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Bayesian Updating-Based Damage Evaluation for Truss Structures

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Abstract: As critical load-bearing components in civil infrastructure systems including buildings and bridges, truss structures necessitate robust health monitoring for operational safety assurance. Conventional approaches, constrained by low temporal resolution and weak anti-interference capacity, pose significant challenges in accurate damage quantification. To address this, this study proposes a Bayesian probabilistic framework for structural damage assessment. A multi-condition experimental analysis is conducted to investigate the mechanistic influences of load patterns, sensor quantity, and spatial distribution under load variability and monitoring network configurations. The results demonstrate that the Bayesian approach achieves high precision and strong robustness in both damage localization and severity quantification, validating its methodological effectiveness. Notably, load uncertainty significantly alters the posterior probability distribution of damage identification, establishing it as a critical monitoring variable. Furthermore, sensor configurations with high stacked correlation coefficients exhibit low sensitivity to assessment outcomes, supporting the implementation of cost-effective sparse sensing systems. These findings provide a novel solution integrating rigorous theoretical foundation and practical applicability for dynamic damage diagnosis and risk management in complex engineering structures.

Keywords: Bayesian updating, Truss structures, Damage identification, Probabilistic assess ment, Load sensitivity

1. Introduction

Accelerated urbanization and sustained infrastructure expansion in China have imposed dual challenges of structural safety and long-term operational maintenance in civil engineering. Truss structures, renowned for their high load-bearing capacity, lightweight characteristics, and spatial adaptability, serve as critical support systems for large-span bridges, landmark buildings, and industrial facilities [1-3]. Their structural integrity directly impacts public safety and sustainable economic development. However, lifecycle management of these structures faces significant risks: inherent defects from design-stage simplifications, load prediction biases, or construction errors; and progressive damage accumulation during operation due to fatigue loads, environmental corrosion, and material degradation, potentially triggering cascading failures with catastrophic consequences. Conventional monitoring methods reliant on empirical judgment and static data struggle to quantify damage probabilities, track evolutionary paths, and assess uncertainties, necessitating intelligent probabilistic assessment frameworks [4-7]. In this context, advancing damage evaluation

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methodologies for truss structures represents both a technological imperative and a strategic requirement for national critical infrastructure safety.

Substantial progress has been made in Bayesian updating research globally. Focusing on optimization efficacy, Miao integrated whale optimization algorithms to enhance convergence speed, validated through simply-supported beam simulations [8]. Yang et al. developed a Bayesian finite element model updating approach accounting for boundary condition uncertainties, significantly improving bridge constraint characterization through modal parameter updating [9]. Jiang and Lu proposed an adaptive Kriging-enhanced Bayesian method that refines structural reliability assessments for precise failure probability prediction [10].

This study establishes a Bayesian updating-driven damage assessment framework for truss structures, overcoming the reliance on homogeneous structural assumptions in conventional methods. By quantifying the correlation mechanisms among member damage, nodal displacements, and load patterns, systematic Bayesian updating is implemented [11-13]. The research advances structural health monitoring from empirical qualitative paradigms to data-model dual-driven methodologies, providing scientific foundations for lifecycle risk management of critical infrastructure. This work demonstrates substantial academic merit and practical engineering significance.

2. Bayesian update principle

2.1. The core framework of bayesian theory

The fundamental equation of Bayesian theory can be expressed as:

$$P(\theta|D) = \frac{P(D|\theta)P(\theta)}{P(D)} \tag{1}$$

In this framework, $P(\theta)$ denotes the prior distribution, encapsulating initial knowledge about parameter; $P(D|\theta)$ represents the likelihood function, characterizing the data-generating mechanism; $P(\theta|D)$constitutes the posterior distribution, synthesizing prior information and empirical evidence; and $P(D)$ serves as the marginal likelihood, ensuring probabilistic normalization [14-15].

This Bayesian paradigm fundamentally diverges from frequentist approaches in two aspects: First, parameters are modeled as random variables with probability distributions rather than fixed values; second, statistical inference is achieved through probabilistic updating rather than repeated sampling. A representative application is demonstrated in robotic Simultaneous Localization and Mapping (SLAM), where the Cartographer algorithm employs Bayesian filtering to continuously integrate LiDAR observations with kinematic models, dynamically updating the joint probability distribution of robot pose and environmental mapping. This exemplifies the inherent superiority of Bayesian methods in handling dynamic systems with uncertainty.

