Study on Damage Inference of Parker Trusses Based on Bayesian Principles

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Abstract. The assessment of the health condition and safety of engineering structures is currently a research focus in the field of civil engineering. The traditional deterministic model for damage recognition is limited by the fine reading of field inspections and the accuracy of experts, resulting in a low recognition rate. Structural damage identification methods that consider uncertainty have been developed due to modelling errors, observation noise, system time variability, and other factors that lead to uncertainty. This study focuses on the Parker truss structure, and a two-dimensional planar finite element model is established by setting various key parameters such as prior distribution, stiffness, modulus of elasticity, node distribution, and external loading. The model is updated using the Bayesian updating principle. This principle is then combined with the finite element model. Opensees software is used for programming, and the Monte Carlo random sampling technique is used for structural damage inference. The study results demonstrate that the method can accurately identify the damage level of Parker truss structures with high robustness. The method can be of reference significance and practical value for identifying damage in truss structures.

Keywords: Bayesian updating principle, Parker truss structure, Monte Carlo random sampling technique.

1. Introduction

With extended use, the present state of a building's structure may differ from its previous state, necessitating a re-evaluation of its dependability. Various factors, such as the structure's ageing, damage caused by disasters, and overloaded operation, can cause alterations in the engineering structure. In reality, significant accidents caused by structural damage are not rare. For instance, in July 2017, the approach bridge to the Third Qianjiang River Bridge collapsed due to differences between the designed and actual structures, as well as a significant discrepancy between the designed and actual operational loads [1]. On 14 August 2018 at 11:36 pm local time, the bridge deck of the Genoa 'Morandi' bridge on the A10 motorway in Italy collapsed suddenly, with over 30 cars driving on it at the time. During the bridge collapse incident, over ten cars, including three heavy lorries, fell into the river. The accident resulted in the tragic loss of 43 lives [2]. This resulted in three vehicles plunging into the river, the loss of one boat, two fatalities, two missing individuals, and three injuries. The investigation concluded that the load-bearing steel cables were partly corroded, significantly reducing their weight support capacity. Furthermore, the actual traffic flow was drastically higher than the bridge's design capacity, thereby contributing to the accident. Throughout history, the construction of large engineering structures such as bridges and buildings has taught us valuable lessons. As such, it is essential to utilise structural damage monitoring and analysis to prevent accidents and avoid unnecessary losses.

With the advancement of science and technology, research into the detection of structural damage has made rapid progress. Several scholars have conducted relevant studies within this field. Present scientific research indicates three primary challenges regarding structural damage. Firstly, how to identify the existence of structural damage. Secondly, how to determine the effects of certainty and uncertainty in structural damage. Finally, how to assess the extent of structural damage is the third challenge [3-5].

Damage identification can be categorised into local and holistic approaches. Conventional non-destructive testing (NDT) methods [6], including ultrasonic, X-ray, magnetic particle, and thermal imaging, are utilised in local methods. These methods employ acoustic, optical, thermal, magnetic, and electrical techniques, which are now technically mature. However, due to methodological limitations, it is not feasible in practical applications to investigate all structural areas simultaneously and continuously. Hence, the employment of local identification methods falls short of satisfying the real-time damage detection requirements of modern structures. As a result, techniques that depend on structural displacements have emerged to predict the damage caused to the structural system. Despite the current methodology for inferring the extent of damage identification relying on structural displacement still being in its infancy, it has the capability of accomplishing the objective of constant monitoring in real-time and the timely detection of damage. Therefore, the improvement of structural safety measures is of paramount importance. Therefore, the method of identifying structural damage location and degree using displacement is currently a popular focus in research.

Traditional deterministic methods for identifying structural damage have primarily focused on localising the damage in time and space, and determining its severity [7, 8]. Technical abbreviations will be explained upon first use. Based on this concept, various identification methods have been developed at home and abroad: identification methods based on kinetic fingerprinting; identification methods based on model correction; identification methods based on wavelet transform; and identification methods based on neural networks. Despite recent advancements in deterministic methods for identifying structural damages, most of the identification methods rely on the initial finite element model. This presents a significant challenge for the identification of increasingly complex structures. Furthermore, the majority of damage identification methods have difficulty detecting extremely small damages, which hinders the practical implementation of deterministic identification methods.

