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Research Article

Damage Identification of Full-Scale Steel Truss Structure Based on Model Condensation and Mean-Value Normalization Regularization Techniques

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Structural health monitoring and damage identification aim to detect the internal damage and evaluate the health conditions of the practical engineering structure, which has been the most popular research field for several decades. The sensitivity-based method incorporated with the regularization techniques is the classical and useful approach, and it can obtain accurate damage detection results. However, with the development of civil engineering structures, this classical method faces two problems: one is it is only applied to simple structures rather than full-scale structures, and second is the iterative calculation efficiency is lower. Therefore, aiming at these drawbacks, the two improvement strategies have been introduced to the original method for its enhancement in the application potential and computational efficiency. The proposed method has been verified based on two examples, i.e., a numerical steel truss with 144 elements and a full-scale experimental steel truss with 160 elements. The results prove that the proposed method has better efficiency and good application potential in the practical full-scale engineering structure.

1. Introduction

With the development of human civilization and science and technology, civil engineering structures, like long-span bridges and high-rise buildings, are constructed worldwide. Such engineering structures enrich the lives of human beings and bring convenience to transportation, business activities, and other human-being social activities. However, accompanying the service time increase, external forces and environmental factors are continuously applied to the structures, leading to internal damage or failure occurring in the hidden place of the structures [1, 2]. The internal damage will further cause the collapse and threaten the safety of users. In this regard, structural health monitoring (SHM) and damage identification have been proposed to evaluate the internal damage and monitor the health condition of the structure [3–7].

In the field of SHM, the most popular way of achieving the targeted goal is to adopt the vibration features of intact and damaged structures to make a comparison [8–10]. Following this idea, through combining the measured and analytical features with the finite element model (FEM) of the structure, the damage site and severity can be determined well. Regarding this point, numerous studies have paid attention to the research topic. For example, Gordan et al. [11] adopted data mining techniques to the field of SHM, the modal parameters were determined as damage detection index, and then a hybrid artificial neural network-based imperial competitive algorithm was proposed to evaluate the damage site and extent, which is well validated based on slab-on-girder bridge structures. Ghaedi et al. [12] combined data mining and inverse analysis to further analyze the target structure; also, different damage scenarios were considered in the study, and the results illustrate the proposed method can achieve accurate damage localization and quantification. The recent advances in data mining in the SHM field are detailed in the paper [13]. Furthermore, there still exists some research that tries to incorporate industry 4.0 technologies [14], computational intelligence [15] and remote sensing [16] into the SHM to consider the multiple factors and lead to the more practical and economical applications of SHM.

The most classical method is sensitivity-based damage identification [17]. The sensitivity-based method for damage identification was originally inspired by the linearization of the changing relationship between the structural damage and the measured vibration features, like structural natural frequencies and mode shapes [18, 19], and some structural time domain responses, i.e., acceleration and displacement [20–22] are also utilized to identify the damage. For instance, Zhu et al. [23] first adopted the times series model to fit the measured acceleration of the structure and then to deduce the sensitivity of coefficients of the time series model concerning the structural stiffness reduction factor (SRF); after that, the sparse regularization method was exploited to output the structural damage location and severity, establishing a link between the regularization method and time series analysis. Furthermore, in order to evaluate the damage identification performance of different regularization methods, Zhang and Xu [24] conducted a comparative study between Tikhonov and sparse regularization. For the condition of bridge structures subject to moving vehicles, Zhang et al. [25] exploited the extended Kalman filter with L_1-norm regularization to solve the damage detection issue with the ill-posed equation. In order to solve the damage evaluation based on the structural static model, Lu et al. [21]. proposed eigenparameter decomposition incorporating sparse regularization to form the new method, and the new objective function is constructed based on decoupling features. Furthermore, Dinh-Cong et al. [26] aimed at the damage detection of composite structures, modal kinetic energy change ratio sensitivity is used to construct the damage equation set, then the Tikhonov regularization and lightning attachment procedure optimization algorithm are used to localize and quantify the damage location and extent. Yang et al. [27] established the eigen equations of a rotating beam, and the modal sensitivity analysis was also used; then, the sparse regularization was introduced to solve the equations set and obtain the damage situation. Moreover, Smith and Hernandez [28] presented an impulse response sensitivity method, combined with the least absolute shrinkage and selection operator, to achieve the structural spatial sparse damage; the noise-polluted measurements and incomplete mode shapes are also investigated well.

The existing literature indicates that sensitivity-based damage identification with the regularization technique has been widely applied to the field of SHM. However, among most of the related studies, scholars always focused on small structures, like a simply-supported beam [29], cantilever beam [30], and several story frames [23]. Such these small structures only have some dozens of degrees of freedom (DOFs) or/and structural elements. In this regard, the damage detection is easy to achieve, and for the full-scale structure, namely, the structure with many DOFs and structural elements, it has not been investigated well. Furthermore, damage identification based on the sensitivity-based method needs to be iteratively calculated, not only including the assembled structural stiffness and mass matrices but also gradually approaching the optimal value. Therefore, these drawbacks both set some obstacles to expanding the sensitivity-based method to damage identification on the full-scale structure. Regarding the abovementioned statement, in this study, a new damage identification method for full-scale structures has been proposed based on model condensation and mean-value normalization regularization techniques. Numerical and experimental examples are both used to validate the proposed method, and the obtained results prove that the proposed method demonstrates faster convergence speed and better applicability in the full-scale structure, which is of great potential in the practical engineering structure.

The remaining contents are organized as follows: Section 2 details the damage identification theory based on the structural dynamics and finite element method, the traditional regularization method in damage identification, and then a novel damage identification method has been proposed. For Sections 3 and 4, the numerical example and experimental validation are adopted to verify the feasibility of the proposed method, respectively; the discussions on the results are also stated here. Finally, in Section 5, several conclusions and outlooks have been put forward.

2. Theoretical Background and Methodology

2.1. Damage Identification Theory

2.1.1. Structural Dynamic Equation. According to the dynamic theory, the free vibration equation of a civil engineering structure can be mathematized as follows [31]:

$$M\ddot{x} + C\dot{x} + Kx = 0, \tag{1}$$

where M, K, and C are structural mass, stiffness, and damping matrices, respectively; $\ddot{x}, \dot{x}$, and x stand for the acceleration, velocity, and displacement of the structure. Then, assuming the damping has been ignored, and the structural eigenvalues and eigenvectors can be obtained based on the following equation [32]:

$$(K - \lambda_i M)\varphi_i = 0, \tag{2}$$

where λ_i means the ith structural eigenvalue; φ_i is the ith structural eigenvector or called mode shapes. Thus, it can be observed that the change in the structural stiffness and mass will cause variations both in the structural eigenvalues and eigenvectors. Thus, the eigen-pair can be determined as a good indicator to detect internal change in a civil engineering structure.

