Application of Optimizing Multifactor Correction in Fatigue Life Prediction and Reliability Evaluation of Structural Components

Yi Zhang
Department of Hydraulic Engineering, Henan Vocational College of Water Conservancy and Environment,
Zhengzhou, 450000, China

***Abstract*—Multi factor correction is optimized for fatigue life prediction and reliability evaluation of structural components. Based on the optimization of Bayesian theory, reliability evaluation is carried out to improve the efficiency of fatigue life prediction and reliability evaluation of structural components. The research results indicate that the crack propagation length increases with the increase in loading time. The average probability density of the modified method is 3.628, while the probability density of the traditional fracture mechanics model is 1.242. Based on the multi factor modified crack propagation prediction model, the predicted data accuracy exceeds the traditional fracture mechanics model. It is consistent with the experimental results. The crack propagation prediction model based on multi factor correction can ensure the accuracy of the prediction. The reliability of the model is evaluated. The average prediction accuracy of multiple sets of data is over 90%. This research method helps predict the fatigue life of structural components and evaluate reliability to ensure the safe operation of construction machinery.**

***Keywords*—Multi factor bayesian theory correction; structural components; fatigue life; reliability; Bayesian theory**

I. Introduction

A. Research Background

Industrial machinery is an important equipment of modern industry and an indispensable core part of the machinery, shipbuilding and other industries. However, with the increasing complexity of construction machinery and the harsh service environment, the fatigue life and reliability of structural parts are increasingly prominent. In this case, accurate prediction of fatigue life and reliability assessment of structural components are particularly important [1]. Due to its large weight and high labor intensity, the minor failure of construction machinery structural parts will cause great losses, and even threaten personal safety in serious cases [2]. If the health status of the equipment is not fully considered and the life of the equipment is regarded as the standard, the blanket elimination of the equipment will lead to a great waste of resources [3]. However, due to the joint action of multiple factors such as material defects and local stress concentration, the damage process of structural parts has been expanded from microscopic to macroscopic, from cavity formation to growth, and from unknowable to observable. The influencing factors span time and space, including known and unknown, and the multi-scale comprehensive effect will have a multi-faceted impact on the evaluation results [4].

B. Research Status

In the existing studies, only the influence of a single factor on the life of structural parts is generally considered, and the evaluation results of this evaluation method are not comprehensive enough. The multi-factor correction method has also been paid more attention, but there are still some limitations. For example, traditional multi-factor correction methods tend to consider only a few major influencing factors and ignore other potential influencing factors. In addition, traditional correction methods are often based on empirical formulas or simple mathematical models, and it is difficult to accurately describe the complex variation laws of fatigue life and reliability of structural parts [5-6].

C. Research Content

Aiming at the limitations of existing studies, this study improved the multi-factor correction to improve the prediction and evaluation accuracy and constructed a fatigue life prediction and reliability evaluation method based on multi-factor optimization and modification. The purpose of this method is to grasp the health state of the structural parts in the process of mechanical production and maintain them in time. The innovation of the research is to predict the life of structural parts from multiple factors and introduce Bayesian theory to optimize the reliability evaluation results.

This research is mainly divided into six sections. Section II is a literature review, introducing the relevant research content of scholars in different fields. Section III is the research method, mainly introducing the fatigue life prediction and reliability evaluation of structural parts based on optimized multi-factor repair. Section IV and Section V are the result analysis, which explains the application analysis of optimized multi-factor correction in fatigue life prediction and reliability evaluation of structural parts. Section VI is the conclusion, and points out the future research direction. A structured roadmap of research content is shown in Fig. 1.

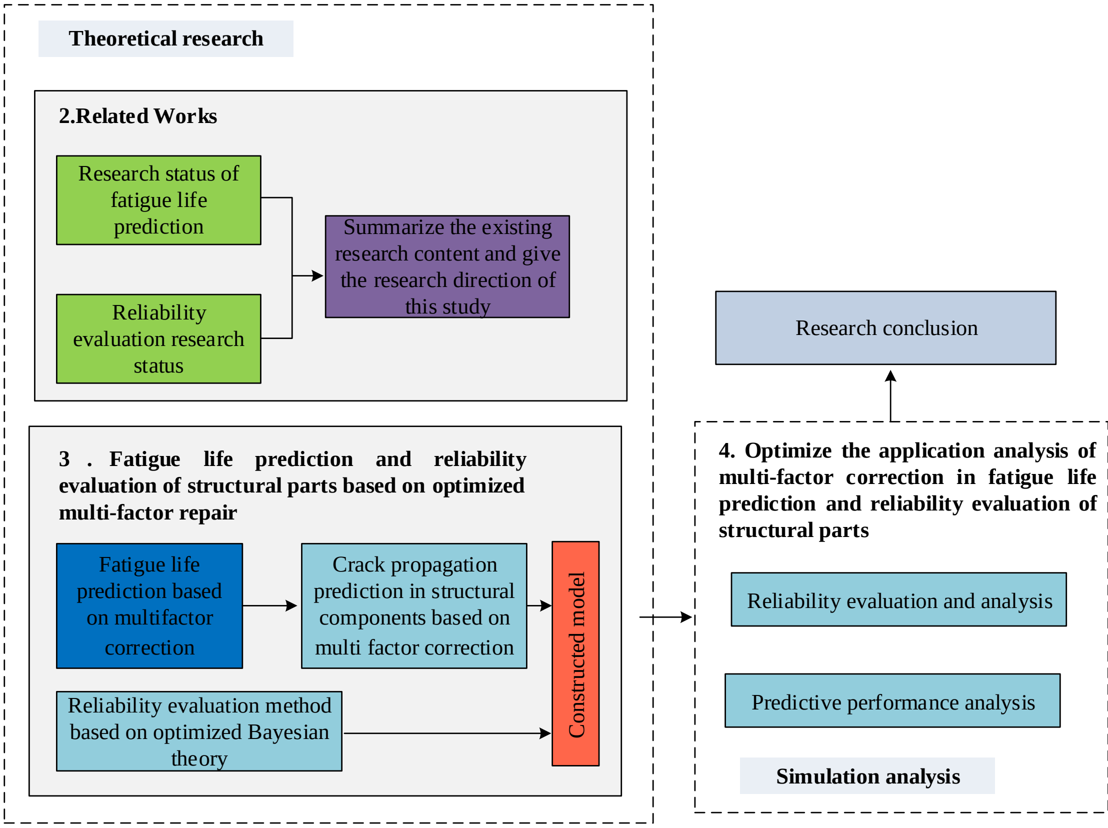

Fig. 1. A structured roadmap for the research content.

