

Study on the Evaluation Method of Truss Mechanical Performance in Old Factories Based on Bayesian Updating

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Abstract: This study focuses on the evaluation of the mechanical performance of trusses in old factory buildings. It innovatively applies the Bayesian updating theory to construct an evaluation system. Considering the uncertainties such as material aging and complex load histories existing in the trusses of old factory buildings, traditional evaluation methods are difficult to accurately describe the fluctuations in their structural performance. This method transforms these uncertainties into probabilistic expressions. By integrating historical inspection data, on - site monitoring data, and mechanical simulation data, and using rejection sampling to screen valid samples, a comprehensive and scientific structural performance evaluation framework based on probabilistic analysis is formed. Verified by practical cases, this framework can provide accurate parameter basis for truss reinforcement, effectively balancing safety and economy. In addition, this method has good universality and can be extended to the fields of safety assessment, protection, and utilization of historical buildings and other old industrial facilities, opening up a new path for the performance evaluation of related structures.

Keywords: Bayesian updating, truss structure, mechanical performance evaluation, uncertainty quantification, old industrial buildings

1. Introduction

In the current era of rapid urbanization, a large number of old factories face challenges in functional transformation and structural safety assessment [1]. Among these, truss structures, due to long-term service, environmental erosion, and the lack of original design documentation, exhibit many uncertainties in their mechanical properties, posing significant safety risks. Accurate evaluation of truss load-bearing performance is crucial for ensuring the rational use and safe operation of old factories.

Traditional deterministic assessment methods, based on fixed material parameters, load modes, and simplified mechanical models, struggle to account for material aging and performance fluctuations caused by complex load histories. For instance, when dealing with the degradation of steel yield strength and node corrosion, traditional methods can only provide a single assessment result, failing to reflect the true safety status [2] and uncertainty [3] range of the structure. This can lead to assessment biases, potentially resulting in economic waste from over-reinforcement or underestimating risks that could cause accidents.

In recent years, probabilistic analysis methods [4] have gained significant attention in the field of structural engineering, with Bayesian updating theory [5-7] showing notable advantages. It can integrate prior information with new observational data, using probabilistic models to update the understanding of structural parameters, providing a powerful tool for addressing uncertainties in old factory trusses. Evaluation methods based on this theory can combine historical design parameters, material test reports, and other prior knowledge with on-site monitoring data to describe the uncertainty of structural load parameters using probability distributions, thus more accurately assessing the safety and reliability of structures.

Currently, Bayesian updating theory has yielded results in areas such as structural health monitoring and seismic engineering, but it is still in the exploratory stage regarding the assessment of load-bearing performance in old factory trusses. A deeper study of its application in this field can address the shortcomings of existing evaluation methods, providing a scientific basis for the maintenance, renovation, and reuse of old factories, thus promoting the development of structural engineering assessment technology [8-10]. This paper introduces Bayesian updating theory to develop a method system suitable for assessing the load-bearing performance of old factory trusses, and validates its effectiveness and feasibility through practical cases, offering a reference for related research and engineering practice.

2. Introduction to Bayesian models

The formula for Bayes theorem is:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \quad (1)$$

Among them, $P(A|B)$ is the posterior probability of event A occurring under the condition of event B occurring, $P(B|A)$ is the likelihood probability of event B occurring under the condition of event A occurring, $P(A)$ is the prior probability of event A occurring, and $P(B)$ is the marginal probability of event B occurring.

2.1. Fixed prior probability

Before obtaining new data, determine the probability distribution of a parameter or event based on existing knowledge and experience, denoted as $P(\theta)$, where θ represents the parameter or event to be estimated. For example, when estimating the probability of a coin landing heads up as θ , if there is no prior information, one might assume that $P(\theta)$ follows a uniform distribution, meaning the probability of landing heads up is equal for all values in the $[0,1]$ interval. By combining historical data from trusses (design parameters, material inspection reports), assign prior probability distributions to uncertain parameters (such as material elastic modulus, load amplitude) (e.g., normal distribution, uniform distribution), quantifying the initial uncertainty [11-12].

