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Identification of Impact Loads and Partial System Parameters Using 1D-CNN

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Abstract—The identification of impact loads and some hard-to-obtain system parameters is crucial for analysis, validation, and evaluation activities in the engineering field. This paper proposes a method based on 1D-CNN to identify impact loads and partial system parameters from the measured responses. To this end, forward computations are conducted to provide datasets consisting of triples $(parameter\ \theta, input\ u, output\ y)$. Two neural networks are then trained: one to learn the mapping from output y to input u and another to learn the mapping from input and output (u, y) to parameter θ. Subsequently, by feeding the measured output response into the trained neural networks, the input impact load and system parameter can be calculated, respectively. The method is tested on two simulated examples and shows sound accuracy in estimating the impact load (waveform and location) and system parameter.

Keywords—Convolutional neural network, impact load identification, system parameter identification, inverse problem.

I. Introduction

THE identification of impact loads plays an important role in structure design, vibration analysis, disaster recognition, and structural health monitoring across aerospace, mechanical, civil, and other engineering fields. Generally, direct measurement by devices is unavailable due to the unpredictive and destructive nature of impact loads, such as burst loads. Therefore, the widely used approaches are to estimate the impact load from structural responses [1]-[2]. With the development of sensing and communication technologies, obtaining these responses has become more affordable and easier. However, identifying the impact load from the measured output remains a challenging inverse problem, characterized by difficulties such as ill-condition and non-linearity.

Many studies have focused on this issue, with the direct inverse method being the most natural approach [3]. To mitigate the effects of an ill-conditioned matrix, regularization techniques that incorporate the priors of impact loads (e.g., sparsity in a transformed domain) are frequently employed [4]-[7]. And linearization is necessary for nonlinear structures to construct the corresponding system matrices. To avoid the computation of a large-scale matrix inversion, the impact load is represented by a weighted superposition of basis functions. The problem is transformed into seeking a set of weights that minimize the gap between the measured responses and the calculated responses under the basis functions. This classic optimization problem can be solved by the least squares method or heuristic searching/evolutionary computing methods, such as genetic algorithm [8]-[11]. However, the results greatly depend on the number and form of selected basis functions.

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Recently, artificial neural networks (ANN) have emerged as a promising approach for identifying impact loads. Due to the strong representation ability of ANN, the nonlinear relationship between input impact loads and output responses can be learned through the training of a large number of prepared data pairs. In addition, neural networks offer greater flexibility in manipulating data dimensions compared to heuristic and evolutionary optimization algorithms. On the premise that the ANN model enjoys good generalization performance, it can estimate the impact load very fast during the inference stage. This feature is particularly appealing for the online tracking, evaluation, and monitoring of structures.

Zhou et al. [12] used a deep recurrent neural network (RNN) model based on long short-term memory (LSTM) layers to identify the impact load of nonlinear structures, showing the capability for identifying the complex impact load even if the impact location is unknown. Li et al. [13] employed Kriging interpolation combined with BP neural network (K-BP) to improve the accuracy of strain field inversion and load identification for carbon fiber reinforced plastic (CFRP). Baek et al. [14] proposed a multi-layered perceptron (MLP) based method to identify impact points and magnitudes of a submerged floating tunnel (SFT) and validated it through numerical simulations and experimental tests. Guo et al. [15] utilized three kinds of machine learning models, gradient boosting decision trees (GBDT) model, convolutional neural network (CNN) model, and bidirectional long short-term memory (BLSTM) model to identify and locate impact loads based on dynamic responses. The performance of different models was compared using a thin-walled cylinder.