II. Related Works

The failure of construction machinery components may cause serious harm. Therefore, the research on FL prediction and reliability evaluation is very important. Due to the high working intensity and high use frequency of structural components, reliability has always been the focus of research in this field. Scholars in different fields have carried out a lot of research and achieved good results.

Kaplan h proposed a new IOT fatigue damage sensor system for residual FL prediction of key mechanical and structural components, which can estimate the cumulative fatigue damage and residual FL. According to the findings, it has high prediction accuracy, which is conducive to checking the operation of structural parts at any time [7]. Prakash designed a probability model based on the Palmgren-Miner rule to better evaluate the fatigue state of ageing infrastructure. Bayesian method is used to estimate the parameters. Markov chain Monte Carlo simulation is applied to predict the FL. According to the findings, it can effectively improve the residual FL prediction accuracy of bridge components [8]. Su and other scholars predicted the FL of steel bridges. Based on the equivalent structural stress, a general fatigue reliability calculation model is established. The practicability and effectiveness of the fatigue reliability model are verified by numerical calculation and sensitivity analysis. It can better solve the classification problem that is difficult to determine in the random FL assessment of steel bridge welded structures [9]. The high pole lamp pole is easy to be affected by the wind load, which causes the fatigue failure of the whole life cycle. Therefore, Tsai l w et al. carried out the FL assessment of the base-pipe joint under the wind load. On this basis, the damage fraction under wind load is used to evaluate the FL of different structural parts. According to the findings, it can provide a general framework for designers and producers to develop high-pole lighting pole equipment [10]. Klemenc and other scholars designed a step-stress accelerated life test to test the FL and structural component reliability of main failure modes. The expected acceleration factor is checked. The experimental results show that the predicted step stress accelerated life test duration has a good correlation with the actual experiment [11].

According to the specific reliability requirements of the current wind turbine life, Nielsen j s et al. proposed a risk-based derivation method for the specific target reliability level of wind turbine life extension. The experimental results show that the target annual reliability index is close to 3.1 [12]. Leonetti and other researchers designed a probabilistic FL prediction model based on S-N curve to evaluate the safety level of non-load bearing cross joints. The results show that the reliability index can be increased by 0.5:1 by using this model, which is conducive to the safety evaluation [13]. To test the fatigue characteristics of the laminated chip assembly under thermal cycle load, Li et al. developed a laminated chip assembly with multiple packaging methods and different chip positions. Through creep FL prediction models under various stress states, the FL of chips is evaluated. The outcomes indicated that the stress of the top mount solder joint is much smaller than that of the bottom mount solder joint. The middle position of the inner ring of the solder joint has the maximum value [14]. To evaluate the reliability of offshore wind turbine support structures with pitting fatigue, Shittu et al. used the damage tolerance modeling method to evaluate the reliability of such structures with pitting fatigue. A non-invasive formula consisting of a series of steps is proposed. At a certain size, the height and width of the pit have a great influence on the structural reliability [15].

From the above research, the FL prediction and reliability evaluation of structural parts are conducive to promoting the safe operation and stability of construction machinery. Then the above studies only consider single factor, and the reliability of prediction and evaluation needs to be improved. Therefore, this study considers multiple factors for comprehensive prediction and evaluation.

III. Fatigue Life Prediction and Reliability Evaluation of Structural Components Based on Optimized Multi Factor Correction

Through multi factor correction, the fatigue life of structural components is predicted. Based on optimized multi factor correction, the crack propagation of structural components is predicted. According to optimized Bayesian theory, reliability evaluation is carried out to improve the efficiency of FL prediction and reliability evaluation of structural components.

A. *Fatigue Life Prediction Based on Multifactor Correction*

With the continuous progress of science and technology, the understanding of fatigue issues continues to deepen. A series of FL prediction methods have been widely applied, such as nominal stress method, field strength method, etc. However, in practical applications, the nominal stress method and local stress-strain method are commonly used. The traditional nominal stress method mainly analyzes the maximum stress of the structure. Based on the maximum stress and the S-N curve of the material, the FL of the structure is predicted [16]. With the continuous development of finite element technology, the combination of traditional nominal stress method and finite element technology is an important research direction for predicting the FL of structural components under complex loads. This method has simple analysis steps, wide applicability, and strong practical value. However, due to the different fatigue characteristic parameters between structural components and material samples, it is difficult to ensure the accuracy of FL prediction between structural components and material samples. Therefore, starting from the actual characteristics of engineering components, the main controlling factors for the FL of structural components are identified and quantified. Furthermore, a set of FL prediction methods for structural components considering the combined effects of multiple factor corrections is established.

Quantitative research on the impact of multiple factors on the fatigue performance of structural components is the basis for accurately predicting the FL of structural components. Stress concentration has a certain impact on the stress state of load-bearing structural components, which in turn affects the FL of the structure. The stress concentration factor is an important indicator that can distinguish the influence degree of stress concentration. There are two commonly used methods for obtaining stress concentration factors, namely the calculation method and the measurement method [17]. The measurement method is mainly aimed at elemental samples and is not suitable for large-sized components. The finite element method and numerical simulation method are more suitable for calculating the stress concentration coefficient of large-sized structural components. The calculation steps are shown in Fig. 2.

