Study on optimization design and wear prediction of TBM cutter based on Standard Ga Algorithm

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Abstract. In tunnel construction, the tunnel boring machine (TBM) emerged in the 1930s has found wide application in tunnel construction due to its high construction efficiency, economy and environmental protection, etc. [1]. For TBM, the cutterhead is a key component and the most vulnerable component [2], and therefore the study on the cutterhead damage enjoys great significance. In the working process of TBM, wear and tear will cause structural failure of the cutterhead, then affect the normal operation of the TBM, and even cause problems such as production shutdown. On this basis, the optimization design of the cutterhead structure and the prediction of the cutterhead wear performance were investigated, thus providing reference for expanding the application of TBM.

1. Methods

1.1 Optimization design of TBM cutterhead

Cutterhead is one of the most critical components of TBM. By introducing the idea of topology optimization, the design of cutterhead hob machine was optimized. For the cutterhead hob machine, the area close to the groove and the outer side panel close to the center of the hob are the main areas prone to initial wear.

Topology optimization is based on finite element analysis, and the variable density method is its corresponding basic theory [3]. In this theory, the discrete processing of the model can be realized by dividing the relevant grid, and then the calculation variable $\rho'$ of this optimization method can be obtained through the additional calculation of the unit grid density, as shown in the following formula.

$$\rho = U\rho'$$  \hspace{1cm} (1)

Where, $U\rho'$ is the relative unit density, and $\rho'$ is the density of unit grid.

Due to the discontinuity of variables, the topology optimization cannot apply to issues with continuous variables. Consequently, the following formulas can be used for the continuous variables.

$$K = (U\rho)^p K_0$$  \hspace{1cm} (2)
\[ C = L^\top D = D^\top K^\dagger D \quad (3) \]

Where, \( K_v \) is the unit stiffness, \( K_0 \) is the inherent intensity, \( p \) is the penalty factor, \( C \) is the compliancy, \( L \) is the load vector, \( K^\dagger \) is the displacement vector, and \( D \) is the deformation displacement vector.

In the optimization design of TBM cutterheads, the purpose of introducing the topology optimization was to minimize the cutterhead units. Consequently, the formula and calculation corresponding to the mathematical model based on TBM cutterhead optimization were as follows:

\[
\begin{align*}
    r &= \frac{V - V_1}{V_0} \\
    s &\leq U_{\min} \leq U_p \leq U_{\max} \\
    C &= L^\top D \\
    L &= K^\dagger D
\end{align*}
\]

(4)

Where, \( r \) is the redundancy and the geometric volume ratio of the material in the calculation domain, \( V \) is the geometric volume of the corresponding model structure, \( V_0 \) is the geometric volume within the corresponding calculation domain structure, \( V_1 \) is the geometric volume of the corresponding structure whose density value is less than the minimum unit density, and \( U_{\max} \) is the density of the maximum unit.

In the optimization design of TBM cutterhead structure, the interior was regarded as a space with uniformly distributed structure, and the simplified conventional TBM cutterhead panel model was imported into Hypermesh to complete the meshing of the model. Then input the load of the TBM cutterhead, and complete the calculation and solution through the combination of EDEM and Topology Optimization modules.

1.2 Realization of GA algorithm under BP optimization

Genetic algorithm (GA) is a type of global optimization algorithm [4]. Compared with traditional algorithm, GA algorithm can offset the defects of the former. The corresponding fitness can reflect the individual quality in the GA algorithm, which can be expressed as:

\[ f(x) = \begin{cases} 
    K_{\max} - I(x) & I(x) \leq K_{\max} \\
    0 & \text{otherwise}
\end{cases} \quad (5) \]

Where, \( f(x) \) is the initial fitness based on the minimum problem, and \( K_{\max} \) is a constant with a sufficiently large value.

On this basis, the fitness based on the maximum problem can be expressed as follows:

\[ f(x) = \begin{cases} 
    M(x) + K_{\min} & M(x) + K_{\min} > 0 \\
    0 & \text{otherwise}
\end{cases} \quad (6) \]

Where, \( M(x) \) is the fitness based on the maximum problem, and \( K_{\min} \) is a constant with a sufficiently small value.

In addition to its good predictive performance, BP neural network, a type of feedforward neural network, can be combined well with other types of algorithms [5]. When completing the evolutionary learning, however, BP neural network will slow its training speed, and falling into the local optimum is also a potential problem. GA algorithm is a global search algorithm tool. On this basis, the two algorithms were combined to predict the wear of the TBM cutterhead hob machine. The implementation of GA algorithm under the optimization of BP algorithm (GA-BP) proposed in this paper was shown in
1.3 Development of TBM cutterhead wear prediction model based on GA-BP algorithm
The GA-BP algorithm was used to predict the wear of the TBM cutterhead hob machine. In the process of developing the prediction model, the relevant variables were first encoded in the form of character strings, and were then stored through the real number vector. The encoding of the character strings was mainly to obtain the initial population. The evolution generation and population size were determined through the calculation of fitness. In this prediction model, the iteration number was 100, and the population size was 50. For the crossover probability in the evolution of an individual, the model determined it as 0.6, and the mutation probability as 0.3. Then the optimal fitness in each generation of the population was calculated to ensure the best output of the starting weight and threshold, followed by establishing the BP neural network. For this neural network, the input layer corresponding to the objective function was composed of 4 nodes, and the output layer was composed of 1 node. The hidden layer corresponding to the neural network model had 3 nodes, 15 weights, and 5 thresholds. When applying the GA-BP algorithm to the prediction of TBM cutterhead wear, the best initial weight and threshold value from the GA algorithm output were assigned to the BP neural network model for prediction, and then the input data were normalized.

