Hindawi
Advances in Materials Science and Engineering
Volume 2020, Article ID 3012471, 10 pages
https://doi.org/10.1155/2020/3012471

Research Article

Fatigue Reliability Analysis of Motor Hanger for High-Speed Train Based on Bayesian Updating and Subset Simulation

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Received 31 January 2020; Accepted 27 February 2020; Published 27 March 2020

Guest Editor: Shun-Peng Zhu

In order to more accurately analyze the fatigue reliability of motor hanger for high-speed train and reduce the influence of uncertain factors, a Bayesian statistical method is introduced to propose a novel fatigue reliability analysis method based on Bayesian updating and subset simulation. First, considering the influence of various uncertain parameters on the first principal stress (FPS) of motor hanger, the ANSYS parametric design language (APDL) is used to establish the parametric model. The D-optimal design of experiment is carried out to calculate the FPS of the motor hanger. Second, the experimental data is fitted by the least square method to establish a polynomial response surface function which characterizes the FPS of the motor hanger, and analysis of variance (ANOVA) is carried out. On this basis, the variation trend of the FPS under parameter fluctuation is calculated, and its probability distribution characteristics are obtained. Based on the MATLAB platform, the Bayesian updating method is adopted to correct the probability and statistical characteristics of the FPS to improve the accuracy of prediction. Finally, the subset simulation (SS) method is used to calculate the fatigue failure probability of the motor hanger. The research results show that the proposed method helps to improve the accuracy and efficiency of fatigue reliability analysis.

1. Introduction

In the design process of mechanical products, the analysis of structural static strength and fatigue strength is the key to ensure that the product meets the standard requirements. However, with the continuous improvement of the operation speed of high-speed trains, in order to ensure the safety and reliability of operation, the design of its key components must meet the requirements of antifatigue design and reliability [1]. Currently, the evaluation of the fatigue performance of key components for high-speed trains is mainly based on fatigue strength and cumulative fatigue damage. The evaluation index can be used to perform fatigue strength analysis and fatigue life prediction on the structure quickly and easily and is easy to compare with the experimental results. But, the disadvantages of this method are that the results of evaluation and analysis are too ideal to consider the design tolerance and manufacturing error, and the comparison with the experimental results is too single and not universal, which is not enough to reflect the fatigue reliability of all products. In response to the above problems, some scholars have combined the reliability theory and fatigue analysis theory to study the fatigue reliability of mechanical products and proposed some fatigue reliability analysis methods [2–12]. Chen et al. [13] proposed a fatigue reliability analysis method that considers the uncertainty of parameters, draws a fatigue limit diagram without safety factor, and gives a more reasonable fatigue reliability analysis result, which is helpful for lightweight design of products. Li et al. [14] established a robust optimization model based on Six Sigma to analyze the fatigue reliability of the pantograph collector head support. This method not only considers the influence of uncertain factors, but also improves the robustness of fatigue life prediction. Bayraktar et al. [15]

considering the number of kilometers and load cycles, statistically evaluated the actual life value. And the theoretical and practical Wohler diagrams S-N is plotted to evaluate the fatigue reliability of the axle. Zhu et al. [16] presented a framework for fatigue reliability assessments and service life prediction based on the estimation of the evolution and probabilistic distribution of fatigue damage over time, and the effectiveness of the method is verified by taking the axle of train as an example. An accelerated life test (ALT) method is proposed by Lu et al. which is first employed to predict the fatigue life of a full-scale bogie frame [17]. This method provides a reference for reliability evaluation of large structures. Zuo et al. [18] studied the fatigue damage of the bogie frame and used the Bayesian updating method to analyze the fatigue reliability of the welded bogie frame. Hu et al. [19] combined finite element method with experiment to evaluate the fatigue reliability of bolster under the application of the design passenger number spectra based on stress-life interference model. The above studies have played an important role in fostering applications of reliability theory for fatigue problems in the structural safety field. For the design process, how to accurately evaluate the fatigue reliability of the structure without experimentation is the premise of predicting whether the design meets the requirements of the standard. Generally, reliability methods based on simulation or approximation have three types: (1) sampling-based methods, (2) moment matching methods, and (3) MPP-based methods. Sampling-based methods are easy to apply and can provide accurate probability estimations with sufficient simulations [20]. Thus, a Bayesian updating combined with subset simulation method is proposed in this article to address the problem.

The contributions of this study are as follows: (1) a response surface function is presented to characterize the functional relationship between random variables and the FPS of the structure; (2) the probabilistic and statistical parameters of the FPS are updated by using Bayesian theory; (3) the limit state equation of fatigue reliability analysis is established; (4) the fatigue failure probability of the motor hanger is calculated by the subset simulation method.

The reminder of the paper is organized as follows. Section 2 reviews Bayesian updating and subset simulation method; we used both methods in fatigue reliability analysis. Section 3 provides details on the proposed approach. Section 4 uses the fatigue reliability analysis of the motor hanger as an example to illustrate its effectiveness and practicality. Finally, Section 5 summarizes and concludes.