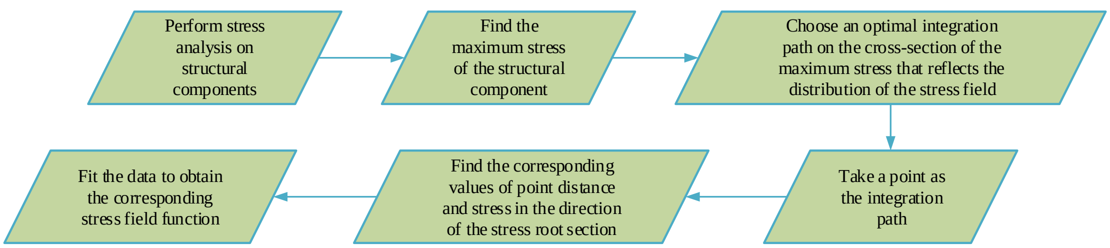

Fig. 2. Calculation steps for stress concentration coefficient.

From Fig. 2, stress analysis is first conducted on the structural component to determine the maximum stress. An optimal integration path is selected on the cross-section of the maximum stress that reflects the distribution of the stress field. Then a point is used as the integration path to obtain the corresponding values of point distance L and stress S in the direction of the stress root section. By fitting these data, the corresponding stress field function can be obtained. The stress field function is used for calculation in Eq. (1). The nominal stress corresponding to the stress field is shown in Eq. (1).

$$S_n = \frac{\int_0^L S(L)dL}{L} = \frac{\sum_{i=0}^{n-1}\int_{L_i}^{L_{i+1}} S_i(L)dL}{L} \tag{1}$$

In Eq. (1)， $L = \sum_{i=0}^{n} L_i$. The nominal stress is taken into Eq. (2) for calculation. The stress concentration factor corresponding to the structural component is obtained.

$$K_t = \frac{S_{\max}}{S_n} \tag{2}$$

To evaluate the prediction accuracy of this method, finite element technology is used to analyze the material standard samples. The size factor of structural components is a parameter that reflects the influence of structural component size on FL. The fatigue limit relationship between structural components and materials is shown in Eq. (3) [18].

$$\sigma_{0r} = \frac{\sigma_r}{K_t}\left[f\left(x_1, x_2\right)\right]^{-1} \tag{3}$$

In Eq. (3), σ_{0r} and σ_r represent the fatigue limit of structural members and materials respectively. $f\left(x_1, x_2\right)$ is a function of the stress field near the local maximum stress. x_1 and x_2 are the coordinate parameters of the plane field respectively. The stress field function can also be expressed by the distance $L(i)$ between a point under the stress integration path in the stress field and the root of the maximum local stress, as shown in Eq. (4).

$$f\left(x_1, x_2\right) = \eta_1 + \eta_2 L(i) + \eta_3 L^2(i) + \eta_4 L^3(i) \tag{4}$$

When the materials of two components are consistent, the size factor between the two components that meet the principle of similarity is shown in Eq. (5).

$$\varepsilon = \frac{\sigma_{0r1}}{\sigma_{0r2}} \tag{5}$$

In Eq. (5), ε represents the size factor. By combining Eq. (3), Eq. (4), and Eq. (5), another representation of the size factor can be obtained, as shown in Eq. (6).

$$\varepsilon = \frac{\int_0^l \left(\vartheta_1 + \vartheta_2 L' + \vartheta_3 L'^2 + \vartheta_4 L'^3\right) dL'}{\int_0^l \left(\eta_1 + \eta_2 L + \eta_3 L^2 + \eta_4 L^3\right) dL} \tag{6}$$

In Eq. (6), $\eta_1, \eta_2, \eta_3, \eta_4$ and $\vartheta_1, \vartheta_2, \vartheta_3, \vartheta_4$ are both coefficients in the fitting function expression. The size factor of a single component can be represented by the integral ratio between the component and the reference sample in the stress field. Different surface treatment methods not only have different effects on the stress state of components, but also have impacts on the FL of components [19]. In addition, the loading method can also affect the FL. The influence of loading method factor on loading form is corrected. The FL prediction expression based on nominal stress is generally shown in Eq. (7).

$$S^m N = C \tag{7}$$

In Eq. (7), S represents stress. N is used to describe the number of loading times for the load. m and C represent parameters related to material and stress ratio. By combining the influence of various factors and Eq. (7), a FL prediction algorithm based on optimized multi factor correction can be obtained, as shown in Eq. (8).

$$\left(\frac{S_{-1}\left[1 - \left(\sigma_m / \sigma_b\right)^2\right]}{K_t} \cdot \varepsilon \cdot \beta \cdot C_L \right)^m N = C \tag{8}$$

In Eq. (8), S_{-1} represents the material fatigue limit under symmetric loading. σ_m is the average stress, $\sigma_m = \dfrac{\sigma_{\max} + \sigma_{\min}}{2}$. $\sigma_{\max}$ and $\sigma_{\min}$ are the maximum and minimum values of stress, respectively. σ_b represents the tensile strength limit of the material. K_t represents the stress concentration factor. β is the surface quality factor. N represents FL. C_L represents the loading method factor. The implementation steps of the FL prediction method based on optimized multi factor correction are shown in Fig. 3.