However, in the context of existing works relying on ANN, the limitation arises from the fact that the system is fully predefined during the dataset construction for training. That is the form of the governing equation is fixed, as well as the parameter values within the equation. As a result, the mapping relationship learned from system output to system input is only suitable for the specific conditions. While in practical scenarios, it is difficult to obtain or measure some system parameters, such as damping, which can also exhibit variations during operation. Therefore, in this paper, the authors attempt to calculate the system outputs under impact loads for different system parameters, forming a dataset consisting of the triple variables of system parameter θ_i, input impact load u_i, and output response y_i: $\{(\theta_i, u_i, y_i)\}$. Two neural network models denoted as the impact load identification network $\mathcal{N}_u$ and the system parameter estimation network $\mathcal{N}_\theta$, based on 1D-CNN, are trained separately. The former is used to learn the mapping

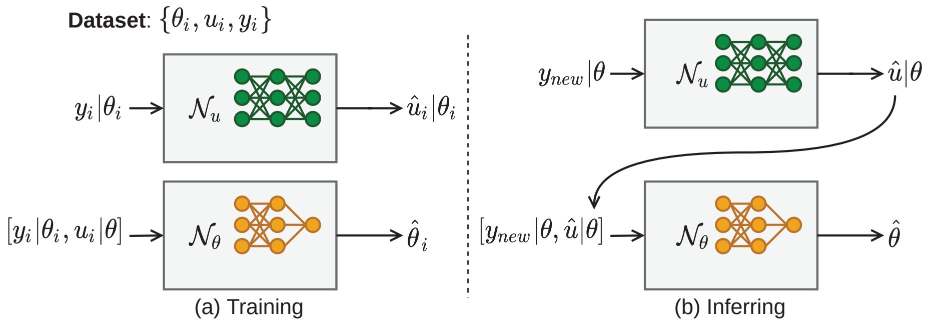

Fig. 1 Framework of the proposed method

from output response to input impact load by arranging the dataset as $\{(y_i; u_i)|\theta_i\}$, and the latter is used to learn the mapping from input impact load and output response to system parameter by organizing the dataset as $\{(u_i, y_i; \theta_i)\}$. Thus, the network can grasp the relationship between the input and output when the system parameter varies within a certain range. Once the output response is determined, the network can further estimate the system parameter.

The proposed method is verified through a nonlinear duffing oscillator and a cantilever beam. The results demonstrate its capability to identify the impact load from the response while considering the indeterminacy of system parameter, and to determine the system parameter in reverse when the impact load is estimated.

II. 1D-CNN Based Impact Load and System Parameter Identification

A. The Proposed Method

For a dynamic system

$$dy/dt = f_\theta(y, u) = f(y, u; \theta), \tag{1}$$

where u, y, and θ represent the system input, output, and parameters, respectively, denoting the solution as

$$y = g(u; f_\theta), \tag{2}$$

the key to identifying the impact load u from the measured output y of the dynamic system f_θ is to determine the inverse transform

$$u = g^{-1}(y; f_\theta). \tag{3}$$

However, in a nonlinear system or an undetermined linear system observed, g^{-1} is hard to obtain explicitly and directly. So, a 1D-CNN layer based neural network is utilized in this paper to represent g^{-1}.

On account of the uncertainty of the structure itself, at the stage of constructing the dataset, the input and output pairs are calculated by taking different system parameters within a certain range, as shown in Fig. 2. The dataset $\{(\theta_i, u_i, y_i)\}$ is utilized in two aspects (Fig. 1(a)), one is to train the impact load identification network $\mathcal{N}_u$ and another is to train the system parameter identification network $\mathcal{N}_\theta$. The impact load identification network $\mathcal{N}_u$ could be regarded as a superset of many possible system models, and the distribution of system parameters is embedded in the network. The architectures of networks will be introduced in the following sections II-B and II-C. When finishing the training of the two networks, they can be used to identify the impact load and system parameter as shown in Fig. 1(b).