2. Bayesian Updating Theory and Subset Simulation Method

2.1. Bayesian Updating Theory. In engineering practice, it is often necessary to make decisions and processes on the data that has already been obtained. These data may include observational data, experimental data, and simulation data. When acquiring new data, it is necessary to update the acquired data to ensure the reliability of the data. In view of the above problems, this paper uses Bayesian method to update and process the uncertainty and difference of simulation data [21, 22].

The basic principle of Bayesian theory can be roughly expressed as using prior distribution and sample information to solve its posterior distribution; that is, the posterior distribution is obtained based on prior information and experimental data [23]. The specific steps for solving it are as follows:

(1) Determine the parameters that need to be solved and set them as random variables

(2) According to the sample data, the corresponding likelihood function and prior distribution function are constructed

(3) The posterior distribution function is obtained by Bayes equation, and the posterior distribution function is used to solve various reliability indexes

Because Bayes method makes full use of prior information and experimental data, the posterior distribution function is more consistent with the probability and statistical characteristics of random variables. The traditional Bayesian equation is given by

$$\pi(\theta \mid x) = \frac{f(x \mid \theta)\pi(\theta)}{p(x)}, \tag{1}$$

where $\pi(\theta \mid x)$ is the posterior distribution function; $\pi(\theta)$ is the prior distribution function; and $p(x)$ is the edge distribution function, and the two types are $p(x) = \sum_{\theta\in\Theta} f(x \mid \theta)\pi(\theta)$ and $p(x) = \int_{\theta\in\Theta} f(x \mid \theta)\pi(\theta)\mathrm{d}\theta$, respectively.

The distribution types of design parameters of key components for high-speed railway are mainly lognormal distribution and normal distribution, and the two probability distributions can be converted to each other. However, the FPS used for fatigue reliability analysis mainly obeys logarithmic distribution. Therefore, the prior distribution of lognormal distribution should be transformed into the prior distribution of normal distribution. The transformation equation can be expressed as

$$\mu_1 = \ln \mu_0 - \frac{(\sigma_1)^2}{2}, \tag{2}$$

$$\sigma_1 = \sqrt{\ln\left[1 + \left(\frac{\sigma_0}{\mu_0}\right)^2\right]}, \tag{3}$$

where μ_0 and σ_0 represent the mean and standard deviation of prior lognormal distribution, respectively, and μ_1 and σ_1 represent the mean and standard deviation of prior normal distribution, respectively.

According to Bayesian theory [24], the posterior distribution function of normal distribution can be obtained from equations (2) and (3), which is written as

$$\mu_2 = \frac{\mu' (\sigma_1)^2 + \mu_1 \left[\left((\sigma')^2 / n' \right) + \sigma_\theta{}^2 \right]}{(\sigma_1)^2 + \left[\left((\sigma')^2 / n' \right) + \sigma_\theta{}^2 \right]}, \quad (4)$$

$$\sigma_2 = \sigma_1 \sqrt{\frac{\left((\sigma')^2 / n' \right) + \sigma_\theta{}^2}{(\sigma_1)^2 + \left[\left((\sigma')^2 / n' \right) + \sigma_\theta{}^2 \right]}}, \quad (5)$$

where μ_2 and σ_2 represent the mean and standard deviation of posterior normal distribution, respectively; μ' and σ' represent the mean and standard deviation of the normal distribution actually obtained from the evaluated parameter, respectively; n' represents the number of statistical samples; and σ_θ represents the standard deviation caused by uncertainties.

Combining equations (2)–(5), the statistical characteristic parameters expression of the evaluated parameters is obtained by Bayesian updating, which is given by

$$\mu_3 = \exp\left[\mu_2 + \frac{(\sigma_2)^2}{2} \right], \quad (6)$$

$$\sigma_3 = \mu_3 \sqrt{\exp (\sigma_2)^2 - 1}, \quad (7)$$

where μ_3 and σ_3 represent the mean and standard deviation of lognormal distribution after Bayesian updating, respectively.

2.2. Subset Simulation Method. The subset simulation method was first proposed by Au and Beck [25], and it is a method that can efficiently deal with high-dimensional and small probability problems. The method can represent the failure probability with a small value as the product of a series of large condition failure probabilities; that is, the simulation process of the small failure probability event is transformed into a series of large event simulation processes. If the intermediate failure event satisfies the nested relationship ($F_1 \supset F_2 \supset \cdots \supset F_m = F$), the target failure probability can be rewritten as

$$\begin{aligned} P_F = P(F) = P(F_m) &= P\left(F_m \mid F_{m-1}\right) P(F_{m-1}) = \cdots \\ &= P(F_1) \prod_{i=2}^{m} P\left(F_i \mid F_{i-1}\right), \end{aligned} \quad (8)$$

where F is the target failure event, $F = \{g(\mathbf{X}) \le b\}$, and b is the critical value of the structural response.

In the reliability analysis, subset simulation starts with direct Monte Carlo in the first step. The probability P_1 is estimated as

$$P(F_1) = \widetilde{P}_1 = \frac{1}{N} \sum_{k=1}^{N'} I_{F_1}(\mathbf{x}_k), \quad (9)$$

$$I_{F_1} = \begin{cases} 1, & \mathbf{x}_k \in F_1, \\ 0, & \mathbf{x}_k \notin F_1, \end{cases} \quad (10)$$

where $\{\mathbf{x}_k \mid k = 1, 2, \ldots, N'\}$ is an independent and identically distributed sample generated by simulation of joint probability density function $q(x)$ with input random vectors; N is the number of sample points per layer; and I_{F_1} is indicator function.

Similarly, the other conditional probabilities are calculated by the idea of equation (9). In the modified Metropolis algorithm, a group of one-dimensional proposal PDFs are used, instead of an n-dimensional proposal PDF which is used in Metropolis algorithm. Thus, the acceptance ratio of individual sample can remain nonvanishing in spite of the increasing of dimension [26, 27]. Thus, in order to efficiently generate conditional samples, this paper implements MCMC simulation based on improved Metropolis–Hastings algorithm.

3. The Analysis Method of Fatigue Reliability

3.1. Fatigue Life Prediction. Fatigue, as the main reason for failure of engineering structures and components, is the main factor affecting the safety of high-speed train operation. Therefore, more and more attention has been paid to antifatigue design in the design process. At present, the prediction of structural fatigue life is mainly based on the *S-N* curve or the *P-S-N* curve. The *S-N* curve represents the stress-life curve, and the *P-S-N* curve is the stress-life curve of the material under different survival conditions. The most commonly used form of *S-N* curve describing materials is the power function form, as follows:

$$S^{-m} \times N = C. \quad (11)$$

Equation (11) can be rewritten as

$$\log C - m \log S = \log N, \quad (12)$$

where m and C are parameters related to material, stress ratio, and loading mode; S represents stress; and N represents lifetime.

According to the design requirements, the material suitable for the motor hanger of high-speed railway trains is S355J2G. However, the mechanical properties of S355J2G are difficult to obtain. For this reason, the material parameters of Q345 similar to its mechanical properties are selected for fatigue reliability analysis [28]. Table 1 gives the main parameters of the material *P-S-N* curve, and the *P-S-N* curve of the material is plotted according to its parameters, as detailed in Figure 1.

3.2. Limit State Equation for Fatigue Reliability Analysis. In this paper, the fatigue lifetime model is selected for fatigue reliability analysis. The model uses fatigue lifetime as the parameter for reliability calculation. The limit state equation can be expressed as

$$Z = N - N_0 = \begin{cases} > 0, \\ = 0, \\ < 0, \end{cases} \quad (13)$$

Table 1: *P-S-N* parameter estimation results of Q345 steel.

Survival rate P	0.50	0.90	0.95	0.99
C	1.84655×10^{33}	$10^{30.008}$	$10^{29.202}$	$10^{27.650}$
m	11.481	10.357	10.078	9.543

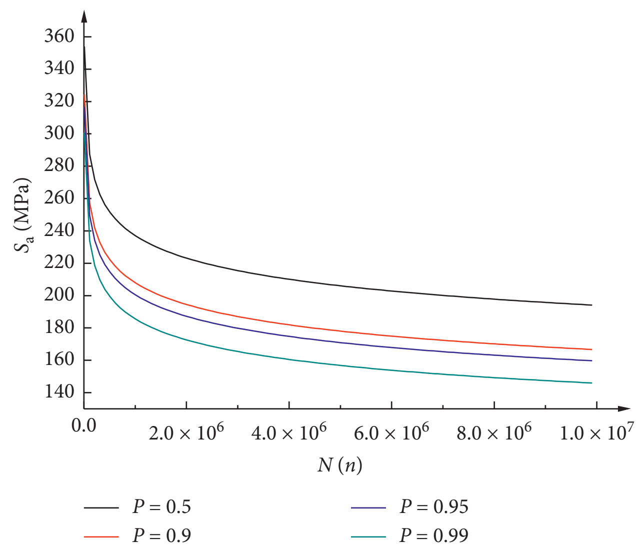

Figure 1: *P-S-N* curve of Q345 steel.

where N is the calculated fatigue lifetime and N_0 is the design lifetime; when $Z > 0$, the structure is in a safe state; when $Z = 0$, the structure is in a limit state; when $Z < 0$, the structure is in a failure state.

From the definition of reliability, the fatigue reliability of the structure is the probability of the function $Z > 0$, and the expression of the reliability is

$$R = P_N(Z > 0). \tag{14}$$

The failure probability of a structure can be expressed as

$$P_f = 1 - R = 1 - P_N(Z < 0). \tag{15}$$

4. Fatigue Reliability Analysis of Motor Hanger for High-Speed Train

Fatigue reliability analysis is an analytical method to improve product quality by combining fatigue lifetime analysis and reliability design. It is essential to ensure that the structural design meets the standard requirements. As the load-bearing structure between the motor and the bogie frame, whether the performance and service time of the structure can meet the requirements is directly related to the normal operation of the train. To this end, this paper takes the motor hanger as the research object and uses Bayesian updating and subset simulation to explore its fatigue reliability, which provides a new idea and method for the fatigue life prediction in the design stage. The specific process of fatigue reliability analysis is provided in Figure 2.