However, due to the high frequency of modelling errors, observation noise, and time-varying systems in civil engineering structures, there exists significant ambiguity in observation data, resulting in uncertain identification of structural damage. The utilization of probabilistic statistical theory in mathematics for damage identification shall emerge as a pioneering trend. Currently, the most prevalent trend is based on the Bayesian method of finite element model correction. For instance, Zhang et al. [9] developed a Monte Carlo approach utilising a response surface methodology, substituting the initial finite element model for the response surface model in computer simulations. Gao [10] discussed the non-deterministic problem of identifying structural damage, and the current traditional two-stage identification method that relies on modal parameter identification. The method uses the structural time-domain response as an observable and applies the Bayesian model updating approach to determine the a posteriori joint distribution of the structural physical parameters. By utilising the suggested component-by-component adaptive Metropolis-Hastings (MH) sampling algorithm with the optimal proposed distribution, the posterior margins of the probability distributions for every physical parameter can be obtained, alongside optimum estimates. This provides a Bayesian approach for detecting physical parameters based on the time-domain response of the structure.

This research investigates the use of the Bayesian updating technique in detecting structural damages. The approach involves obtaining posterior information by gaining both a priori information on the overall parameter distribution prior to testing and actual sample information. This permits an understanding of the effect on the overall parameter distribution after the acquisition of sample information. The study utilises the displacement response of the truss model during loading experiments as the basis for updating the structure's damage identification. To enhance the effectiveness of damage identification, the optimisation of loading tests is examined.

2. Methodology

This study employs a combination of the Bayesian updating principle and finite element analysis to infer structural damage in the Parker truss structure. The Opensees software is used for programming, and the Monte Carlo random sampling technique is used to build the finite element model. The experiment is divided into two parts.

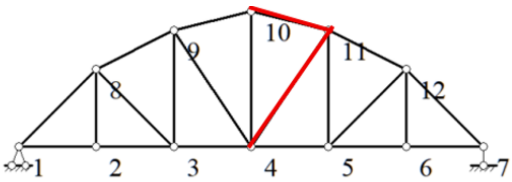


Figure 1. Parker Truss Model

Fig. 1 shows a Parker truss structure in the first part. Two structural damages are assumed to be present, one in rods 10-11 and the other in rods 4-11. The rods of 10-11 are referred to as 10 rods, while the rods of 4-11 are referred to as 18 rods. The degree of damage can be assessed by measuring the stiffness of the rods, which is reflected in the data as an average. For the purpose of simulation, this experiment assumes that the stiffness of the 10-rod is 2.1 ($10^5 kN{\cdot}m^2$) and the stiffness of the 18-rod is 1.685 ($10^5 kN{\cdot}m^2$). The model should be defined as 2D in opensees, with corresponding points and supports set, and the undamaged rods' true stiffness entered. The modulus of elasticity for the rod material should be set to $10^5 kN$ to create a realistic model. The experiment applies a vertical downward load of 100KN uniformly on the structure to generate displacement at each node. The displacement of selected points in the x and y directions is monitored and correlated with the set parameter x. The real displacements of the points are then determined and the x-parameter is updated.

