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.

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].

Yongfeng FANG
Wenliang TAO
Kong Fah TEE

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) 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 modern society. The 5V (volume, velocity, variety, veracity, value) of big data have been defined and they are believed as important as the modern society.
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 $A_1$, $A_2$, $\ldots$, $A_i$, $\ldots$, $A_n$, respectively. The number of the loads is denoted as $m_i$ in each $A_i$, where $i = 1, 2, 3 \ldots$

In each $A_i$, a structural load is denoted as $S_{A_i}$, and its corresponding stress is denoted as $\delta_{A_i}$. For all $S_{A_i}$ in each $A_i$, the maximum load is determined and it is denoted as $S_{\text{max}\_A_i}$ and its corresponding stress is denoted as $\delta_{\text{max}\_A_i}$. 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 $S_{\text{max}\_A_i}$ [5]. Based on the above assumption, structural reliability under the $m_i$ times of the maximum load $S_{\text{max}\_A_i}$ 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 $S_{\text{max}\_A_i}$ are $G_i(s_{\text{max}\_A_i})$ and $g_i(s_{\text{max}\_A_i})$, respectively, then the cumulative probability distribution of $s_{\text{max}\_A_i}$ under $m_i$ times random loads can be written as follows:

$$F_i(s_{\text{max}\_A_i}) = [G_i(s_{\text{max}\_A_i})]^{m_i}$$

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

$$f_i(s_{\text{max}\_A_i}) = m_i [G_i(s_{\text{max}\_A_i})]^{m_i-1} g_i(s_{\text{max}\_A_i})$$

Suppose the probability density function $f(\delta)$ of the random variable $\delta$ 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 as follows.

$$P_i = \frac{\int_{-\infty}^{\delta} f_i(s_{\text{max}\_A_i}) \delta_{\text{max}\_A_i} - \delta \, ds_{\text{max}\_A_i}}{\int_{-\infty}^{\delta} f_i(s_{\text{max}\_A_i}) \delta_{\text{max}\_A_i} - \delta \, ds_{\text{max}\_A_i}}$$

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

$$P_{n_1}, P_{n_2}, \ldots, P_{n_i}, \ldots, P_{n_n}$$

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

$$p_r = \min\{P_{n_1}, P_{n_2}, \ldots, P_{n_i}, \ldots, P_{n_n}\}$$

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

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

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

$$\mu_{F_i} = \int_{-\infty}^{\infty} s_{\text{max}\_A_i} f_i(s_{\text{max}\_A_i}) ds_{\text{max}\_A_i}$$

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

$$\mu_{F_i} = \int_{-\infty}^{\infty} s_{\text{max}\_A_i} m_i [G_i(s_{\text{max}\_A_i})]^{m_i-1} g_i(s_{\text{max}\_A_i}) ds_{\text{max}\_A_i}$$

Eq (8) can then be simplified as follows:

$$\mu_{F_i} = s_{\text{max}\_A_i} [G_i(s_{\text{max}\_A_i})]^{m_i}$$

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

$$D_{F_i} = E(s_{\text{max}\_A_i}^2) - E(s_{\text{max}\_A_i})^2$$

Eq (10) can be computed as follows:

$$D_{F_i} = \int_{-\infty}^{\infty} s_{\text{max}\_A_i} f_i(s_{\text{max}\_A_i}) ds_{\text{max}\_A_i} - \mu_{F_i}^2$$
Based on a conservative perspective, in order to increase $\mu_F$ value significantly, $s_{\max A}$ in Eq. (11) can be reduced by replacing $(\mu_{\max A} - 3\sigma_{\max A})$ in the denominator of Eq (11) as follows:

$$D_{Fi} = \frac{\mu_{\max A}^2 - 6\mu_{\max A}\sigma_{\max A} + 9\sigma_{\max A}^2 - (\mu_F)^2}{2\mu_{\max A}^2}$$

(12)

In addition, it can be derived that the relationship between $\sigma_{Fi}$ and $D_{Fi}$ as follows:

$$D_{Fi} = (\sigma_{Fi})^2$$

(13)

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

$$\beta_i = \frac{\mu_S - \mu_{\max A}}{\sqrt{\sigma^2 + D_{Fi}}}$$

(14)

where $\mu_S$ and $\sigma_S$ 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

$$\beta = \min\{\beta_1, \beta_2, \ldots, \beta_i, \ldots, \beta_n\}$$

(15)

then $\beta$ 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 $\lambda$ is allocated according to the proportion of the six types of vehicles as shown in Table 3.

The reliability values $P_1, \ldots, P_i, \ldots, P_6$ 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 0.99999963 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 $\beta_1, \ldots, \beta_i, \ldots, \beta_6$ 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>
<thead>
<tr>
<th>Type of vehicle</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>V</th>
<th>VI</th>
</tr>
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<tbody>
<tr>
<td>Ratio</td>
<td>95.60</td>
<td>1.171</td>
<td>1.15</td>
<td>0.744</td>
<td>0.43</td>
<td>0.37</td>
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<table>
<thead>
<tr>
<th>Type of vehicle</th>
<th>Mean (MPa)</th>
<th>Standard deviation (MPa)</th>
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<tr>
<td>I</td>
<td>22.37</td>
<td>1.961</td>
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<td>II</td>
<td>41.25</td>
<td>3.602</td>
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<tr>
<td>III</td>
<td>58.80</td>
<td>5.135</td>
</tr>
<tr>
<td>IV</td>
<td>75.64</td>
<td>6.606</td>
</tr>
<tr>
<td>V</td>
<td>80.53</td>
<td>7.032</td>
</tr>
<tr>
<td>VI</td>
<td>90.75</td>
<td>7.925</td>
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<tr>
<th>Type of vehicle</th>
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<td>II</td>
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<td>III</td>
<td>0.069</td>
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<td>IV</td>
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<td>V</td>
<td>0.0444</td>
</tr>
<tr>
<td>VI</td>
<td>0.0222</td>
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<table>
<thead>
<tr>
<th>Type of vehicle</th>
<th>Reliability $P_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>0.9999999</td>
</tr>
<tr>
<td>II</td>
<td>0.9999999</td>
</tr>
<tr>
<td>III</td>
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<tr>
<td>IV</td>
<td>0.9999995</td>
</tr>
<tr>
<td>V</td>
<td>0.9999992</td>
</tr>
<tr>
<td>VI</td>
<td>0.9999963</td>
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</table>
have been obtained after the big data was classified. The structural re-
and distribution. The different types of stress response of the structure
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 re-
liability 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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Yongfeng FANG
School of Mechanical Engineering
Guizhou University of Science Engineering
Qixingguan, Bijie, 551700, China

Wenliang TAO
School of Information Engineering
Guizhou Minzu University
Huaxi, Guiyang, 551000, China

Kong Fah TEE
School of Engineering
University of Greenwich
Kent, ME4 4TB, UK

E-mails: fangyf_9707@126.com, wltao@gzu.edu.cn, k.f.tee@greenwich.ac.uk