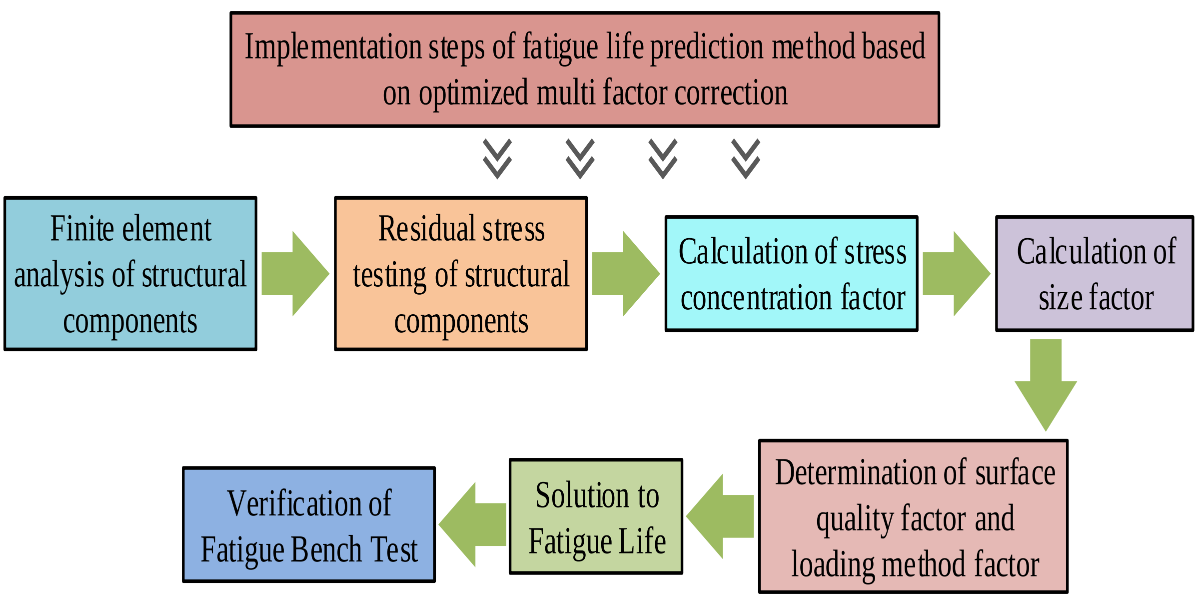

Fig. 3. Implementation steps of fatigue life prediction method based on optimized multi factor correction.

From Fig. 3, during the implementation process, a finite element model of the structural component is first established and analyzed. Residual stresses in the structural components are tested. Then, stress concentration factors and size factors are calculated. Then, the surface quality factor and loading method factor are determined. After solving the FL, the fatigue bench test can be verified.

B. Crack Propagation Prediction in Structural Components Based on Multi Factor Correction

Crack propagation information is an important feature in the reliability evaluation of structural components. Accurately predicting crack development is crucial for grasping the reliability of structural components. However, due to structural and other factors, a crack propagation prediction model containing structural and other factors is established to quantitatively correct each influencing factor. Although existing fracture mechanics calculation methods cannot simultaneously correct multiple influencing factors, there is already a method that utilizes multiple factors to correct the S-N curve [20]. The current judgment method is based on the development of cracks to fracture as the basis for determining failure. Therefore, the traditional FL prediction method based on S-N curve cannot be applied to the crack development stage of structural components. The core issue is that it does not include parameters that reflect its development process. The multi factor joint correction method is adopted based on the failure criterion of crack development to fracture. The stress concentration coefficient is introduced to accurately describe the crack length, thereby achieving prediction of crack length. Based on the multi factor correction method for predicting the FL of structural components in the previous section, the structural factors, average stress, and other factors on the FL are quantitatively represented, as shown in Eq. (8). The failure criterion is based on the extension of cracks towards the fracture state. K_t is the only parameter in the algorithm that can be associated with the crack length a, as shown in Eq. (9).

$$K_t = \frac{\sigma_{\max}}{\sigma_n} \tag{9}$$

In Eq. (9), σ_n represents the nominal stress. The expression is shown in Eq. (10).

$$\sigma_n = \frac{\sum_{i=0}^{n-1} \int_{r_i}^{r_{i+1}} \sigma_i dr}{A} = \frac{\int_0^A \sigma_i dr}{A} \tag{10}$$

In Eq. (10), r_i represents the distance between any point in the stress field and the maximum stress position at the crack root, $A = r_{\max}$. σ_i represents the stress value at any point along the stress field path. Combining Eq. (9) and Eq. (10), the expression for the stress concentration factor can be obtained, as shown in Eq. (11).

$$K_t = A \Big/ \int_0^A \frac{(a+r)}{\sqrt{2ar + r^2}} dr \tag{11}$$

By combining Eq. (8) and Eq. (9), the crack propagation length can be obtained when the working time N is specified, as shown in Eq. (12) [21].

$$S_{-1} \cdot \left[1 - \left(\sigma_m / \sigma_b\right)^2\right] \cdot \left(\frac{C}{N}\right)^{-\frac{1}{m}} \cdot \varepsilon \cdot C_L \cdot \beta = A \Big/ \int_0^A \frac{(a+r)}{\sqrt{2ar + r^2}} dr \tag{12}$$

The implementation process of the crack propagation prediction model based on multi factor correction under constant amplitude load is explained, as shown in Fig. 4.

From Fig. 3, during the implementation process, the stress at the crack root of the structural component is first analyzed. Then the material parameters and correction factors are determined. Then the crack propagation of the structural component is predicted. Finally, the acoustic emission test is verified.

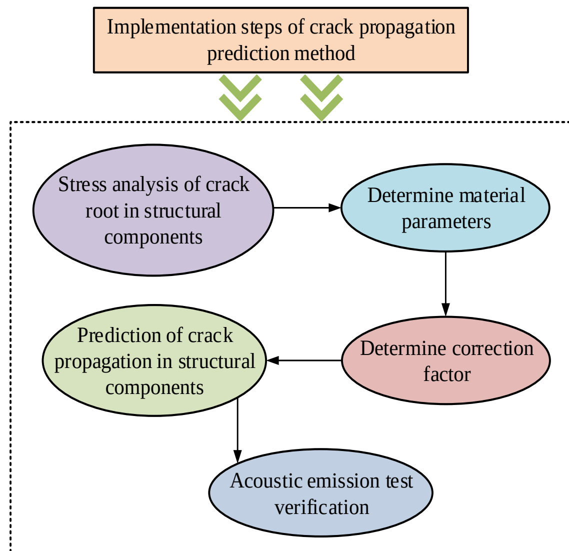

Fig. 4. Implementation steps of crack propagation prediction method.

