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Optimization of structural damage identification method based on finite element method and Bayesian updating

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Abstract: The application of Bayesian updates to the finite element method for structural damage detection represents an avant-garde approach in the industry. Its merit lies in astutely transforming the influence of uncertainty into a forward problem. Nonetheless, the selection of simulation experiments and loading measurement schemes still relies to a certain extent on exhaustive methods. In this paper, based on the finite element method and Bayesian method, the OpenSees software platform is used to compare the actual experimental values with a large number of simulation experiments. The sensitivity of loading and measuring schemes is clarified, and the significance of simulation experiments in finding efficient schemes and reducing detection costs is verified. Concurrently, taking a truss structure as a case study, the combination of structural optimization and simulation experiment is deeply studied. The conclusion of this paper can provide a way to improve the level of simulation experiments and save computing resources.

Keywords: Damage Detection, Bayesian Methodology, Finite Element Analysis, Truss Structures.

1. Introduction

With the passage of service time, building structures are susceptible to various elements within the natural environment [1,2]. Factors such as water, chemical corrosion, external loads, and the increased impact of wind in coastal areas contribute to the deterioration of building structures. Consequently, structural damage in buildings is an inevitable issue, and it profoundly impacts the quality and service life of these structures after a certain period of time. Therefore, early detection and identification of structural damage are of paramount importance. Detecting and addressing damages that occur during usage or have the potential to appear can significantly extend the operational lifespan of building structures [3]. The identification of structural finite element parametersplays a pivotal role in this context. Conducting research in this area is particularly advantageous for achieving automated structural damage analysis [4,5].

The general process of structural damage identification comprises three stages: data acquisition, signal processing, and damage diagnosis. Data acquisition is the prerequisite for damage diagnosis, while signal analysis and processing are pivotal for effective diagnosis. To extract sensitive features related to damage, a model is established, based on Bayesian theory, utilizing the structural modal parameters and the structural dynamic characteristic equation [6]. This model helps identify the physical parameters of the structure, which are then employed to assess the extent of structural damage based on the obtained stiffness parameters. The analysis data for damage identification algorithms is generated through this process. The research and development of these algorithms form the core of damage identification, relying on techniques like Monte Carlo sampling to establish the correspondence between characteristic parameters and the state of damage, ultimately enabling the identification of the occurrence, location, and extent of structural damage [7].

The Bayesian method is considered a cutting-edge approach in the industry. Its fundamental principle lies in deriving prior probabilities from past empirical data and readily observable data. By utilizing Bayesian principles and mathematical models, it then infers posterior probabilities, thereby deducing the condition of structural damage [8]. Its advantage lies in the rational incorporation of uncertainty from mechanical analysis into the framework, transforming the inverse problem caused by uncertainty into a forward problem [9]. Consequently, this method relies on experimental data support and is relatively challenging to establish for multi-dimensional complex systems [10]. Therefore, most existing methods resort to exhaustive methods, neglecting the inherent characteristics of the structure and the abstract relationships between exhaustive results. This optimization study primarily utilizes initial simulation results to infer the next simulation approach, aiming to continuously approach the real situation. In practical applications, this is advantageous for reducing the cost of structural damage detection.

2. Research Methodology and Objectives

Initially, the research involves conducting finite element simulations with multiple selected points on the hyperstatic truss structure. Based on the obtained results and the known characteristics of the structure, the next loading plan is formulated. This analysis method is repeated iteratively. Eventually, the data generated after rejection sampling and the incorporation of real values is compared to the normal distribution. This is done to screen for reasonable loading schemes. In order to minimize the disparity between test results and actual damage, a comparative analysis is conducted between experimental results and control group data. Further refinement of the loading plan is achieved through this process, ultimately optimizing structural damage identification. It is in order to obtain the posterior distribution function using probability density functions. This is employed to infer internal parameters of the structure, such as tensile and compressive stiffness, and subsequently deduce the structural damage status. To achieve this, it is essential to understand the prior distribution of tensile and compressive stiffness for various truss components and the expected parameters for damaged components. Single loading experiments are conducted to obtain displacements, and Bayesian methods are used to obtain posterior distributions that closely approximate real values through simulated component experiments. The primary objective of the research is to validate this method and attempt to identify loading and measurement patterns and their underlying principles that lead to more accurate results.