4.1. Finite Element Analysis of Motor Hanger. The premise of fatigue reliability analysis for motor hanger is to calculate its FPS under fatigue conditions. The research object of this paper is the motor hanger of high-speed train, which is bolted to the bogie frame to fix the motor. The motor hanger is mainly plate welded, and the partial opening is used to reduce the quality. Figure 3 shows the specific installation position and structure type. The numerical analysis by the finite element method is performed to obtain the FPS of the motor hanger. It is modeled by shell and solid mode, given in Figure 4. The motor hanger is modeled using beam188, shell181, solid 185, rigid, and rbe3 elements. It is meshed to have 50,879 elements, including 21,766 triangular and quadrilateral shell elements and 28,973 tetrahedral and hexahedral solid elements.

In the finite element model, the reasonable application of load cases is the key to ensure the accuracy of the analysis results. Generally, the boundary conditions of the test components under normal operating conditions should be consistent with those under test assembly conditions. The elastic connector on the bogie can be replaced by a rigid member, but the direction and magnitude of the load acting on the test piece cannot be changed. Figure 5 displays the load direction of motor hanger, which is positive upward. The loads are calculated according to EN13749 standard and analyzed by finite element method. Figure 6 plots the result of the finite element analysis. It can be clearly seen from the figure that the maximum FPS is 119.23 MPa, which occurs on the motor boom.

4.2. Establishment of Response Surface Function. The purpose of establishing the response surface function is to obtain the functional relationship between the random variables and the FPS and then to observe the influence of the uncertainties on it. As one of the surrogate models, the response surface can more accurately represent the functional relationship between input and output. Compared to other surrogate models, the response surface belongs to the display function that can be more easily used for reliability calculations [29]. Due to the poor approximation ability of the linear response surface, the quadratic response surface with cross terms is adopted. The basic equation is given by

$$y = \sum_{i=1}^{n} c_{ii} x_i^2 + \sum_{i>j}^{n} c_{ij} x_i x_j + \sum_{i=1}^{n} c_i x_i + c_0, \tag{16}$$

where n is the number of uncertain variables, c_0 is the constant, and c_i, c_{ii}, and c_{ij} are the polynomial coefficients, respectively.

According to the stress plot in Figure 6, the random variables which have great influence on the stress plot are selected as random variables. Considering the uncertainty of design parameters, the upper and lower limits of size parameters are set according to tolerance, and the upper and lower limits of load are obtained according to test conditions. Table 2 displays the specific parameters for random variables.

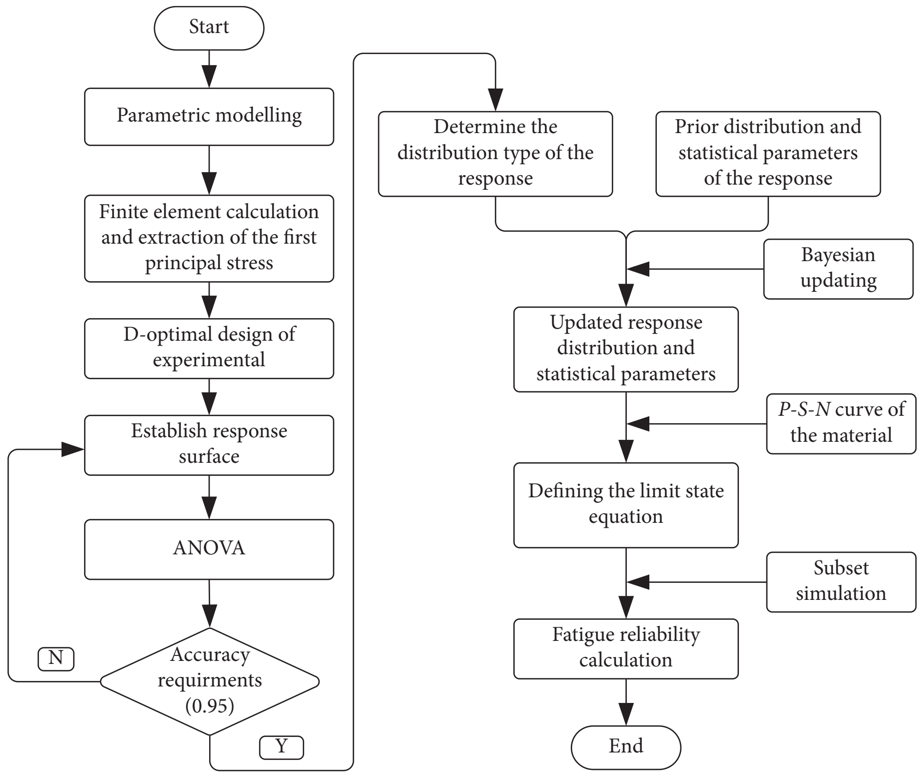

Figure 2: The analysis process of fatigue reliability.