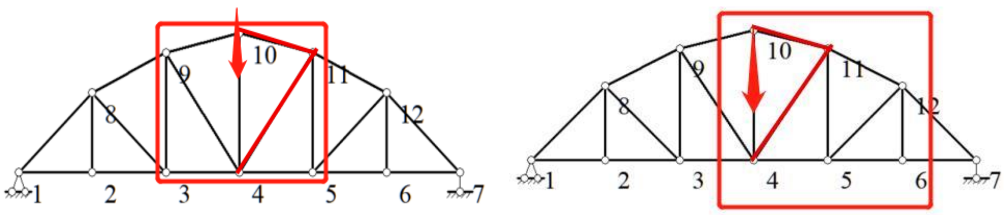
The second part of the experiment involves building a finite element model to simulate the Parker truss structure. This model is then used to perform Bayesian updating of the output displacements. The x- and y-direction displacements of the monitoring locations are defined and correlated with the parameter s. To perform Bayesian updating of the model, a loop system is created using a Monte Carlo random sampling technique. The recurrent system's number of cycles is predetermined, and the prior distribution of the stiffness of the damaged bars is given. The parameter re represents the stiffness of the damaged rods, which is related to the prior distribution. In this experiment, the a priori distribution was set uniformly to U [1.05,2.31] for 10 bars and U [0.42,1.89] for 18 bars. The analysis updated the s-parameters and outputted the displacements at each point of the finite element model. The x-parameters were compared with the s-parameters. A relative error limit of 5% was set uniformly on the data as it is more conducive to accuracy improvement than the absolute error of 0.5mm.

Finally, only the displacements that meet the error conditions after comparison are accepted, and the remaining ones are rejected. By considering the mechanical relationship between the displacement and stiffness of the monitoring point, the parameter RE is used to obtain a stiffness distribution that closely approximates the true value, i.e., the a posteriori distribution.

3. Results and Discussion

An experiment was conducted to investigate the physical properties. The experiment involved varying several variables, including the observation sites, load application sites, number of monitoring sites, load magnitude, a priori distribution, and number of cycles.

3.1. Experimental Monitoring Site Changes



(a) Variable Group (b) Control Group

Figure 2. Experimental Monitoring Site Schematic Changes

The experiment was conducted with a variable group and a control group for comparison. The monitoring points for the variable group were set at positions 3, 4, 5, 9, 10, and 11, as shown in Fig. 2. The monitoring points for the control group were set at positions 4, 5, 6, 10, 11, and 12. All other variables were kept constant. The rejection sampling algorithm, using the Monte Carlo random sampling technique, produced data for the variable and control groups by altering the experimental monitoring sites. The results are presented in Table 1 and Table 2.

Table 1. Experimental Variable Group Data for Monitoring Site Changes

Pole No.	Mean value	Standard deviation	Data volume	Prior distribution	Inaccuracies	Cyclic number
Pole 10	2.056706	0.132351	12050	U [1.05,2.31]	Relative error5%	100000
Pole 18	1.635105	0.143276	12050	U [0.42,1.89]	Relative error5%	100000

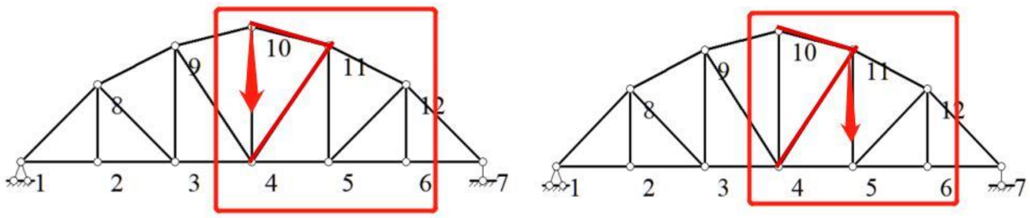
Table 2. Experimental Control Group Data for Monitoring Site Changes

Pole No.	Mean value	Standard deviation	Data volume	Prior distribution	Inaccuracies	Cyclic number
Pole 10	2.058505	0.131242	12147	U [1.05,2.31]	Relative error5%	100000
Pole 18	1.63537	0.143009	12147	U [0.42,1.89]	Relative error5%	100000

Tables 1 and 2 show that, all other things being equal, the mean values for the experimental and control groups are very similar, and the acceptance rates of the data are approximately the same. Therefore, it can be concluded that changing the location of the experimental monitoring sites had little effect on the results of the experimental monitoring.

3.2. Changing the Point of Load Application

The following section outlines the experimental steps and results regarding the effects of changing the load application point.



(a) Variable Group (b) Control Group

Figure 3. Schematic Diagram of Changing the Point of Load Application

The experiment involved setting up separate variable and control groups. The variable group was subjected to a vertical load of 100 KN at the 10 o'clock position, while the control group was subjected to the same load at the 11 o'clock position, as shown in Fig. 3. All other variables remained constant. The data presented were obtained by using different models for Part I and Part II.