3. Bayesian Updating for Truss Structure Damage Estimation

Taking the hyperstatic truss structure shown in figure 1 as an example, assuming the tensile and compressive stiffness $\mathbf{E_a}$ after damage is uniformly 100,000 kN*m^2, and considering the positions of damaged members, a preliminary loading scheme is preselected as shown in table 1.

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Table 1. Loading Scheme.

Scheme	Nodes	Loading capacity (kN)	Direction
1	11	30	Straight down
2	4,5	15,15	Straight down
3	11,4,5	Node 11 loads 30, node 4 and node 5 loads 15	Straight down
4	5	100	Straight down

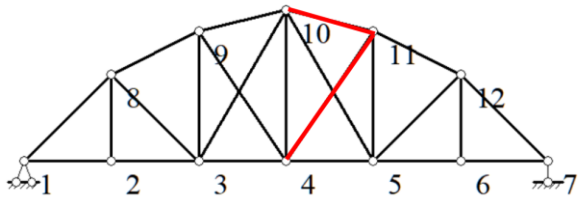
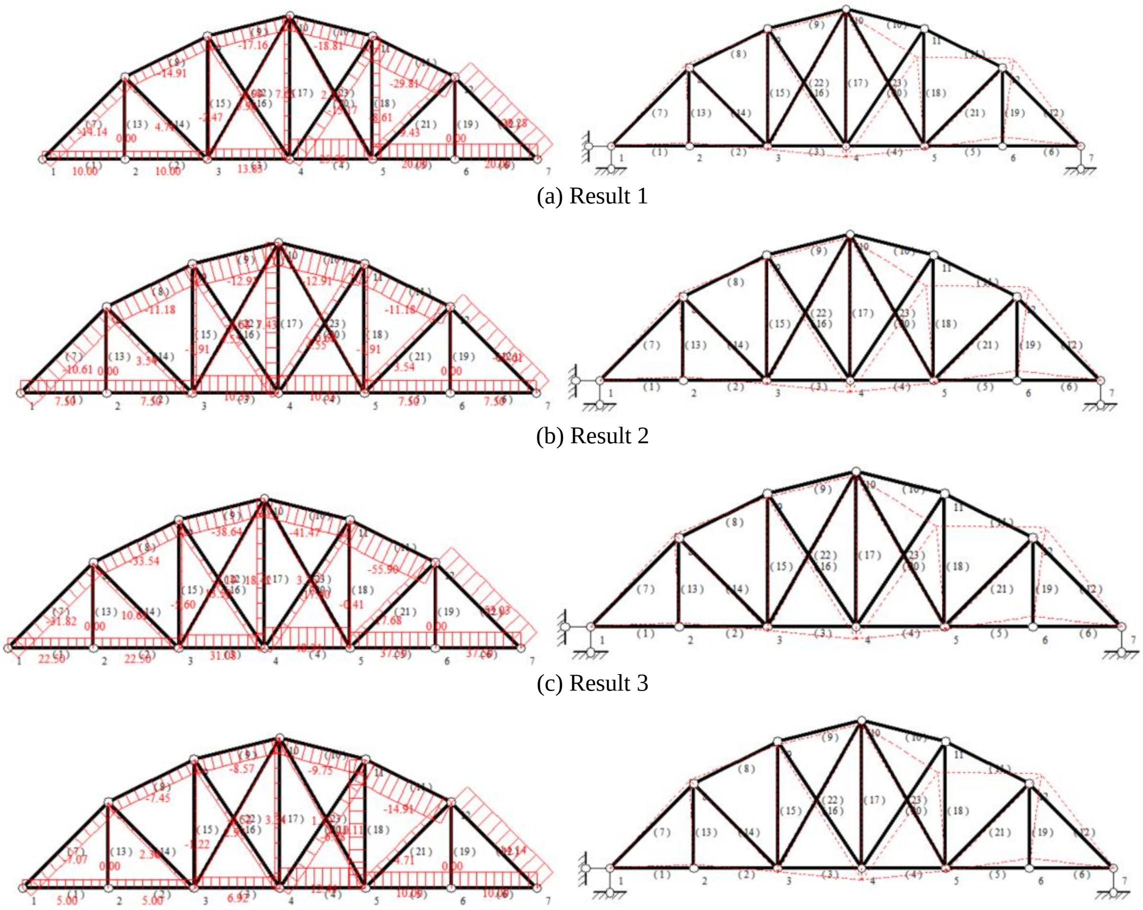


Figure 1. Schematic Diagram of the Study Structure.