2.2. Likelihood function

Given the parameter θ , calculate the probability of new observed data D appearing, which is the likelihood function $P(D|\theta)$. For example, in the coin-tossing scenario mentioned above, if n coin tosses are conducted and k heads are observed, assuming each toss is an independent and identically distributed Bernoulli trial, then the likelihood function:

$$P(D|\theta) = \theta^k(1 - \theta)^{n - k} \quad (2)$$

2.3. Derive the posterior distribution

According to Bayes theorem, the posterior probability $P(\theta | D)$ is calculated by combining the prior probability and the likelihood function:

$$P(\theta|D) = \frac{P(D|\theta)P(\theta)}{P(D)} \quad (3)$$

Among them, $P(D) = \int P(D | \theta) P(\theta) d\theta$ (for continuous cases) or $P(D) = \sum P(D | \theta) P(\theta)$ (for discrete cases), is the normalized constant obtained by calculating $P(D | \theta) P(\theta)$ for all possible θ and then summing or integrating. The purpose is to ensure that the posterior probability $P(\theta | D)$ satisfies the properties of a probability distribution (i.e., the integral or sum equals 1). Based on Bayes' formula $P(\theta | D) \propto P(\theta) \cdot L(\theta | D)$, it integrates the prior distribution $P(\theta)$ with the likelihood function $L(\theta | D)$, updating the posterior distribution $P(\theta | D)$ of the parameters, thereby correcting the understanding of the load-bearing parameters of the truss.

2.4. Rejective sampling

Randomly draw parameter samples from the prior distribution, calculate the likelihood function value for each sample, and retain samples that meet the preset criteria (such as a likelihood threshold) while rejecting those that do not. Use the accepted samples to fit the posterior distribution, analyze the probability characteristics of truss load parameters (mean, variance, etc.), and evaluate the reliability [13] of the structure under different loads. This provides theoretical support for assessing the safety of old factory trusses and formulating reinforcement strategies [14].

3. Case analysis

3.1. Project overview

The current situation of old industrial buildings, characteristics of a textile factory (built in 1992), four-span continuous steel truss (span 16m), 4m high (Figure 1), the yield strength of steel is degraded, and the key nodes are corroded.

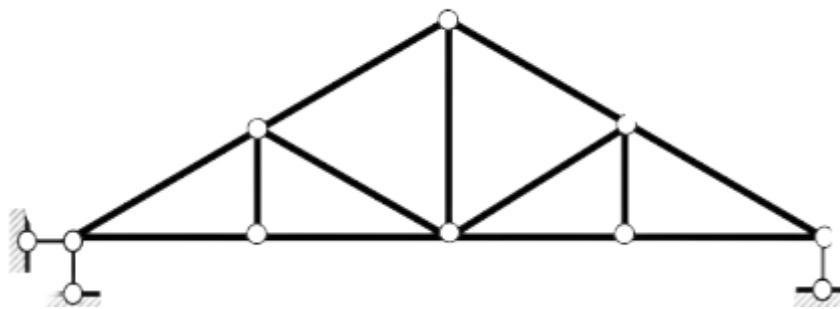


Figure 1: Truss model

3.2. Parameter Bayesian update

Based on the characteristics of truss structures, a mechanical model is established using finite element methods or structural mechanics solvers (Figure 2), defining unit stiffness and describing the stress, strain, and displacement responses of the truss under load. According to historical load

data from old factories and regulatory requirements, structural mechanics simulators are used to simulate load application (Figure 3), obtaining theoretical force response data for the truss. Based on posterior distribution results, the uncertainty of truss load performance is quantified to determine whether the structure meets the safety threshold [15], guiding maintenance and renovation decisions for old factory trusses. By comparing measured data (on-site strain and displacement monitoring values) with simulated data, a likelihood function is constructed based on the distribution of observation errors. For example, if the error follows a normal distribution, the likelihood function reflects the match between measured data and model-predicted data.