C. Reliability Evaluation Method Based on Optimized Bayesian Theory

In practical applications, due to various uncertain factors, there is a deviation between the predicted results obtained by a single numerical prediction model and the actual situation. Therefore, based on the Bayesian theory of dynamic distribution parameters, existing numerical prediction models and experimental data are organically integrated. Corresponding prior and posterior probability distribution models are constructed to achieve accurate reliability evaluation of structural components. If the initial reliability of different materials is divided according to certain parameters and the ordered reliability between test data is characterized by a certain increasing coefficient, then the NHPP model based on Bayesian theory can be used to evaluate the reliability of components under different initial damage conditions.

The conventional Bayesian theory is no longer applicable to the reliability of components with cracks in different initial crack states, such as non-uniform crack situations. If a parameter based on initial reliability can be established and the ordered reliability between test data can be characterized, an ordered Bayesian model can be used to evaluate the reliability of materials in different initial states. The specific process is shown in Fig. 5.

From Fig. 5, the reliability sequence model is combined with NHPP. The sequence relationship between various test data and overall process parameters is fused through Bayesian theory to obtain a Gama Beta prior probability distribution suitable for NHPP model parameters. Then, Bayesian theory is combined with likelihood functions of multiple test processes to obtain the NHPP posterior probability distribution. Afterwards, the existing measured data is used to predict and evaluate the reliability of component crack development under different initial conditions. In this research, the stress concentration factor is selected as a parameter that reflects the reliability gradient relationship between different data values of structural components, namely the progressive factor.

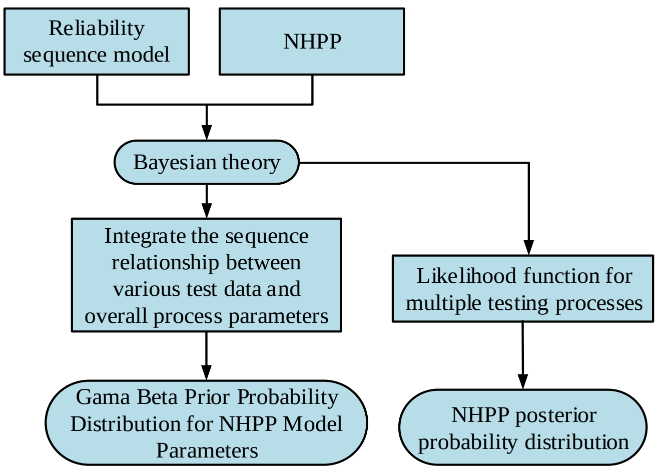

Fig. 5. Specific process of research.

The progressive factor is a very important parameter in establishing the reliability ordering relationship between data. Therefore, data statistics are conducted to determine the discreteness. $\left[\delta_{j,L},\delta_{j,U}\right]$ serves as the value space for the progressive factor to reduce the impact of calculation errors in stress concentration factors on the progressive factor. The corresponding first-order and second-order matrix expressions are shown in Eq. (13).

$$\begin{cases} E\left\{\delta_j\right\}=\dfrac{\delta_{j,U}+\delta_{j,L}}{2} \\ E\left\{\delta_j^2\right\}=\dfrac{\delta_{j,U}^3+\delta_{j,L}^3}{3\left(\delta_{j,U}+\delta_{j,L}\right)} \end{cases} \tag{13}$$

In Eq. (13), $E\left\{\delta_j\right\}$ and $E\left\{\delta_j^2\right\}$ represent the progressive factor value space considering calculation errors. In the prior distribution based on Bayesian theory NHPP, there is no conjugate prior distribution of parameters. Therefore, the main problem is to accurately describe prior information and determine prior distribution. When the initial crack is very small, two methods are usually used to construct an uninformed prior distribution, namely constructing an uninformed prior distribution, or using existing theoretical models to predict prior information. The expression for constructing an uninformed prior distribution using the Box-Tao method is shown in Eq. (14).

$$\pi\left(\alpha,\beta\right)\infty\left(\frac{1}{\beta_1\alpha^2}\right),\alpha>0,\beta_1>0 \tag{14}$$

By standardizing the description of prior information and integrating information between different types of data, Bayesian reliability sequences for different cracks are constructed. In posterior reasoning, based on Bayesian theorem and combined with group likelihood function, the posterior distribution of NHPP parameters is obtained. To further verify the feasibility and analytical accuracy of the model, fatigue loading tests were conducted on components with different initial crack lengths. Among them, the ordering relationship is the fundamental condition for the application of the model. Therefore, the sequencing relationship between the analyzed data is verified. The statistical criteria for validation are shown in Eq. (15).

$$F*=\frac{L^*_{N+1,j}-L^*_{N_i,j}}{L^*_{N+1,j+1}-L^*_{N_i,j+1}}\geq 1 \tag{15}$$

In Eq. (15), j and $j+1$ represent two data groups. $F*$ is the test statistic. $L^*_{N+1,j}$ represents the crack propagation length corresponding to the number of N_i load actions in the organized data. After satisfying the serialization relationship in the model assumption, Eq. (12) can be used to predict the crack propagation data under annotated loads.

IV. Application Analysis of Optimized Multi Factor Correction in FL Prediction and Reliability Evaluation of Structural Components

For the prediction and reliability evaluation of FL for structural components, the crack propagation under constant load and the reliability of structures under different initial crack states are analyzed to promote the reliability evaluation and safe operation of engineering machinery structural components.

A. *Prediction Analysis of Crack Propagation Under Constant Load*

The accuracy of predicting crack propagation based on multi factor correction under constant load is verified. A structural component with a crack length of 600mm, a crack width of 100mm, and a crack length of 50mm is selected as the analysis object. The crack propagation model will be calculated according to the parameters calculated in the method to obtain the crack length propagation curve. The results are shown in Fig. 6.

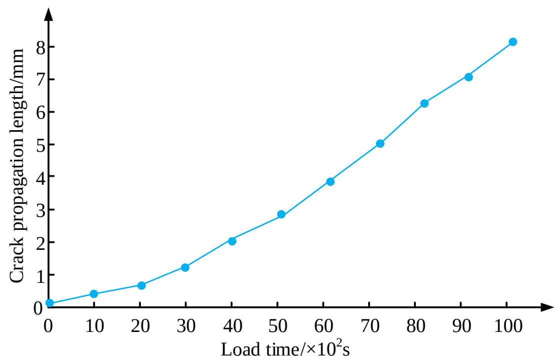

Fig. 6. Crack propagation curve based on multi factor correction.