A structural mechanics solver was employed for preliminary solving, and the axial force diagram and displacement diagram of the structure under the predetermined loading conditions are shown in figure 2. Therefore, displacements at points 3, 4, 5, 9, 10, and 11, which exhibited greater displacements, were selected for measurement. In the static analysis process, it was found that when the nodes connected to members bearing higher axial forces were chosen as measurement nodes, the selected scheme exhibited higher sensitivity [11].



(a) Result 1

(b) Result 2

(c) Result 3

(d) Result 4

Figure 2. Preliminary Solution Axial Force and Displacement Diagrams for Four Loading Schemes.

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The known experimental displacement values for loading tests are provided in table 2.

Table 2. Experimental Displacement Values for Loading Tests.

	X (m)	Y (m)
3	0.0034640	-0.0209780
4	0.0052730	-0.0260060
5	0.0088960	-0.0270460
9	0.0098350	-0.0209120
10	0.0083890	-0.0247480
11	0.0025840	-0.0276150

Then the code can be entered according to the syntax of the Tcl language, as shown in figure 3.

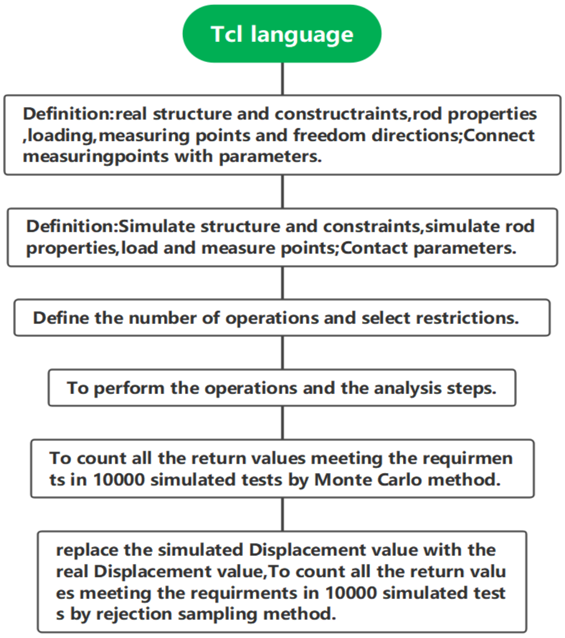
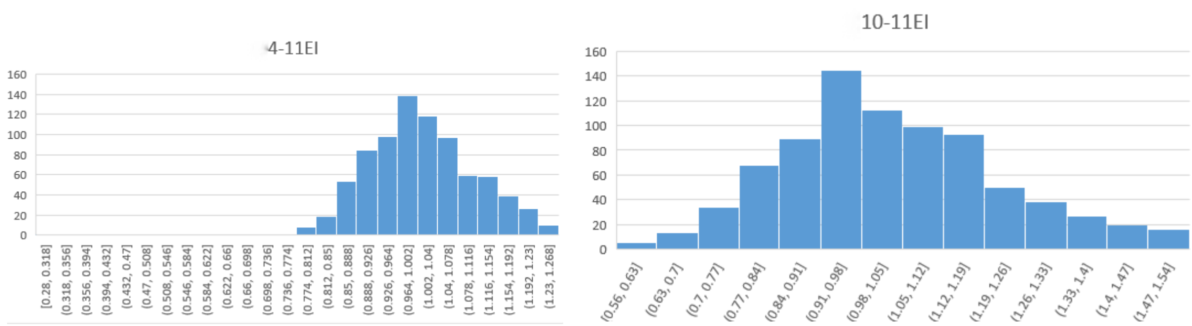


