Hindawi
Structural Control and Health Monitoring
Volume 2024, Article ID 2353457, 12 pages
https://doi.org/10.1155/2024/2353457

Research Article

Data-Driven Fatigue Failure Probability Updating of OSD by Bayesian Backward Propagation

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Received 1 December 2023; Revised 1 February 2024; Accepted 16 February 2024; Published 29 February 2024

Academic Editor: Wenai Shen

This study introduces a data-driven approach for updating the fatigue failure probability of the orthotropic steel deck (OSD) using Bayesian backward propagation. The OSD in steel bridges is considered as a parallel system composed of two critical fatigue-prone components, namely, the rib-to-diaphragm and rib-to-deck joints. A probabilistic model for fatigue reliability is established based on the equivalent structural stress method and limit state function. The system-level fatigue reliability model is then constructed, taking into account the correlations between limit states of individual components through Bayesian network forward propagation. The key advantage of the Bayesian network-based framework is its ability to perform backward propagation, allowing for the updating of failure probabilities for critical components when the system-level failure of the OSD is observed. Consequently, the proposed approach enables the identification of vulnerable components through data-driven fatigue failure probability updating. Finally, the approach is applied to a real instrumented steel bridge to determine the time-dependent fatigue failure probability at both the system and component levels over its service life. The results show that the component-level fatigue failure probability model will underestimate the fatigue life in comparison to the system-level model. Meanwhile, the proposed method could identify vulnerable components by quantifying the fatigue failure probability of in-service steel bridges.

1. Introduction

The orthotropic steel deck (OSD) is an important element in many large-scale bridges and urban viaducts due to its numerous benefits such as lightweight, high load-bearing capacity, and quick construction [1–3]. However, the OSD of long-span bridges can experience fatigue cracks at the joints, specifically the connections between the rib and deck, as well as the rib and diaphragm. These cracks can occur due to various factors including combined traffic loads [4, 5], residual stress from welding [6, 7], and environmental effects [8, 9]. The presence of these fatigue cracks can cause severe damage to the steel bridges, resulting in significant losses in terms of both human life and economic resources [10]. It is worth noting that different fatigue failure modes exhibit varying fatigue properties and impacts on the long-term durability of the OSD [11, 12]. Such evaluation will enable engineers and designers to gain valuable insights into enhancing the fatigue performance of the OSD, consequently ensuring the safety and longevity of long-span bridges and urban viaducts.

To accurately evaluate the fatigue performance of the OSD, it is crucial to collect measured stress data that take into account the real geographical environment, terrain roughness, and structural shape. This is the first and most important step in the evaluation process, as accurate stress data are essential for understanding how the structure will perform under fatigue loading. Recent advances in sensing and data acquisition technologies, communication algorithms, computational techniques, and data management systems have enabled online structural health monitoring (SHM) [13–19]. It has gained widespread application in civil engineering over the past decade. By integrating SHM data, researchers have been able to monitor the fatigue damage and assess data-driven fatigue reliability of structures [20]. SHM data were used to assess the fatigue reliability of retrofitting distortion-induced cracking in steel bridges [21]. A conceptual SHM system was proposed for monitoring the fatigue damage of structures [22]. SHM data were utilized to assess fatigue damage in the Runyang suspension bridge and Runyang cable-stayed bridge. The use of SHM allows for more accurate evaluation of fatigue behavior, as it directly utilizes in-field stress data. This means that the evaluation can take into account real-world conditions and the unique characteristics of each structure, resulting in more accurate and reliable assessments of fatigue performance.

Specifically, one commonly utilized approach in fatigue assessment is the data-driven method, which relies on the S-N curve derived from structural health monitoring (SHM) data. This approach enables the prediction of fatigue life under specific stress levels for various structures such as high-rise buildings, long-span bridges, and wind turbines [23–25]. For instance, the authors in [26] developed a model that considers the impact of initial cracks and stress ratios on the fatigue performance of damaged steel plates reinforced with carbon fiber-reinforced polymer plates [26]. These aforementioned studies have demonstrated the accurate prediction capabilities of the S-N curve method for fatigue life [27–30]. However, deterministic models used in these studies do not consider the inherent uncertainty in monitoring data and do not account for model errors [31, 32]. Therefore, it is necessary to develop probabilistic models based on the S-N curve, which can effectively quantify the uncertainty and variability involved in the assessment process.

The Bayesian model, considered as one of the most crucial probabilistic models, incorporates prior information from other sources to perform inference with small datasets [33]. In a study by [34], a combination of the Bayesian model and reliability theory was utilized to develop an anomaly index for evaluating the health condition of expansion joints and issuing damage alarms when the probability of damage surpasses a specific threshold [34]. The authors in [35] proposed a Bayesian procedure to quantify modeling uncertainty, encompassing uncertainty in statistical model selection and distribution parameters [35]. The Bayesian model can quantify the uncertainty in the parameters of the joints. Moreover, the Bayesian network, which extends the Bayesian model, enables the consideration of interactions between system joints, such as the OSD, which consists of rib-to-deck joints and rib-to-diaphragm joints [3, 36–38].

This paper introduces a novel approach for updating the fatigue failure probability of the OSD using Bayesian backward propagation. The proposed approach employs an equivalent structural stress method and limit state function to establish a probabilistic model of fatigue reliability. In addition, a system-level fatigue reliability model is constructed, taking into account the correlations between limit states at the component level, using a Bayesian network forward propagation. The key advantage of the Bayesian network-based framework is its ability to perform backward propagation, allowing for the updating of failure probabilities for critical components when the system-level failure of the OSD is observed. The framework of Bayesian network-based backward propagation is then utilized to update the failure probability of critical components when system-level failure of the OSD is observed. To validate the proposed approach, three numerical simulation case studies are conducted. Furthermore, the approach is applied to a real instrumented steel bridge to determine the time-dependent fatigue failure probability at both the system and component levels throughout its service life.

2. Bayesian Network for the OSD

2.1. Fatigue Reliability Model. Deterministic fatigue model assumes that the parameters are constant, disregarding any uncertainty that may arise from instrument errors and environmental influences. To improve the precision of fatigue reliability evaluation, we present an analytical method to calculate the probability of fatigue by considering the variability in parameters for the master S-N curve [39–41]. The main advantage of the master S-N curve method is that one single curve could be used for different types of weld joints. It will facilitate the selection of the fatigue curve [42, 43]. The master S-N curve is represented as follows:

$$S_r = C_r N^h, \tag{1}$$

$$S_r = \sigma_{\max} - \sigma_{\min}, \tag{2}$$

$$C_r = C\Delta_r^d, \tag{3}$$

where C, Δ_r, and h are constants for a given material; in this paper, the statistical basis of mean is used to calculate the fatigue probability, that is, $C = 19930.2$. C_r is a random variable; $-d$ is a probability factor, which is considered to follow the Gauss distribution N (0, 1); S_r is the equivalent structural stress range (ESSR); N is the total the number of cycles (NC); $\sigma_{\max}$ is the maximum structural stress; and $\sigma_{\min}$ is the minimum structural stress.

The Palmgren Miner linear cumulative rule is a commonly employed method for assessing fatigue damage over a specific duration. This rule can be mathematically expressed as [44, 45]

$$D = \sum_{i=1}^{n} \frac{c_i}{N_i} = \frac{c_1}{N_1} + \frac{c_2}{N_2} + \cdots + \frac{c_n}{N_n}, \tag{4}$$

$$D = \lim_{\Delta S_r \longrightarrow 0} \sum_{i=1}^{n} \frac{c_i}{N_i} = \int_{S_r} \frac{c_{\text{sum}} f(S_r)}{N} \text{d}S_r, \tag{5}$$

$$g\left(D_f, S_e, C_e, n_{\text{tot}}, t\right) = D_f - t \times D = 0, \tag{6}$$

$$p_f = P\left\{D_f - t \times \int_0^{\infty} \frac{c_{\text{sum}} f(S_r) C_r^{1/h}}{S_r^{1/h}} \text{d}S_r \leq 0\right\}, \tag{7}$$

$$\beta = \Phi^{-1}\left(1 - p_f\right) = -\Phi^{-1}\left(p_f\right), \tag{8}$$

where D is the fatigue damage; c_i is the NC for the ith cycle; N_i is calculated by the master S-N curve method as expressed in equation (1); $f(S_r)$ is the probability density function (PDF) of the ESSR, which can be fitted by the finite mixture (FM) method [46]; c_{sum} is the total NC in a period time; t is the service life; and D_f is the fatigue damage at failure, which is considered to follow the Lognormal distribution (0, 0.294) [47, 48].

2.2. System-Level Assessment Model for the OSD. Bayes' theory, initially introduced by Thomas Bayes, is a mathematical framework that elucidates the relationship between two events. Mathematically, Bayes' theorem can be expressed as follows [49]:

$$P(X \mid Z) = \frac{P(X)P(Z \mid X)}{P(Z)}, \tag{9}$$

where $P(X)$ is the probability of event X; $P(Z)$ is the probability of event Z; $P(X \mid Z)$ is the probability of event X after the event Z; and $P(Z \mid X)$ is the probability of event Z after the event X.

Specifically, to address complex multievent problems involving numerous events $Z = \{X_1, X_2, \ldots, X_i\}$, an extended version of the Bayesian model is used. The Bayesian network enables the calculation of interactions and correlations between the joints of the system, providing a comprehensive assessment. This can be mathematically expressed as follows:

$$\begin{aligned} p(Z) &= p\{X_1, \cdots, X_n\} = \prod_{i=1}^{n} p\left(X_i \middle| M_i\right) \\ p\left(X_i\right) &= \sum_{\text{except}X_i} p(Z), \end{aligned} \tag{10}$$

where M_i is the parent node of X_i. For example, node X_1 links node X_2 indicating that X_1 is a cause of X_2. In other words, X_2 is called a child node of X_1, and X_1 is a parent node of X_2. As shown in equation (7), the probability of each event X_i can be inferred from the known probability of the event Z. Specifically, the event S can be represented as the OSD in the bridge, and each event X_i can be represented as the joints in the OSD.

Typically, the OSD consists of three types of thin plates: deck, rib, and diaphragm [50]. When a vehicle passes over the OSD, the wheel load induces local stress and deformation at the joints most susceptible to fatigue, namely, the rib-to-deck and rib-to-diaphragm connections, as illustrated in Figure 1.

Commonly, the OSD is regarded as a parallel system, where failures occur only when all nodes fail simultaneously, as shown in the following [13]:

$$\begin{aligned} P(Z = \text{safety} \mid X = \text{safety}, Y = \text{failure}) &= \text{failure} \\ P(Z = \text{safety} \mid X = \text{failure}, Y = \text{safety}) &= \text{failure} \\ P(Z = \text{safety} \mid X = \text{safety}, Y = \text{safety}) &= \text{safety}, \end{aligned} \tag{11}$$

where X is a node that represents the rib-to-deck in the bridge and Y is another node representing the rib-to-diaphragm in the bridge. The union of X and Y, denoted as Z, represents the OSD in the bridge.

