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Straddle-Type Monorail State Assessment Based on Adaptive Whale Optimization Algorithm

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Abstract. The condition parameter evaluation of straddle-type monorail beam based on finite element model modification is a high-dimensional parameter optimization problem, which tends to fall into local optimization. The whale optimization algorithm has the advantages of few required parameters, and good optimization search, while it has rarely been applied in the bridge engineering field, and its applicability needs further verification. Therefore, an analytical framework based on the adaptive whale optimization algorithm and deflection influence line is constructed using finite element model modification techniques, and its feasibility is verified for high-dimensional parametric state assessment of straddle-type monorails. The results show that the adaptive whale optimization algorithm can be used in the condition assessment of straddle-type with a maximum error of 3.5% in the identification of high-dimensional (20-dimensional) parameters, and the accuracy and rate of the algorithm are optimized for the standard whale optimization algorithm; in addition, using the deflection influence line of 1/4 span, mid-span and 3/4 span as the optimization target can reduce the error and improve the accuracy of the condition assessment of rail beams.

Keywords. straddle-type monorail; adaptive whale optimization algorithm; finite element model modification

1. Introduction

As the primary force-bearing component of the straddle-type monorail [1], the track beam is subjected to the coupling effects of load, environmental erosion, material aging, and other factors during long-term service. This inevitably results in resistance decay and functional degradation, thereby compromising the safety of the track beam. Without proper intervention, it can cause frequent maintenance and repair and, in extreme cases, lead to catastrophic accidents [2-3]. Accurately identifying bridge damage and assessing

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the operational status of track girders is crucial for scientifically maintaining track girders and ensuring safe traffic.

Track beams are typically made of reinforced concrete materials, and the assessment methods for them have mainly been borrowed from highway bridges. In recent years, a series of bridge condition assessment methods have been established such as reliability theory [4-5], hierarchical analysis [6], machine learning [7], finite element model (FEM) modification [8-10], and so on. The finite element model modification method has garnered significant interest due to its clear physical meaning and strong mechanical analysis capabilities. The core of this method is to modify the design parameters in the FEM according to certain mathematical theories and methods, so that the numerical results calculated by the FEM match with the actual test results, and to evaluate the bridge condition by the modified material parameters.

Finite element model correction essentially belongs to the solution of the inverse problem [11]. In track beam model correction, the number of correction parameter dimensions is increased to accurately locate the damage location. In solving large-scale optimization problems, the complexity of the problem grows exponentially with the increase in the number of dimensions of the search space [12]. Therefore, selecting the appropriate optimization technique is crucial for finite element model correction of straddle-type monorail. Population intelligent optimization algorithms are a class of optimization techniques based on iterative evolutionary search of populations, which are more suitable for solving large-scale optimization problems because of their strong global search capability, potential parallelism, and distributed nature [13].

The whale optimization algorithm (WOA) is a nature-inspired algorithm established by Mirjalili et al. to optimize the solution of the objective function by simulating the foraging behavior of whale schools. The algorithm has the advantages of few required parameters, and good optimization search in finding the optimal solution [14]. This method has been proved to be significantly better than the particle swarm algorithm and the gravitational search algorithm in terms of solution accuracy and convergence speed performance [15]. Therefore, since the WOA algorithm was proposed, numerous scholars have modified the WOA to improve its practicality [16-20]. Kong et al. established an adaptive whale optimization algorithm (AWOA) to optimize the WOA from two perspectives of adjusting the search weights and search strategies [20].

This study aims to utilize the adaptive whale optimization algorithm to develop an evaluation method based on finite element model correction and investigate its effect on the state assessment of straddle-type monorail. The specific contents of the study are as follows: Firstly, according to the characteristics of straddle-type monorail track beam, Young's modulus of each section is selected as the optimization parameter, and deflection influence line difference is constructed as the optimization objective. Then, WOA and AWOA are used to update the parameters using the self-programming finite element software as the solver to realize the FEM correction. On this basis, combined with two specific conditions to analyze the efficiency of the adaptive whale optimization algorithm.