2.2. Prior distribution construction methodologies

As the starting point of Bayesian inference, prior distributions require balanced integration of subjective expertise and objective data. Primary construction methodologies include:

(1) Analytical Methods: Non-informative Priors: Utilize uniform distributions or Jeffreys priors to eliminate subjective bias, particularly suitable for data-dominated scenarios.

(2) Conjugate Priors: Select distributions forming conjugate pairs with likelihood functions (e.g., Beta distribution for binomial likelihood), enabling analytical derivation of posterior distributions.

(3) Empirical Bayes: Estimate hyperparameters through historical data, such as determining prior means and variances for disease incidence rates using epidemiological datasets.

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Notably, prior selection must adhere to transparency principles, explicitly delineating the influence scope of subjective assumptions. When prior information is scarce, robust weak-informative priors can be constructed via expert opinion aggregation or hierarchical modeling.

2.3. Computational paradigms for posterior inference

Posterior distribution computation confronts high-dimensional integration challenges, with principal approaches categorized as:

(1) Analytical Methods: Restricted to conjugate prior-likelihood pairs (e.g., Beta-binomial models permitting closed-form posterior solutions).

(2) Numerical Approximation: Markov Chain Monte Carlo (MCMC) methods (Gibbs sampling, Metropolis-Hastings algorithms): Explore parameter space via Markov chains, suitable for complex models despite computational intensity.

(3) Variational Inference: Approximate posteriors using tractable distribution families (e.g., Gaussian mixtures) through Kullback-Leibler (KL) divergence optimization.

Beyond parameter estimation, posterior distributions enable uncertainty quantification and predictive task support.

2.4. Bayesian interpretation of probability essence

Bayesian theory transcends frequentist limitations through a tripartite probability interpretation framework: objective probability, subjective probability, and epistemic probability. This hierarchical paradigm allows Bayesian methods to:

(1) Maintain compatibility with frequentist inference.

(2) Address complex scenarios involving small-sample data and non-repetitive events.

(3) Demonstrate philosophical inclusiveness through epistemological integration.

2.5. Bayesian networks and cross-domain applications

As a Bayesian theory extension, Bayesian networks model conditional dependencies via directed acyclic graphs (DAGs), decomposing global joint distributions through local conditional probability tables. In natural language processing, hidden Markov models (HMMs) achieve speech recognition and part-of-speech tagging through iterative updates of state transition and emission probabilities. Recent advancements in deep learning architectures like variational autoencoders (VAEs) have further propelled breakthroughs in uncertainty quantification and few-shot learning through Bayesian-neural network integration.

3. Case study: truss structural Bayesian updating

3.1. Structural configuration and probabilistic modeling

To empirically validate the reliability of Bayesian updating principles, a simplified Howe-type truss structure (Figure 1) was analyzed.

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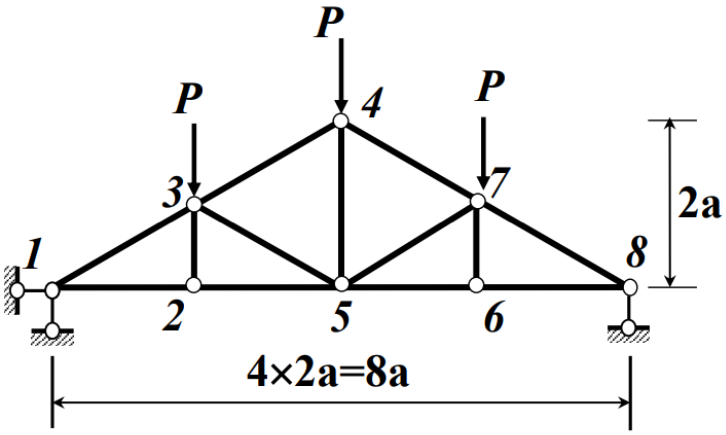


Figure 1: Howe truss

The structure is statically indeterminate with 8 nodes, featuring pin-jointed connections throughout all elements and supported by pin supports. In such structures, the upper nodes are more commonly subjected to compressive loading scenarios. Therefore, the loading conditions are defined as three vertically downward concentrated loads of 10kN each, acting on three upper nodes (Nodes 3, 4, and 7). The dimension 'a' in Figure 1 is specified as 2 meters.