2.1.2. Damage Identification Model. Zhou et al. [33] have comprehensively summarized several techniques to simulate structural damage, including structural element stiffness reduction, element mass increase, cracked beam element, and crack spring element. The conclusion of this research also points out that structural damage greater than 15% can be well identified based on the structural element stiffness reduction method. According to this valuable conclusion, meanwhile, considering the function of civil engineering is to support the external load, internal damage or failure in the structure will cause a change in the mechanical performance or carrying capacity and the actual damage extent in the subsequent experimental example. Thus, this study assumes that the internal structural damage can be seen as the stiffness declination, but the mass has not changed [34]. Regarding this assumption and adopting the classical finite element theory, the internal damage of a structure can be measured and localized through introducing the SRF, and then it can deduce the overall stiffness matrix of the structure as follows [35, 36]:

$$K = \sum_{n=1}^{Nele} (1 - \alpha_n) k_n, 0 \leq a_n \leq 1, \tag{3}$$

where α_n denotes the nth SRF, which can reflect the damage extent and site; k_n is the nth structural element stiffness matrix; *Nele* is the total number of structural elements, which is determined based on the situation of element mesh.

2.2. Regularization Techniques in Damage Identification

2.2.1. Structural Eigen-Pair Sensitivity Analysis. Referring to theories of structural dynamics and finite element method, taking the partial derivation of structural ith eigen-pair to the nth SRF, the equation can be written as follows [37]:

$$\frac{\partial \lambda_i}{\partial \alpha_n} = -\varphi_i^T K_n \varphi_i, \tag{4}$$

$$\frac{\partial \varphi_i}{\partial \alpha_n} = \sum_{k=1,k\neq i}^{nmod\Sigma} \frac{\varphi_k^T K_n \varphi_i \varphi_k}{\lambda_k - \lambda_i}, \tag{5}$$

where *nmod* is the total number of considered structural modes, and K_n is the nth structural elemental matrix. The above equations are also called the structural modal parameters sensitivity coefficients.

2.2.2. Regularization Method for Inverse Problem. Based on the linear algebra theory, the relationship between the input and output of the system can be described as follows [38]:

$$A \times x + z = b, \tag{6}$$

where b is the interest output that can be observed, A stands for the mapping matrix, x is the input vector, and z means the noise pollution. When the measured output is less than the unknown input, this mathematical equation is ill-posed, and it is difficult to obtain a correct solution in this situation. Regarding this problem, regularization techniques can be adopted to rewrite the above equation as follows [39]:

$$\min_x \|x\|_1, \text{subject to } \|Ax - b\|_2 \leq \varepsilon, \tag{7}$$

where ε is the error tolerance, and Equation (7) can be transformed into Lagrangian form as follows:

$$J = \min_x \frac{1}{2} \|Ax - b\|_2^2 + \beta \|x\|_1, \tag{8}$$

where β is the regularization parameter, and it is used to balance the residual term and regularization term, which can be obtained using the L-curve method. Furthermore, due to the introduction of the L_1 regularization term, the obtained solution is a sparse vector; thus, such method is also called the sparse regularization technique.

2.2.3. Structural Damage Identification Based on Regularization Method. When the damage has occurred in the structure, the distribution of structural damage usually shows a sparse feature; namely, except for the specific damage site, the elements in SRF are almost close to zeros. Second, due to the incomplete measurements, the measured modal parameters are limited; only the first several modes can be collected. Meanwhile, the structural eigen-pair sensitivity analysis satisfies the application requirements of the regularization technique. Therefore, the damage identification process based on the regularization method can be described as the following equation [40]:

$$J = \min_\alpha \frac{1}{2} \|S\alpha - f\|_2^2 + \beta \|\alpha\|_1, \tag{9}$$

where α is the SRF; $f = [\Delta\lambda, \Delta\varphi]^T$ means change in structural eigen-pair between intact and damaged structure; and $S = [S_\lambda, S_\varphi]^T = [\frac{\partial \lambda_i}{\partial \alpha_n}, \frac{\partial \varphi_i}{\partial \alpha_n}]^T$ denotes eigen-pair sensitivity matrix [41]. Thus, the damage severity and location can be identified through solving Equation (9).

2.3. The Proposed Damage Identification Method. It is known that the modeling difficulty and computational complexity will increase with the expansion of physical geometry size, especially for some full-scale bridges and high-rise buildings. These problems are always reflected in the following aspects: (1) increasing nodes and elements in the FEM cause the sizes of structural stiffness and mass matrices to be very large, then the existing solution method cannot meet the requirements, further inducing the incorrect results [42]; and (2) the iterative calculations in the damage identification need to repeatedly assemble the structural overall stiffness matrix, the more complex structure, the lower convergence speed in the optimization process.

For the purpose of satisfying the requirements of damage detection for a full-scale structure, in this study, some new strategies have been proposed to achieve successful damage detection based on the regularization technique. At first, the model condensation technology is adopted to reduce the size of the FEM, only master DOFs are retained, but slave DOFs will be condensed, and then, for the low iterative calculation efficiency, the max-value normalization strategy is applied to the sensitivity matrix to improve the convergence speed. The details are described in the following sections.

2.3.1. FEM DOFs Reduction Based on the Model Condensation Technology. Based on the displacement balance relationship, the displacement of all DOFs of a structure can be defined as follows [43]:

$$a = \begin{bmatrix} a_m \\ a_s \end{bmatrix}, \tag{10}$$

where a_m and a_s stand for the displacement in master and slave DOFs, respectively. Then, a transform matrix T can be defined to establish the relationship between the displacement in master and slave DOFs, namely:

$$a_s = Ta_m. \tag{11}$$

Then, Equation (11) can be written as follows:

$$a = \begin{bmatrix} a_m \\ a_s \end{bmatrix} = \begin{bmatrix} I \\ T \end{bmatrix} a_m = T^* a_m, \tag{12}$$

where I means the identity matrix; T^* is $n \times n_m$ matrix, in which n is the total number of DOFs, and n_m is the total number of considered master DOFs. Then, according to the above content and Equation (2), the following block equation can be obtained [44]:

$$Ka = \begin{bmatrix} K_{mm} & K_{ms} \\ K_{sm} & K_{ss} \end{bmatrix} \begin{bmatrix} a_m \\ a_s \end{bmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}. \tag{13}$$

Then, to expand the second of Equation (13), it can be written as follows:

$$K_{sm} a_m + K_{ss} a_s = 0. \tag{14}$$

So, a_s can be deduced as follows:

$$a_s = -K_{ss}^{-1} K_{sm} a_m. \tag{15}$$

Based on the above equation, the transform matrix T can be written as follows:

$$T = -K_{ss}^{-1} K_{sm}. \tag{16}$$

When the transform matrix T has been obtained, the original FEM with large size can be reduced based on the following equation:

$$K^R = [T^*]^T [K][T^*], \tag{17}$$

where K^R is the reduced stiffness matrix of the structure, and $T^* = [\, I - K_{ss}^{-1} K_{sm} \,]^T$. Meanwhile, the structural mass matrix can be reduced according to the same idea.