2. Optimization Algorithm

2.1. Whale Optimization Algorithm

Based on the characteristics of humpback whale group hunting behavior, the WOA algorithm abstracted three behaviors: encircling prey, bubble-net attacking, and search for prey [14].

(1) Encircling prey

During this stage, whales are not aware of the location of the food source, and they get information about the location of the food through teamwork. Each whale represents an individual, and its position in the search space represents a solution. The whale closest to the food corresponds to a local optimal solution for all the current whales, and the rest of whales swim towards this position. The mathematical model of this stage behavior can be expressed as:

$$\vec{X}_{(t+1)} = \overrightarrow{X_{(t)}}^{*} - A \bullet D \tag{1}$$

Where: $D = | C \bullet \overrightarrow{X_{(t)}}^{*} - \overrightarrow{X_{(t)}} |$, t is the number of current iterations; X^{*} is the global optimal whale position, X is the position of other whales. A and C can be expressed by the following equations, respectively

$$A = 2a \cdot r - a \tag{2}$$

$$C = 2 \cdot r \tag{3}$$

$$a = 2 - 2t / t_{\max} \tag{4}$$

in which r random number of [0,1]. $t_{\max}$ is the maximum number of iterations.

(2) Bubble-net attacking

This stage simulates the behavior of whales feeding and spitting bubbles by moving in an upward spiral and constantly contracting the envelope. In the spiral update position, the distance from the individual whale to the current optimal location of the whale is firstly calculated, and then swims to the optimal individual by means of spiral movement. The mathematical model can be expressed as follows:

$$\overrightarrow{X_{(t+1)}}^{*} = D' \bullet e^{bl} \bullet \cos(2\pi l) + \overrightarrow{X_{(t)}}^{*} \tag{5}$$

where $D' = | \overrightarrow{X_{(t)}}^{*} - \overrightarrow{X_{(t)}} |$ and indicates the distance from the individual whale to the current optimal dominant whale, b is a constant for associated with the shape of the logarithmic spiral.

When $| A | < 1$, the whale approaches the whale with the best current position within the encircling circle. Meanwhile, the mathematical model assumes that the whale implements the encircling prey behavior and the spiral update behavior with probability 0.5, respectively, is as follows:

$$\overrightarrow{X_{(t+1)}} = \begin{cases} \overrightarrow{X_{(t)}}^* - A \cdot D, p < 0.5 \\ D' \cdot e^{bl} \cdot \cos(2\pi l) + \overrightarrow{X_{(t)}}^*, p \geqslant 0.5 \end{cases} \tag{6}$$

(3) Search for prey

When $|A| \geq 1$, the whales randomly contract outside the contraction envelope to find the optimum. Specifically, a whale position is randomly chosen as the global optimal position, and the other whales converge to it. Using this approach enables the individual whale to perform a global search and obtain a global optimal solution.

2.2. Adaptive Whale Optimization Algorithm

In order to enhance the accuracy and convergence speed, Kong et al. developed an adaptive whale optimization (AWOA) algorithm that optimizes the WOA from two perspectives: adjusting the search weights and search strategies [20].

(1) Adaptive adjustment weights

A suitable weight value is very helpful for the improvement of the algorithm's optimizing ability. Since the linear inertia weight adjustment strategy of WOA in the process of optimal solution will affect the convergence speed of the algorithm if it is not chosen properly. The parameter *w* is introduced to describe the weights that surround the prey behavior and the spiral update behavior, and Equation 6 can be written as

$$\overrightarrow{X_{(t+1)}} = \begin{cases} w \cdot \overrightarrow{X_{(t)}}^* - A \cdot D, p < 0.5 \\ D' \cdot e^{bl} \cdot \cos(2\pi l) + w \cdot \overrightarrow{X_{(t)}}^*, p \geqslant 0.5 \end{cases} \tag{7}$$

in which *w* can be adaptively changed according to the current distribution:

$$w = d_1 \cdot (X_{\text{worst}} - X_{\text{best}}) + d_2 \cdot (x_i^{\text{upper}} - x_i^{\text{lower}}) / t \tag{8}$$

where: x_i^{upper} and x_i^{lower} represent the upper and lower bounds of the optimization variables, respectively; X_{worst} and X_{best} are the worst whale position and the best whale position, respectively. This adjustment can achieve two effects: 1) at the early stage of the calculation, since the whales are relatively dispersed, choosing larger weights can avoid the algorithm from falling into a small search area prematurely and speed up the global search capability of the algorithm; 2) at the later stage of the iteration, the algorithm can change the size of the weight value adaptively according to the distribution of the individuals in the current population, so that it can finely search around the optimal solution and speed up the convergence speed.