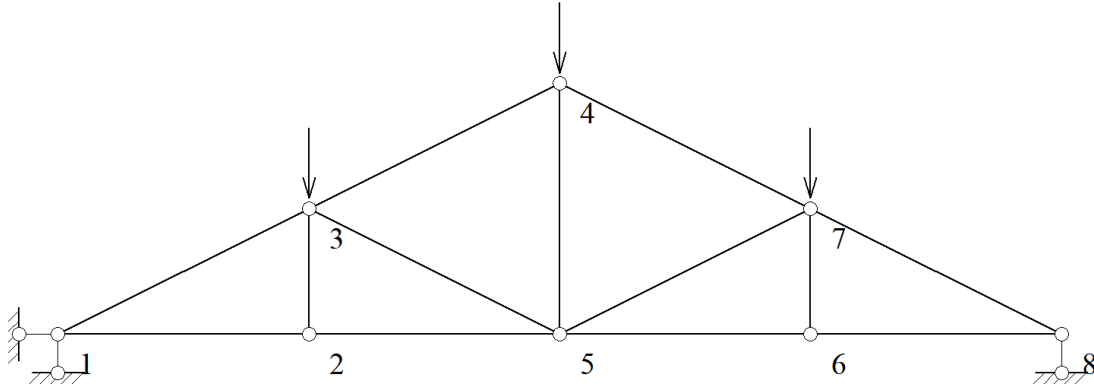


Figure 2: Load application on the truss

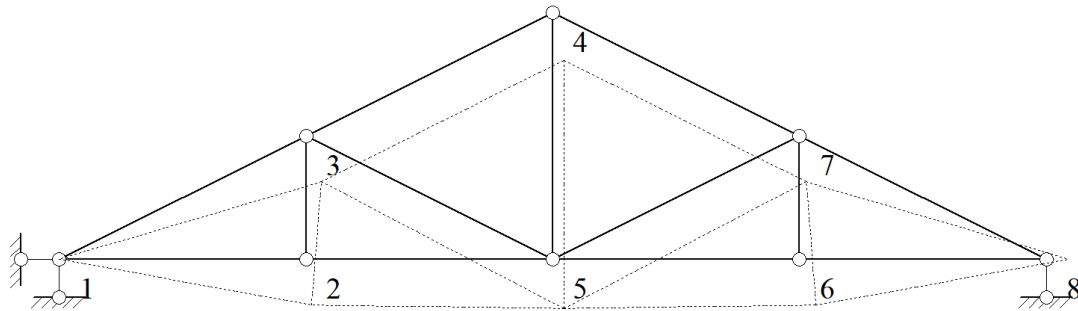


Figure 3: Deformation of the truss after loading

Upper chord EA1, lower chord EA2, web EA3

Random sampling analysis was conducted at points 2 and 5, using the virtual work theorem to derive the displacement formula. A load test of $P=10\text{kN}$ was performed on the model, measuring a displacement of 71mm at point 5 and 69mm at point 2. With EA1 following a normal distribution $N(16000 \text{ kN}, 1600 \text{ kN})$ and EA3 uniformly distributed $U(7000 \text{ kN}, 9000 \text{ kN})$ as prior information, updates were made to EA1 and EA3 (errors conforming to a normal distribution with a standard deviation of 1 mm).

$$\Delta_5 = \frac{25\sqrt{5}Pa}{2EA_1} + \frac{24Pa}{EA_2} + \frac{2Pa}{EA_3}$$

$$\Delta_2 = \frac{10\sqrt{5}Pa}{EA_1} + \frac{24Pa}{EA_2} + \frac{(5\sqrt{5}+4)Pa}{4EA_3} \quad (4)$$

3.3. Comparison of EA1 update effect before and after

From the histogram (Figure 4) and the data in it, it can be seen that EA1 has a better update result and conforms to normal distribution