2.3.2. Improving Convergence Speed Using Sensitivity Matrix with Mean-Value Normalization. Considering the damage in the different structural elements will show diverse influence on the structural modal parameters, such differences will cause the elements of the sensitivity matrix to have some magnitude differences [45, 46]. These differences lead to a low convergence speed when the iterative calculation is conducted. In this regard, the mean-value normalization strategy is proposed to enhance the convergence speed. The details are shown as follows: based on Equation (9), the mean-value of each mode is applied to the contribution corresponding to the sensitivity matrix; therefore, Equation (9) can be rewritten as follows:

$$J = \min_{\alpha} \frac{1}{2} \| S^* \alpha - f \|_2^2 + \beta \|\alpha\|_1, \tag{18}$$

where $S* = [\frac{S_1}{\overline{f}_1} \quad \cdots \quad \frac{S_n}{\overline{f}_n}]$, in which S_n and $\overline{f}_n$ are the nth column of the sensitivity matrix corresponding to the nth structural element and the mean-value of the nth modal parameters.

Thereby, the abovementioned strategies have been incorporated into the original regularization method, and to form a novel way for highly effective damage identification, the specific procedures are illustrated in Figure 1.

3. Numerical Example

3.1. A Brief Description of Numerical Example. In this section, a numerical space steel truss is used to verify the proposed method. The numerical example is shown in Figure 2. The truss has 48 nodes and 144 elements; the material properties, such as Young's modulus, density, and cross-sectional area are 6.964×10^{10} Pa, 2,714 kg/m^3, and 3.76×10^{-3} m^2, respectively. There are three types of bars with different lengths; the lengths are 1.73, 1.64, and 0.3 m, and the simply supported constraints are applied to the truss.

In order to evaluate the feasibility of the proposed method, several damage cases have been preset through the stiffness reduction on the corresponding structural element; the environmental interference is also considered by the introduction of random noise to the modal data [47], and the details are listed in Table 1. For the noise pollution method, it can be described as follows:

$$f^* = f \cdot [1 + (2 \cdot \text{rand} - 1) \times \gamma], \tag{19}$$

where f and f^* denote the modal data without and with noise pollution, respectively; rand stands for the random number between [0,1]; γ indicates the noise pollution level.

3.2. Results and Discussions of Numerical Example. Based on the preset damage case in Section 3.1. This section has adopted the proposed method to identify the damage location and severity of the numerical example. The first ten natural frequencies and mode shapes are determined as the damage features. When the preset iteration number meets, the iterative calculation will be terminated and output the results. The obtained results and computational costs are listed in Figures 3–5 and Figure 6, respectively.

From Figure 3, it can be seen that the two methods can both localize the site of single-element damage cases under

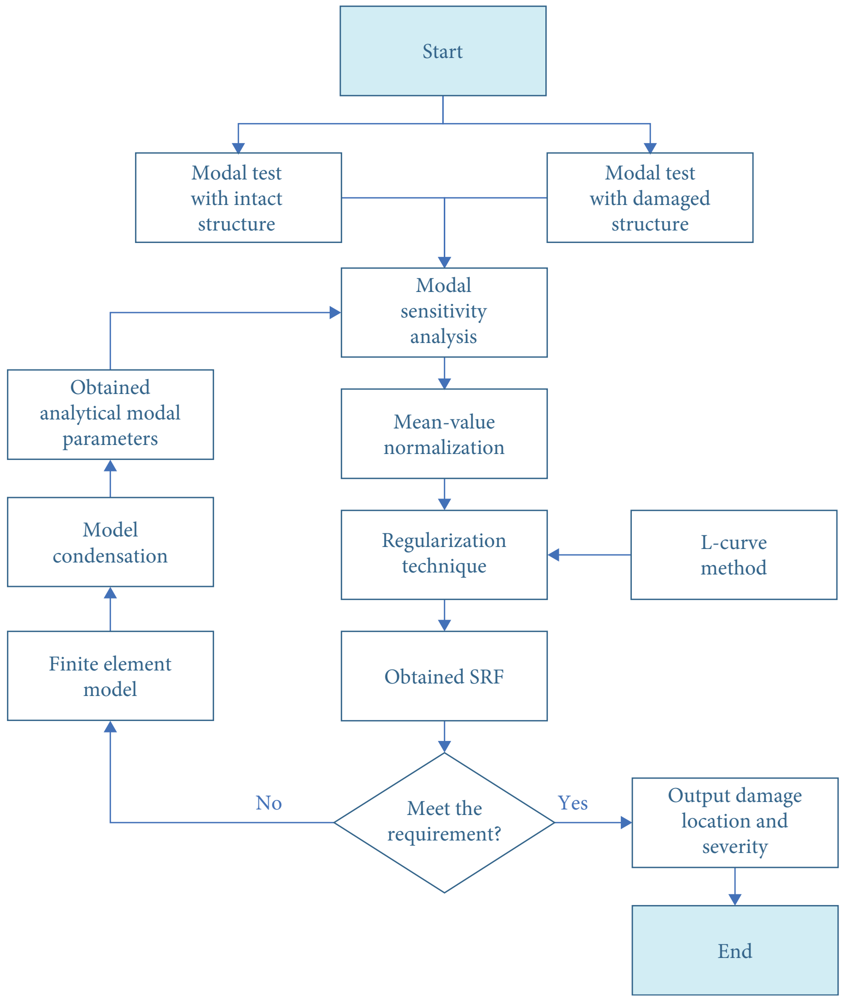


Figure 1: The flowchart of the proposed method.

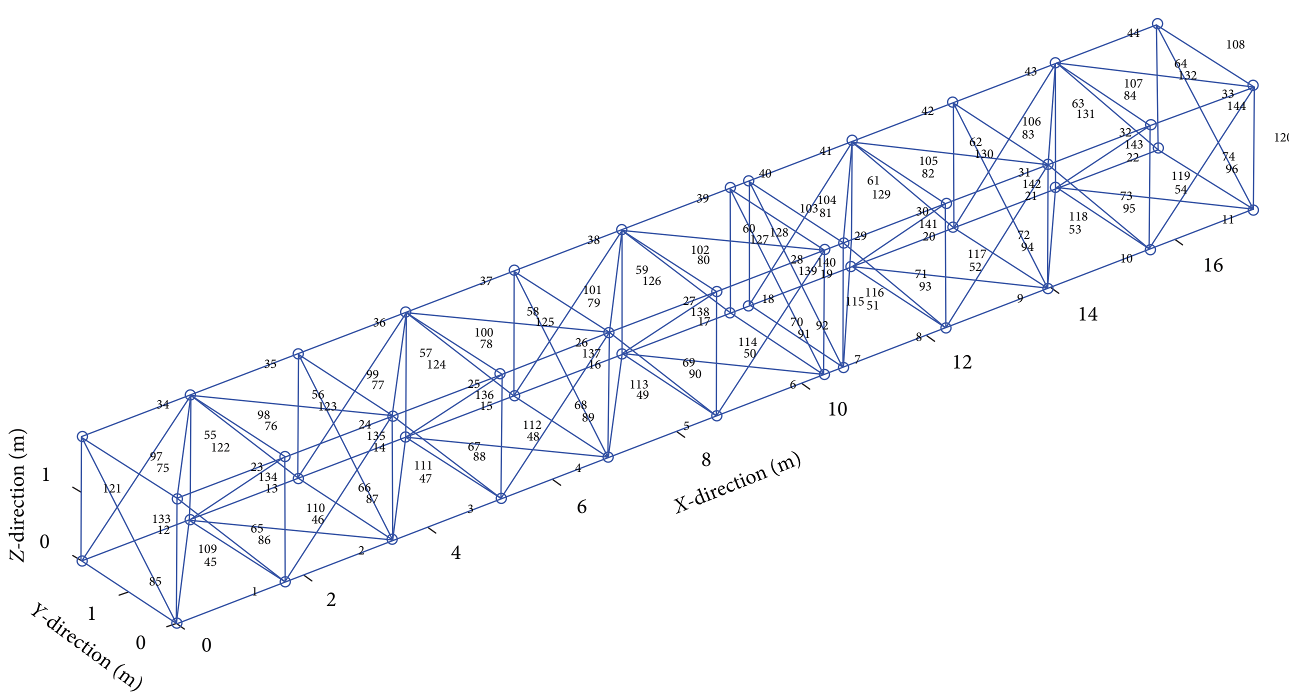
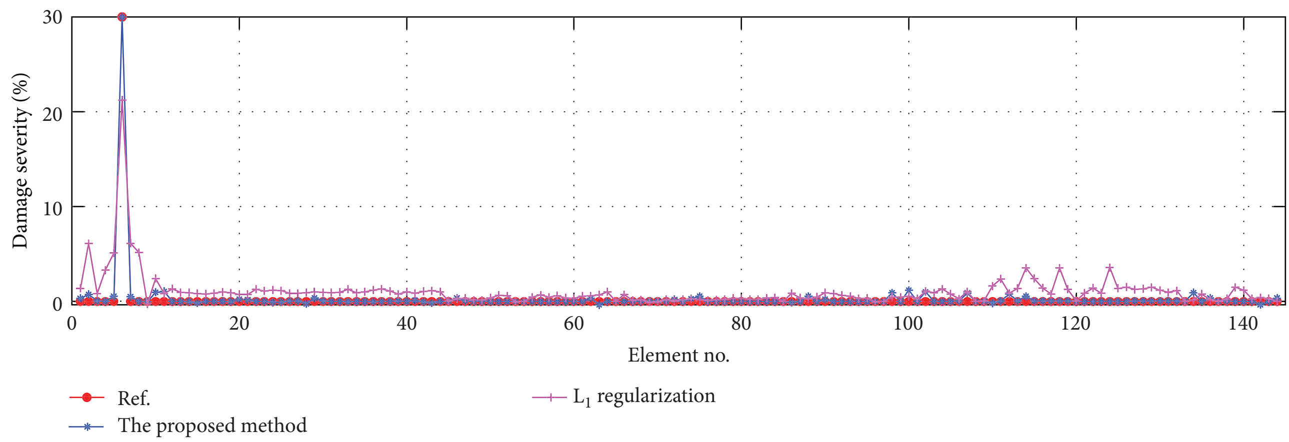


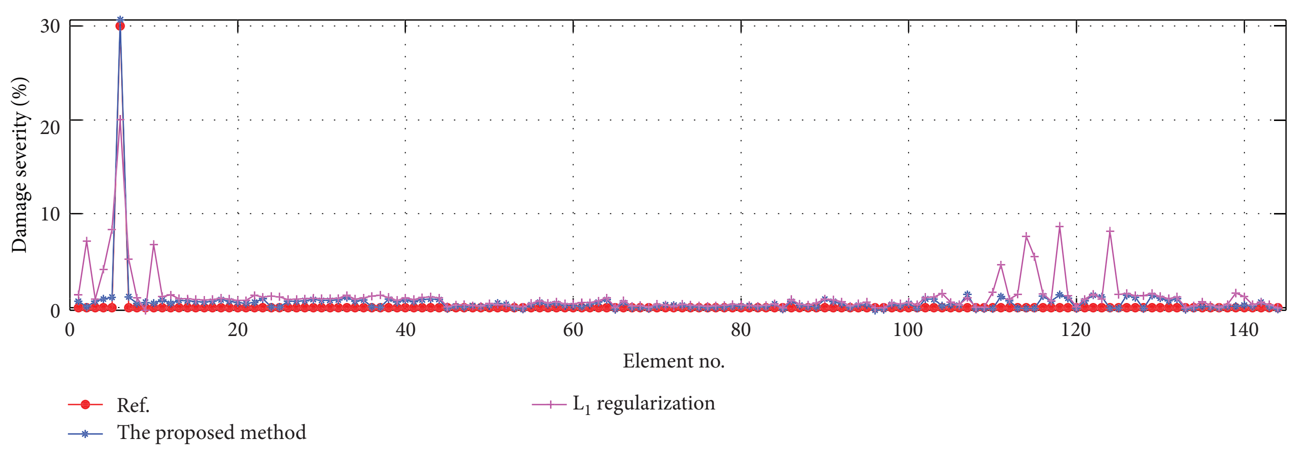
Figure 2: The numerical space steel truss.

Table 1: The simulated damage cases.

Environmental interference	Damage case no.	Damage severity @ location
1%, 3%, and 5% random noise	1	30% @ 6#
	2	30% @ 6# 10% @ 36#
	3	30% @ 6# 10% @ 36# 15% @ 112#



(a)