(2) Adaptive adjustment strategy

In the random search phase, the probability of random search can be increased by adjusting the probability threshold Q to avoid falling into a local optimum.

$$Q = |\overline{f} - f_{\min}| / |f_{\max} - f_{\min}| \tag{9}$$

where: $\overline{f}$, $f_{\min}$, and $f_{\max}$ are the average fitness value, the best fitness value, and the worst fitness value of the whale population, respectively. For each whale, a random number between [0, 1] is compared numerically with the calculated probability threshold Q. If this random number is less than Q, the whale position is updated randomly. This design enables the algorithm to generate a set of solutions randomly with a large probability in the early iterative stage, enhancing the global search capability of the algorithm.

3. Optimization Target Based on the Difference of Displacement Influence Line

The finite element correction process t of the cross-seat monorail track beam is shown in Figure 1. As shown in Figure 1, the method mainly contains three elements: constructing the objective function, selecting the correction parameters and updating the correction parameters. Updating the correction parameters is mainly achieved by the optimization algorithm. For cross-seat monorail, the correction parameter is generally the track beam stiffness, which is mainly realized by correcting the Young's modulus of the material. Therefore, the focus in this section is on the construction of the optimization objective function.

Compared to the objective function created using dynamic parameters (such as frequency, vibration type, modal curvature, strain mode), an objective function built on static parameters (such as strain, deflection) only needs to account for the structural stiffness and doesn't require consideration of damping characteristics, among others. Furthermore, the application shows that the strain and deflection are measured with high accuracy and good stability in the field under the abnormal environment. Therefore, this study constructs the objective function based on the static parameter of deflection.

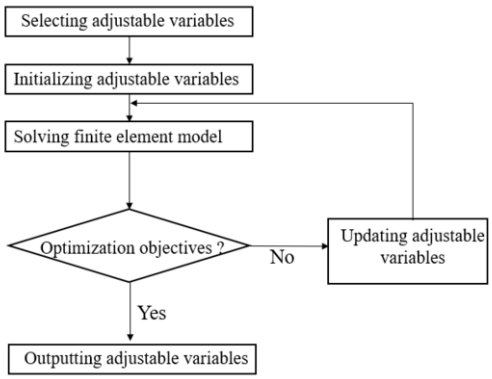

Figure 1. Flow chart of Finite element model.

Considering that the data collected by the deflection sensors are affected by temperature and load, which are difficult to be used directly for analysis, the deflection data need to be fused. The deflection influence line (DIL) records the deflection response of the vehicle load at different locations, which contains rich structural information. In addition, Liu et al. successfully extracted the DIL of a straddle seat monorail track beam using a regularization method [21]. Therefore, the absolute error between the calculated

DIL and the measured DIL is used as the objective function for optimization, which can be expressed as

$$F = \sum_{i=1}^{n} \left| di_c - di_m \right| \tag{10}$$

where di_c is the calculated value of the DIL, di_m is the measured value of the DIL, and i is the load loading position.

In order to make the results more accurate, the displacement influence lines of several key points can be used to jointly construct the objective function as follows:

$$F = \sum_{k=1}^{m} \sum_{i=1}^{n} \left| di_c - di_m \right| \tag{11}$$

where k is the number of the deflection influence line.

4. Calculation Analysis

The straddle-type monorail of Chongqing Line 2 is selected for the study. The material is concrete C60, the span diameter is 20m, and the cross section is shown in Figure 2. A finite element calculation model of the straddle monorail is established using self-programming software, with beam cells employed for cell types and a mesh length of 0.05 meters.