Table 3. Modifying the dataset of load application points

Pole No.	Mean value	Standard deviation	Data volume	Prior distribution	Inaccuracies	Cyclic number
Pole 10	2.058505	0.131242	12147	U [1.05,2.31]	Relative error5%	100000
Pole 18	1.63537	0.143009	12147	U [0.42,1.89]	Relative error5%	100000

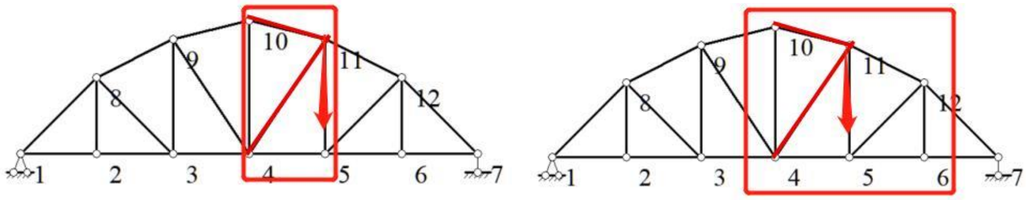
Table 4. Controlling the data group for load application point changes

Pole No.	Mean value	Standard deviation	Data volume	Prior distribution	Inaccuracies	Cyclic number
Pole 10	2.029263	0.160509	5570	U [1.05,2.31]	Relative error5%	100000
Pole 18	1.721549	0.083742	5570	U [0.42,1.89]	Relative error5%	100000

Tables 3 and 4 show that, all else being equal, the data for the variable group is similar to that of the control group for 10 rods. However, for 18 rods, the data for the variable group is less accurate than that of the control group, and the standard deviation is much larger. The stiffness inferred from the data with the load applied at the 11-point position is more accurate than the stiffness inferred from the data with the load applied at the 10-point position.

3.3. Number of Measurement Points

The following section outlines the impact of altering the number of monitoring sites. The experimental steps and results are presented below.



(a) Variable Group (b) Control Group

Figure 4. Schematic of changing the number of monitoring sites

The experiment involved setting up a variable group and a control group. The monitoring points in the variable group were reduced to four points (4, 5, 10, and 11), while the monitoring points in the control group remained at six points (4, 5, 6, 10, 11, and 12), as shown in Fig. 4. All other quantities remained unchanged. By changing both the first and second parts of the code, the following data is obtained.

Table 5. Variable data set for adjusting the number of monitoring sites.

Pole No.	Mean value	Standard deviation	Data volume	Prior distribution	Inaccuracies	Cyclic number
Pole 10	2.029331	0.158945	5664	U [1.05,2.31]	Relative error5%	100000
Pole 18	1.72148	0.083734	5664	U [0.42,1.89]	Relative error5%	100000

Table 6. Change in the number of monitoring sites in the control group data.

Pole No.	Mean value	Standard deviation	Data volume	Prior distribution	Inaccuracies	Cyclic number
Pole 10	2.029263	0.160509	5570	U [1.05,2.31]	Relative error5%	100000
Pole 18	1.721549	0.083742	5570	U [0.42,1.89]	Relative error5%	100000

Tables 5 and 6 show that the mean and standard deviation of the variable group and the control group are similar, indicating that the inferred stiffness distributions are close. Additionally, the acceptance rates of the two groups are comparable. Therefore, it can be concluded that varying the number of monitoring sites has little to no effect on the experimental monitoring.

3.4. Adjusting the Load Size

The following section outlines the experimental steps and data related to the effect of changing the load size on the results.

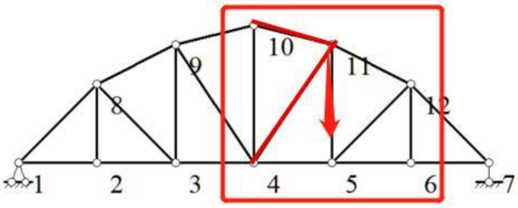


Figure 5. Schematic Diagram of Truss Points and Loads

In this experiment, the truss monitoring points and load application points were identical for both the variable and control groups, as depicted in Fig. 5. The load size of the control group remained constant, while the variable group's load was set to 1000KN in a vertical downward direction. Modifications were made to the models in the first and second sections, and the load size was adjusted to 1000KN in both load setting sections, resulting in the following data.