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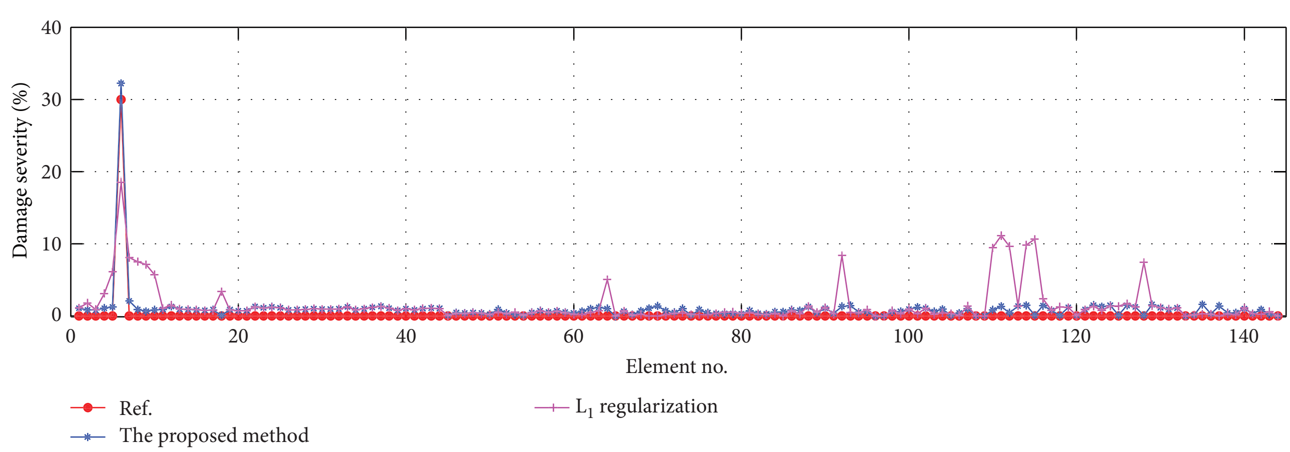

(c)

Figure 3: Damage identification for damage case 1 of numerical example: (a) 1% noise, (b) 3% noise, and (c) 5% noise.

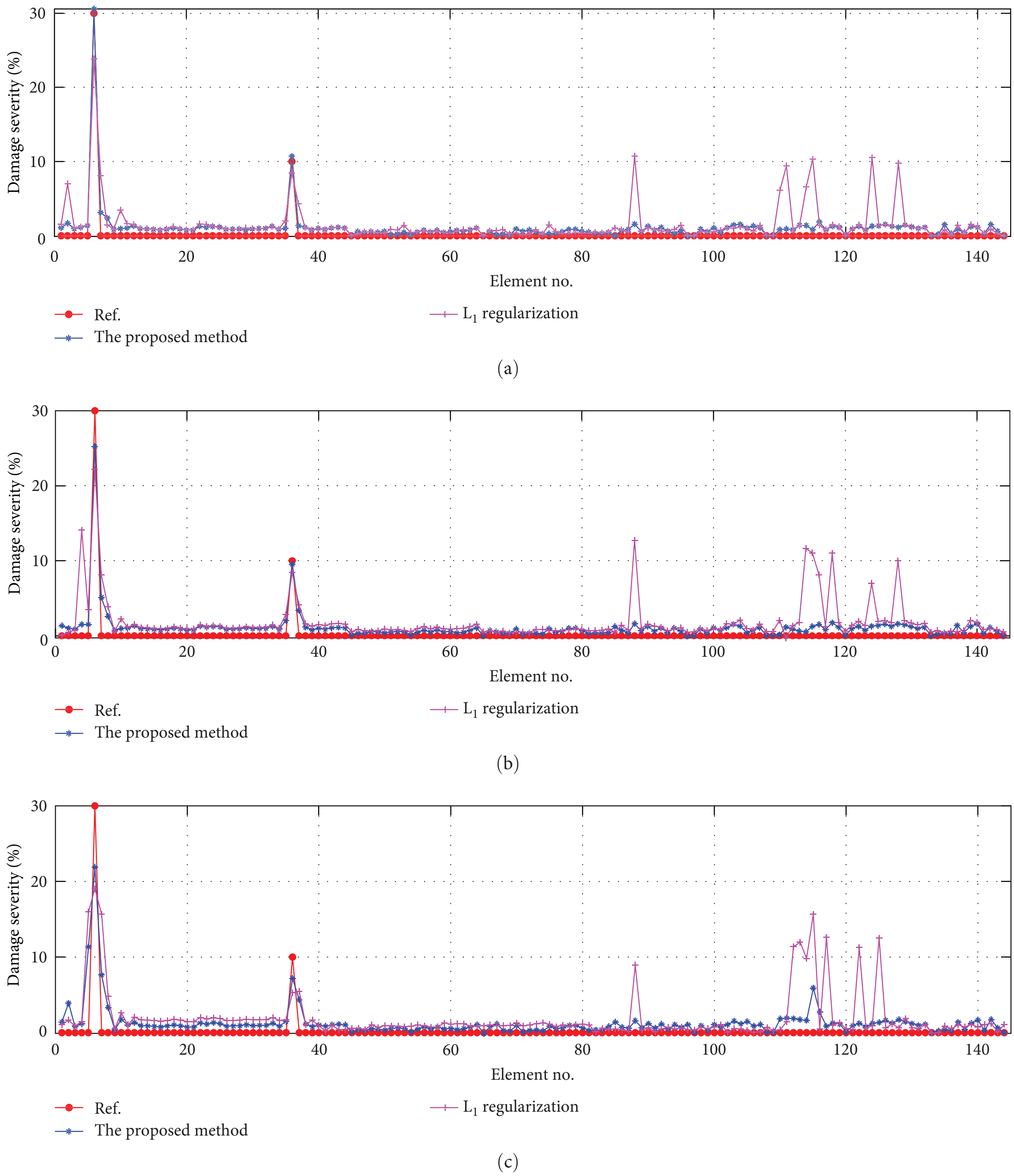

FIGURE 4: Damage identification for damage case 2 of numerical example: (a) 1% noise, (b) 3% noise, and (c) 5% noise.

different levels of noise interference. However, it can be observed that there are some obvious false detections in the results of the L_1 regularization method. Also, it can be found that the proposed method can achieve more accurate damage localization and severity quantification; namely, the identification errors are less than the traditional L_1 regularization method, which means the proposed method is superior in the damage identification issue.

Figure 4 illustrates the results of the two-element damage case, and it is obvious that the false identifications are more serious than the single-element damage case as the complexity of the damage case increases. There are obvious false identifications that occur in the L_1 regularization method, but for the proposed method, the results are still accurate; only under the situation of 5% noise level, the errors can be observed clearly, which means the proposed method shows good noise robustness.