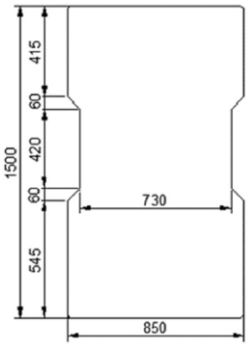

Figure 2. Schematic diagram of straddle-type monorail beam section (Unit: mm).

In the finite element model, the track beam is divided into 20 equal sections at 1 m spacing, the change in condition of the track beam is simulated by adjusting the ratio of the Young's modulus of the material in each section to its theoretical value ($a = E_{now} / E_{ini}$). Therefore, the optimization variables are the Young's modulus of the 20 sections ($a_1, a_2, ...a_{20}$). Considering the fact that the design of the track beam is given a certain degree, the variation range of a is [0.5-1.5]. The optimization target is chosen as 1/4 span, mid-span, and 3/4 span of the DIL. In this study, three calculation models are set up, among which model_1 is the intact model ($a_1, a_2, ...a_{20} = 1$ were 1); model_2 was

randomly set up with one damage ($a_7 = 0.8$), and model_3 is randomly set up with three damages ($a_3 = 0.9$, $a_7 = 0.8$, $a_{15} = 1.2$). The specific details are shown in Figure 3.

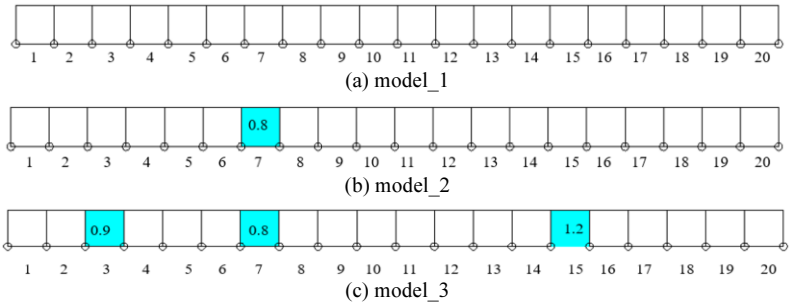

Figure 3. Schematic diagram of the calculation model.

Figure 4a and Figure 4b show the calculated results of the deflection influence line for the three models at the 1/4-span and 3/4-span measurement points, respectively. It can be seen that the DIL shows the overall three curve variation pattern and the largest value of the DIL near the middle of the span. Comparing the difference of DIL between model_1 and model_2, the difference of DIL is obvious in the change of state position of the track beam (unit 7 and 6-7m from the left end). In addition, the closer the measurement point is to the condition change, the larger the range of DIL change. Model_1 and model_3 deflection influence line differences also demonstrate a similar pattern. This is because the simulated condition is a localized condition change of the track beam, and the change is only obvious near the damage point.

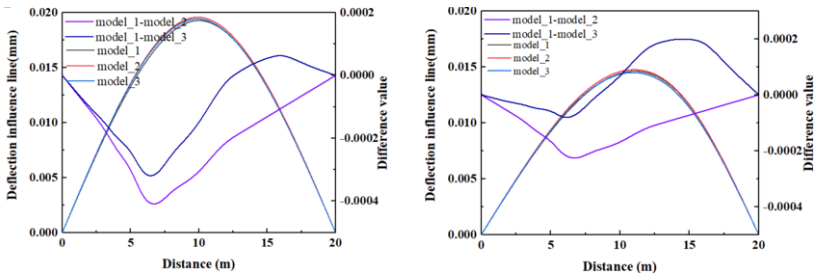

Figure 4. Deflection influence line calculation results.

Using 1000 iterations as the convergence condition, the results of the parameter corrections of the WOA and AWOA algorithms for the rail beam model 2 are shown in Table 1. We can see that the maximum identification error is 5.8%, which indicates that the WOA and the AWOA can be well used for straddle-type monorail condition assessment. To further quantify the advantages and disadvantages of the two optimization algorithms, the number of iterations when the objective function is less than 1E-5 is used as a measure of convergence speed index, and the maximum error and average error are used to measure the accuracy index, respectively. Figure 5 shows the iteration curves of the two algorithms for model_2. It can be seen that the convergence speed of AWOA is significantly higher than that of WOA.