From Fig. 6, the crack propagation length increases with increasing loading time. When the loading time is 2000s, the crack propagation length is 0.9mm. When the loading time is 10000s, the crack propagation length is 8.5mm. To analyze the accuracy of prediction, crack propagation prediction is carried out based on multi factor correction. The loading times are fixed. The results are shown in Fig. 7.

From Fig. 7(a), (b), (c), (d), and (e) represent the probability density at 2000, 4000, 6000, 8000, and 10000 loading times, respectively. The horizontal axis stands for the crack propagation length, and the vertical axis stands for the probability density. CM represents the correction method. FM stands for fracture mechanics. The curve in the figure represents the probability density distribution corresponding to the acoustic emission test data. Each crack propagation length value corresponds to a probability density value. The probability density values corresponding to the modification method and fracture mechanics method are marked in the figure. The red area represents the difference in probability distribution between the two methods. According to the analysis results, the average probability density of the modified method is 3.628. The probability density of traditional fracture mechanics models is 1.242. Based on the multi factor modified crack propagation prediction model, the accuracy of the predicted data is significantly higher than that of traditional fracture mechanics models. It is consistent with the experimental results. Therefore, a crack propagation prediction model based on multi factor correction can ensure the accuracy of the prediction.

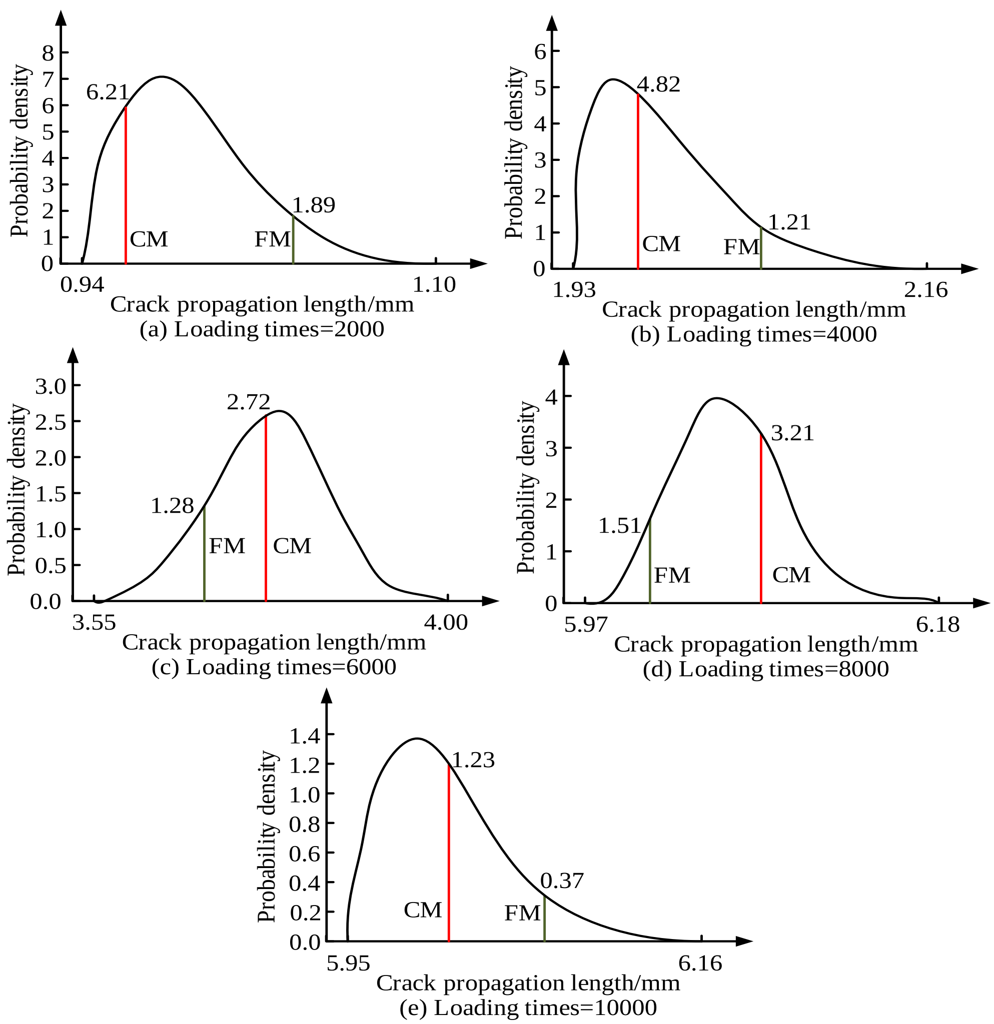

Fig. 7. Probability density distribution of predicted data.

B. Structural Reliability Evaluation Analysis Under Different Initial Crack States Based on Bayesian Theory NHPP

To further verify the feasibility and accuracy of the model, crack lengths of 5mm, 10mm, and 15mm are prepared. Fatigue loading experiments are conducted on components with different initial crack lengths. The fatigue crack propagation life of the structural components is displayed in Table I. In order to evaluate the generalization ability of the model and verify its accuracy in practical applications, the method of cross-validation is used to retrain and test the model. The performance of the model is evaluated by dividing the raw data into K parts and recycling K-1 of them as training data and the remaining part as test data. In the experiment, the study chose to use 10-fold cross-validation to perform this step. The first group has an initial crack length of 5mm, the second group is 10mm, and the third group is 15mm. The sequencing accuracy is analyzed. In the initial state, the experimental data and maximum probability prediction results of the posterior process model are compared. The prediction accuracy of the test data is obtained. Table II displays the results.

The combination of known critical fracture crack length and predicted data can obtain the predicted reliability gradient process of structural components under different initial crack states. The results are shown in Fig. 8.