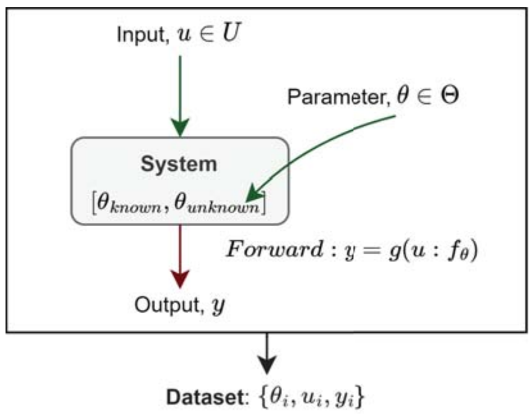

Fig. 2 Construction of dataset

B. Impact Load Identification Network

The impact load identification network, $\mathcal{N}_u$, consists of three CNN blocks and flows with a ReLU activate function (Fig. 3). Two skip connections are added between the CNN blocks, as drawn in the figure. Each CNN block, detailed in the enlarged box, consists of a 1D-CNN layer with a kernel size K_i that maps the channels from C to O_i, followed by a ReLU layer, and another 1D-CNN layer with the same kernel size K_i that maps the channels from O_i back to C. Zero padding is adopted in each 1D-CNN layer to maintain the sequence length L unchanged. To finally determine the network, the size parameters $\{\underbrace{O_1, K_1}_{\text{1st block}}; \underbrace{O_2, K_2}_{\text{2nd block}}; \underbrace{O_3, K_3}_{\text{3rd block}}\}$ need to be set.

The loss function is defined as the mean square root (MSE) of the predicted and the true impact loads as

$$\mathcal{L}_u = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{1}{CL}\sum_{j=1}^{C}\sum_{k=1}^{L}\left(\hat{u}_{j,k}^{i} - u_{j,k}^{i}\right)^2\right) \tag{4}$$

where N is the total number of samples, C is the number of channels, and L is the length of the sequence of the impact load time-history.

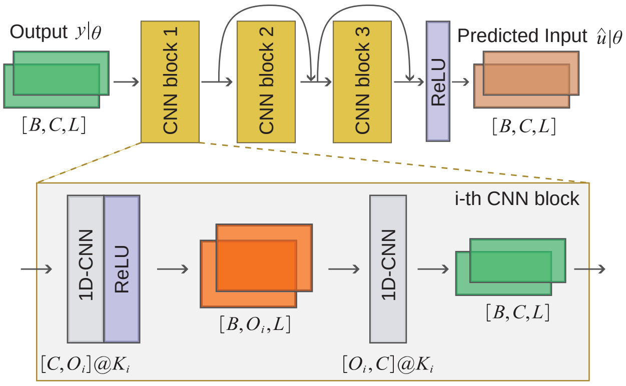

Fig. 3 Impact load identification network $\mathcal{N}_u$

C. System Parameter Identification Network

The system parameter identification network, $\mathcal{N}_\theta$, maps the concatenate of the input and output (with multi-channel input/output requiring vectorization) to the desired parameter. The network consists of three sets of 1D-CNN layer and ReLU layer, followed by a final linear layer (Fig. 4). The three 1D-CNN layers, each with a kernel size of K, transform the channels from 1 to O and back to 1, as depicted in the figure. In order to gradually reduce the dimensionality, a stride of size S is utilized in the 1D-CNN layers. The input size of the linear layer is derived accordingly. To completely determine the network, the parameters $\{O, K, S\}$ need to be set.

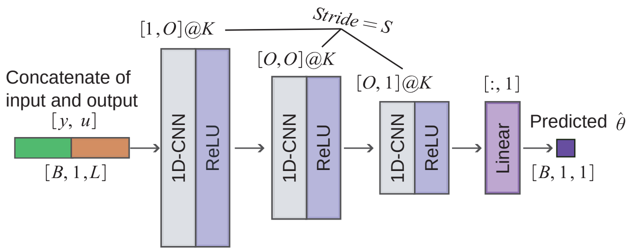

Fig. 4 System parameter identification network $\mathcal{N}_\theta$

The loss function is defined as the MSE of the predicted and the true system parameters as

$$\mathcal{L}_\theta = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{\theta}^i - \theta^i\right)^2 \tag{5}$$

where N is the total number of samples.