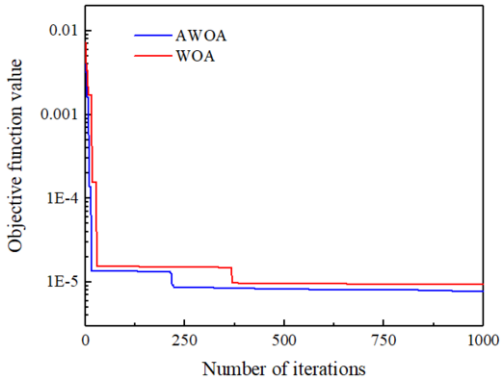

Figure 5. Schematic diagram of the calculation model.

Table 1. Data of model_2 parameter identification results.

Parameter	Theoretical value	Optimization value (WOA)	Optimization value (AWOA)	Parameter	Theoretical value	Optimization value (WOA)	Optimization value AWOA
α_1	1	0.942	0.966	α_{11}	1	1.012	0.993
α_2	1	1.031	1.031	α_{12}	1	0.989	1.006
α_3	1	0.971	1.01	α_{13}	1	0.978	1.011
α_4	1	1.014	0.992	α_{14}	1	1.02	0.986
α_5	1	0.987	1.014	α_{15}	1	0.986	0.992
α_6	1	1.006	1.011	α_{16}	1	1.024	0.989
α_7	0.8	0.775	0.783	α_{17}	1	0.996	1.017
α_8	1	1.018	1.015	α_{18}	1	0.978	1.022
α_9	1	0.983	0.987	α_{19}	1	1.035	0.973
α_{10}	1	0.995	1.012	α_{20}	1	0.964	1.033

Table 2 shows the convergence speed and the optimization-seeking accuracy of model 2 and model 3. In model 3, the maximum errors of WOA and AWOA are 5.2% and 3.8%, respectively, when three measurement points of deflection influence line data are used to construct the optimization objective. while the maximum errors of WOA and AWOA are 8.9% and 8.5% when only a single measurement point in the span is used. The parameters cannot be accurately identified because of the small effect on the span-centered influence line when the change of track beam condition occurs at the end step. Therefore, we suggest to use these three deflection influence lines as optimization data in the actual project. In addition, compared with the difference in optimization accuracy and efficiency caused by different measurement points, the effect of single condition change and multiple condition changes of the track beam is not obvious, so the AWOA can also be used to analyze multiple condition changes of the track beam.

Table 2. Data of convergence speed and optimization accuracy data.

Model	Optimization method	Measurement points	Average error	Maximum error	Number of iterations
Model_2	WOA	mid span	2.18%	5.9%	423
		1/4 span, mid span, 3/4 span	2.08%	5.8%	368
	AWOA	mid span	1.66%	3.6%	246

Model_3	WOA	1/4 span, mid span, 3/4 span	1.61%	3.4%	215
		mid span	2.83%	11.9%	1152
	AWOA	1/4 span, mid span, 3/4 span	2.08%	5.2%	406
		mid span	2.66%	10.5%	957
		1/4 span, mid span, 3/4 span	1.63%	3.5%	253

5. Conclusion

An analytical framework based on the adaptive whale optimization algorithm and deflection influence line is constructed using finite element model modification techniques, and its feasibility is verified for high-dimensional parametric condition assessment of cross-seat monorails. The following conclusions are drawn:

(1) In terms of the efficiency of the optimization algorithm, the Whale Optimization Algorithm and Adaptive Whale Optimization Algorithm have a maximum error of 5.8% and 3.5% in the identification of high-dimensional (20-dimensional) parameters of the cross-seat monorail track beam, both of which can be used in the condition assessment of the track beam. In addition, the adaptive whale optimization algorithm optimizes the accuracy and rate of the standard whale optimization algorithm;

(2) In terms of optimization target selection, when multiple condition changes occur in the track beam, compared to using only the mid-span influence line data, using the 1/4 span, mid-span, and 3/4 span deflection influence lines as the optimization target can reduce the error from 10.5% to 3.5% (solved by the adaptive whale optimization algorithm) and improve the accuracy of the track beam state assessment.

Declaration of Competing Interest

The authors wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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