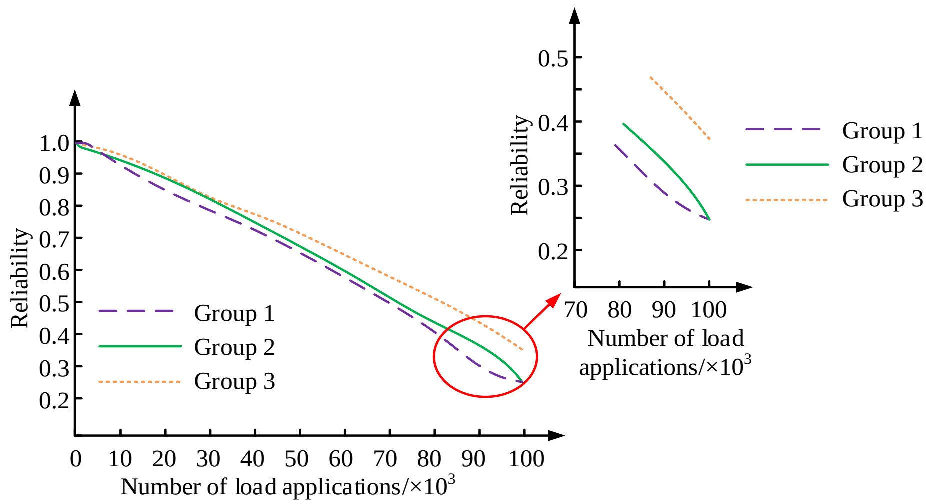

Fig. 8. The gradual process of predictive reliability of structural components under different initial states.

TABLE I. CRACK PROPAGATION INFORMATION OF COMPONENTS IN DIFFERENT INITIAL STATES

Initial crack length=5mm		Initial crack length=10mm		Initial crack length=15mm	
Number of load applications ($\times 10^4$)	Crack propagation length/mm	Number of load applications ($\times 10^4$)	Crack propagation length/mm	Number of load applications ($\times 10^4$)	Crack propagation length/mm
1	4.20	1	4.81	1	5.12
2	8.65	2	9.96	2	10.62
3	13.41	3	15.36	3	16.37
4	18.35	4	21.03	4	22.43
5	22.91	5	26.25	5	27.96
6	28.21	6	32.26	6	34.47
7	33.09	7	37.93	7	40.51
8	38.60	8	44.31	8	47.18
9	43.94	9	50.38	9	53.77
10	51.18	10	58.65	10	62.56

TABLE II. ACCURACY OF PREDICTION RESULTS

Initial crack length(mm)(Group)	Average prediction accuracy (%)
5(Group 1)	91.41
10(Group 2)	92.13
15(Group 3)	92.80

From Fig. 8, the predicted reliability of structural components under three different initial crack states decreases with the increase of load actions. When the load times are 100×10^3, the reliability of the first and second group of data is 0.28.

It can be seen that the reliability of the second group of data continues to decline. While the third group of data tends to be stable.

The reliability is ranked from high to low in the third group, the second group, and the first group.

C. Structural Reliability Evaluation Results Under Different Initial Crack States

In practical engineering, it is common to face the reliability evaluation of multiple similar structural components. Therefore, fatigue loading experiments are conducted on structural components with different initial crack lengths of 10mm, 25mm, 38mm, and 43mm. The fatigue crack propagation data of structural components are illustrated in Table III.

In Table III, the first group has an initial crack length of 10mm, the second group is 25mm, the third group is 38mm, and the fourth group is 430mm. Similarly, for the data in Table III, a cross-validation approach was adopted to train and test the model. Table IV displays the accuracy of the test data.

Afterwards, the known critical fracture crack length is combined with predicted data to obtain the reliability gradient process of structural components under different initial crack states, as shown in Fig. 9.

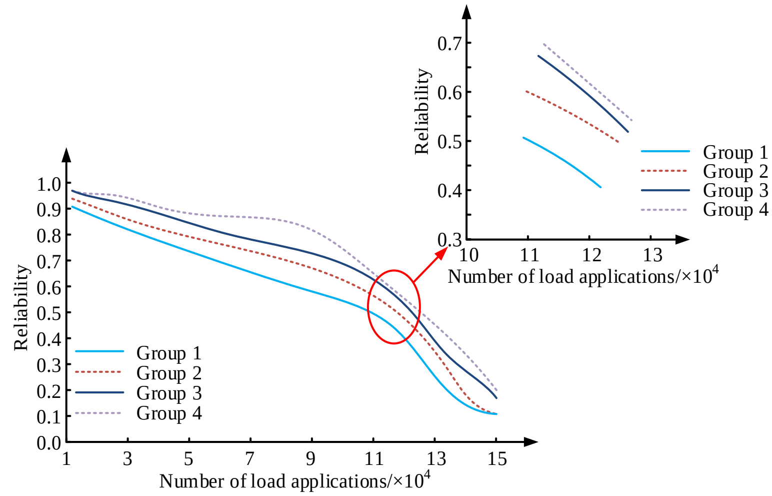

Fig. 9. Gradual process of component reliability under four different initial states of cracks.

TABLE III. CRACK PROPAGATION OF COMPONENTS CORRESPONDING TO DIFFERENT INITIAL CRACK SIZES

Initial crack length=10mm		Initial crack length=25mm		Initial crack length=38mm		Initial crack length=43mm	
Number of load applications ($\times10^4$)	Crack propagation length/mm	Number of load applications ($\times10^4$)	Crack propagation length/mm	Number of load applications ($\times10^4$)	Crack propagation length/mm	Number of load applications ($\times10^4$)	Crack propagation length/mm
1	3.92	1	6.31	1	9.24	1	10.88
2	9.16	2	14.40	2	21.15	2	21.55
3	14.46	3	21.01	3	29.56	3	30.27
4	18.56	4	25.91	4	35.23	4	37.46
5	21.06	5	29.18	5	38.95	5	43.51
6	22.10	6	31.20	6	41.43	6	48.81
7	22.49	7	32.73	7	43.45	7	53.75
8	23.75	8	34.83	8	45.76	8	58.76
9	27.95	9	38.94	9	49.05	9	64.24
10	38.01	10	46.75	10	54.08	10	70.55
11	57.29	11	60.35	11	61.57	11	78.13
12	72.23	12	76.10	12	79.98	12	87.32
13	86.75	13	92.49	13	96.35	13	98.58
14	105.89	14	112.35	14	115.18	14	123.04
15	128.91	15	130.25	15	138.63	15	146.35