Using the Bayesian theorem, it is possible to infer the failure probability of components X, Y, and system Z, along with the fails sequence of X and Y. This can be mathematically expressed as follows [14–16]:

$$\begin{aligned} P(Z = \text{safety}) = {} & P(Z = \text{safety} \mid (Y = \text{safety} \mid X = \text{safety})) \times P(Y = \text{safety} \mid X = \text{safety}) \\ & + P(Z = \text{safety} \mid (X = \text{safety} \mid Y = \text{safety})) \times P(X = \text{safety} \mid Y = \text{safety}) \\ & + P(Z = \text{safety} \mid (X = \text{safety}, Y = \text{safety})) \times P(X = \text{safety}, Y = \text{safety}), \end{aligned} \tag{12}$$

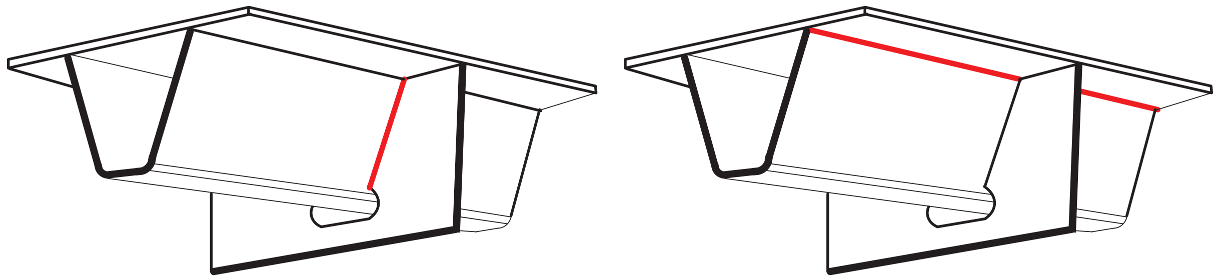

FIGURE 1: Fatigue-prone joints: (a) rib-to-diaphragm and (b) rib-to-deck.

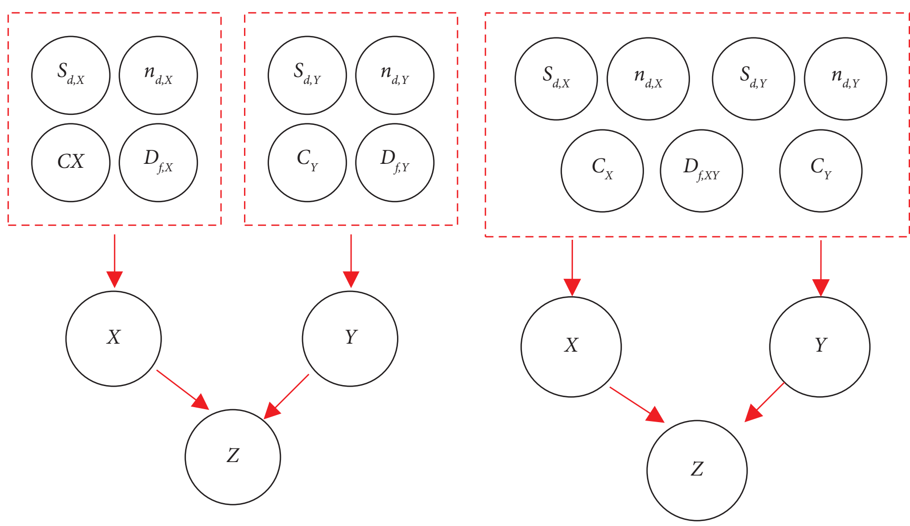

FIGURE 2: Bayesian network for orthotropic steel deck system: (a) uncorrelation of the random variable and (b) correlation of the random variable.

where $Y = \text{safety} \mid X = \text{safety}$ represents the occurrence of Y fails following X fails, $X = \text{safety} \mid Y = \text{safety}$ denotes the occurrence of X fails following Y fails, and $X = \text{safety}$, $Y = \text{safety}$ represents the simultaneous occurrence of X and Y fail.

The fatigue reliability probability equation in the Bayesian network takes into account the correlations between random variables. In Figure 2(a), it can be observed that the input random variables are not correlated, which can result in inaccurate reliability evaluations. However, in Figure 2(b), when certain input random variables such as S_d, D_f, and n_d are correlated, these correlated random variables can be grouped together into a root node, which is associated with their joint probability.

In addition, the failure probability of Z, can be computed using probability theory, that is,

$$P_f(Z = 1) = P_f(D_X \leq D_{\mathrm{fY}}, D_Y \leq D_{\mathrm{fX}}) + P_f(D_X \leq D_{\mathrm{fX}}, D_{\mathrm{fY}} \leq D_Y \leq D_{\mathrm{fZ}}) + P_f(D_Y \leq D_{\mathrm{fY}}, D_{\mathrm{fX}} \leq D_X \leq D_{\mathrm{fZ}}), \tag{13}$$

where D_{fX} and D_{fY} represent the fatigue damage at fails for point X and point Y, respectively. The variables D_X and D_Y represent the fatigue damage for point X and point Y, respectively. In addition, D represents the fatigue damage at fails for the entire system S. Moreover, the proposed method has the potential to be used for the more random variables. The system-level reliability will be determined as well when the components increase from 2 to more.

2.3. Monte Carlo Method. As indicated in equation (8), exact inference poses a challenging problem due to its exponential complexity in relation to the number of states and the degree of nodes in a Bayesian network. The degree of a node refers to the number of edges connected to it [17]. The Monte Carlo (MC) method is gaining popularity for solving complex and intractable multidimensional integrations in Bayesian Networks, which can be mathematically expressed as follows [18, 19]:

