Proceedings of CONF-MSS 2026 Symposium: Mechanical Control and Automation
DOI: 10.54254/2755-2721/2026.BJ31851

# *Durability Identification Analysis of Parker Truss Members Based on OpenSees and Monte Carlo Simulation*

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***Abstract.*** To address the difficulty in accurately quantifying corrosion damage in Parker truss bridge members during their service life, this paper proposes a member durability identification method based on a combination of OpenSees finite element simulation and the Monte Carlo method. Taking the Parker truss as the research object, damage conditions are simulated by reducing the cross-sectional area of the members. A finite element model is established using OpenSees, and a stochastic simulation process is designed to invert the remaining cross-sectional area of the members from the nodal displacement response based on the rejection sampling algorithm in Bayesian updates. By changing the load application position, the histograms of damage identification results under different stress points are compared to find the optimal stress point for damage identification. Finally, structural mechanics analysis is used to explain the mechanism of the above phenomenon: the optimal stress point can maximize the sensitivity of the damaged member to the overall structural displacement, thereby selecting high-confidence parameter samples through the likelihood function in the stochastic simulation.

***Keywords:*** Parker Truss, Damage Identification, Opensees, Monte Carlo Simulation, Structural Mechanics Analysis.

## 1. Introduction

As an important part of the transportation lifeline, steel truss bridges are inevitably affected by environmental corrosion, fatigue loads and material aging during long-term service [1]. The reduction of the effective cross-sectional area will directly lead to the degradation of the stiffness of the components, thereby changing the stress performance of the structure, and in severe cases, it may even cause bridge collapse accidents. Therefore, how to effectively identify damage and assess the durability of truss bridges during service has become a key issue that needs to be addressed in the field of civil engineering. Parker truss bridges are one of the preferred bridge types for long-span bridges, with features such as structural stability and flexible erection methods. The main truss structure is mainly composed of tie rods and compression rods. Individual components mainly bear axial loads, which can give full play to the strength of the material and reduce the self-weight while enhancing the structural stiffness. However, due to the large number of members and complex node connections, as well as the influence of factors such as measurement noise, traditional detection methods or local non-destructive testing are usually inefficient and difficult to reach hidden parts

[2,3]. In recent years, with the increasing application of health monitoring systems in large bridge structures, data-driven bridge structure safety performance assessment technology has been widely applied in the face of massive data volume and numerous dimensions of information [4]. Therefore, applying Bayesian updates to damage identification of Parker truss bridges can not only enable data inference of unmonitored parts through monitoring data of several units, but also further analyze the state changes of the structure based on the data inference results of the structure, thereby quickly realizing the safety performance assessment of this type of bridge structure [5,6].

Therefore, this paper introduces probabilistic statistical methods, such as Monte Carlo simulation, to treat damage identification as a probabilistic inference problem. This not only provides an estimate of the damage but also assesses the confidence level of the identification results, which has important theoretical significance and practical engineering value.

## 2. Theoretical basis and algorithm principle

### 2.1. Finite element analysis principle of planar truss structures

The Parker truss, the subject of this study, is a typical truss structure. In finite element analysis, the truss structure is discretized into two-force member elements connected by nodes, and the deformation resistance of the members is proportional to the cross-sectional area.

In practical engineering, the decline in the durability of steel truss bridges is mainly manifested by the loss of effective cross-sectional area caused by corrosion. Based on this physical phenomenon, this paper defines the damage of members as the reduction of cross-sectional area [7].

### 2.2. Bayes' theorem and the research object of the project

Structural damage identification in this study is essentially an inverse mathematical problem. Due to unavoidable environmental noise and instrument errors in actual measurements, deterministic deduction methods often struggle to obtain a unique solution or suffer from poor stability. Therefore, this paper introduces a Bayesian probabilistic inference framework, treating the cross-sectional area of the member to be identified as a random variable [8,9]. By applying the same force to different truss nodes and using the displacement of key nodes as a metric, the received data is statistically analyzed. By comparing the approximation of the effective cross-sectional area of the member obtained from different stress points with the actual damage, the optimal stress point for identifying the member's durability is determined.