Table 7. Modifying the dataset for the load size variable.

Pole No.	Mean value	Standard deviation	Data volume	Prior distribution	Inaccuracies	Cyclic number
Pole 10	2.027384	0.157153	5567	U [1.05,2.31]	Relative error5%	100000
Pole 18	1.722669	0.081739	5567	U [0.42,1.89]	Relative error5%	100000

Table 8. Modifying the data of the control group for load size

Pole No.	Mean value	Standard deviation	Data volume	Prior distribution	Inaccuracies	Cyclic number
Pole 10	2.029263	0.160509	5570	U [1.05,2.31]	Relative error5%	100000
Pole 18	1.721549	0.083742	5570	U [0.42,1.89]	Relative error5%	100000

Tables 7 and 8 show that there is almost no significant difference in the mean, standard deviation, and amount of data between the variable group and the control group. This suggests that the magnitude of the load has little effect on the results of the experiment.

3.5. Modifying the Prior Distribution

The following section outlines the specific experimental steps and data related to the effect of changing the a priori distribution on the experimental results. The experiment utilises the same points and load settings as shown in Fig. 5, but alters the a priori distribution of damaged rods by changing the presumed range of damage. Specifically, the variable group modifies the a priori distribution of 10 rods to U [1.15,2.21], while the a priori distribution of 18 rods remains unchanged. The modification of the prior distribution for the 10 rods in the second part of the model led to the subsequent data.

Table 9. Modifying the data of previously distributed sets of variables

Pole No.	Mean value	Standard deviation	Data volume	Prior distribution	Inaccuracies	Cyclic number
Pole 10	1.982055	0.129503	5605	U [1.15,2.21]	Relative error5%	100000
Pole 18	1.739792	0.07682	5605	U [0.42,1.89]	Relative error5%	100000

Table 10. Modifying the a priori distribution of data in the control group

Pole No.	Mean value	Standard deviation	Data volume	Prior distribution	Inaccuracies	Cyclic number
Pole 10	2.029263	0.160509	5570	U [1.05,2.31]	Relative error5%	100000
Pole 18	1.721549	0.083742	5570	U [0.42,1.89]	Relative error5%	100000

Tables 9 and 10 show a small deviation in the data, except for the variable group. The acceptance rate of both data groups is distributed around 5.55%, and the standard deviation is similar, indicating a relatively similar distribution of data. The inferred stiffnesses are also close. Therefore, it can be concluded that the change in the a priori distribution has no significant effect on the experimental results.

3.6. Increasing the Number of Cycles

The following section outlines the specific experimental steps and data related to the effect of increasing the number of cycles on the experimental results. The experiment utilises the same monitoring point location and load as shown in Fig. 5. The number of cycles is increased from 100,000 to 200,000, with a 95% confidence level. The obtained data is presented below.

Table 11. Adding data for cyclic variable groups

Pole No.	Mean value	Standard deviation	Data volume	Prior distribution	Inaccuracies	Cyclic number	Confidence value
Pole 10	2.030484	0.157385	11547	U [1.05,2.31]	Relative error5%	200000	0.002871
Pole 18	1.721364	0.082201	11547	U [0.42,1.89]	Relative error5%	200000	0.001499

Table 12. Adding data for cyclic control groups

Pole No.	Mean value	Standard deviation	Data volume	Prior distribution	Inaccuracies	Cyclic number	Confidence value
Pole 10	2.029263	0.160509	5570	U [1.05,2.31]	Relative error5%	100000	0.004215
Pole 18	1.721549	0.083742	5570	U [0.42,1.89]	Relative error5%	100000	0.002199

The CONFIDENT function in Excel software was used to derive confidence values for both the variable and control groups in this experiment. This suggests an improvement in the experiment's accuracy. Table 11 and Table 12 show that doubling the number of cycles for the variable group did not result in a significant change in the mean, but it did decrease the standard deviation and confidence value. It can be concluded that increasing the number of cycles improves the accuracy of the experimental results.