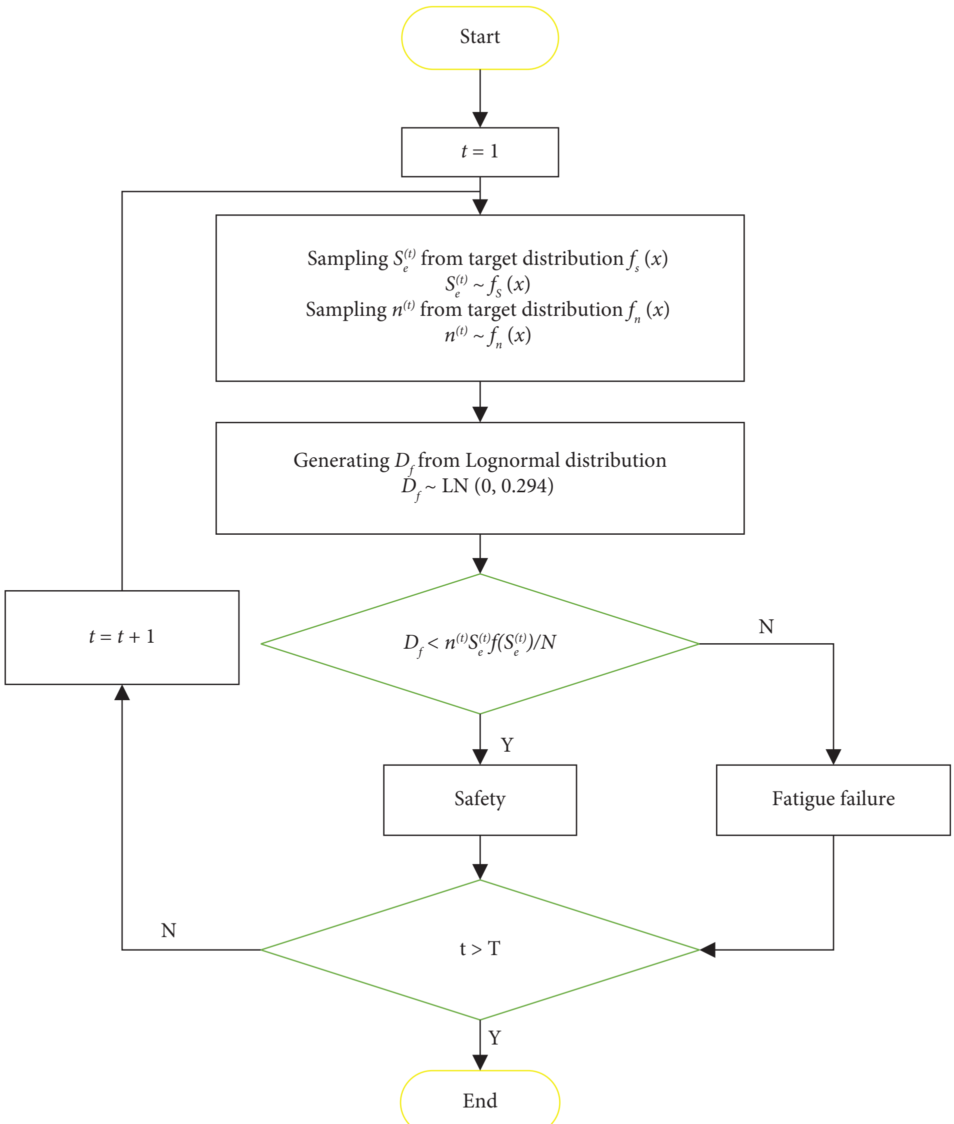

Figure 3: Flowchart of Bayesian network for orthotropic steel deck at system level.

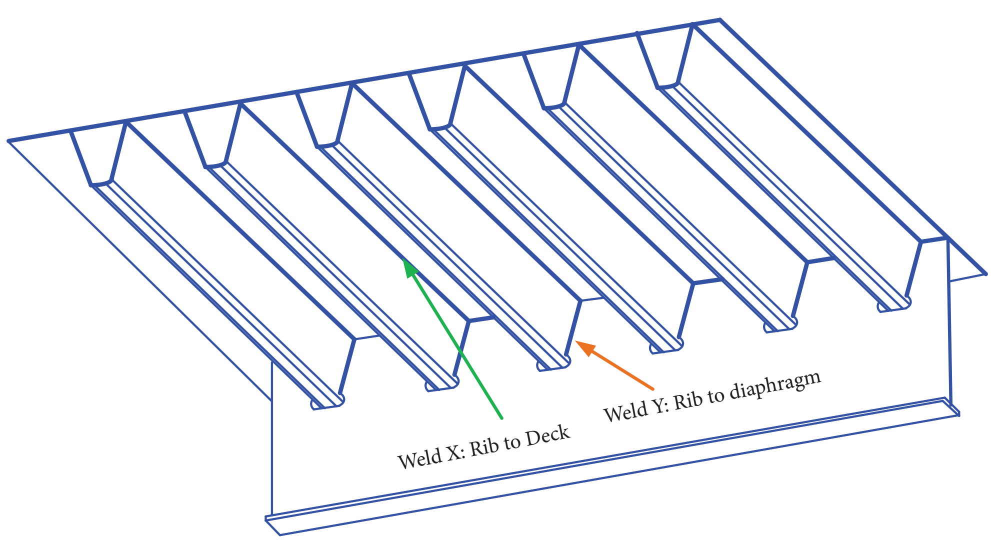

Figure 4: Orthotropic steel bridge deck.

Table 1: PDF in numerical case studies.

Numerical case study	Joints	S_d		n_d	
		μ	σ	μ	σ
1	X	ln (10)	0.1	ln (1000)	0.1
	Y	ln (10)	0.05	ln (1000)	0.05
2	X	ln (10)	0.1	ln (3000)	0.05
	Y	ln (5)	0.1	ln (2000)	0.05
3	X	ln (10)	0.1	ln (1000)	0.05
	Y	ln (5)	0.1	ln (5000)	0.05