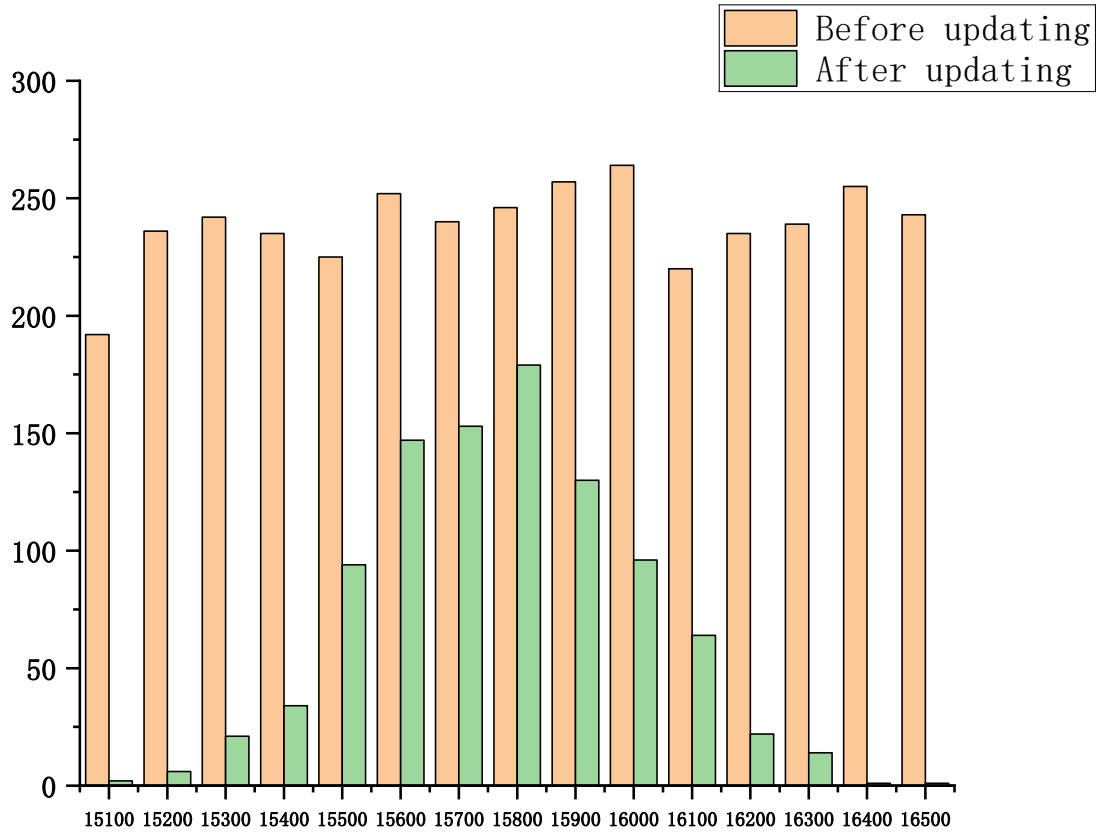


Figure 4: Bayesian update histogram of EA1

The EA1 update has shown good results and conforms to a normal distribution: From the histogram comparing data before and after the EA1 update, it is evident that the distribution of data before the update was relatively scattered, while the distribution became more concentrated after the update. For instance, around 15600 kN, the amount of data corresponding to this value was relatively even before the update, but after the update, the number of data points near this value significantly increased, becoming the peak area of the distribution. This indicates that Bayesian updating theory can effectively utilize new data (such as the displacement measurement data from point 2 and point 5) to correct the understanding of EA1, and the updated results conform to the characteristics of a normal distribution. This not only verifies the effectiveness of Bayesian updating theory in handling such parameter uncertainty issues but also demonstrates that the theory can accurately characterize the probability characteristics of the key load-bearing parameter, the material's elastic modulus (EA1), providing more reliable data support for structural load performance evaluation.

3.4. Data comparison before and after EA3 update

From the histogram (Figure 5), it can be seen that the update effect of EA3 is not obvious