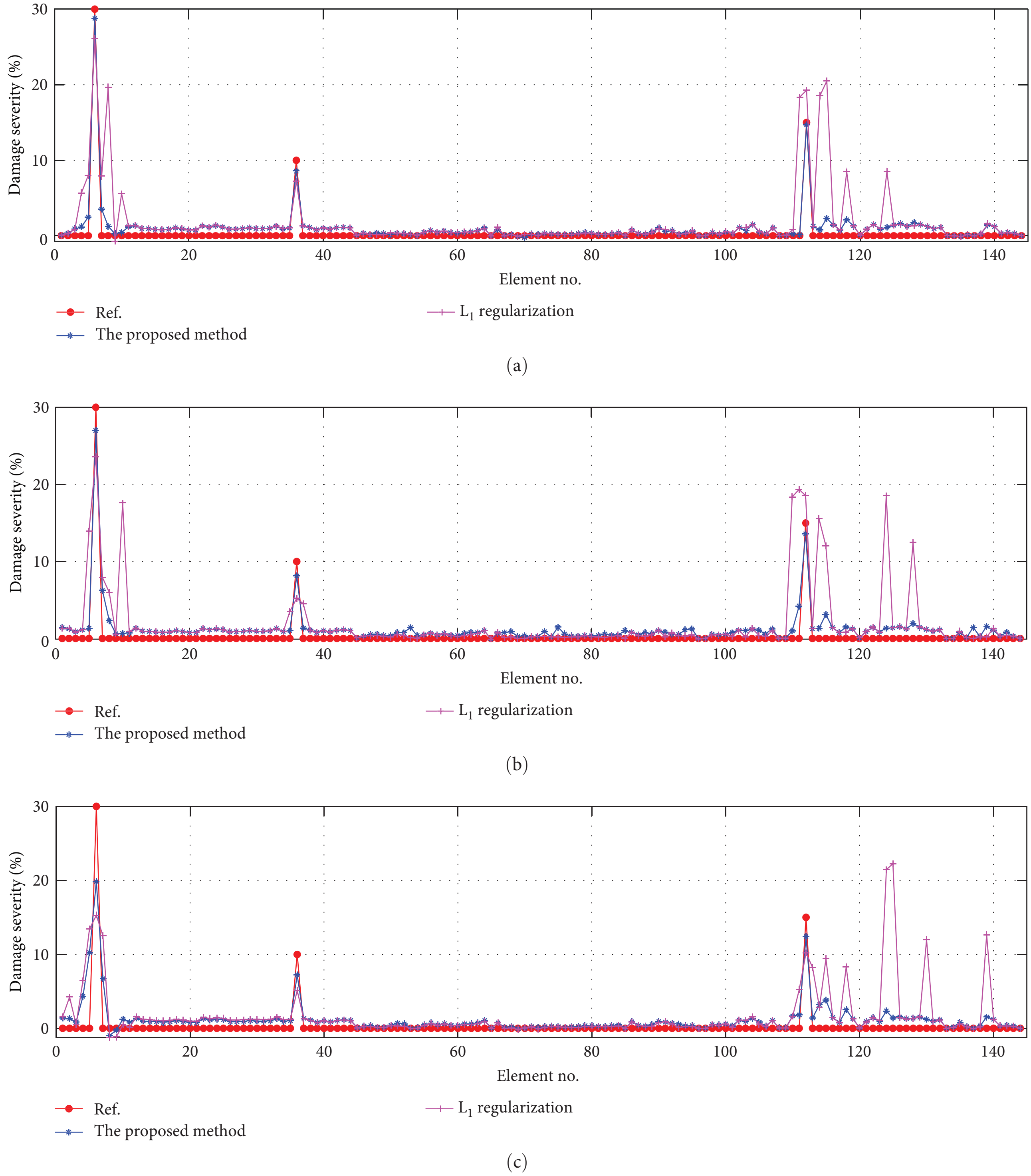

Figure 5: Damage identification for damage case 3 of numerical example: (a) 1% noise, (b) 3% noise, and (c) 5% noise.

As shown in Figure 5, for the multiple-element damage case, the L_1 regularization method illustrates serious damage identification errors and the false detection of structural elements exceeds 5. It can be owed that the method cannot achieve the global optima in the issue of damage identification. However, the proposed method still keeps good detection accuracy, not only in damage localization but also in extent quantification; false identifications exist but are fewer, which further proves that the proposed method can be determined as a high-performance approach in structural damage detection.

Figure 6 illustrates the average iteration curves of two methods under different levels of noise interference for the same iteration number; the proposed method shows a faster

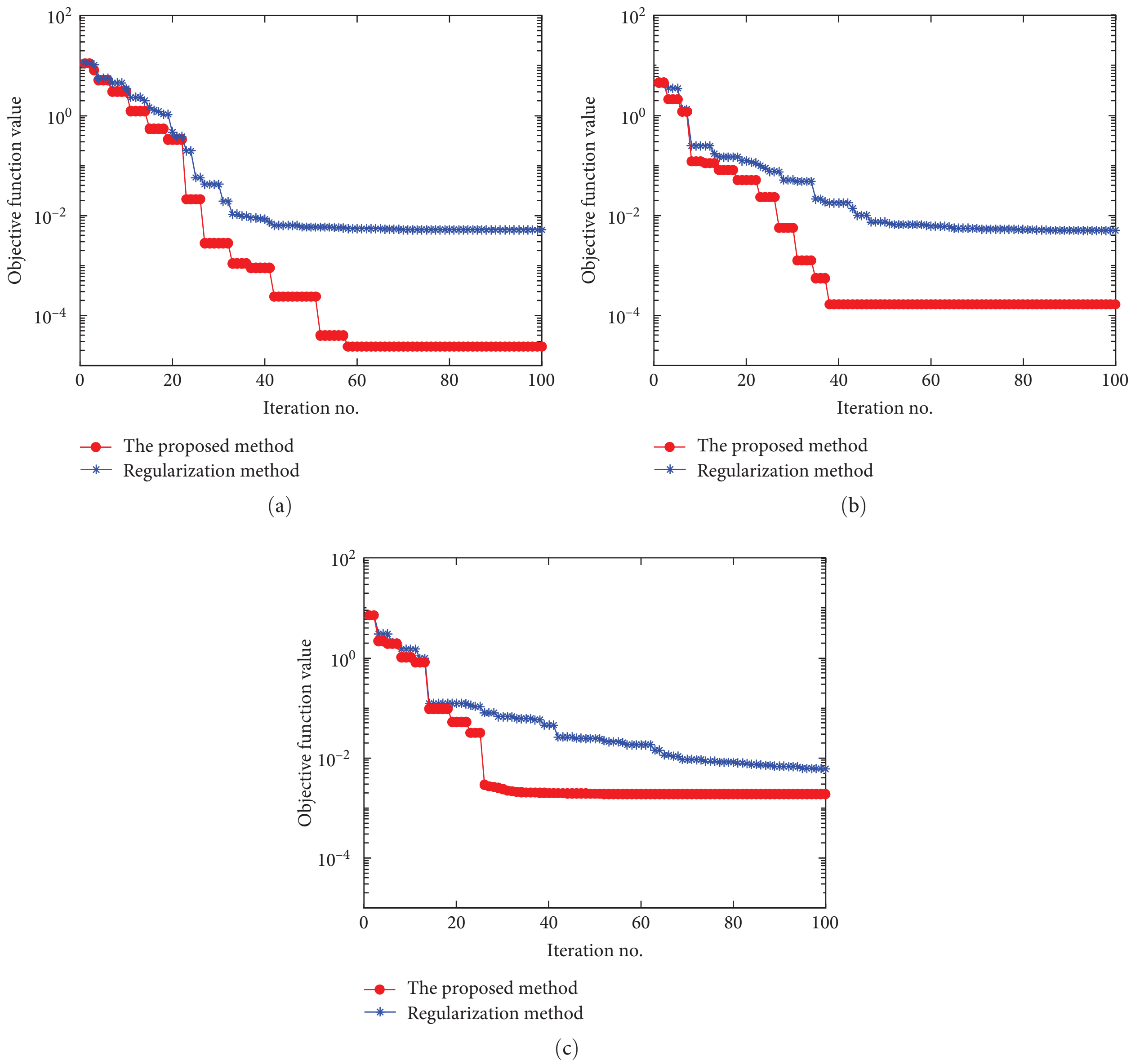

Figure 6: Average iteration curves for three damage cases: (a) damage case 1, (b) damage case 2, and (c) damage case 3.