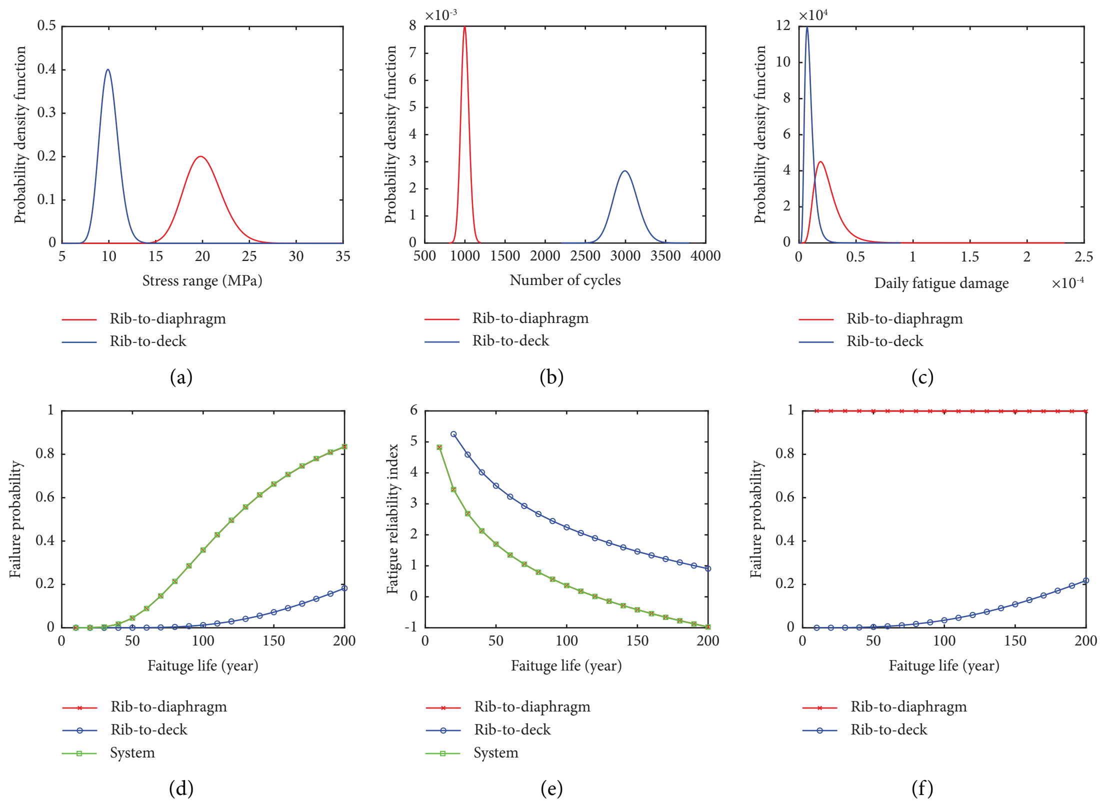

Figure 5: Schematic diagram of case study 1: (a) daily stress range; (b) daily number of cycles; (c) daily fatigue damage; (d) failure probability; (e) fatigue reliability index; (f) component fatigue failure probability when the system failure is observed.

$$E[z(v)] = \frac{1}{m}\sum_{j=1}^{m} z\left(v^{(t)}\right) \underset{m\longrightarrow\infty}{\longrightarrow} \int z(v)t(v)\mathrm{d}v, \qquad (14)$$

where v represents a random variable and $z(v)$ denotes the function of v. The symbol E refers to the mathematical expectation of $z(v)$, and $t(v)$ denotes the target function of v.

The flowchart of the Bayesian network employed for assessing fatigue system reliability is presented in Figure 3. It is evident from Figure 3 that a considerable number of iterations are required to solve the Bayesian network, thereby underscoring that the accuracy of the solution relies on the number of samples, denoted as n.

3. Fatigue Reliability of Orthotropic Steel Bridge Decks

3.1. Numerical Case Study. As depicted in Figure 4, the fatigue-prone joints of the OSD are categorized as follows: the rib-to-deck joint (represented by X) and the rib-to-diaphragm joint (represented by Y). In addition, three numerical case studies are conducted to examine the effects of different distributions of ESSR and NC on these two joints, as illustrated in Table 1. In first study 1, the ESSR and NC values for joint X are identical to those of joint Y. In numerical case study 2, the ESSR and NC values for joint X are higher than those of joint Y. Finally, in numerical case

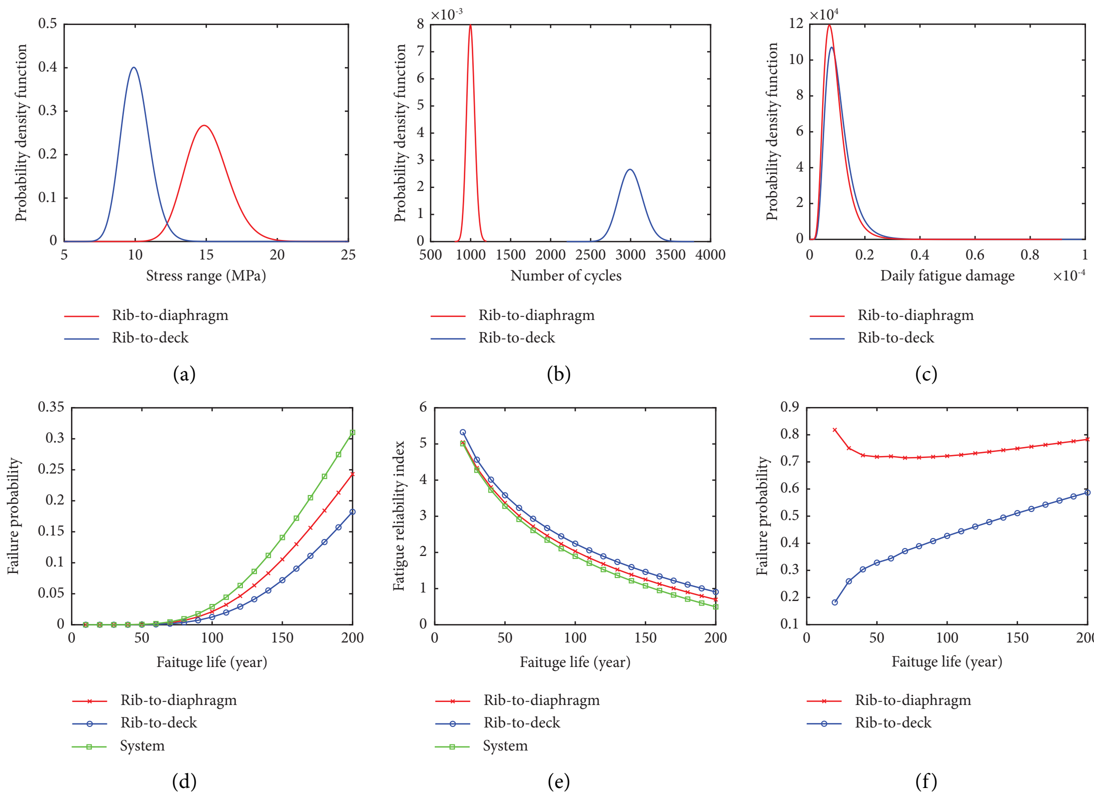

Figure 6: Schematic diagram of case study 2: (a) daily stress range; (b) daily number of cycles; (c) daily fatigue damage; (d) failure probability; (e) fatigue reliability index; (f) component fatigue failure probability when the system failure is observed.

study 3, the ESSR value for joint X is higher than that of joint Y, but the NC value for joint X is lower than that of joint Y.

In the first study, it was observed that the probabilities of simultaneous X and Y fail, as well as Y fails after X fails and X fails after Y fails, were found to be negligible compared to the overall Z fails probability, as portrayed in Figure 5(a). Similarly, the reliability indices of Y fails after X fails, X fails after Y fails, simultaneous X and Y fails and the system also exhibited a similar trend, as depicted in Figure 5(b). This is illustrated in Figure 5(c), where the probability of simultaneous X and Y fails tends to approach unity, indicating that the failure probability of Z can be adequately represented by the probability of simultaneous X and Y fails. Consequently, it is evident that the X and Y joints play crucial roles in the OSD, emphasizing the necessity to simultaneously consider their fatigue performance in accurately assessing changes in the OSD's failure probability.

In study 2, p_f and the β values of the Y fails after X fails, the X fails after Y fails, the X and Y simultaneous fails, and Z are analyzed. As shown in Figures 6(a) and 6(b), p_f and β values of the Y fails after X fails and the X fails after Y fails are nearly zero, indicating a negligible probability of these simultaneous fails occurring. On the other hand, p_f and β values of the X and Y simultaneous fails are also close to zero, implying a low likelihood of this specific combination of fails. However, it is observed that p_f and β values of the Y fails after X fails are close to one, indicating that the Z's failure probability can be described accurately by considering the Y fails after X fails. This inference is depicted in Figure 6(c), where it is evident that the p_f value of the Y fails after X fails is almost one, validating the significance of the X joint in influencing the OSD's p_f. Consequently, it can be concluded that considering the fatigue performance of the X joint is crucial for accurately describing the change in the OSD's p_f.

In the numerical case study 3, it is observed that the failure probabilities of Y after X fails, X after Y fails, X and Y simultaneous fails, and the overall Z fails exhibit variations amongst each other, as depicted in Figure 7(a). Similarly, the corresponding fatigue reliability indices of Y after X fails, X after Y fails, X and Y simultaneous fails, and Z fails also demonstrate this variability, as shown in Figure 7(b). This inference is illustrated in Figure 7(c), highlighting the significant influence of Y after X fails and X and Y simultaneous fails on the Z's fails probability. Therefore, it can be concluded that the failure of X is essential in determining the overall failure of Z, and there is a high likelihood of Y failing shortly after X. Hence, it is crucial to consider the simultaneous fatigue performance of X and Y to thoroughly evaluate any changes in the OSD's failure probability. Furthermore, the component-level fatigue failure probability model will underestimate the fatigue life in comparison to the system-level model according to Figures 6 and 7.