III. Numerical Experiment

To generate the dataset $\{(\theta_i, u_i, y_i)\}$, three kinds of impact loads, triangular, half-sine[10], and Gaussian [12] forms are utilized (Fig. 5). The expressions are written in (6), (7), and (8), respectively.

$$u_{tri}(t) = \begin{cases} 0, & 0 \le t < t_a, t \ge t_b \\ p_{max}\,(t - t_a)\,/\,(t_c - t_a)\,, & t_a \le t < t_c, \\ p_{max}\,(t_b - t)\,/\,(t_b - t_c)\,, & t_c \le t < t_b, \end{cases} \tag{6}$$

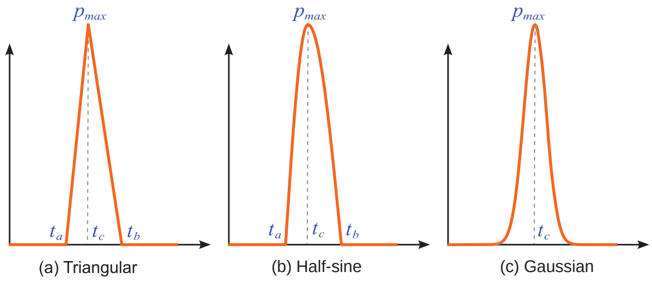

Fig. 5 Forms of impact loads considered

where t_a and t_b are the start time and stop time of the impact load, and t_c is the time corresponding to the maximum impact load p_{max}.

$$u_{sin}(t) = \begin{cases} 0, & 0 \le t < t_a, t \ge t_b \\ p_{max}\sin\left(2\pi\omega_1\left(t - t_a\right)\right), & t_a \le t < t_c, \\ p_{max}\sin\left(2\pi\omega_2\left(t - 2t_c + t_b\right)\right) & t_c \le t < t_b, \end{cases} \tag{7}$$

where $\omega_1 := 1/4(t_c - t_a)$ and $\omega_2 := 1/4(t_b - t_c)$.

$$u_{Gau}(t) = p_{max}\exp\left(-\left(t - t_c\right)^2 / \left(2\sigma^2\right)\right) \tag{8}$$

where σ is the standard deviation of the Gaussian distribution.

These impact load expressions are parameterized, and the parameters are uniformly sampled in the corresponding range

$$\begin{aligned} t_a &\sim U(0, 0.1), \\ t_b &\sim t_a + U(0.01, 0.1), \\ t_c &\sim U(t_a, t_b), \\ p_{max} &\sim U(100, 1000), \\ \sigma &\sim U(0.005, 0.01). \end{aligned} \tag{9}$$

A. Duffing Oscillator

The duffing oscillator expressed as

$$m\ddot{y} + c\dot{y} + \kappa y + \alpha y^3 = u(t) \tag{10}$$

is utilized to valid the proposed method, where the parameters are specified as $m = 1$, $\kappa = 10000$, $\alpha = 10000$, and c is uniformly sampled from $U(1, 10)$. The force u is sampled from the three types of impact loads given by (6), (7), and (8), with their respective parameters sampled according to (9). A total of 3000 samples $\{(c_i, u_i, y_i)\}$ are generated. The sampling frequency is 1000 Hz, and the analysis duration is 1 second.

The parameters for the impact load identification network $\mathcal{N}_u$ are set as $\{O_1, K_1; O_2, K_2; O_3, K_3\} = \{16, 128; 16, 64; 16, 32\}$, and for the parameter identification network $\mathcal{N}_\theta$ are set as $\{O, K, S\} = \{4, 64, 4\}$.

