

Article

WavLoadNet: Dynamic Load Identification for Aeronautical Structures Based on Convolution Neural Network and Wavelet Transform

Xiaoqiang Zhang ¹, Wenbo He ^{2,3,*}, Qiang Cui ^{4,5}, Ting Bai ¹, Baoqing Li ³, Junjie Li ¹ and Xinmin Li ^{1,*} 

¹ School of Information Engineering, Southwest University of Science and Technology, Mianyang 621010, China; xqzhang@swust.edu.cn

² Key Laboratory of Civil Aviation Aircraft Airworthiness Certification Technology, