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A NEW COMPUTATIONAL METHOD FOR STRUCTURAL RELIABILITY WITH BIG DATA

NOWA METODA OBLICZENIOWA OCENY NIEZAWODNOŚCI KONSTRUKCJI W OPARCIU O BIG DATA

A new computational method for structural reliability based on big data is proposed in this paper. Firstly, the big data is collected via structural monitoring and is analyzed. The big data is then classified into different groups according to the regularities of distribution of the data. In this paper, the stress responses of a suspension bridge due to different types of vehicle are obtained. Secondly, structural reliability prediction model is established using the stress-strength interference theory under the repeated loads after the stress responses and structural strength have been comprehensively considered. In addition, structural reliability index is calculated using the first order second moment method under vehicle loads that are obeying the normal distribution. The minimum reliability among various types of stress responses is chosen as the structural reliability. Finally, the proposed method has been validated for its feasibility and effectiveness by an example.

Keywords: *big data, reliability, probability, stochastic loads, structure.*

W artykule zaproponowano nową metodę obliczeniową oceny niezawodności konstrukcji w oparciu o tzw. duże dane (ang. big data). W metodzie tej, duże dane gromadzi się poprzez monitorowanie konstrukcji, a następnie analizuje. W dalszej kolejności, dane są kwalifikowane do różnych grup zgodnie z ich rozkładem. W przedstawionej pracy, rejestrowano reakcje naprężeniowe mostu wiszącego na obciążenia różnymi typami pojazdów. Następnie, po dokładnym zbadaniu reakcji naprężeniowych i wytrzymałości konstrukcji mostu, utworzono model predykcyjny niezawodności konstrukcji z wykorzystaniem teorii obciążeniowo-wytrzymałościowej (ang. stress-strength interference) w warunkach powtarzających się obciążeń. Ponadto, wykorzystano metodę estymacji momentów (FOSM) do obliczenia wskaźnika niezawodności konstrukcji przy obciążeniach ruchem pojazdów zgodnych z rozkładem normalnym. Najmniejszą wartość niezawodności spośród wartości obliczonych dla różnych typów reakcji naprężeniowych przyjęto jako niezawodność konstrukcji. Proponowaną metodę zweryfikowano pod kątem możliwości praktycznego wykorzystania i skuteczności na przykładzie mostu wiszącego w Chinach.

Słowa kluczowe *: big data, niezawodność, prawdopodobieństwo, obciążenia stochastyczne, konstrukcja.*

1. Introduction

In modern manufacturing companies, big data is being captured by using lasers, sensors, wireless networks, etc. These big data include the processing of manufacturing processes, the effects of temperature, vibration, reliability data, etc. The big data is processed in the computer by using different algorithms for improving the products and to increase the competitiveness of the enterprise in the market. Big data is widely used to discover and develop new technologies, methods and decisions. Big data has been paid attention and researched in the modern society. The 5V (volume, velocity, variety, veracity, value) of big data have been defined and they are believed as important as the meaning of new technology [9, 14, 20].

The application principles of big data in the field of security engineering have been analyzed, the theoretical system of the secure big data application was established, the safe big data processing procedure was given, and the theoretical guidance was provided for the application of big data in the field of security science and engineering [11, 15]. With the massive operational data of the equipment, the big data processing technology could be applied to the reliability research of the large-capacity power and electronic systems.

The reliability research has been developed by using the latest theoretical results of big data science based on the data ubiquitous relationship. The big data is done with distributed algorithms, and a feasible algorithm was given by Al-kahtani and Karim [1].

The application of big data in traffic reliability operation has been put forward. It is believed that the new opportunities will be brought to innovation in traffic management and decision-making paradigm [4]. The data quality and data characteristics were analyzed, and the highway reliability estimation methods have been proposed [3, 23, 21]. The reliability of the system was predicted and analyzed using big data, and the prediction model was developed. The proposed method has been compared with the existing methods and their prediction model is better the others.

For most engineering structures, massive data would be generated during their service lifetime such as bridges, wind towers, pipelines and automobile chassis [22]. These structures are subjected not only a large amount of imposed load, but also other loads such as wind, corrosion, vibration, etc. The data is acquired timely, and the data would be analyzed and sorted. The structural reliability can be predicted using the data, and thus the effective maintenance and maintenance measures for the structure are proposed [19, 16, 7].

The existing bridge structures are normally evaluated using big data. It is suggested that the early maintenance of the bridge is very important [10, 2, 24]. A faster detection method which is nonlinear and more practical and feasible has been proposed using big data collected from the structural health monitoring for a large reinforced concrete structure in Italy [17]. The wind turbine failure model and the maintenance decision system is also established using big data which is obtained from the weather and wind power equipment [8,18]. However, there are few related works on the reliability of structures using big data. In most cases, big data has no obvious distribution rules, but in some cases, it is necessary to use these big data to evaluate the structural reliability.

In this paper, the collected big data is classified according to different types of vehicle. The structural stress response due to six types of vehicle is obtained. The structural reliability prediction model is developed based on the structural stress response and strength. Finally, the method is validated by using an example.

2. The Big Data of Structural Stress

During the structural service lifetime, massive structural health monitoring data of a structure can be produced because it is constantly subjected to imposed loads. The loads can be classified according to the characteristic of the data, they are classified as A_1, A_2, …, A_i, …, A_n, respectively. The number of the loads is denoted as m_i in each A_i, where i, m are 1, 2, 3 ... .

In each A_i, a structural load is denoted as S_{A_i}, and its corresponding stress is denoted as s_{A_i}. For all S_{A_i} in each A_i, the maximum load is determined and it is denoted as $S_{\max A_i}$ and its corresponding stress is denoted as $s_{\max A_i}$. Based on the conservative reliability analysis, during structural service period, a structure is assumed not subjected to a single continuous load, but multiple series of random loads. If the structure does not fail under the maximum load of these series of random loads, then the structure is considered safe under these series of random loads [6]. Hence, it is assumed that structural reliability under m_i load of S_{A_i} is equivalent to the reliability under m_i load of $S_{\max A_i}$ [5]. Based on the above assumption, structural reliability under the m_i times of the maximum load $S_{\max A_i}$ can be used to predict structural reliability under m_i times of S_{A_i} in each A_i.

3. Structural Reliability with Big Data

Suppose the probability distribution function and the probability density function of $s_{\max A_i}$ are $G_i(s_{\max A_i})$ and $g_i(s_{\max A_i})$, respectively, then the cumulative probability distribution of $s_{\max A_i}$ under m_i times random loads can be written as follows:

$$F_i(s_{\max A_i}) = [G_i(s_{\max A_i})]^{m_i} \tag{1}$$

The probability density function $f_i(s_{\max A_i})$ of the Eq. (1) can be obtained as follows:

$$f_i(s_{\max A_i}) = m_i[G_i(s_{\max A_i})]^{m_i-1} g_i(s_{\max A_i}) \tag{2}$$

Suppose the probability density function $f(\delta)$ of the random variable δ of the structural strength is obtained, the formulation of the structural reliability can be derived using the stress-strength interference theory under the A_i type of big data loads as follows.

$$\begin{aligned} p_{r_i} &= \int_{-\infty}^{\infty} f(\delta) \int_{-\infty}^{\delta} f_i(s_{\max A_i}) ds_{\max A_i} d\delta = \int_{-\infty}^{\infty} f(\delta) \int_{-\infty}^{\delta} m_i[G_i(s_{\max A_i})]^{m_i-1} \cdot g_i(s_{\max A_i}) ds_{\max A_i} d\delta \\ &= \int_{-\infty}^{\infty} f(\delta)[G_i(\delta)]^{m_i} d\delta \end{aligned} \tag{3}$$

Based on the n types of A_1, A_2, …, A_i, …, A_n of structural loads, a formulation of structural reliability can be obtained by using Eq. (3). Thus, each reliability can be obtained as follows, respectively:

$$p_{r_1},\ p_{r_2},\ \ldots,\ p_{r_i},\ \ldots,\ p_{r_n} \tag{4}$$

The minimum value of Eq. (4) is determined as the structural reliability under the big data loads:

$$p_r = \min\{p_{r_1}, p_{r_2}, \ldots, p_{r_i}, \ldots, p_{r_n}\} \tag{5}$$

If $g_i(s_{\max A_i})$ is a normal distribution, then p_{r_i} can be computed by using the first-order second-moment method.

Suppose $\mu_{\max A_i}$ is the mean of $s_{\max A_i}$, $\sigma_{\max A_i}$ is the standard deviation of $s_{\max A_i}$, β_i is the structural reliability index for each A_i type of loads, the computational procedure for β_i is given as follows.

The mean of $F_i(s_{\max A_i})$ is denoted as μ_{F_i}, it can be obtained by using Eq. (2).

$$\mu_{F_i} = \int_{-\infty}^{\infty} s_{\max A_i} f_i(s_{\max A_i}) ds_{\max A_i} \tag{7}$$

Then, Eq. (8) can be obtained by using the Equations (1) and (7) as follows:

$$\mu_{F_i} = \int_{-\infty}^{+\infty} s_{\max A_i} \cdot m_i[G(s_{\max A_i})]^{m_i-1} \cdot g_i(s_{\max A_i}) ds_{\max A_i} \tag{8}$$

Eq (8) can then be simplified as follows:

$$\mu_{F_i} = s_{\max_{A_i}}[G(s_{\max A_i})]^{m_i} \tag{9}$$

The standard deviation of $F_i(s_{\max A_i})$ is denoted as σ_{F_i}, whereas the deviation of $F_i(s_{\max A_i})$ is denoted as D_{F_i}, which can be obtained by using Eq. (2) as follows:

$$D_{F_i} = E(s^2_{\max A_i}) - E(s_{\max A_i})^2 \tag{10}$$

Eq.(10) can be computed as follows:

$$D_{F_i} = \int_{-\infty}^{\infty} s^2_{\max A_i} \cdot f_i(s_{\max A_i}) ds_{\max A_i} - \mu^2_{F_i} \tag{11}$$

Based on a conservative perspective, in order to increase μ_{F_i} value significantly, $s_{\max A_i}$ in Eq. (11) can be reduced by replacing ($\mu_{\max A_i} - 3\sigma_{\max A_i}$) in the denominator of Eq (11) as follows:

$$D_{F_i} = \mu^2_{\max A_i} - 6\mu_{\max A_i}\sigma_{\max A_i} + 9\sigma^2_{\max A_i} - (\mu_{F_i})^2 \tag{12}$$

In addition, it can be derived that the relationship between σ_{F_i} and D_{F_i} as follows:

$$D_{F_i} = (\sigma_{F_i})^2 \tag{13}$$

Considering Eq. (10) and Eq. (13), structural reliability index under ith type of big data loads can be calculated as follows:

$$\beta_i = \frac{\mu_\delta - \mu_{F_i}}{\sqrt{\sigma^2_\delta + D_{F_i}}} \tag{14}$$

where μ_δ and σ_δ are the mean and standard deviation of structural strength, respectively.

For the loads that are non-normal distribution, it can be converted to equivalent normalization to compute structural reliability index by using Eq. (14). If

$$\beta = \min\{\beta_1, \beta_2, \cdots, \beta_i, \cdots, \beta_n\} \tag{15}$$

then β is the final structural reliability index which can be obtained by examining the normal distribution table.

4. Numerical Example

The structural health monitoring data was collected for a large spanning suspension bridge in China with 3 GB data per day, that is 1 TB big data every year [12]. The collected load data comprises of vehicles passing through the bridge in the whole year of 2015.

The reliability of the welding joint of U stiffener and roof, which is the weak link of the bridge [13], under the passing vehicle loads on the bridge in 2015 is studied. The passing vehicles of the whole year are divided into six types according to the number of axles of the vehicle as follows:

Type I, 2 axles 2 axles,
Type II, 3 axles 2 axles,
Type III, 4 axles 3 axles,
Type IV, 5 axles 3 axles,
Type V, 6 axles 3 axles,
Type VI, 6 axles 4 axles.

The ratios of the loads for the six types of vehicles are show in Table 1. The stresses of the six types of vehicles obey the normal distribution, and their mean and standard deviation are shown in Table 2.

The strength of the welding joint of U stiffener and roof is also assumed to obey the normal distribution with the mean of 345 MPa and the standard deviation of 15 MPa. In this example, the theoretical lifetime of the part is 204 years, whereas the actual observed lifetime is 165 years (Ma et al 2017). According to the traffic intensity of the most intercity highway vehicles, the intensity of amplification $\lambda = 6$ is obtained. The λ is allocated according to the proportion of the six types of vehicles as shown in Table 3.

The reliability values P_1 , $\cdots$, P_i , $\cdots$, P_6 are computed by using Eq. (5) as shown in Table 4. As can be seen from the above example, the reliability of the welding joint of U stiffener and roof is 0.9999963 for type VI vehicle according to the lifetime of the suspension bridge which was computed by using the big data. It is proved that the bridge is reliable within the actual service life.

The reliability indices β_1 , $\cdots$, β_i , $\cdots$, β_6 are computed by using Eq. (14) as shown in Table 5.

As can be seen from Table 5, the reliability index of the welding joint of U stiffener and roof for type VI vehicle is 5.09, according to the Gaussian distribution table, its probability value is about 0.999999961. It is shown that Eq. (15) can be used to compute structural reliability too. The results of the Eq. (5) and Eq. (15) are equal to

Table 1. The ratio of the six types of vehicle when they pass through the suspension bridge

Type of vehicle	I	II	III	IV	V	VI
Ratio	95.60	1.171	1.15	0.744	0.43	0.37

Table 2. The mean and standard deviation of the six types of vehicles

Type of vehicle	Mean (MPa)	Standard deviation (MPa)
I	22.37	1.961
II	41.25	3.602
III	58.80	5.135
IV	75.64	6.606
V	80.53	7.032
VI	90.75	7.925

Table 3. The intensity of the six types of vehicle when they pass through the suspension bridge

Type of vehicle	I	II	III	IV	V	VI
λ_i	5.736	0.1026	0.069	0.0258	0.0444	0.0222

Table 4. The reliability of welding joint of U stiffener and roof under the six types of big data loads

Type of vehicle	I	II	III	IV	V	VI
Reliability P_i	0.9999999	0.9999999	0.9999998	0.9999995	0.9999992	0.9999963

Table 5. The reliability index of welding joint of U stiffener and roof under the six types of big data loads

Type of vehicle	I	II	III	IV	V	VI
Reliability index βi	15.47	10.16	7.36	5.89	5.648	5.09

each other. The structural reliability can be computed if the big data is obeyed the normal distribution.

In addition, it can also be seen that type I vehicles produce a small impact on the welding joint of U stiffener and roof due to its small load, although its strength is large. Although the load of type VI vehicles has less strength, the reliability of the joint has greatly influence because its load is large. This also puts forward corresponding requirements for the management and maintenance of the bridge, if necessary, the vehicles with larger loads must be restricted to ensure the reliability of the bridge.

5. Conclusion

The collected big data has been analyzed according to its source and distribution. The different types of stress response of the structure have been obtained after the big data was classified. The structural reliability computational model was proposed using the stress-strength interference theory according to the different types of structural stress response and structural strength. The different structural reliabilities were computed according to the different strengths, respectively. The minimum of these reliabilities is the reliability of the structure. It is shown that the method is feasible and effective by using an example.

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