During the training of the networks $\mathcal{N}_u$ and $\mathcal{N}_\theta$, the dataset is divided into training, validation, and testing sets with a ratio of 70%:15%:15%. The batch sizes are set to 20 and 10, respectively. The Adam optimizer [16] is used. The initial learning rate is set as 0.001 and it decreases by a factor of 0.95 when the current loss on the validation dataset exceeds the

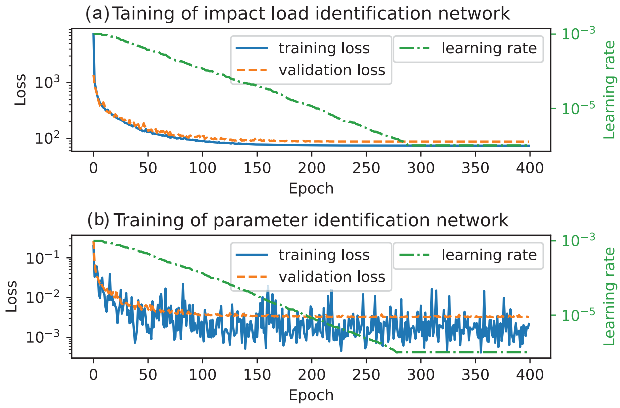

Fig. 6 Training process of the duffing oscillator case

previous one. Once the learning rate is lower than 0.000001, it will stop decreasing.

Fig. 6 plots the training and validation losses. After about 200 epochs, the losses tend to converge. The results of the trained networks on the test dataset are shown in Fig. 7. The MSE and relative error (RE) are defined as

$$\mathrm{MSE} = \|\hat{u} - u\|_2^2 / \|u\|_2^2 \times 100\%, \tag{11}$$

and

$$\mathrm{RE} = |\hat{\theta} - \theta| / \theta \times 100\%. \tag{12}$$

It is observed that the maximum MSE of impact load identification is about 10%, with a mean MSE of 0.50% across 450 tests. The maximum RE for identifying the parameter c is about 20%, with a mean RE of 2.19%.

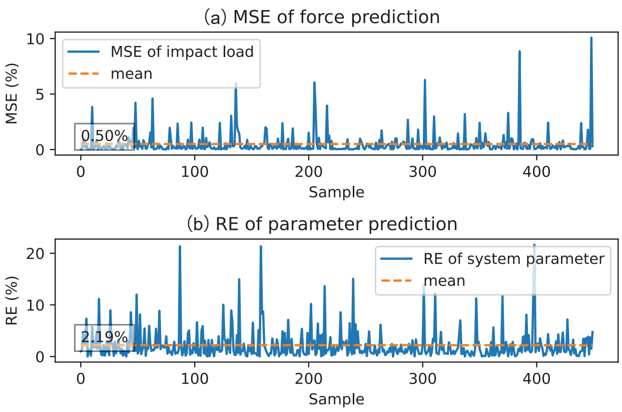

Fig. 7 Test results of the duffing oscillator case

B. Cantilever Beam

In this section, a cantilever beam (Fig. 8) is analyzed. The structural parameters are listed in TABLE I. Forward computations for preparing the dataset are carried out using finite element method (FEM). The beam is divided into 20 elements, and the nodes 5, 9, 13, 17, and 21 are observed.

In the FEM model, Rayleigh damping is adopted, and regard the damping ratio c is treated as an uncertain system

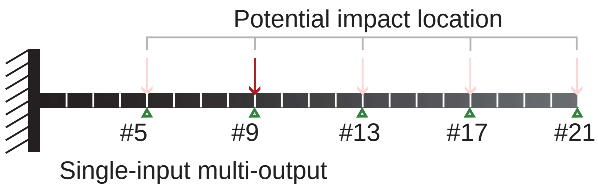

Fig. 8 The cantilever beam model

TABLE I
PARAMETERS OF THE CANTILEVER BEAM

Length	Width	Height	Young's modulus	Mass
5.0m	0.4m	0.2m	205GPa	2450kg/m^3

parameter. Parameter c is sampled from a uniform distribution $U(0.001, 0.05)$; the impact load is sampled in the same way in Section III-A and randomly applied to one of the five observed nodes, with the other nodes set to zero. The responses at all five observed nodes are measured, resulting in a total of 10000 samples $\{(c_i, u_i, y_i)\}$. The sampling rate is 1000 Hz, and the total analysis duration is 0.5 second.

The parameters of network $\mathcal{N}_u$ and $\mathcal{N}_\theta$ are also set as $\{O_1, K_1; O_2, K_2; O_3, K_3\} = \{16, 128; 16, 64; 16, 32\}$ and $\{O, K, S\} = \{4, 64, 5\}$, respectively. The related settings of network training are kept consistent with those used in the case of duffing oscillator (see Section III-A).

The training and validation losses are plotted in Fig. 9. After about 300 epochs, the losses have converged.

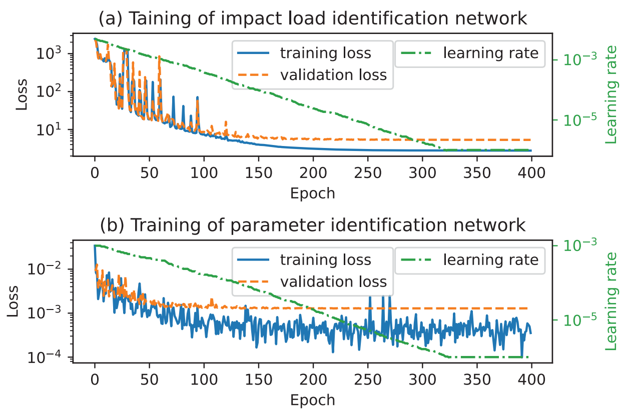

Fig. 9 Training process of the cantilever beam case

Fig. 10 shows the test results of this example. It suggests that the maximum MSE of the impact load identification is about 10%, with a mean MSE of 0.18% across 1500 trials. The maximum identification RE of the damping ratio c exceeds 50%, but the mean RE is 2.55%. In this case, the input dimension resulting from the concatenation of input load and output response is $5 \times 1000 \times 0.5 \times 2 = 5000$. This is relatively large, posing challenges for the fitting and generalization of the network.

Fig. 11 dives into the results of two specific tests. The predicted waveform of impact load closely match the truth, and the method can accurately locate the position of impact load.

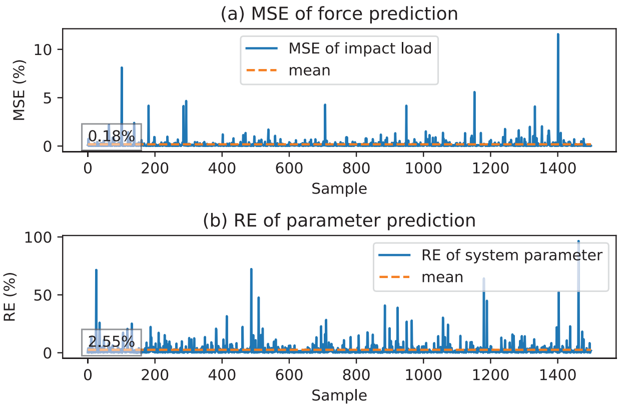

Fig. 10 Test results of the cantilever beam case

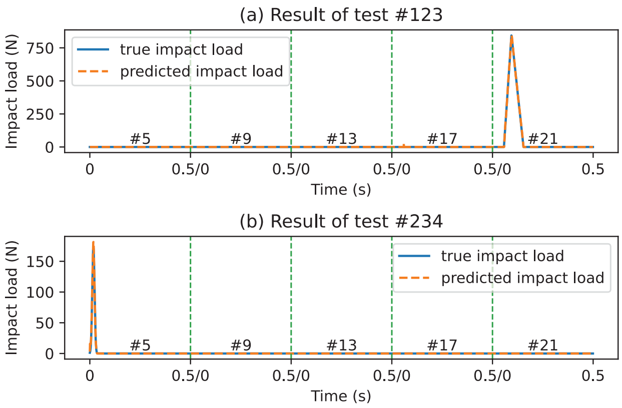

Fig. 11 Diving into the results of two tests of the cantilever beam case

IV. Conclusion

This paper proposes a method using a 1D-CNN based neural network to identify impact loads while considering the uncertainty of system parameters. Additionally, it introduces an approach to estimate the unknown system parameter based on the identified impact load and the measured response utilizing another 1D-CNN based neural network. Two numerical examples, i.e., a nonlinear single-DOF duffing oscillator and a 5-DOF linear cantilever beam, are utilized to validate the method. On the testing dataset, the mean MSEs of impact load identification in the two cases are 0.50% and 0.18%, respectively, and the mean REs of system parameter identification are 2.19% and 2.55%, respectively.

In future work, we will investigate the proposed method's robustness to noise and evaluate its performance on experimental and realistic structures.

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References

[1] R. Liu, E. Dobriban, Z. Hou, and K. Qian, "Dynamic load identification for mechanical systems: a review," *Arch. Comput. Methods Eng.*, 1–33, 2021.

[2] T.S. Jang, H. Baek, S.L. Han, and T. Kinoshita, "Indirect measurement of the impulsive load to a nonlinear system from dynamic responses: inverse problem formulation," *Mech. Syst. Sig. Process.*, 24 (6), 1665–1681, 2010.

[3] H. Inoue, N. Ikeda, K. Kishimoto, T. Shibuya, and T. Koizumi, "Inverse analysis of the magnitude and direction of impact force," *JSME Int. J. Ser. A, Mech. Mater. Eng.*, 38 (1), 84–91, 1994.

[4] G. Yan, H. Sun, and O. Büyüköztürk, "Impact load identification for composite structures using Bayesian regularization and unscented Kalman filter," *Struct. Control Health Monit.*, 24, e1910, 2017.

[5] J. Jiang, H. Tang, M.S. Mohamed, S. Luo, and J. Chen, "Augmented Tikhonov Regularization Method for Dynamic Load Identification," *Appl. Sci.*, 10, 6348, 2020.

[6] Y. Li, X. Wang, Y. Xia, and L. Sun, "Sparse Bayesian technique for load identification and full response reconstruction," *J. Sound Vib.*, 553, 117669, 2023.

[7] Y. Liu, L. Wang, "A two-step weighting regularization method for stochastic excitation identification under multi-source uncertainties based on response superposition-decomposition principle," *Mech. Syst. Signal Process.*, 182, 109565, 2023.

[8] B. Qiao, X. Zhang, C. Wang, H. Zhang, and X. Chen, "Sparse regularization for force identification using dictionaries," *J. Sound Vib.*, 368, 71–86, 2016.

[9] J. Liu, X. Sun, X. Han, C. Jiang, and D. Yu, "A novel computational inverse technique for load identification using the shape function method of moving least square fitting," *Comput. Struct.*, 144, 127–137, 2014.

[10] G. Yan and L. Zhou, "Impact load identification of composite structure using genetic algorithms," *J. Sound Vib.*, 319, 869–884, 2009.

[11] R. Hashemi and M. Kargarnovin, "Vibration base identification of impact force using genetic algorithm," *Int. J. Mech. Syst. Sci. Eng.*, 1 (4), 204–210, 2007.

[12] J. Zhou, L. Dong, W. Guan, J. Yan, "Impact load identification of nonlinear structures using deep Recurrent Neural Network," *Mech. Syst. Signal Process.*, 133, 106292, 2019.

[13] J. Li, J. Yan, J. Zhu, and X. Qing, "K-BP neural network-based strain field inversion and load identification for CFRP," *Measurement*, 187, 110227, 2022.

[14] S.-M. Baek, J.-C. Park, and H.-J. Jung, "Impact load identification method based on artificial neural network for submerged floating tunnel under collision," *Ocean Eng.*, 286, 115641, 2023.

[15] C. Guo, L. Jiang, F. Yang, Z. Yang, and X. Zhang, "Impact load identification and localization method on thin-walled cylinders using machine learning," *Smart Mater. Struct.*, 32, 065018, 2023.

[16] D. P., Kingma, and J. Ba, "Adam: A method for stochastic optimization," *arXiv preprint*, arXiv:1412.6980, 2014.