iterative efficiency, and the needed iteration times can be reduced; regarding this point, it can be owed to the mean-value normalization strategy, which can improve the iterative efficiency of the computational process. To summarize, the proposed method has good damage detection performance; also, it has faster calculation efficiency, which is more suitable for the damage identification of the full-scale structure.

4. Experimental Validation

4.1. A Brief Description of Experimental Example. In this section, an experimental space steel truss bridge is used to verify the proposed method [48, 49]. The experimental example is shown in Figure 7, where the numbers with yellow color are used to indicate the sensor order, and numbers with a white background and red color stand for structural element numbers. There are five damage cases have been considered in the experiment through the stiffness reduction in a single bar, and the details are shown as follows: (1) damage case 1: 52.7% in element 3; (2) damage case 2: 52.7% in element 18; (3) damage case 3: 42.5% in element 6; (4) damage case 4: 72.5% in element 16; and (5) damage case 5: 60% in element 11.

4.2. The FEM of the Experimental Structure. Based on the design data of the truss, the material properties, such as Young's modulus, density, and cross-sectional area are 18.5 GPa, 8,000 kg/m^3, and 0.0387 m^2, respectively. For the longitudinal, vertical, and transversal bars, the lengths are 0.3937, 0.4, and 0.3937 m, respectively. The FEM of the truss is coded based on the MATLAB platform with 56 nodes and 160 elements; the total number of DOFs is 336 (Figure 8). The structure is modeled

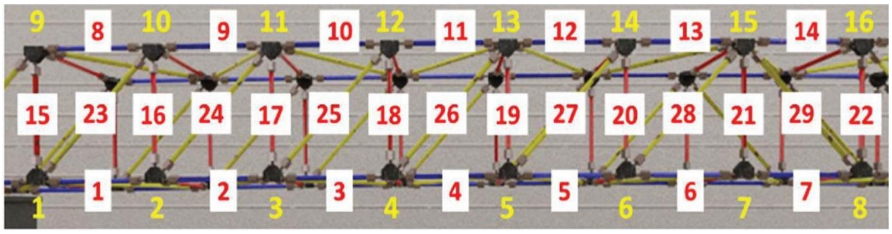

Figure 7: The experimental space steel truss.

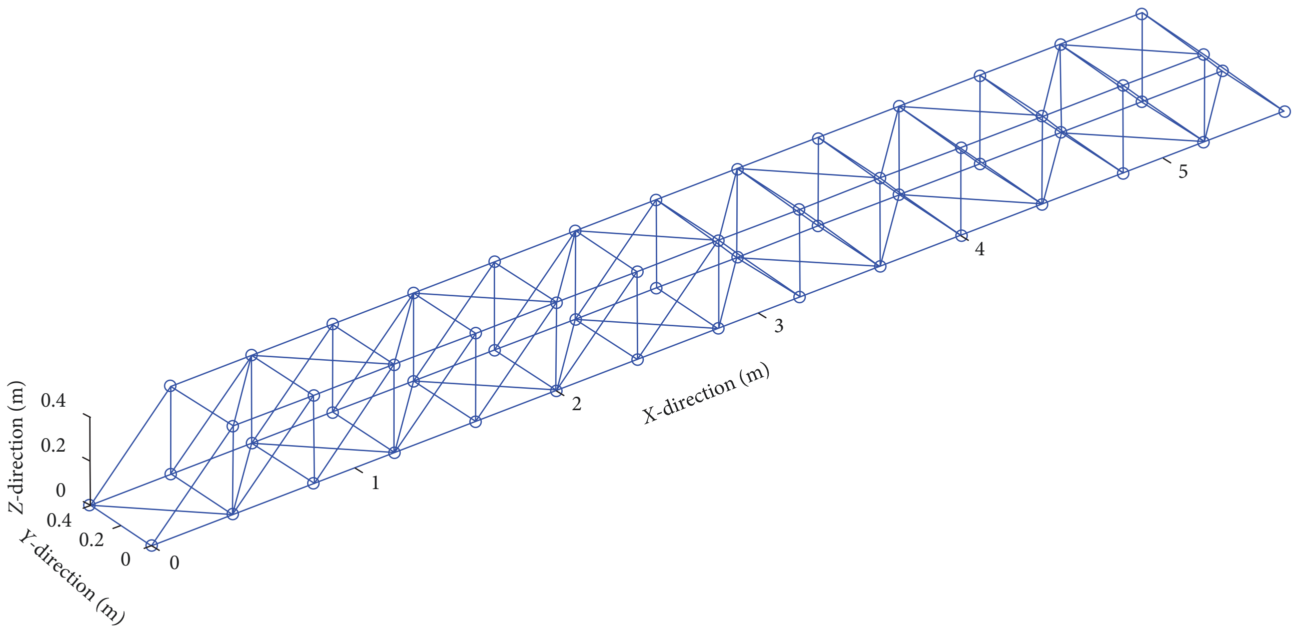

Figure 8: The FEM of experimental space steel truss.

Table 2: The comparison between experimental and analytical modal parameters.

Mode	Experimental frequency (Hz)	Before updating			After updating		
		Analytical frequency (Hz)	Error (%)	MAC	Analytical frequency (Hz)	Error (%)	MAC
1	7.9688	7.7132	5.72	0.9312	7.967	0.02	0.9912
2	26.7188	25.4561	8.47	0.9252	26.702	0.06	0.9831
3	37.2656	35.4521	5.67	0.9032	37.246	0.05	0.9742
4	41.7188	40.7541	3.75	0.8903	41.708	0.03	0.9683

based on the three-dimensional beam element with 12 DOFs, and for the boundary conditions, the simply supported constraints are applied to the steel truss.

The comparative results between the experimental and analytical structural dynamical properties are listed in Table 2. From the comparison, it can be observed that there are some discrepancies between the actual structure and simulated model before the model updating, which can be attributed to the structure simplification, uncertainties in the boundary conditions, construction errors, etc. Therefore, the Jaya optimization algorithm is used to correct the initial FEM to obtain the benchmark FEM. After the updating, it can be seen that the errors between frequencies are very small, and MAC values both exceed 0.95, which means the updated FEM can reflect the actual structure well.