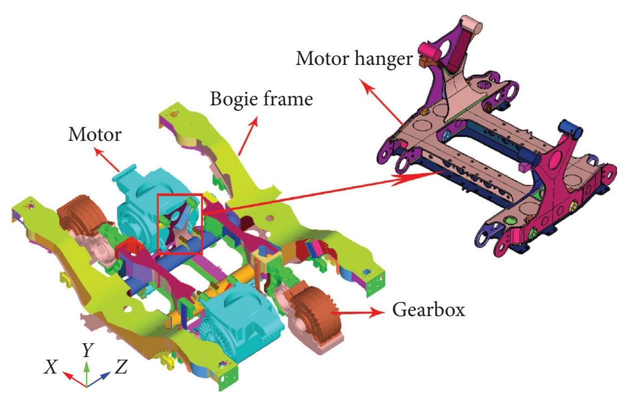

Figure 3: Geometric model of motor hanger.

The premise of establishing response surface function is to do the design of experiment for random variables. According to the design of experiment scheme, the finite element model is invoked to solve the problem, and the corresponding response of each scheme is obtained. In this paper, the D-optimal design of experiment method is used to carry out the experimental design; see Table 3.

According to (16), the experimental data in Table 3 is fitted by least squares method to obtain a response surface function, which characterizes the function relationship between the random variable and the FPS.

$$\begin{aligned} S1 = {} & +426.60 + 43.658 \times \mathrm{TH1} - 73.68 \times \mathrm{TH2} + 3.457 \times 10^{-3} \times F_1 - 4.444 \times 10^{-3} \times F_2 - 2.50 \times \mathrm{TH1} \times \mathrm{TH2} + 1.6 \times 10^{-4} \\ & \times \mathrm{TH1} \times F_1 + 3.99 \times 10^{-4} \times \mathrm{TH1} \times F_2 + 4.929 \times 10^{-5} \times \mathrm{TH2} \times F_1 - 4.103 \times 10^{-4} \times \mathrm{TH2} \times F_2 - 2.909 \times 10^{-9} \times F_1 \times F_2 \\ & - 3.265 \times \mathrm{TH1}^2 + 5.156 \times \mathrm{TH2}^2 - 10^{-7} \times F_1^2 + 1.036 \times 10^{-7} \times F_2^2. \end{aligned} \tag{17}$$

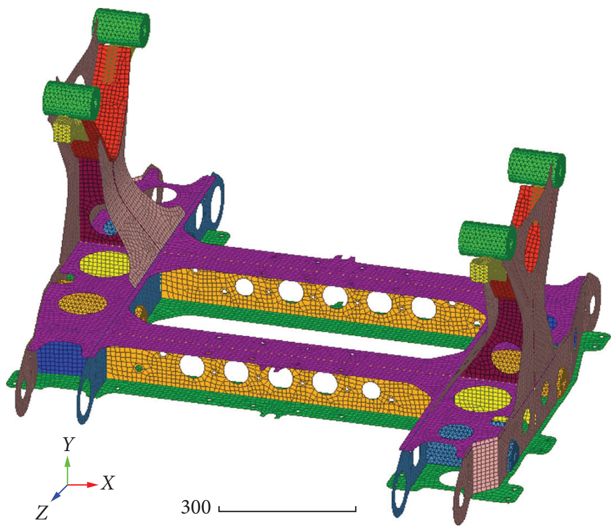

Figure 4: Finite element model of motor hanger.

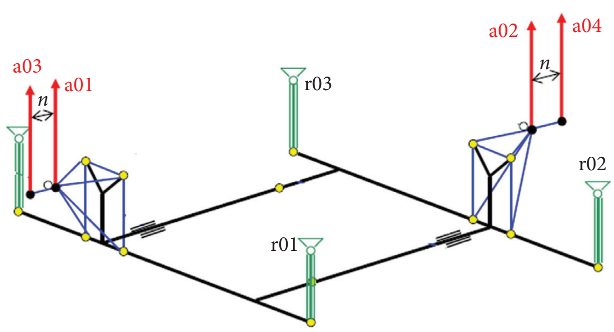

Figure 5: Load direction of motor hanger.

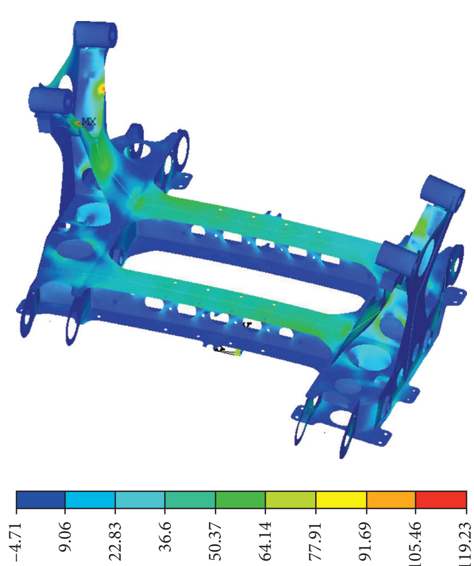

Figure 6: FPS plot of motor hanger.

The fitting accuracy of the response surface function is the basis and premise to ensure the accuracy of the subsequent reliability analysis. According to the fitting result $R^2 = 0.9964$, indicating that the fitting accuracy is high. To further verify the accuracy of the response surface function, the ANOVA is adopted to analyze the function in this paper. Some results are provided in Table 4.