According to Bayes' theorem, the posterior probability distribution of the parameters can be determined by both the prior distribution and the likelihood function:

$$P(\theta|D) = P(D|\theta)\,{}^{*}P(\theta) \tag{1}$$

In the formula:

$P(\theta)$ is the prior distribution, representing a preliminary judgment of the cross-sectional area of the member based on experience before obtaining observation data;

$P(D|\theta)$ is the likelihood function, representing the probability of observing data D given the parameter $\theta$.

$P(\theta|D)$ is the posterior distribution, which is the corrected estimate of parameter $\theta$ after incorporating the observed data D.

### 2.3. Solution of the inverse problem of damage identification

To numerically extract parameter samples from complex posterior distributions, this paper employs the rejection sampling algorithm from the Monte Carlo method. The specific algorithm flow is as follows:

Step 1 (Modeling and storing actual displacements): Create a 2D structural model of the Parker truss, set the actual effective cross-sectional area of the damaged members to be identified, set the stress points to be checked, perform static analysis on the modeled truss structure, and store the actual displacements of key nodes.

Step 2 (Randomizing the effective cross-sectional area of the members to be tested): Rebuild the 2D structural model of the Parker truss, set the effective cross-sectional area of the members to be tested in the new model to a random value between 0.2 and 1.1 times the initial area, run static analysis, and extract the displacement response of key nodes as simulation data.

Step 3 (Likelihood Assessment): Substitute the simulated data and the observed data under actual damage conditions into the Gaussian likelihood function to calculate the nonnormalized likelihood value of the sample.

Step 4 (Acceptance/Rejection Decision): Generate a random number u that is uniformly distributed in the interval [1]. If u is less than or equal to the likelihood value of the sample ($u \leq L$), then accept the sample and store it in the "Success" set; otherwise, reject the sample.

Step 5 (Statistical Analysis): Repeat the above steps 10,000 times to obtain a sufficient number of valid samples. Finally, perform statistical analysis on the successful sample set and plot a frequency distribution histogram. This allows for analysis of the advantages and disadvantages of damage identification at different stress points.

## 3. Parker truss damage model construction

A 2D model was constructed using the OpenSees finite element analysis platform. The structure has a total span of 60m and is divided into 6 sections, each 10m long. The materials and truss elements of each section were defined. Predetermined section reduction factors were applied to specific key components to construct a realistic structural model incorporating known damage information. The resulting nodal displacements were then used as simulation observation data as shown in Figure 1 .

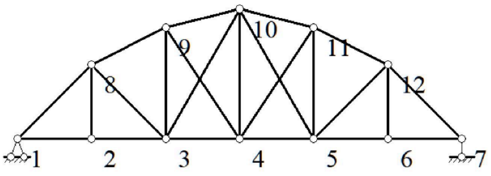

Figure 1. Truss model diagram(picture credit: original)

At the algorithm implementation level, to overcome the limitation of deterministic inversion methods in quantifying measurement errors, this paper independently developed a complete Monte Carlo simulation program based on the Tcl scripting language. The Monte Carlo loop is expanded, and 10,000 random samples are taken. The effective cross-sectional area of the member under test is uniformly linearly randomized between 0.2 and 1.1 times the original area. Static analysis using OpenSees yields the simulated displacement values of key nodes. A likelihood function is defined, and the measurement error is set as a relative error of 5% of the true displacement. The likelihood values of the true displacement of the key nodes and different simulated displacements are calculated. To filter parameters that conform to the actual damage state from a massive amount of random samples, this paper introduces the rejection sampling algorithm from Bayesian updates. This algorithm filters samples based on the closeness between simulated and observed displacements, retaining samples with high consistency and discarding samples with large deviations, thus successfully transforming the deviation of the structural response into the posterior probability distribution of the member damage parameters.

Building upon this foundation, this paper focuses on exploring the impact of the key variable of "force application location" on the accuracy of damage identification. Multiple comparative experiments were conducted by applying static loads to different nodes of the model, and frequency distribution histograms of the identification results under each working condition were generated. Data analysis shows that the location of load application plays a decisive role in the convergence and accuracy of the identification results; incorrect load application locations can cause the damage signal to be overwhelmed by measurement noise, leading to identification failure.