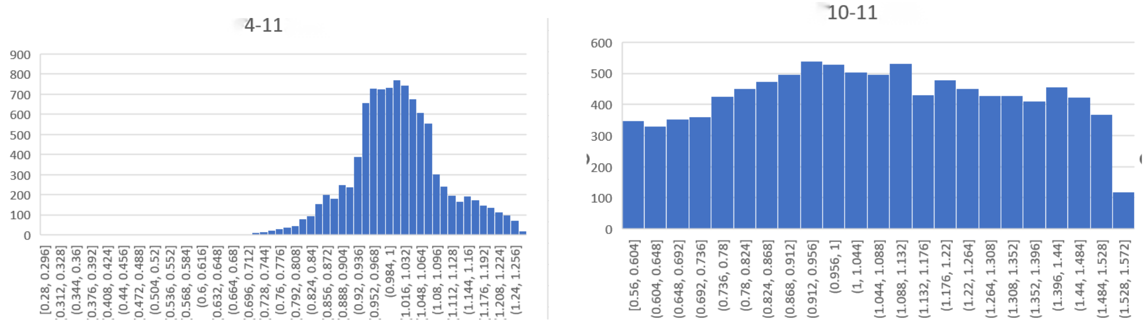
Figure 3. TCL code writing steps.

Based on the code settings, the lower the success rate, the higher the sensitivity of the loading and measurement node scheme in a fixed-number simulation experiment. In this scenario, the loading and measurement methods are more suitable. The rejection sampling data figures for the four sets of loading results and the substitution of real values are in figure 4~6, and table 3.



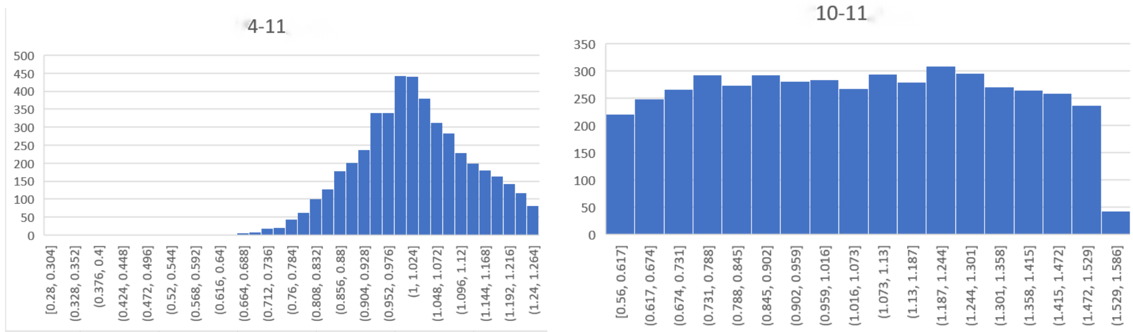
(a) 4-11EI (b) 10-11EI

Figure 4. First set of results.



(a) 4-11EI b) 10-11EI

Figure 5. Second set of results.



(a) 4-11EI (b)10-11EI

Figure 6. Third set of results.

Table 3. Fourth set of results.

Conlumn1	Conlumn2
1.234856662	1.33591875
1.197179181	1.170495643
1.194706364	0.769854451
1.170008665	1.195646896
1.208163553	0.564839741
1.223097588	0.681166719

By comparing the two approaches undertaken in this execution, it is generally observed that under typical conditions, when the loading position is closer to the damaged rod, the success rate is lower. Consequently, in such cases, the selected loading scheme exhibits higher sensitivity in conjunction with the designated measurement nodes (as depicted in figures 4 and 5).

However, it is important to note that the data obtained from the final set of rejection sampling trials proved challenging to fit into a normal distribution plot (as seen in figure 7). This discrepancy may be attributed to the presence of some residual error between the chosen loading scheme and the actual damage conditions.

4. Exploration of Optimization Approaches for Loading Schemes

The numerical distribution plots formed after loading at a single point deviate significantly from a normal distribution. For the 2nd, 3rd, and 4th sets of loading schemes, when real measurement values are incorporated, the number of effective data points obtained from 10,000 trials is almost negligible. Upon closer examination of the original truss structure, it's evident that several loading points still have considerable deviations from the actual damage location. Hence, the primary reason for the

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inconclusive image results is the considerable distance between the loading points and the damage points, making it challenging to establish an ideal damage observation scenario.