In Table 4, the F and P values are the main indicators used to evaluate the significance of the response surface function and its random variables. The larger the F value, the more significant it is; on the contrary, the smaller the P value, the more significant it is. As can be seen from Table 4, the function generally presents a very significant level, $P < 0.0001$, indicating that the fitting accuracy of response surface is high. Among the four random variables, random variable TH1 is the most significant, which indicates that the small fluctuation of the random variable TH1 has a greater impact on the FPS. The other three random variables did not exhibit a very significant level, only that their small fluctuations had little effect on the FPS. Because of space, the interaction among random variables cannot be given. Through analysis, it is found that the interaction among random variables in response surface function is relatively low, which indicates that the interaction between random variables has less influence on response. By comparing the results of the first and second significance of random variables, it can be seen that the second significance of TH1 decreases and the second significance of TH2, F_1, and F_2 increases, indicating that the selection of random variables is reasonable. In summary, the response surface function can be used for fatigue reliability analysis of subsequent motor hanger.

4.3. Determination of the FPS Distribution Type and Bayesian Updating. For equation (13), the uncertainty of the calculated lifetime N results in three different states of the structure. As the main factor affecting the calculated lifetime N, accurate probability distribution of the FPS is the key to improve the accuracy of reliability analysis. For this reason, the FPS under random parameter fluctuation is obtained by using Monte Carlo method for 10000 calculations based on equation (17). The FPS is fitted by MATLAB 2015b to determine its probability distribution characteristics, as shown in Figure 7. From Figure 7, it can be seen that the FPS obeys lognormal distribution, and the fitting curve has high accuracy, $R^2 = 0.99349$. In order to accurately estimate the fatigue reliability of the structure, simulation data are used as real measurement data for Bayesian updating because there is no experimental data in the design process. The prior distribution data of the FPS are obtained from the experimental data of similar products. The data of prior distribution obey the lognormal distribution of $N(4.945, 0.041)$, and the real measured data obey the lognormal distribution of $N(4.962, 0.0425)$. Two kinds of distribution data are substituted into equations (2)–(7) to obtain the probability and statistical parameters of the FPS after Bayesian updating. Figure 8 plots the probability distribution of the FPS before and after Bayesian updating. It can be seen from Figure 8 that the mean of FPS value after the Bayesian updating is slightly smaller than that of the FPS obtained by the actual engineering, and the corresponding variance is also reduced.

Table 2: Statistical characteristic of random variables.

Design parameters	Sign	Unit	Lower limit	Mean value	Upper limit
Steel plate thickness 1	TH1	mm	7.7	8.0	8.3
Steel plate thickness 2	TH2	mm	9.7	10.0	10.3
Vertical load 1	F_1	N	23040.0	25600.0	28160.0
Vertical load 2	F_2	N	23040.0	25600.0	28160.0

Table 3: Statistical characteristic of random variables.

Experiment number	Factors				Response
	TH1 (mm)	TH2 (mm)	F_1 (N)	F_2 (N)	$S1$ (MPa)
1	7.967	10.300	25625.600	26880.000	143.48
2	7.916	9.700	23040.000	25472.000	144.88
3	7.700	9.700	28160.000	23040.000	149.18
4	7.925	10.300	25676.800	23040.000	147.27
5	8.300	9.700	23961.600	23040.000	137.75
6	7.979	9.967	23756.800	28160.000	143.39
7	7.700	10.300	23040.000	28160.000	148.68
8	8.300	10.300	23040.000	23040.000	137.42
9	8.060	9.700	26368.000	24925.400	142.13
10	8.300	10.300	28160.000	28160.000	137.42
...	...	...	...	...	...
18	7.916	9.988	28160.000	28160.000	144.68
19	7.937	10.021	28160.000	24003.000	144.25
20	8.300	9.700	23040.000	28160.000	137.75
21	8.300	10.186	28160.000	23040.000	137.49
22	8.300	10.063	25011.200	26137.600	137.56
23	7.700	10.300	28160.000	25651.200	148.68
24	7.700	10.300	23040.000	28160.000	148.68
25	8.300	10.300	28160.000	28160.000	137.42

Table 4: ANOVA for response surface $S1$ quadratic model.

Source model	Sum of squares	Df	Mean square	F value	P-value	
Model	567.09	14	40.51	199.31	<0.0001	Significant
TH1	391.63	1	391.63	1927.02	<0.0001	
TH2	0.065	1	0.065	0.32	0.5833	
F_1	0.10	1	0.10	0.50	0.4948	
F_2	1.36	1	1.36	6.69	0.0271	
...	...	...	...	...	...	
$TH1^2$	0.26	1	0.26	1.30	0.2805	
$TH2^2$	0.76	1	0.76	3.74	0.0820	
F_1^2	1.28	1	1.28	6.31	0.0308	
F_2^2	1.29	1	1.29	6.34	0.0305	
Residual	2.03	10	0.20			
Lack of fit	2.03	5	0.41			
Pure error	0.000	5	0.000			
Cor total	569.12	25				

This proves that the Bayesian updating method not only reduces the uncertainty of FPS, but also reduces the distortion and uncertainty of the detected data. In the design sense, Bayesian updating reduces the uncertainty of the simulation results.