In the preliminary experiment, it was found that main factors that affect TBM cutterhead wear were rotation speed of TBM cutterheads, height value corresponding to wear-resistant layer, TBM cutterhead advance distance and wear constant, etc. To this end, with the aforementioned factors considered, TBM cutterhead wear prediction model established on GA-BP algorithm will be described as:

\[
P = \left[-0.13 - 0.72 \cdot s + 0.19 \cdot d \frac{14.76}{\sqrt{h}} - 0.38 (\frac{w}{d^{0.48}})\right] \cdot e^5
\]

(7)

In the above formula, \(P\) is average wear corresponding to TBM cutterheads, \(s\) is the rotation speed of cutterheads, \(d\) is the advance distance of cutterheads, \(h\) is the thickness of wear-resistant layer and \(w\) is the wear constant of cutterheads.

1.4 Performance analysis
To analyze and characterize the wear-resistant performance of optimized TBM cutterheads, the paper makes a comparison on the stress and stiffness of cutterheads before and after optimization. TBM cutterhead panel will be viewed as a thin plate, and damping function is ignored in modal analysis, under which premise the cutterhead panel vibration will be represented as:

\[\left([K] - \omega_0^2 [M]\right)A = 0\]

(8)
In the above formula $[K]$ is stiffness matrix, $[H]$ is mass matrix, and $A'$ is coefficient matrix and $\omega_0$ is fixed frequency. Among them, the particles and collision occurring in the process of TBM cutterhead advance will result in wearing. The greater the fixed frequency was, the larger the stiffness would be. Based on the above analysis, fixed frequency will be adopted as the evaluation index for stiffness in this paper.

To examine the validity of predication model, 50 groups of calculated data in the preliminary experiment were acquired in the adopted MATLAB platform, where training data, verification data and test data groups were automatically divided with the performance characterized through the training of network model. Besides, error $MAPE$ and prediction precision $Accuracy$ are introduced in this paper to analyze the prediction effect of the model, with relevant formula respectively represented as:

$$MAPE = \frac{\sum_{i=1}^{6} \left| \frac{E_i}{Y_i} \right|}{N}$$

(9)

$$Accuracy = (1 - MAPE) \times 100\%$$

(10)

In the above formula $E_i$ is error produced in the prediction process, $Y_i$ is the expectation, and $N$ is the quantity of test samples.

2. Results and discussion

2.1 Comparison of cutterhead performance before and after the optimized design

Taking the center panel(Cp), central hole(Ch) and mucking channel(Mc) of TBM cutterheads as the comparison parts, the stress changes of TBM cutterheads before and after optimized design were acquired and shown in Figure 2.

![Figure 2 Stress changes of cutterheads before and after optimization](image)

Figure 2 Stress changes of cutterheads before and after optimization

It can be seen clearly from the figure that stress of optimized TBM cutterhead Cp declined by 6.72% compared with that of original TBM cutterheads, stress corresponding to Ch falling by 10.3% and Mc stress falling by 8.1%. Hence, physical and mechanical properties corresponding to the site of TBM cutterheads prone to wear were enhanced to a certain extent after optimization, which showed that wear resistance of such sites was improved.

From the perspective of average wear, changes of TBM cutterheads before and after optimization were shown in Figure 3.
Figure 3 Changes of average wear of cutterheads before and after optimization

It was not difficult to find out in the figure that average wear corresponding to optimized cutterheads declined by about one time, and the curve of optimized cutterheads became gentler, which further indicated the improvement of wear performance of optimized cutterheads.

Based on the analysis of stiffness, variation of fixed cutterhead frequency before and after optimization was shown in Figure 4.

Figure 4 Changes of fixed cutterhead frequency before and after optimization

It can be seen from the figure that the growth of fixed frequency corresponding to optimized TBM cutterheads was respectively 4.22%, 3.41% and 6.49% under different modes of Step 1, Step 2 and Step 3, which revealed the improvement of stiffness performance after TBM cutterheads were optimized.

2.2 Prediction of cutterhead wear performance based on GA-BP algorithm

With the output error of network model as the evaluation index, MSE was used a measurement index of network performance, See Figure 5 for the training progress of GA-BP network.
It can be seen from the figure that network performance became better with an increasing number of iterations, which was specifically embodied in a constant decline of MSE value. Generally, errors between target data and training data were gradually narrowed as the training process moved ahead.

See Figure 6 for the comparison between expected output value of network model and actual output value.

It can be seen from the figure that the data gap between actual and expected output of network model was moderate, indicating a sound prediction effect.

Based on errors and precision, the prediction effect of network model was shown in Figure 7.

It can be found from the predicted data in graph that GA-BP network prediction model saw sound
results in the prediction of TBM cutterhead wear performance, with the prediction error merely as 0.038 while prediction precision reaching 96.24&. Errors corresponding to actual output value and predicted output value of the network model were within a rather small scope, indicating that the network prediction model registered a sound prediction effect.

3. Conclusion
This paper introduces topology optimization to the optimized design of TBM cutterhead hob machinery and GA-BP network model to the prediction of cutterhead wear performance. Through comparison of changes of cutterhead performance before and after optimization, it is found that stress and stiffness performance of optimized cutterheads register a notable improvement with a sound prediction effect of GA-BP network model. The research provides some data support for the optimization and life prediction of TBM cutterhead structure, but factors that affect TBM cutterheads aren’t included on by one. Considering that the prediction results are obtained from the model, a more detailed analysis will be conducted in the future research.

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