Consequently, in this section, we opted to increase the number of loading points in the first group, selecting points 4, 5, 10, 11, and 12, each loaded with a force of 50 kN in a downward direction. The results obtained after running the analysis in OpenSees are in table 4.

Table 4. Acceptance rate of four groups of loading schemes.

Number of schemes	1	2	3	4
Accepted samples	1875	1702	1720	1314
Rejected samples	8125	8298	8280	8686
Acceptance rate	18.75%	17.02%	17.2%	13.14%

The rejection sampling results generated after running are shown in the figure 7.

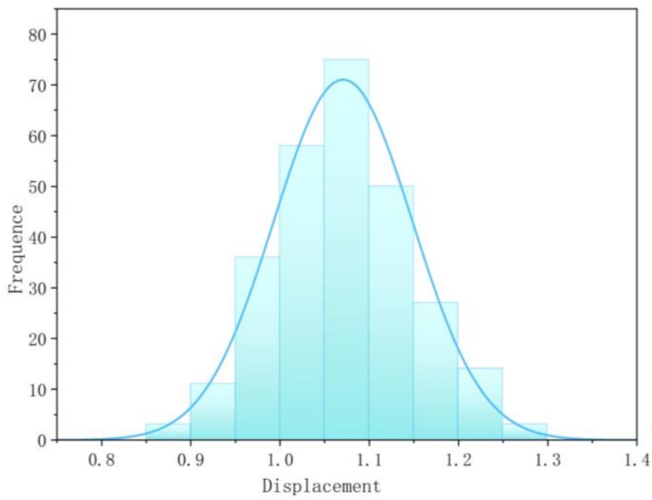

Figure 7. Scheme 1 Return Results.

The figure for the first scheme exhibits a normal distribution. From this, it can be seen that this loading scheme contains actual damage points. To determine the specific damage condition, loading points will be reduced from both the left and right directions, and the numerical distribution images formed after removing loading point 4 and the numerical distribution images after adding real values are observed, as shown in figure 8.

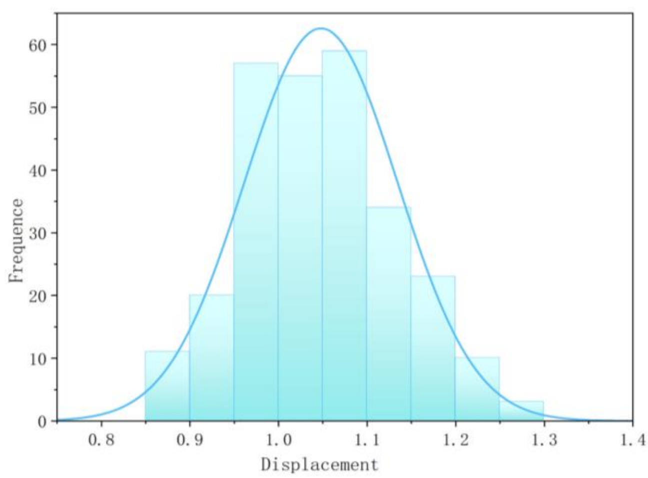

Figure 8. Scheme 2 Return Results.

Numerical distribution images formed after removing loading points 4 and 12, and numerical distribution images after adding real values are shown in figure 9.

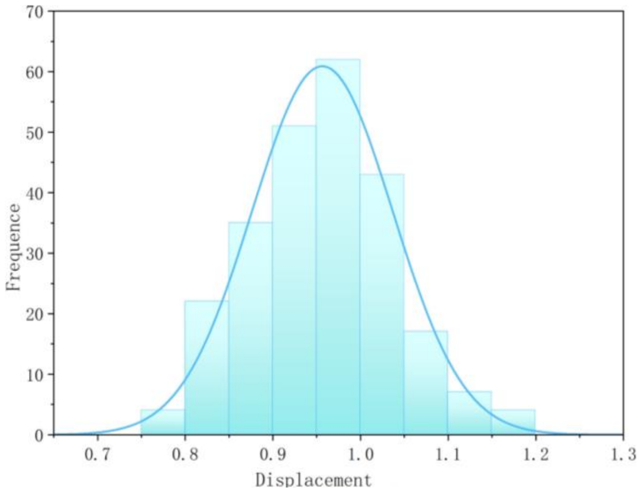

Figure 9. Scheme 3 Return Results.