TABLE V. ACCURACY OF FOUR SETS OF TEST DATA PREDICTION RESULTS

Initial crack length(mm)(Group)	Average prediction accuracy (%)
10(Group 1)	90.99
25(Group 2)	91.21
38(Group 3)	92.84
43(Group 4)	92.95

From Fig. 9, the predicted reliability of structural components under four different initial crack states decreases with the increase of the load actions. When the load times are 12×10^4, the reliability of the third set of data is almost close to that of the fourth set of data, but it is still lower than that of the fourth set of data after that. The reliability is ranked from high to low in the fourth group, the third group, the second group, and the first group.

The fatigue life prediction and reliability of structural parts are evaluated by considering many complex factors. In order to test the superiority of the multi-factor evaluation method, the performance of the study was compared with that of the single factor evaluation method. The comparative single-factor evaluation methods included initial crack length, material type, loading frequency, and ambient temperature. Under the same experimental conditions, four groups of structural parts with different initial crack lengths were predicted and evaluated by using these four single factor evaluation methods. The experimental results are shown in Table V.

TABLE VI. COMPARISON OF PREDICTION ACCURACY BETWEEN MULTI-FACTOR AND SINGLE-FACTOR EVALUATION METHODS

Initial Crack Length (mm)	Evaluation Method	Average Prediction Accuracy (%)	Evaluation Accuracy (%)
10	Single Factor (Initial Crack Length)	82.35	82.45
	Single Factor (Material Type)	84.02	83.74
	Single Factor (Loading Frequency)	80.47	80.45
	Single Factor (Ambient Temperature)	87.84	87.45
	Multi-Factor Evaluation Method	92.45	92.74
25	Single Factor (Initial Crack Length)	82.45	83.45
	Single Factor (Material Type)	83.97	84.05
	Single Factor (Loading Frequency)	80.42	80.94
	Single Factor (Ambient Temperature)	87.15	87.84
	Multi-Factor Evaluation Method	92.48	93.05
38	Single Factor (Initial Crack Length)	82.48	82.01
	Single Factor (Material Type)	83.89	84.94
	Single Factor (Loading Frequency)	80.74	90.14
	Single Factor (Ambient Temperature)	87.56	85.74
	Multi-Factor Evaluation Method	93.08	94.78
43	Single Factor (Initial Crack Length)	82.84	82.41
	Single Factor (Material Type)	82.97	83.06
	Single Factor (Loading Frequency)	80.15	81.15
	Single Factor (Ambient Temperature)	87.45	88.01
	Multi-Factor Evaluation Method	92.56	92.45

It can be seen from Table V that under any initial crack length, the prediction accuracy of the multi-factor evaluation method is higher than that of the single-factor evaluation method. This shows that considering the combined influence of many factors is very important to accurately predict the fatigue life and reliability of structural parts. Especially in the complex working environment and variable load conditions, the single factor evaluation method often cannot fully reflect the actual state of the structural parts, while the multi-factor evaluation method can more accurately describe the performance change and reliability gradient process of the structural parts.

V. THE RESULTS OF THE RESEARCH

In the process of crack growth prediction analysis under constant load, it is found that the crack growth length increases with the increase of loading time. When the loading time was 2000s, the crack growth length was 0.9mm, and when the loading time was 10000s, the crack growth length was 8.5mm. This indicates that the crack growth rate is not linear, but the crack growth rate is slow at the initial stage of loading, and then gradually accelerates. In order to better understand this nonlinear crack growth process. Under different loading times, the predicted probability density value of CM is significantly higher than that of FM, and the average probability density number of the modified method is 3.628, while the probability density number of the traditional fracture mechanics model is 1.242. Based on the multi-factor modified crack growth prediction model, the predicted data accuracy is significantly higher than that of the traditional fracture mechanics model. In reliability evaluation analysis, the longer the initial crack length, the higher the reliability. In comparison with the experimental results of other methods, the prediction accuracy and reliability evaluation accuracy of the proposed method are both above 90%, which are 92.64% and 93.26%, respectively. In conclusion, the multi-factor evaluation method has obvious superiority and wide application prospect in the fatigue life and reliability evaluation of structural parts.

VI. Conclusion

Construction machinery is important in the "the Belt and Road" initiative. With the advancement of modernization construction, its development prospects are still broad. Continuously improving the safety and reliability of construction machinery can better support national economic development and ensure that it plays a positive role in the application of various industries. The operational safety and stability of construction machinery are crucial for the economic benefits of enterprises and the safety of personnel. For predicting and evaluating the FL of structural components, multiple complex factors need to be considered. It is a challenge that must be faced in practical engineering. Multiple factors are modified for predicting the FL and reliability evaluation of structural components. According to the research results, the crack propagation length increases with increasing loading time. When the loading time is 2000s, the crack propagation length is 0.9mm. When the loading time is 10000s, the length is 8.5mm. In the process of single-factor and multi-factor comparison, the prediction accuracy and evaluation accuracy of multi-factor reached 92.64% and 93.26%, respectively. Moreover, in the comparison experiment between the modified method and the traditional fracture mechanics model, the average probability density number of the modified method is 3.628, while the probability density number of the traditional fracture mechanics model is 1.242. Based on the multi-factor modified crack growth prediction model, the accuracy of the predicted data is significantly higher than that of the traditional fracture mechanics model, and is consistent with the experimental results. The crack propagation prediction model based on multi factor correction can ensure the accuracy of the prediction. Subsequent research will investigate the impact of residual stress on crack propagation patterns.

Statements and Declarations

Competing Interests: The author(s) declare none.

Availability of data and materials: The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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