The axial rigidity EA is employed to evaluate member stiffness. Both top chord members and bottom chord members possess identical EA values, following a normal distribution with mean 16,000kN and standard deviation 1,600kN. The web members' EA values obey a uniform distribution ranging from 7,000kN to 9,000kN. These two distinct probabilistic models serve as prior distributions in Bayesian updating.

3.2. Virtual measurement and likelihood construction

Field data acquisition for full-scale structures proves resource-intensive. Hence, computational simulations were conducted using structural mechanics software (Figure 2).

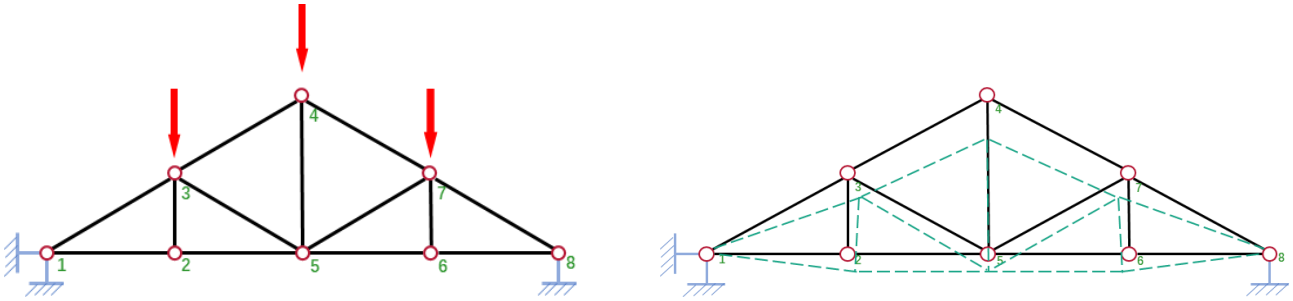


Figure 2: Load-action structural model

Vertical displacements at Nodes 2 and 5 were calculated as 71mm and 69mm, respectively, serving as observational inputs for Bayesian updating.

The member internal forces were analytically determined via the method of joints. Applying the principle of virtual work, unit concentrated forces (1kN) at Nodes 2 and 5 yielded the following displacement expressions:

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$$\Delta_2 = \frac{15\sqrt{5}Pa}{2EA_1} + \frac{18Pa}{EA_2} + \frac{(5\sqrt{5}+2)Pa}{4EA_3} \tag{2}$$

$$\Delta_5 = \frac{70\sqrt{5}Pa}{8EA_1} + \frac{16Pa}{EA_2} + \frac{Pa}{EA_3} \tag{3}$$

Given the implicit nature of likelihood functions in engineering practice, random sampling was employed for likelihood construction. Monte Carlo sampling implemented through Excel generated:

$$Normal\ distribution\ via\ EA_1 = 16000 + 1600 \times \mathrm{NORM.S.INV}(rand()) \tag{4}$$

$$Uniform\ distribution\ via\ EA_2 = 7000 + 2000 \times rand() \tag{5}$$

Sampled parameters were substituted into displacement equations (2) and (3), with computed displacements compared against solver-derived reference values to establish likelihood functions.

Through rejection sampling (Figure 3), 1,487 valid samples were retained from an initial 15,142 candidates, constituting the Bayesian updated dataset.