4.3. Results and Discussions of Experimental Validations. Based on Section 4.2, in this section, according to the experimental example, the measured natural frequencies and mode shapes of five damage cases are input to the proposed method to check the capability of damage identification further. The obtained damage identification results are shown in Figure 9.

Figure 9 illustrates the damage identification results of five damage cases. It can be seen that all the damage locations are detected well; however, the damage extent quantifications

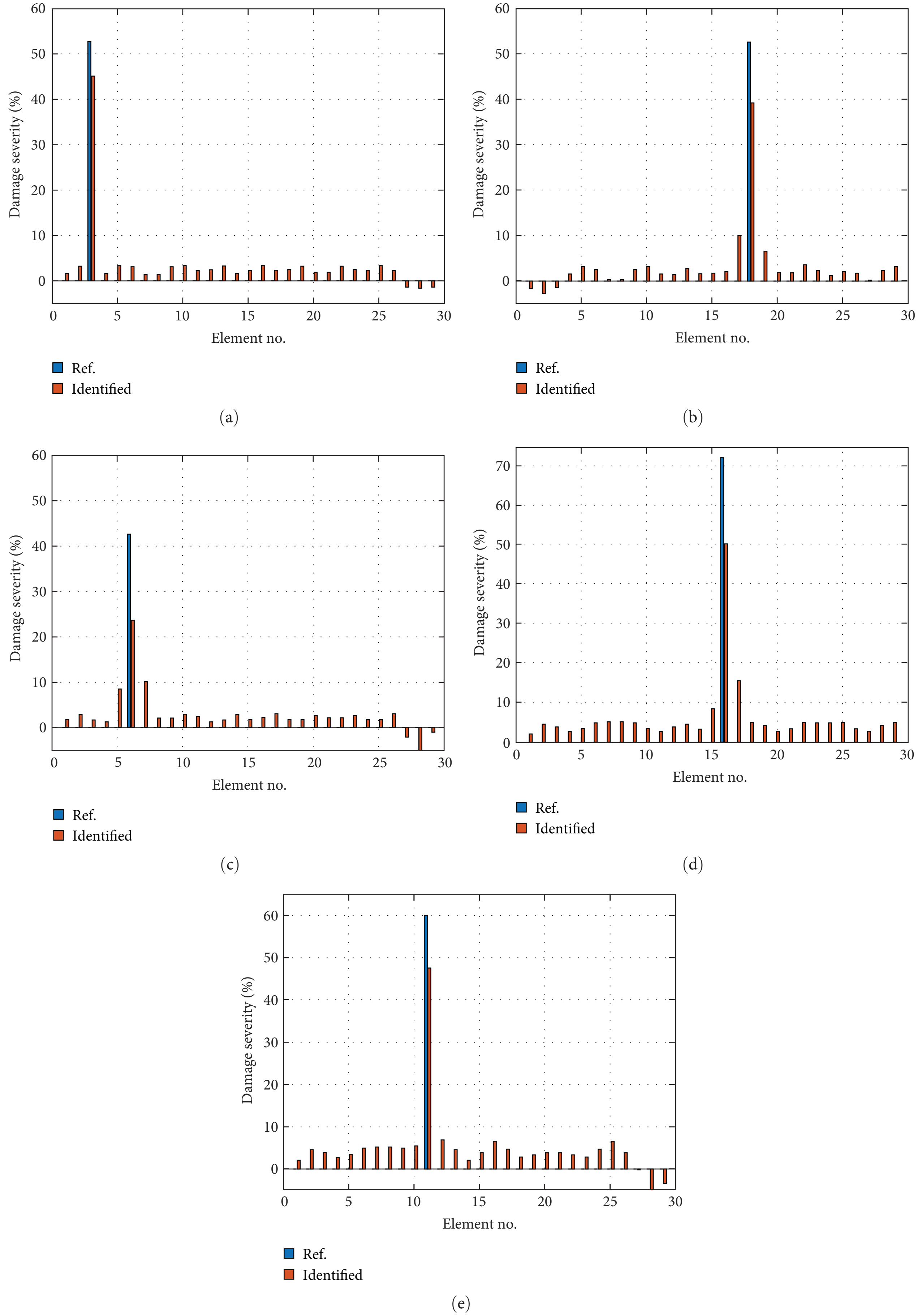

Figure 9: Damage identification results of experimental space steel truss: (a) damage case 1, (b) damage case 2, (c) damage case 3, (d) damage case 4, and (e) damage case 5.

show some errors. These errors can be explained as modeling errors, measurement uncertainties, unknown boundary conditions, etc. In conclusion, the proposed method can be validated based on the experimental structure well; according to the damage identification results, it is obvious that the locations of the damaged elements are all identified, and the actual damage situations can be reflected well. Thus, the proposed method shows good performance in the damage localization and quantification in the experimental example, whose application feasibility is generally ensured.

5. Conclusions and Outlook

In this study, a new damage identification method has been proposed based on model condensation and normalization regularization techniques to solve the damage identification issue of the full-scale structure. Numerical and experimental examples are both used to verify the proposed method; the obtained results prove the proposed method has faster convergence efficiency and good damage detection performance. There are several conclusions can be drawn as follows:

(1) Model condensation can be used to reduce the total number of DOFs of the FEM, so that the analytical modal analysis based on the reduced FEM can be accelerated.
(2) The introduction of normalization regularization techniques can improve the low convergence efficiency of the iteration process of the damage identification and further achieve the high efficiency in the damage detection.
(3) The proposed method, namely, the regularization damage identification, incorporates model condensation strategies and the mean-value normalization technique, which shows a superiority in the computational cost reduction over the traditional L_1 regularization method. Also, the damage identification performance for the full-scale structure can be well ensured. Thus, this method is of great potential in the application of actual structures, like long-span bridges and high-rise buildings.

And, for the outlook, several points can be addressed as follows:

(1) This study has investigated the serious structural damage situations; however, it is very common to observe a very slight damage severity in the practical. Future research should pay more attention to slight damage cases.
(2) High-level environmental noise extensively exists in the issue of damage identification, and noise-robustness is a good criterion to evaluate the superiority of the regularization-based damage identification method. How to ensure the damage detection accuracy of the proposed method under the condition of significant noise is the key work we should do in the next.
(3) Finally, another limitation of this study is that some practical engineering structures are lacking to further validate the proposed method, and some complex bridges or skyscraper buildings should be studied in the future.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Conceptualization, data curation, validation, and methodology were contributed by Huihui Chen; formal analysis, resources, supervision, and writing—review and editing were contributed by Haidong Zhang; writing—review and editing, polishing language, data validation, organizing manuscript, revision and modification, and proof manuscript were contributed by Xiaojing Yuan.

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