## 4. Comparison of identification results and deployment scheme

Table 1. Standard deviation and mean of different nodes

| Node | Standard deviation | Mean |
|---|---|---|
| 2 | 0.11197 | 0.74401 |
| 3 | 0.06968 | 0.71930 |
| 4 | 0.06360 | 0.72352 |
| 5 | 0.05054 | 0.69258 |
| 6 | 0.06808 | 0.72879 |
| 8 | 0.11302 | 0.73985 |
| 9 | 0.07338 | 0.72565 |
| 10 | 0.05582 | 0.71146 |
| 11 | 0.07668 | 0.69971 |
| 12 | 0.06765 | 0.74142 |

By comparing and analyzing the histograms of the success data, it can be seen that the data at nodes 2 and 8 are too scattered and have high uncertainty. The data at nodes 6 and 12 are too small and have high uncertainty. Nodes 3 and 4 exhibit multi-peak patterns and have high uncertainty as shown in Table 1. Based on the specific data standard deviation, mean, and histogram shape, it can be concluded that nodes 5, 10, and 11 are the optimal bar damage identification points.

## 5. Mechanical mechanism analysis of the optimal stress point

### 5.1. Force analysis of node 5

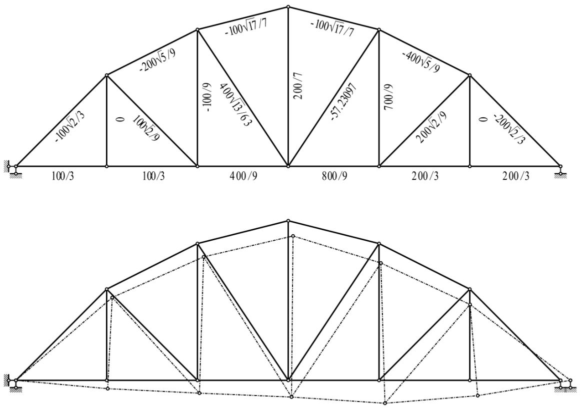

Figure 2. Force and deformation of node 5(picture credit: original)

The axial force of member 10 is 58.90 kN, and the axial force of member 18 is 57.23 kN. Although the damaged member is not directly connected to node 5, the load at node 5 will cause severe shear deformation and bending moment within that span. To resist the downward load at node 5, the truss must transfer the force to the upper chord through the web system. The stress at node 5 will cause a large vertical deflection in the entire x=40 section, and damaged members 10 and 18 are the key components resisting this local deformation. Therefore, members 10 and 18 will experience significant offsets as shown in Figure 2.

### 5.2. Force analysis of node 10

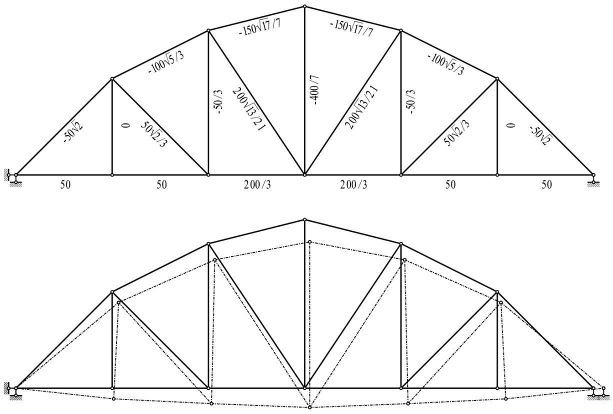

Figure 3. Force and deformation of node 10(picture credit: original)

The axial force of member 10 is 88.35 kN, and the axial force of member 18 is 34.34 kN. Node 10 is the endpoint of the damaged member 10. According to Saint-Venant's principle and the force characteristics of trusses, when the load is directly applied to the end node of a member, the member will directly participate in the distribution and transmission of the load [10]. Therefore, member 10, as the main compression member, will generate a huge axial force to balance the external load as shown in Figure 3.