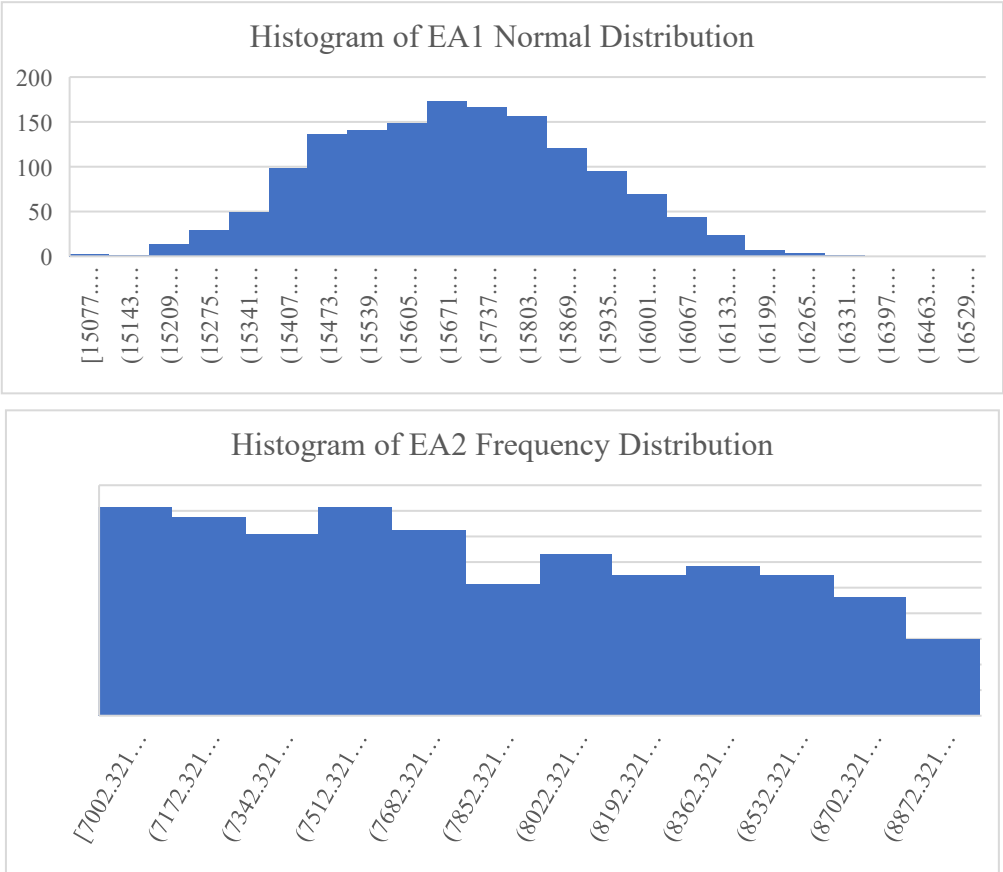


Figure 3: Histogram of EA updating effectiveness

4. Results analysis

4.1. Validation of updating effectiveness

Prior to Bayesian updating, multiple EA parameter sets were generated from prior distributions via random sampling. The scatter plot (pre-update) of EA_1 and EA_3 versus EA_2 (Figure 4) showed significant dispersion across 15,142 samples.