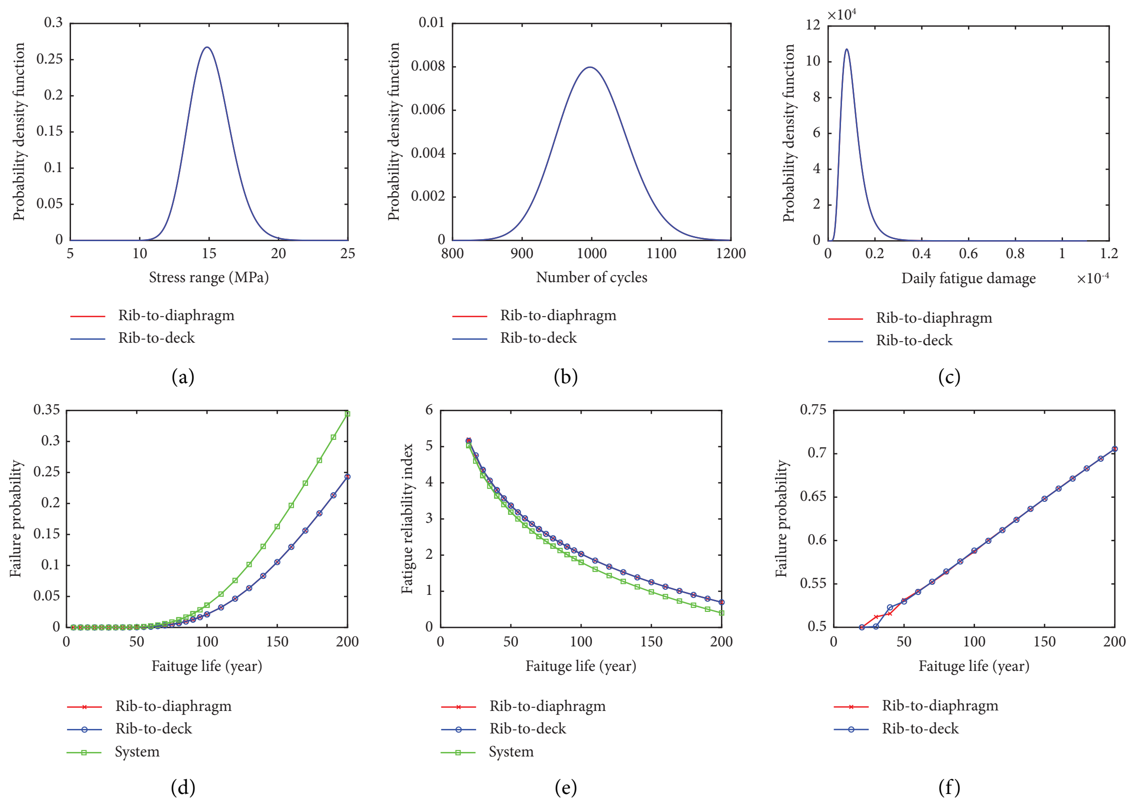

Figure 7: Schematic diagram of case study 3: (a) daily stress range; (b) daily number of cycles; (c) daily fatigue damage; (d) failure probability; (e) fatigue reliability index; (f) component fatigue failure probability when the system failure is observed.

3.2. Application to the Investigated Bridge. The studied bridge, depicted in Figure 8(a), is a steel bridge situated in Hangzhou, China. This bridge holds vital significance as a transportation link spanning the Beijing-Hangzhou Grand Canal, with a main bridge length of 130 m. The main bridge deck takes the form of an orthotropic steel deck, measuring 14 mm in thickness, and features a U-shaped stiffener with dimensions of 8 mm thickness and 280 mm height.

A SHM system was installed to monitor the ESSR and NC of welded joints on the investigated bridge, as shown in Figure 9.

By utilizing the SHM data, the Bayesian network enables the calculation of both the system's and the two joints' p_f for the investigated bridge. As depicted in Figure 10(a), there exist variations in the p_f values for the fails of Y after X, the fails of X after Y, simultaneous fails of X and Y, and the overall Z fails. Similarly, Figure 10(b) illustrates the fluctuations in the fatigue reliability index for the fails of Y after X, the fails of X after Y, simultaneous fails of X and Y, and the Z fails. In addition, when the Z's p_f value is known, the p_f values for the fails of Y after X, the fails of X after Y, and the simultaneous fails of X and Y can be inferred by employing the Bayes theorem. Demonstrated in Figure 10(c), the p_f value for simultaneous fails of X and Y greatly influences the probability of Z fails.

Figure 8: The investigated bridge.

The findings from the analysis of the three numerical case studies and the SHM data for the studied bridge indicate that when the ESSR and the NC for the joints are similar or comparable, it is necessary to consider the fatigue performance of the joints concurrently to capture the variation in p_f of the OSD. Conversely, when the ESSR and NC of the