### 5.3. Force analysis of node 11

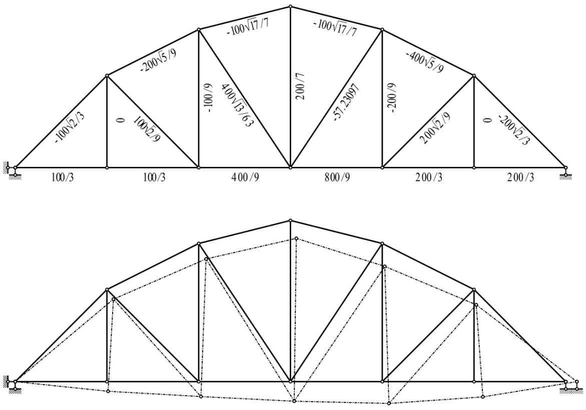

Figure 4. Force and deformation of node 11 (picture credit: original)

The axial force of member 10 is 58.90 kN, and the axial force of member 18 is 57.23 kN. This is similar to the situation at node 5. The forces acting on node 11 are the same as those acting on node 10. However, node 11 is also the endpoint of both member 10 and member 18. Therefore, member 10, as a compression member, will generate axial force to balance the external load. Member 18, as an important web member supporting node 11, must share significant shear and axial forces as shown in Figure 4.

### 5.4. Force analysis of node 2

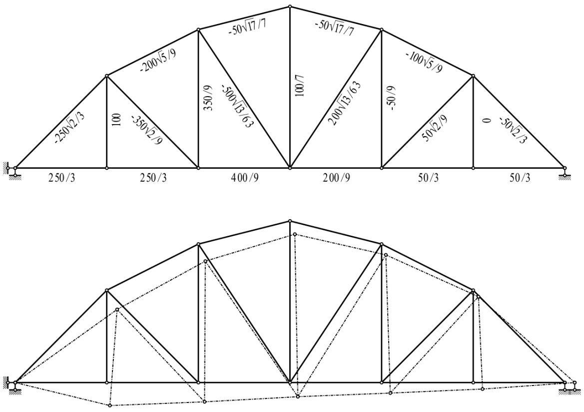

Figure 5. Force and deformation of node 2 (picture credit: original)

The axial force of member 10 is 29.45 kN, and the axial force of member 18 is 11.45 kN. Node 2 is the furthest node from members 10 and 18. Therefore, according to Saint-Venant's principle and the force characteristics of the truss, when node 2 is under stress, the deformation of members 10 and 18 accounts for a very small proportion of the total deformation, and the axial forces are also equal and small as shown in Figure 5.

This corresponds to the large total amount and wide distribution of data in the histogram, proving that the durability of members 10 and 18 is not important for the displacement of the node at this point [10]. Therefore, the obtained data have high uncertainty and is not suitable for identifying the durability of members 10 and 18.

## 6. Conclusion

This project established a Parker truss model using OpenSees and successfully achieved the inversion from structural displacement response to member durability indices by generating a large number of random samples using the Monte Carlo method. Data analysis shows that this method can effectively handle uncertainties in measurement data, and the distribution characteristics of the parameters to be identified are clearly displayed through the posterior probability density histogram.

When loads are applied to nodes 5, 10, and 11, the posterior distribution histograms of the parameter identification show the greatest convergence, with sharp peaks concentrated near the true values. This indicates that at these stress points, the data contains the most damage information and the identification uncertainty is the lowest, verifying the feasibility and accuracy of this method in structural damage identification.

Furthermore, combined with the mechanical mechanism of trusses, the intrinsic mechanism of the optimal stress condition is revealed: the ability to accurately identify the stress points for durability depends on whether applying loads at those stress points can maximally affect the proportion of deformation of damaged members in the total deformation.

This project combines the application of Bayesian updating and structural mechanics analysis in truss structure damage identification, and provides guidance for sensor placement and loading test strategies in structural health monitoring (SHM). That is, when performing damage identification, priority should be given to loading positions close to suspected damage areas or positions that can cause large deformation of damaged components, to overcome environmental noise interference and improve identification accuracy.

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