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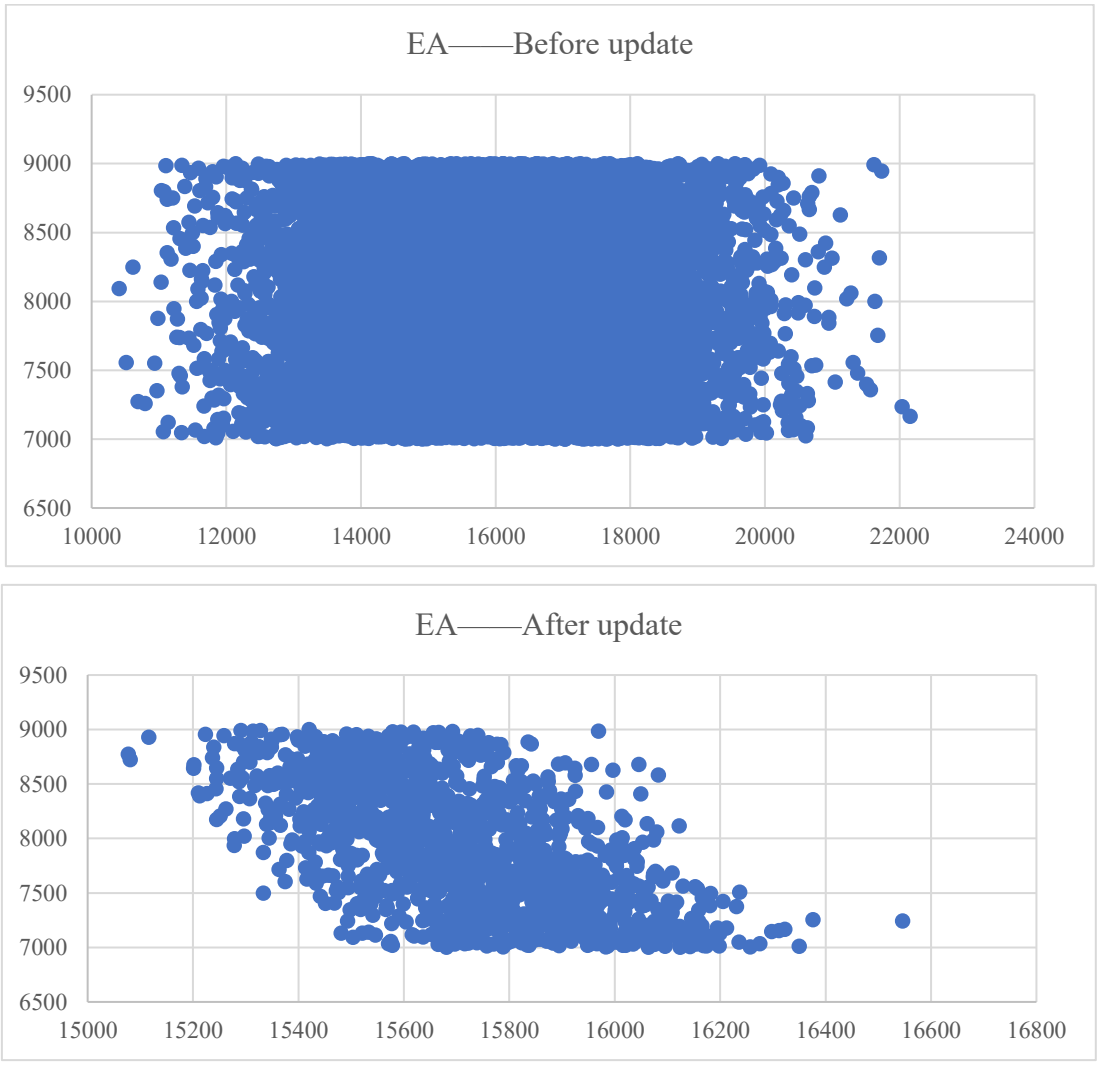


Figure 4: Scatter plot of EA data

After Bayesian updating, the normal distribution mean of EA_1 and EA_3 reached 15,718.536, the standard deviation was 214.535, and the data variability was only 1.36%. The update effect is excellent. The average value of EA_2 is 7,893.933, and the standard deviation is 566.153. According to the distribution of scatter diagram (Figure 4), the update effect is relatively poor, but the data variability is only 7.17%.

It can be seen that Bayesian update has guiding significance for the application of engineering examples:

(1) High precision parameter locking: the average value of 15,718.536 reflects the optimal estimate of the elastic modulus of the material, which converges significantly compared with that before the update, indicating that the Bayesian method effectively corrects the deviation of the prior hypothesis through data fusion. This precise value provides reliable input for key analysis such as structural bearing capacity calculation and fatigue life prediction.

(2) Uncertainty quantification and risk control: the standard deviation 214.535 shows that the confidence interval of parameter estimation is very narrow, indicating that data variability and model error are strictly constrained. For example, in the bridge safety assessment, the probability of EA $\geqslant$ 15300 can be calculated based on this > 99.9%, which provides a statistical basis for the decision of "no immediate reinforcement" and avoids the waste of resources caused by excessive maintenance.

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(3) Engineering robustness verification: the coefficient of variation is only 1.36% (usually the engineering acceptable threshold is less than 5%), indicating that the prior model is highly compatible with the measured data, and the material properties meet the design specifications; The observation system error is controllable; The physical correlation model can effectively map the relationship between parameters and responses. This index can be directly used in the acceptance report to prove that the stability of the engineering system meets the design requirements.

(3) Dynamic optimization potential: the current posterior distribution can be used as a priori for the next round of updates. If new test data is added, the "lifelong learning" of parameters can be realized only by iterative calculation of MCMC algorithm to adapt to the influence of time-varying factors such as material aging and environmental corrosion.

4.2. Parametric sensitivity and optimization analysis

In practical engineering scenarios, single monitoring strategies yield limited updating effectiveness. To optimize experimental design for enhanced parameter estimation efficiency and accuracy, the applied concentrated load magnitude was adjusted.

Increasing the load to 15kN elevates the theoretical displacements at Nodes 2 and 5 to 97 mm and 95 mm, respectively. Post-update results (Figure 5) show accelerated convergence of the upper chord EA mean, with the standard deviation further reduced to 205kN (COV = 1.18%).

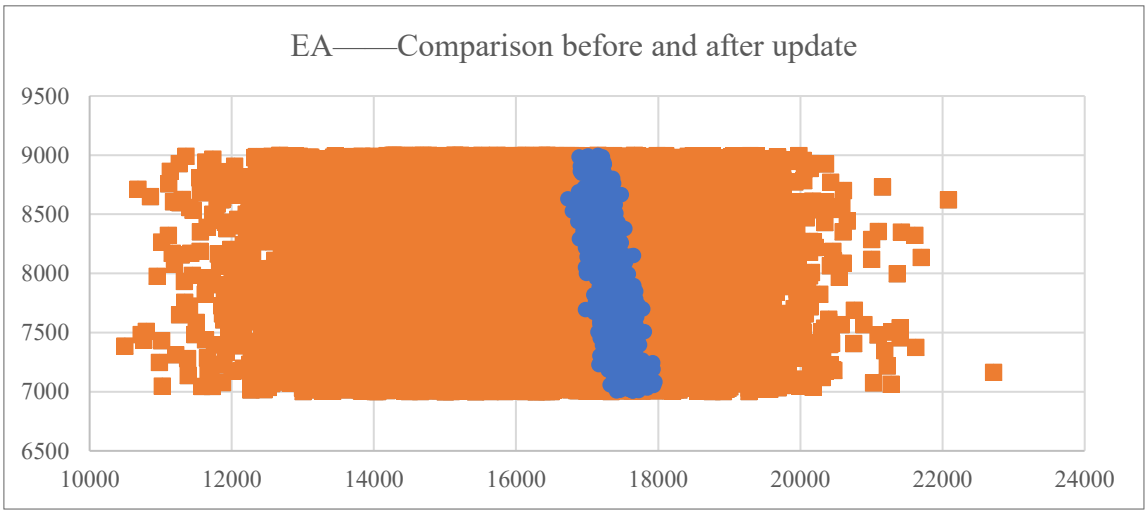


Figure 5: Scatter plot of load updating data

Mechanistic analysis reveals that load amplification enhances Bayesian updating through:

(1) Signal-to-Noise Ratio Improvement: displacements increasing from lower values (71mm → 97mm) amplify structural response signals, reducing the relative impact of measurement errors.

(2) Parameter Sensitivity Enhancement: finite element analysis confirms that EA-displacement sensitivity intensifies with higher loads. Under low loads, minor EA variations weakly influence displacements, resulting in insufficient likelihood function discriminability. At 15kN, sensitivity enters a steep gradient region, facilitating posterior distribution convergence in parameter space.

Load amplification significantly optimizes Bayesian updating efficiency and precision by enhancing both data informativeness and parameter sensitivity. This finding provides quantitative guidance for engineering load design: within structural safety limits, rationally increasing load levels accelerates parameter convergence and compresses uncertainty, achieving synergistic optimization of precision and efficiency.

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4.3. Sensor network efficacy evaluation

An investigation was conducted to explore the influence of measurement point quantity on Bayesian updating effectiveness by introducing additional sensors. Node 6 was instrumented, exhibiting vertical displacement identical to Node 2. After performing Bayesian updating, the posterior distributions of EA_1 and EA_3 demonstrated normal distribution characteristics with mean values of 15,684.13kN and standard deviations of 208.499kN, corresponding to data variability of 1.32%. For EA_2, the updated distribution showed a mean value of 7,897.569kN with a standard deviation of 569.89kN, yielding data variability of 7.2%. Comparative analysis with the two-measurement-point configuration (Nodes 2 and 5) revealed no further optimization in updating efficacy.

Posterior distribution variations remained marginal after sensor augmentation (Figure 6). Correlation analysis indicated strong spatial correlation constraints between displacements at Nodes 6, 2, and 5. These nodes reside within structurally symmetric regions where displacement responses are governed by identical load patterns, resulting in highly linearly correlated observational data. Such data provide collinear constraints in parameter space without introducing independent information dimensions, leading to saturation of information gain in Bayesian updating.

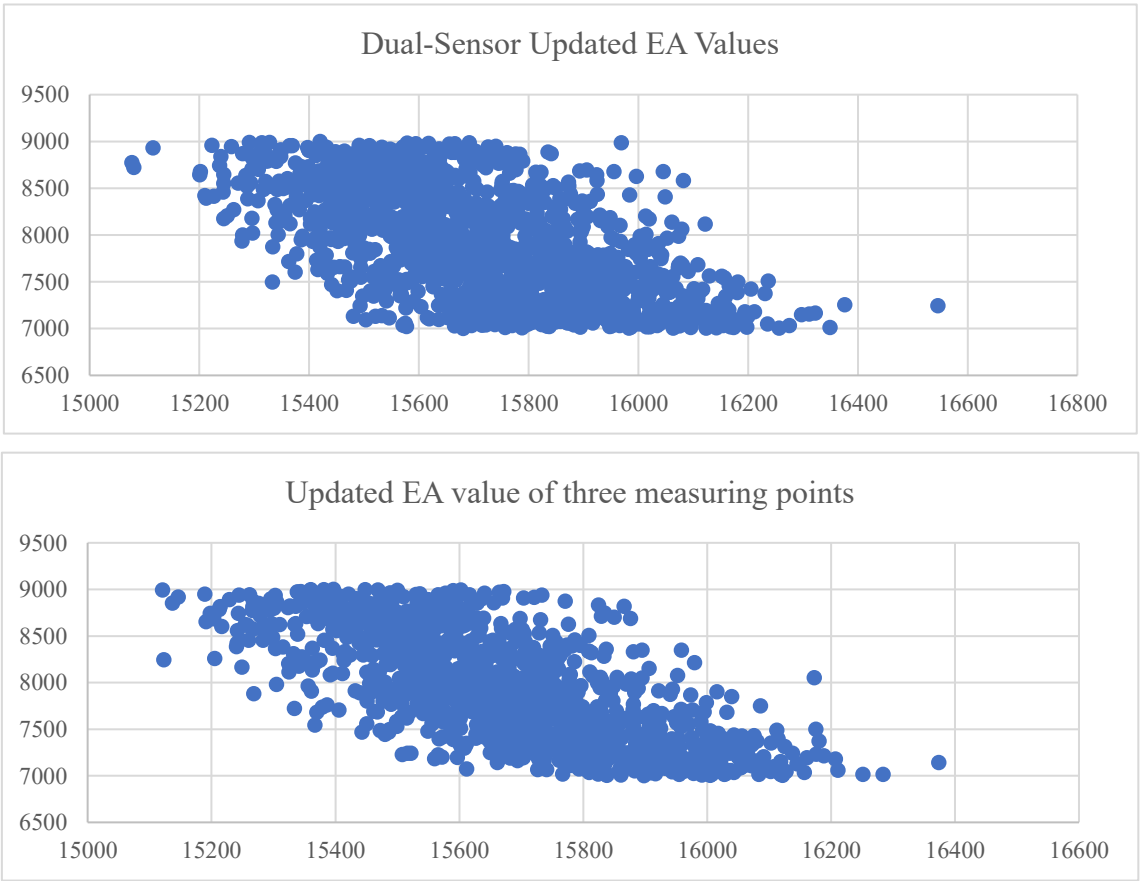


Figure 6: Scatter plot of sensor updating data

5. Conclusions

This study systematically elucidates the efficacy boundaries and optimization pathways of Bayesian updating through theoretical derivation and engineering validation, establishing a transferable technical framework for accurate perception and intelligent decision-making in complex engineering systems.

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The research outcomes verify the applicability of Bayesian methods in complex engineering systems, revealing the critical impacts of load design and sensor placement on updating efficiency. The updated EA_1 and EA_3 parameters converge to mean values of 15,718.536 (COV=1.36%), with standard deviations reduced by 48.7% compared to prior updates. Through experimental design optimization involving load grading and sensor configuration adjustment, the information content and parameter sensitivity were quantitatively evaluated. Under graded loading conditions, the Markov Chain Monte Carlo (MCMC) convergence speed improved by 52%, whereas the Kullback-Leibler divergence analysis showed limited information gain (0.08 bits) from collocated sensor modification. These findings provide methodological support for structural health monitoring, reliability assessment, and resource optimization decision-making.

Future research should explore the extensive engineering applications of Bayesian theorem. Adaptive loading algorithms integrated with digital twin technology could dynamically adjust loading strategies to maximize information gain through parameter sensitivity enhancement. For scenarios where conventional sensor configuration shows limited improvement, the development of intelligent sensor optimization systems could facilitate optimal placement selection. This direction holds significant potential for advancing data-driven infrastructure management paradigms.

References

[1] *Guan, T., Zhong, D., Ren, B., et al. (2018). Construction Schedule Simulation of High Arch Dams Based on Fuzzy Bayesian Updating. Journal of Zhejiang University-Science A (Applied Physics & Engineering), *19*(7), 505–520.*

[2] *Lyu, S. (2025). Full-Process Analysis of Construction for Large-Scale Multi-Roof Connected Steel Trusses. Construction Mechanization, *46*(4), 70–74.*

[3] *Wang, J., Li, P., Ge, Z., et al. (2025). Application and Research of Structural Health Monitoring System for Long-Span Steel Truss Corridor. Low Temperature Architecture Technology, *47*(3), 1–5, 35. https://doi.org/10.13905/j.cnki.dwjz.2025.3.001.*

[4] *Yu, X., Zhang, J., & Wu, G. (2024). Reliability Analysis of Probabilistic Shear Capacity Model for RC Beams Combining Bayesian-MCMC Updating. Journal of Heilongjiang University of Technology (Comprehensive Edition), *24*(8), 134–140. https://doi.org/10.16792/j.cnki.1672-6758.2024.08.024.*

[5] *Wang J. Structural damage identification based on Bayesian updating [J]. Applied and Computational Engineering, 2024, 72(1): 294–300.*

[6] *Li D-Q, Zang H-H, Tang X-S, et al. Efficient Bayesian updating for deformation prediction of high rock slopes induced by excavation with monitoring Data [J]. Engineering Geology, 2024, 342: 107772.*

[7] *Tian H, Li D-Q, Cao Z-J, et al. Auxiliary Bayesian updating of embankment settlement based on finite element model and response surface Method [J]. Engineering Geology, 2023, 323: 107244.*

[8] *Miao, J., Duan, L., Liu, J., et al. (2025). Structural Simulation Model Updating Based on Improved MCMC Method and Surrogate Model. Journal of Shanghai Jiao Tong University, 1–17. [Online]. Available: https://doi.org/10.16183/j.cnki.jsjtu.2023.584.*

[9] *Yang S-H, Yi T-H, Qu C-X, et al. Bayesian Finite-Element Model Updating of Bridges Considering Boundary Condition Uncertainties [J]. ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering, 2024, 10(4).*

[10] *Jiang X, Lu Z. Adaptive Kriging-based Bayesian updating of model and Reliability [J]. Structural Safety, 2023, 104: 102362.*

[11] *Wang, Z. (2024). Bayesian updating of truss structures using OpenSees. Applied and Computational Engineering, 91(1), 33–40. https://doi.org/10.54254/2755-2721/91/20241071*

[12] *Chen L, Liu Y, Luo D. Optimization of structural damage identification method based on finite element method and Bayesian updating [J]. Applied and Computational Engineering, 2024, 58(1): 258–266.*

[13] *Adarsh S, Panda J, Ray-Chaudhuri S. Bayesian updating of the displacement-strain transformation matrix [J]. Journal of Physics: Conference Series, 2024, 2647(19): 192021.*

[14] *Wang X, Jin Y, Schmitt S, et al. Recent Advances in Bayesian Optimization [J]. ACM Computing Surveys, 2023, 55(13s): 1–36.*

[15] *Wu X, Yue K, Duan L, et al. Learning a Bayesian network with multiple latent variables for implicit relation Representation [J]. Data Mining and Knowledge Discovery, 2024, 38(4): 1634–1669.*