Numerical distribution images formed after removing loading points 4 and 10 and numerical distribution images after adding real values are shown in figure 10.

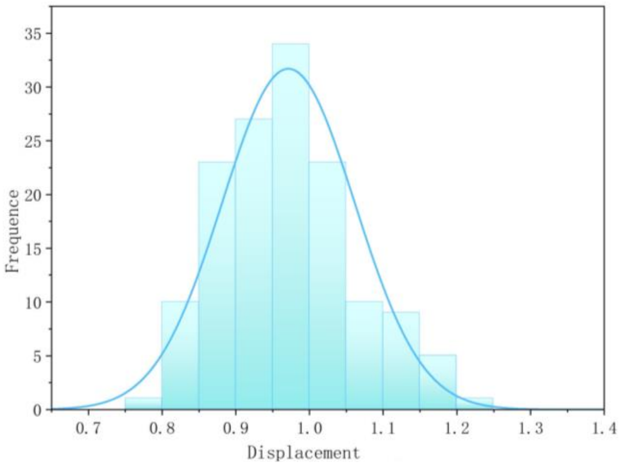

Figure 10. Scheme 4 Return Results.

Based on the status of the images generated from numerical data in each section, it can be preliminarily determined that Scheme 3 and Scheme 4, specifically the left cluster closer to the original loading point, are more likely to exhibit damage. Next, further calculations will be performed based on the measured real values, referencing the second set of images in each section. Clearly, the image formed by Scheme 4 closely resembles a normal distribution. Therefore, applying a 50 kN load to points 5, 11, and 12 of the structure is the most reasonable and closest to the real damage scenario.

In the above process, through an analysis of the truss structure's characteristics, a considerable number of loading points were initially set in the first loading scheme. When an approximation of a normal distribution image was obtained, the location of the damage within this loading range was determined. Subsequently, optimization was performed by reducing loading points from different directions, and after observing the resulting numerical images, Scheme 2 was eliminated. Finally, based on the results of Schemes 3 and 4, a test involving real values was conducted, and their images

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were verified. It was concluded that Scheme 4 is the most reasonable, thus optimizing the structural damage identification method.

5. Conclusion

This paper has optimized the damage identification method for truss structures based on the finite element method and Bayesian updating. Initially, the known structural characteristics were used to make preliminary damage predictions, forming an understanding of the structural peculiarities and determining the nodes and magnitudes for the first Opensees loading. In the first loading, an attempt was made to cover as many potential damage points as possible, preparing for the subsequent classification inference. For the results of the first loading, once it was determined that the graph exhibited basic normal distribution characteristics, the initial loading scheme was divided into several parts, each of which was separately subjected to Opensees loading and data collection. The results were then fitted using Tcl language to compare with the actual deformations of the truss members. The compatibility of each part's results with normal distribution patterns was analyzed separately. The loading scheme with the highest degree of conformity to the normal distribution image was considered the loading scheme closest to the real damage scenario.

Based on these methods, this paper confirmed the guiding role of simulation experiments in real damage detection and proposed an optimization direction for simulation experiments: in truss structures, simulation experiments are generally more efficient when the loading points are closer to the damaged members or when the loading points are located on members experiencing higher axial forces. Therefore, during the initial design of simulation experiments, it is advisable to consider conducting static analysis to optimize the loading scheme. This process should involve reducing the loads on less sensitive members and increasing the loads on highly sensitive members. Employing this method can enhance the efficiency of simulation experiments.

In conclusion, this optimization method efficiently identified a set of loading scenarios closest to real damage. Compared to the previous method of randomly setting loading points and values, this approach is significantly more efficient and accurate. Moving forward, it is possible to combine the underlying logic of Bayesian updating to conduct more detailed tracing and analysis of the data that has been excluded. On the other hand, the scope of research on using the finite element method to infer structural damage can be expanded beyond truss structures, increasing its applicability across various domains.

Authors Contribution

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

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