4.4. *Fatigue Reliability Analysis Based on Subset Simulation.*

The FPS of the motor hanger after Bayesian updating obeys the lognormal distribution of $N(4.9451, 0.0409)$. The symmetrical cyclic load spectrum specified in the EN13749 standard is selected, and the stress ratio is $R = -1$. The P-S-N curves with survival rates of 95% and 99% are selected, respectively, and the design lifetime is 10 million cycles. According to equations (11)–(13), the fatigue failure probability of the motor hanger is calculated by SS. Figures 9 and 10 display the CDF curves for fatigue failure probabilities at different survival rates, respectively. The estimated fatigue failure probabilities and the number of required samples are listed in Table 5.

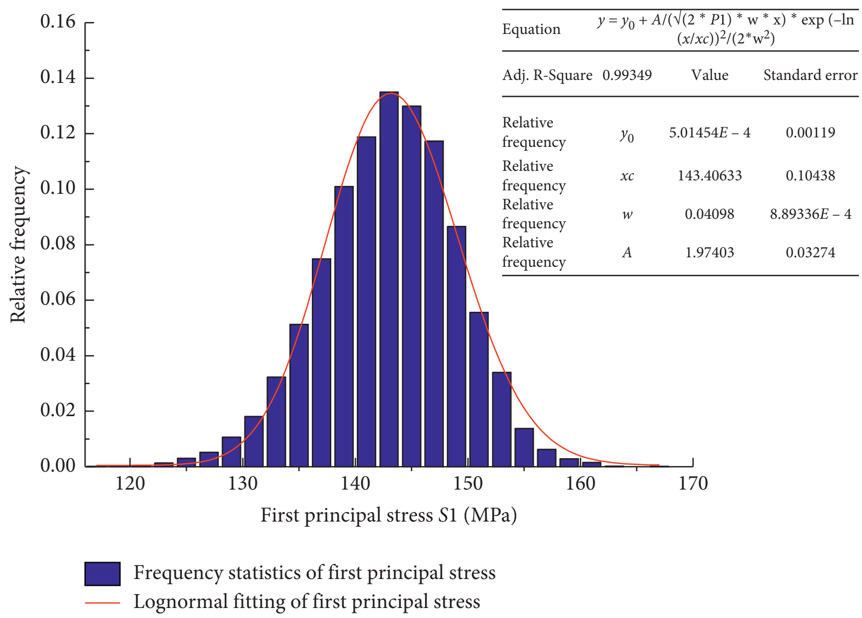

Figure 7: Lognormal distribution fitting of FPS.

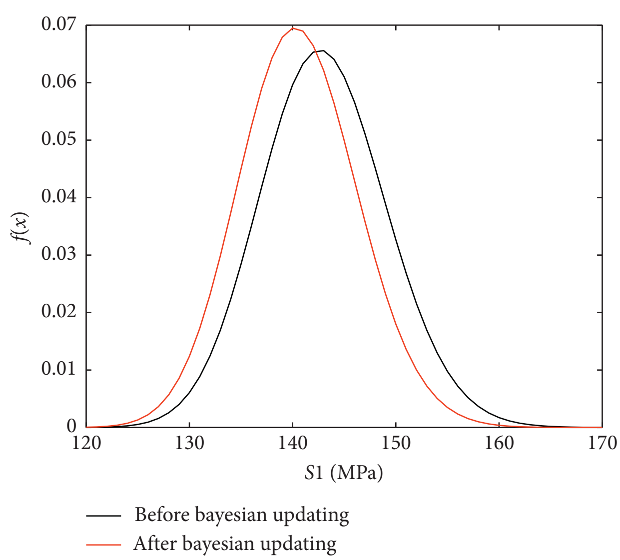

Figure 8: Comparison of probability and statistics characteristics of FPS.

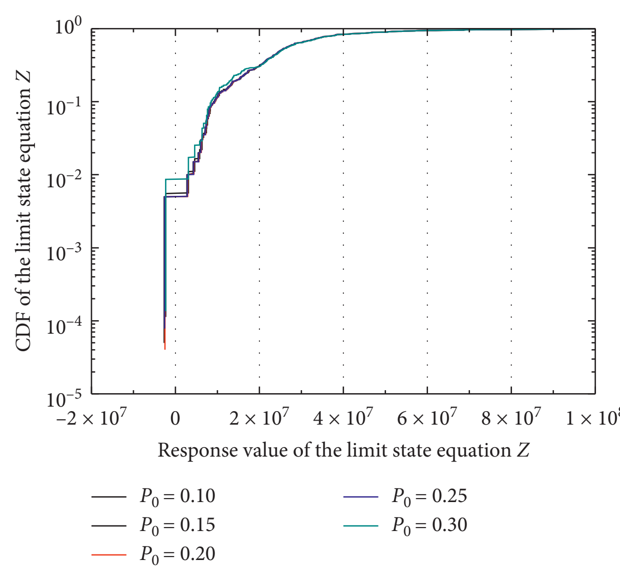

Figure 9: CDF of survival rate at 95%.