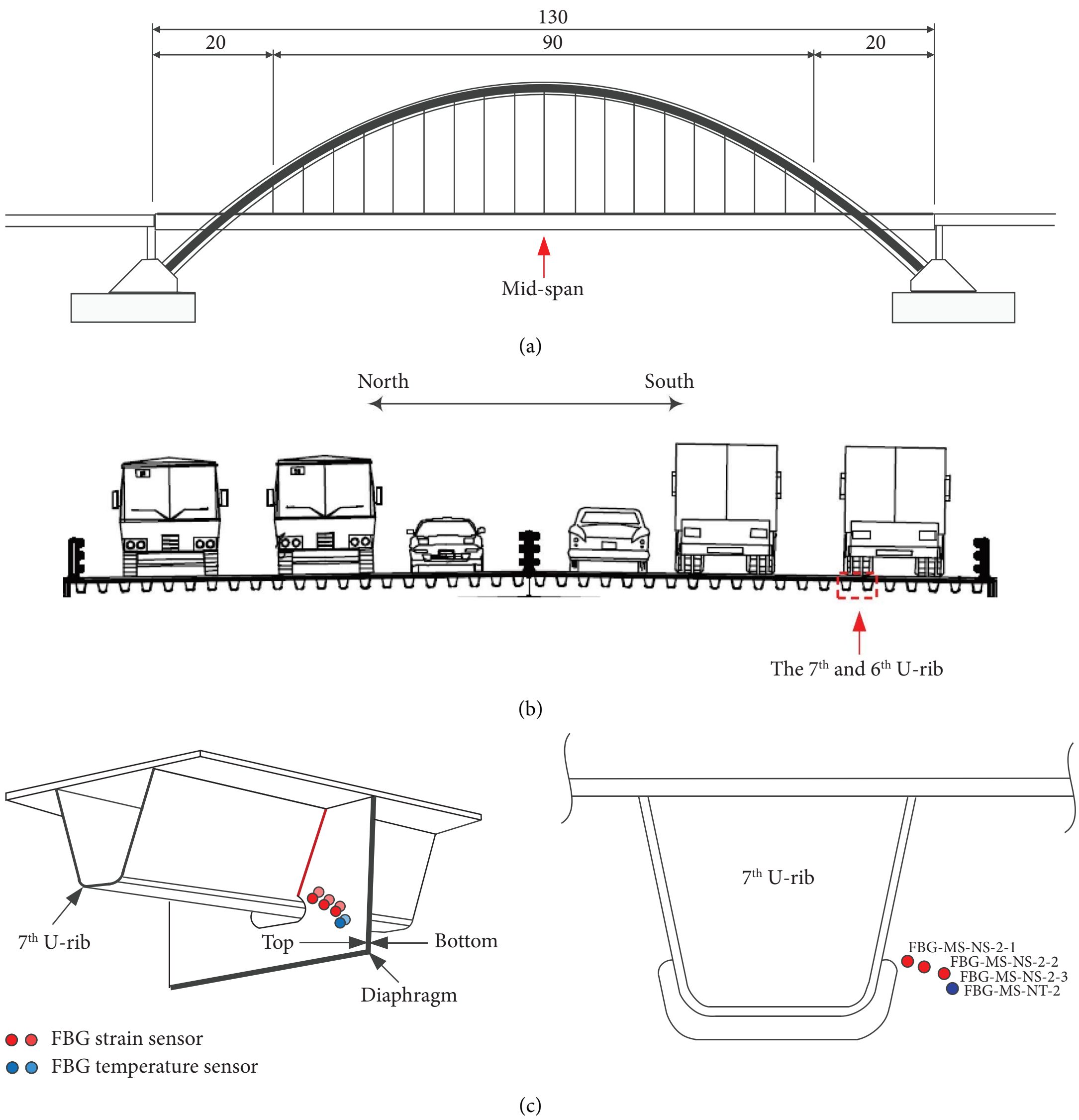

Figure 9: Schematic diagram of the investigated bridge and its SHM system: (a) main view; (b) side view; (c) the SHM of the joints.

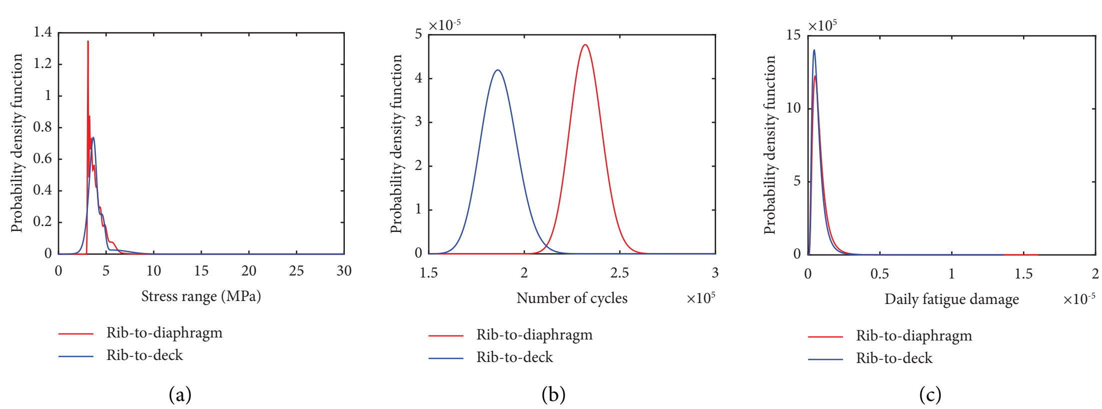

Figure 10: Continued.

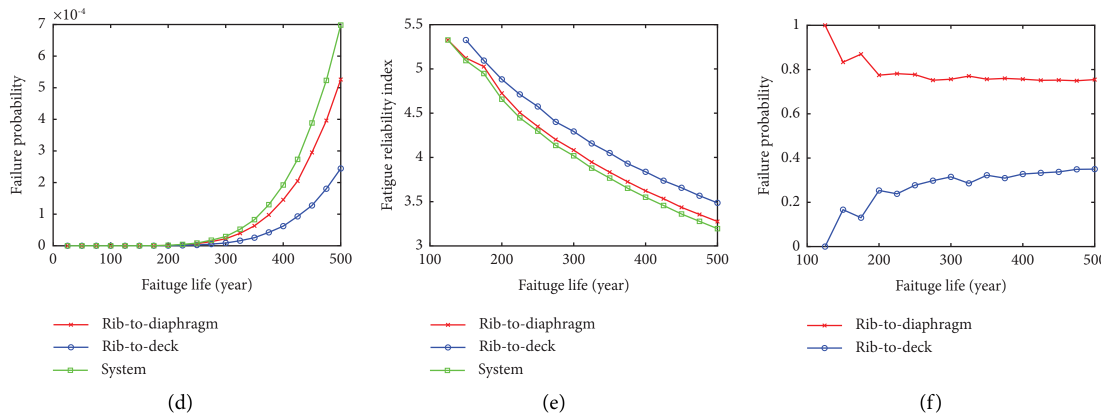

FIGURE 10: Schematic diagram of the investigated bridge: (a) daily stress range; (b) daily number of cycles; (c) daily fatigue damage; (d) failure probability; (e) fatigue reliability index; (f) component fatigue failure probability when the system failure is observed.

joints are significantly different, p_f of the OSD can be adequately described by focusing on the joints with higher ESSR and NC.

4. Conclusions

This paper introduces a novel method for updating the fatigue failure probability of the OSD using Bayesian backward propagation. The researchers developed a fatigue reliability model for the OSD, considering both rib-to-deck joints and rib-to-diaphragm joints. They conducted three case studies to demonstrate the applicability of their model. Finally, they applied the approach to a real steel bridge to determine the time-dependent fatigue failure probability at both system and component levels within the service life. The main conclusions of the study are as follows: (i) the component-level fatigue failure probability model will underestimate the fatigue life in comparison to the system-level model. The use of a Bayesian network allows for the updating of critical component failure probabilities based on observed system-level failure. (ii) The fatigue failure probability of the system is closely related to the welded joint with greater damage, when there is a significant difference in the daily damage degree of the two types of welded joints. When the daily damage degree is similar or the same, both welded joints jointly determine the fatigue failure probability of the system. (iii) For the investigated bridge in this study, both joints have impact on the fatigue performance. The rib-to-diaphragm joint in particular exhibits relatively large fatigue damage in comparison to the rib-to-deck joint.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The work described in this paper was jointly supported by the Zhejiang Engineering Research Center of Intelligent Urban Infrastructure (Grant no. IUI2023-YB-12), the Fundamental Research Funds for the Central Universities (Grant no. xzy012023075), the Shaanxi Provincial Natural Science Foundation of China (Grant no. 2021JQ-035), and the National Natural Science Foundation of China (Grant no. 52178306).

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