3.7. Optimising Damage Monitoring Programmes

The experiments yielded an optimised scheme for detecting damage.

(1) The selection of monitoring sites and their number did not significantly affect the results. Therefore, the six sites (4, 5, 6, 10, 11, and 12) shown in Fig. 6 were chosen for monitoring in this experiment.

(2) In this experiment, a load of 100KN was applied vertically downward to the 11-point location of the Parker truss, as shown in Fig. 6, to obtain more accurate data on the effect of the two damage locations, rods 10 and 18.

(3) The settings of U [1.05,2.31] for rod 10 and U[0.42,1.89] for rod 18 were kept constant since the damage at these locations was not sensitive to changes in the a priori distribution.

(4) To distinguish the data from the variable experiments, the protocol sets the stiffness after damage to 1.651 (10^5 kN·m²) for the 10-rod and 0.889 (10^5 kN·m²).

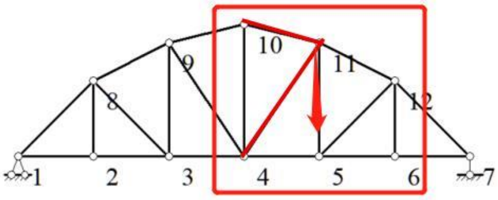


Figure 6. Optimisation Scheme Schematic Diagram

The initial step in constructing the Parker truss structure involves building the first section. In the code section of the constructed bars, the stiffness of the 10 and 18 bars is modified. The six monitoring points are associated with the parameter x, and their corresponding true displacements are analysed, updated, and outputted as shown in Table 13.

Table 13. Monitoring Point Displacement Value

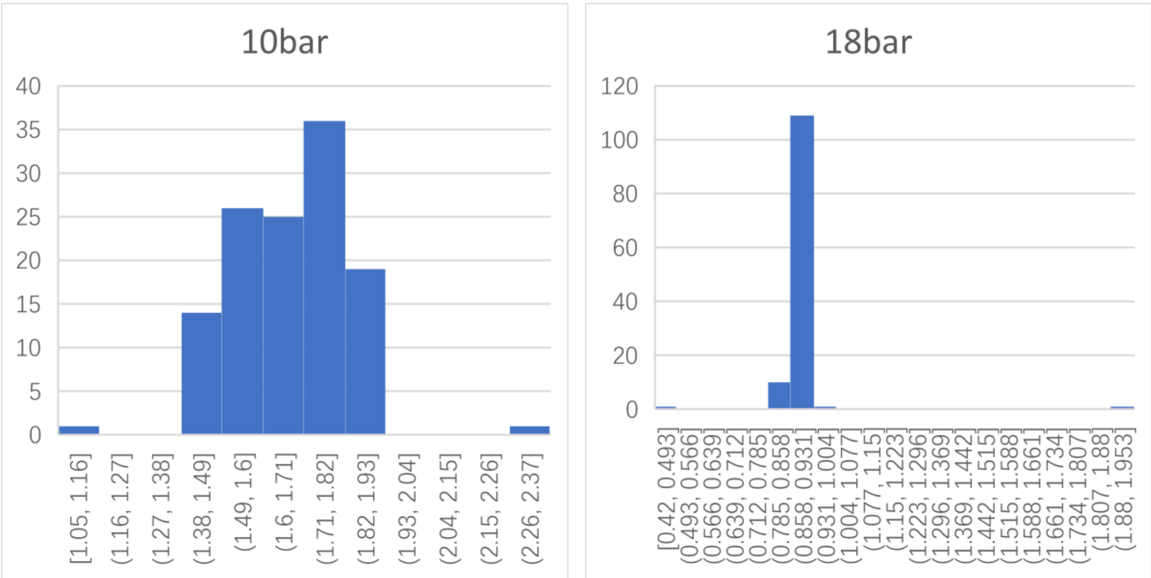
Measurement Points and Directions	Displacement Value
Point4 vertical displacement	0.025389
Point4 transverse displacement	0.005334
Point5 vertical displacement	0.03409
Point5 transverse displacement	0.009653
Point6 vertical displacement	0.022368
Poinnt6 transverse displacement	0.012828
Point10 vertical displacement	0.022883
Point10 transverse displacement	0.007323
Point11 vertical displacement	0.035957
Piont11 transverse displacement	0.000264
Point12 vertical displacement	0.022368
Point12 transverse displacement	0.001581