It can be seen from Figures 9 and 10 that the overall fatigue failure probability with survival rate of 99% is higher than the survival rate of 95%, indicating that the selection of the material *P-S-N* curve has a direct impact on the fatigue reliability analysis results of the structure, and should be paid attention to during the design process. Then, Figures 9 and 10 plot the CDF for $P_0 = 0.15$, 0.20, 0.25, and 0.30. The purpose of this comparison is to see how SS behaves differently by adopting different values of P_0 for the fatigue reliability analysis of motor hanger; P_0 is the conditional failure probability of subset simulation. In Figure 9, the CDF plot with $P_0 = 0.3$ significantly deviates from the rest. However, the CDF plot with $P_0 = 0.1$ significantly deviates from the rest. It can be seen that the selection of P_0 is very important for estimating the fatigue failure probability. Although Zuev et al. [30] proposed the values of P_0 selected from the interval [0.1, 0.3] would produce similar efficiency with similar accuracy, the accuracy is still different for different subjects. For the fatigue reliability analysis of the motor hanger, when the survival rate is 95%, the failure probability obtained by Monte Carlo simulation is 0.0015; $P_0 = 0.10$, 0.15, 0.20, and 0.25 are suitable for reliability analysis, while $P_0 = 0.30$ is not proper. Similarly, when the survival rate is 99%, the failure probability obtained by Monte Carlo simulation is 0.1880; $P_0 = 0.15$, 0.20, and 0.25 are suitable for reliability analysis, while $P_0 = 0.1$ and 0.30 are

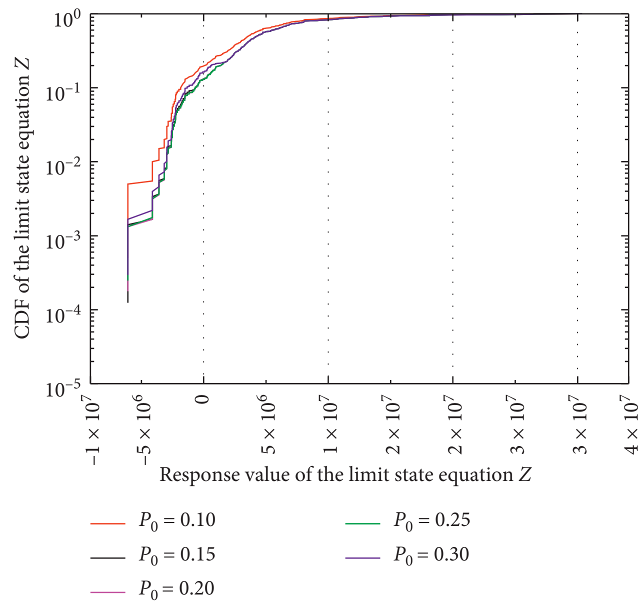

Figure 10: CDF of survival rate at 99%.

Table 5: Estimated failure probabilities and the number of samples with different p_0.

Survival rate P (%)	Conditional failure probability p_0	0.10	0.15	0.20	0.25	0.30
95	Failure probability P_f	0.005	0.0055	0.005	0.005	0.0086
	Number of samples	560	540	680	650	620
99	Failure probability P_f	0.1	0.15	0.1950	0.1950	0.2340
	Number of samples	380	370	360	350	340

not proper. For the calculation of Monte Carlo failure probability, 10 000 sample points are used, while the SS method is only 4%–7% of Monte Carlo, which greatly improves the calculation efficiency.

5. Conclusions

This study presents a novel fatigue reliability analysis method based on Bayesian updating and subset simulation to improve the accuracy of structural fatigue performance evaluation at the design stage. In order to reduce the uncertainty of fatigue lifetime calculated by simulation analysis, the Bayesian method is used to update the probability and statistical parameters of the FPS for the motor hanger. Compared with the original data, the mean and variance of the FPS after the update are reduced, which improves the robustness of the data. Meanwhile, the SS method is adopted to calculate the fatigue failure probability under different survival rates and different conditions failure probabilities, and the CDF curve of fatigue failure probability is given. The fatigue failure probability of motor hanger under *P-S-N* curve with 95% survival rate is $P_0 = 0.1$ $P_f = 0.005$, $P_0 = 0.15$ $P_f = 0.0055$, $P_0 = 0.20$ $P_f = 0.005$, $P_0 = 0.25$ $P_f = 0.005$. The fatigue failure probability of motor hanger under *P-S-N* curve with 99% survival rate is $P_0 = 0.15$ $P_f = 0.15$, $P_0 = 0.20$, $P_f = 0.1950$, $P_0 = 0.25$ $P_f = 0.1950$. This not only proves the influence of the *P-S-N* curve with different survival rates on the fatigue failure probability, but also verifies that the reasonable selection of conditional failure probability is helpful to improve the accuracy of the SS. In a word, the proposed method helps the design stage to more accurately assess whether the fatigue lifetime of the structure meets the standard requirements. At the same time, it is also applicable to the fatigue reliability analysis of other large complex structures.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

Acknowledgments

The authors would like to acknowledge the National Natural Science Foundation of China under Contract no. 51875073, the Scientific Research Project of Education Department of Liaoning Province under Contract no. JDL2019005, the Dalian Science and Technology Innovation Fund Plan under Contract no. 2019J11CY017, and the Innovation Team Support Plan of Liaoning Higher Education under Contract no. LT2016010.

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