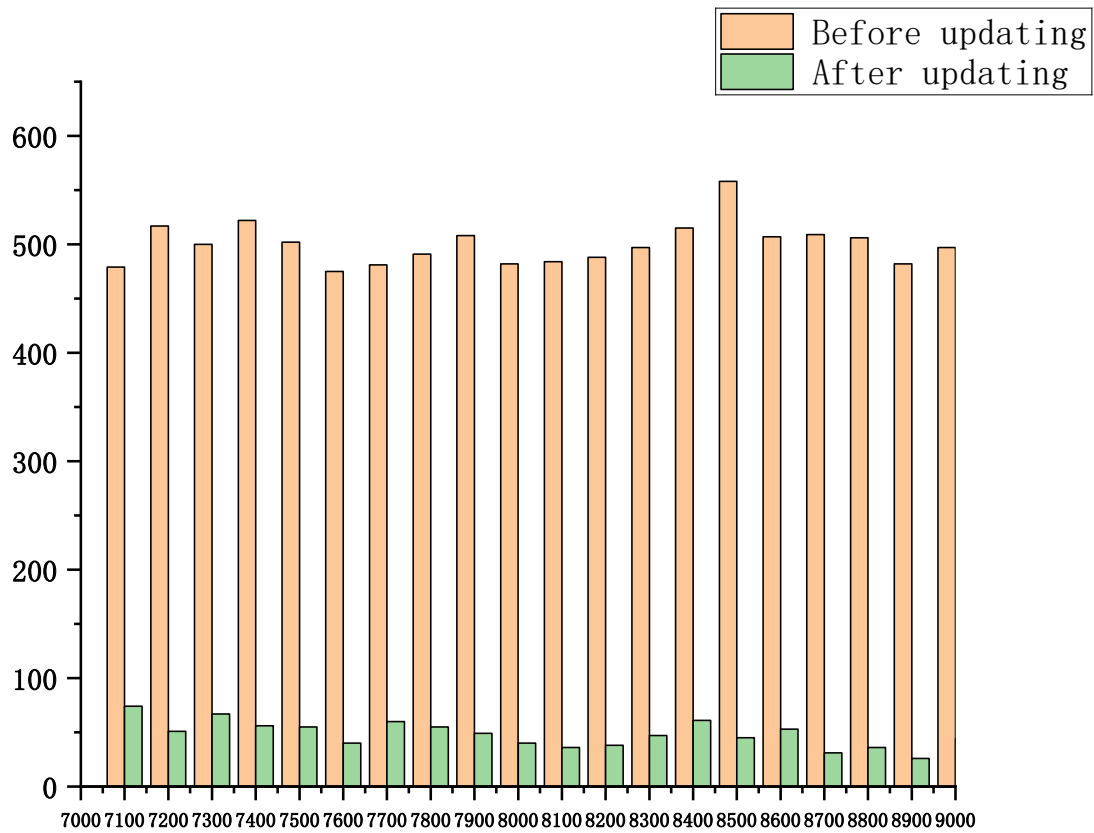


Figure 5: EA2 Bayesian update histogram

The EA3 update effect is not significant: Compared to the data before and after the EA3 update, there is no significant change in distribution. For example, the number of data points corresponding to each value from 7100kN to 9000kN shows little fluctuation before and after the update, without exhibiting the clear concentration trend or distribution characteristics seen with EA1. This may be due to an unreasonable selection of the prior distribution (uniform distribution $U(7000\text{kN}, 9000\text{kN})$), making it difficult to effectively adjust the understanding of EA3 when combining new data for updates. It could also be because all factors affecting EA3 were not fully considered during the construction of the likelihood function, resulting in limited contribution of new data to its update. This result suggests that when applying Bayesian update theory, it is necessary to carefully select the prior distribution and comprehensively consider all factors influencing the parameters to improve the effectiveness of structural parameter updates and assessment accuracy.

3.5. Verification result

The overall validation of the Bayesian updating theory partially confirms its effectiveness: despite the unsatisfactory update effect of EA3, the good performance of EA1's update demonstrates that the Bayesian updating theory has certain advantages in handling uncertainties related to old factory trusses. It can integrate prior information from historical data (such as the initial normal distribution of EA1 and the initial uniform distribution of EA3) with on-site measurement data (displacement data from points 2 and 5). Through probabilistic analysis, it reveals the distribution characteristics of structural load parameters (at least for EA1), compensating for the shortcomings of traditional deterministic evaluation methods, providing a more scientific basis for structural safety assessment and reinforcement decisions.

4. Conclusion

Bayesian updating theory can effectively address the uncertainty issues caused by material aging and complex load history in old factory trusses. Through probabilistic analysis, it clearly reveals the distribution characteristics of structural force parameters, overcoming the limitations of traditional deterministic evaluation methods.

In the future, this approach can be further combined with long-term monitoring data and more complex load conditions to optimize model parameters and sampling methods, enhancing the universality and accuracy of the evaluation system.

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