using this method, 28 sets of
samples were extracted from the value space of the design variables, and the ANSYS module was used to analyze the reliability of 28 pairs of scissors with different design variables. The 28 samples and reliability values are shown in Table 5.

| Serial number | D3/mm  | D16/mm | … | E/Gpa  | v   | Reliability |
|---------------|--------|--------|---|--------|-----|-------------|
| 1             | 6.26   | 9.75   | … | 162    | 0.24| 0.5069      |
| 2             | 6.38   | 9.92   | … | 165    | 0.24| 0.6202      |
| …             | …      | …      | … | …      | …   | …           |
| 26            | 9.30   | 14     | … | 132    | 0.35| 0.9994      |
| 27            | 9.43   | 14.18  | … | 235    | 0.35| 0.9998      |
| 28            | 9.56   | 14.35  |   | 238    | 0.36| 0.9999      |

### 4.4 Neural network model determination

In order to build a BP neural network model, three parameters need to be determined: input layer, hidden layer and output layer. The number of neurons in the input layer is 6, and the number of neurons in the output layer is 1. The selection of the number of neurons in the hidden layer is crucial for the BP neural network. First, according to the empirical formula: $k = \sqrt{mn} + a$ (m is the number of neurons in the input layer, n is the number of neurons in the output layer, k is the number of neurons in the hidden layer, and a is a constant between 1 and 10). The empirical formula is used to calculate the number of neurons in the hidden layer is $3-13$. Then, after comprehensively comparing the training errors under different hidden layer nodes, the number of neurons in the hidden layer is 13.

According to the mechanism setting of the mechanism of the structural reliability neural network model, the implicit layer neuron transfer function uses the S-type tangent function tansig, the output layer neuron transfer function uses the S-type logarithmic function logsig, and uses the newff() function to create the nerve. Network model.

### 4.5 Analysis of neural network calculation results

The procedure of BP neural network is written in MATLAB. The first 24 sets of data of 28 groups of data in Table 3 are used as the training samples of the model, and the scissors support reliability neural network model is trained. The last 4 sets of data are the test samples of the model, and the model is detected. The accuracy of the prediction. The prediction results of the neural network model are shown in Table 6.

| Serial number | Reliability | Reliability Predictive value | Relative error |
|---------------|-------------|-----------------------------|----------------|
| 1             | 0.9984      | 0.9773                      | 2.1%           |
| 2             | 0.9994      | 0.9838                      | 1.5%           |
| 3             | 0.9998      | 0.9878                      | 1.2%           |
| 4             | 0.9999      | 0.9903                      | 0.9%           |

It can be seen from Table 6 that the maximum relative error of the predicted value of the scissors neural network model is 2.1%, the minimum relative error is 0.9%, and the prediction accuracy of the neural network is high. It is proved that the BP-based neural network model is applied to the scissors support. Feasibility of reliability calculation of lifting mechanism.

### 5. Conclusion

(1) Static analysis of the scissor lift mechanism was carried out using the finite element analysis software ANSYS Workbench, and the design variables related to the reliability of the scissor lift
mechanism were determined. Through the response surface fitting, the influence trend of some design variables on the maximum deformation is obtained. The reliability analysis of the scissors support lifting mechanism with different design variables is carried out. Combined with the probability analysis method, the influence of random variables on the maximum deformation of the lifting mechanism is obtained. The reliability of the scissors lift mechanism under different parameters.

(2) The BP-based neural network is used to establish the reliability prediction model of the scissors lift mechanism. The neural network predicts the calculation. The results show that the maximum reliability of the neural network is 2.1% and the minimum error is 0.9%. It proves the feasibility of the neural network to calculate the reliability of the scissors lift mechanism. It only needs to determine the relevant design variables of the scissors lift mechanism, and it can analyze the reliability of the front link of the hydraulic support and provide the reliability evaluation for the scissors lift mechanism. New ideas and methods.

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