Next, a finite element model is constructed for the second part based on Fig. 6. The damaged rod stiffness is replaced by the parameter RE, allowing for arbitrary stiffness values and defined monitoring point displacements.

The cyclic system was established using the Monte Carlo method. The number of cycles was set to 100,000, and the error range was determined. The a priori distribution was inputted and correlated with the stiffness of the damaged bars. The analysis was conducted to obtain the posterior distribution, as presented in Table 14 and Fig. 7.

Table 14. A Posteriori Distribution After 100,000 Cycles by using the Optimisation Scheme

Pole identifier	Mean value	Standard deviation	Data volume	Prior distribution	Inaccuracies	Cyclic number	Confidence value
Pole 10	1.672098	0.131602	120	U[1.05,2.31]	Relative error5%	100000	0.023546
Pole 18	0.887871	0.023112	120	U[0.42,1.89]	Relative error5%	100000	0.004135



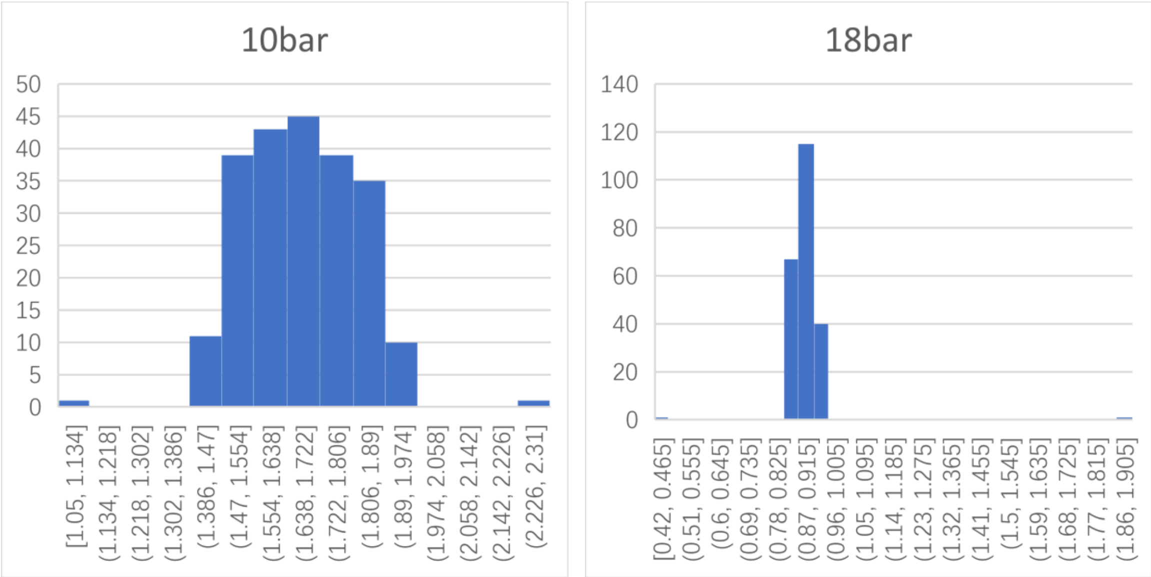
(a) (b)

Figure 7. Histogram of the posterior distribution of 100000 cycles of the optimisation scheme

Table 14 and Fig. 7 show that the mean values are very close to the true values and the histogram distribution is denser. This suggests that the stiffness derived from this scheme is more accurate. However, the acceptance rate is only 0.12%. After increasing the number of cycles to 200000, the experimental results are as follows. The abscissa of the histogram is the stiffness, and the vertical coordinate is the frequency

Table 15. A Posteriori Distribution After 200,000 Cycles by using the Optimisation Scheme

Pole identifier	Mean value	Standard deviation	Data volume	Prior distribution	Inaccuracies	Cyclic number	Confidence value
Pole 10	1.672586	0.132838	224	U[1.05,2.31]	Relative error5%	200000	0.017396
Pole 18	0.887492	0.02295	224	U[0.42,1.89]	Relative error5%	200000	0.003005



(a) (b)

Figure 8. Histogram of the posterior distribution of the optimisation scheme for 200000 cycles

Table 15 and Fig.8 show that the amount of data has only nearly doubled and the acceptance rate is only 0.112%. The mean and histogram distribution show no significant change, and the confidence value is significantly lower. This indicates that the data is still more accurate. The abscissa of the histogram is the stiffness, and the vertical coordinate is the frequency

In summary, by monitoring points 4, 5, 6, 10, 11, and 12, applying a 100KN vertical downward load at point 11, and setting a relative error of 5%, the a posteriori distribution derived from this loading scheme is closer to the true value.

4. Conclusion

(1) This paper proposes a highly accurate damage inference scheme for the Parker truss structure using a two-dimensional planar finite element model. According to the principle of Bayesian updating, the damage estimation of Parker truss structures is data-mined and imported into the finite element model. The classical data statistics method of sampling and Monte Carlo's rejection method are used to obtain a more accurate identification effect through verification. The comparative study of the experimental programme shows that changes in experimental monitoring locations and points, load magnitude, and a priori distribution have little effect on the final identification effect, indicating good robustness. The damage recognition method based on Bayesian updating demonstrates high efficiency and accuracy.

(2) The rejection sampling method has limitations that result in a low acceptance rate of data. Therefore, there is significant room for improvement in the acceptance efficiency of this experiment. Increasing the number of cycles can improve the accuracy of the experimental results.

(3) The principle of Bayesian updating and the method of finite element modelling offer a concise and intuitive approach. There is a considerable degree of freedom in collecting and screening data, not limited to the type of prior distributions and data sampling methods used in this experiment. The Bayesian updating principle is expected to play a crucial role and hold significant potential in the field of structural damage monitoring in the future.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

References

[1] Zhu Jiahao, Chen Xiuling, Lu Conglin. Sources of risk and prevention in bridge engineering. Xinjiang Nonferrous Metals, 2022, 45 (02): 96 - 98.

[2] Wang Feng, Wu Huayong, Zhao Rongxin. Causes and lessons learnt from bridge collapse accidents in recent three years at home and abroad. Urban Road and Bridge and Flood Defence, 2020, (07): 73 - 76+13.

[3] Li Hui, Bao Yuequan, Li Shunlong et al. Structural health monitoring data science and engineering. Engineering Mechanics, 2015, 32 (08): 1 - 7.

[4] Zhu Hongping, Yu Jing, Zhang Junbing. Research status and prospect of structural damage dynamic detection and health monitoring. Engineering Mechanics, 2011, 28 (02): 1 - 11+17.

[5] Guo Huiyong, Li Zhengliang, Peng Chuan. Research and progress of structural damage dynamic identification technology. Journal of Chongqing Architecture University, 2008, (01): 140 - 145.

[6] Li Hongnan, Gao Dongwei, Yi Tinghua. Research status and progress of civil engineering structural health monitoring system. Progress in Mechanics, 2008, (02): 151 - 166.

[7] Du Siyi, Yin Xuegang, Chen Huai. A regenerative finite element method for identifying structural damage based on frequency variation. Engineering Mechanics, 2007 (04): 66 - 70+192.

[8] Zhao Yinan, Gong Maosheng, Yang You. A review of research on structural damage identification methods. World Earthquake Engineering, 2020, 36 (02): 73 - 84.

[9] Zhang Qinghua, Li Qiao, Tang Liang. Probabilistic reliability method for structural damage identification of cable-stayed bridges. Journal of Railway, 2005, (03): 70-75.

[10] Gao Yanbin. Improvement and application of structural damage identification method based on Bayesian model updating. Institute of Engineering Mechanics, China Earthquake Administration, 2016.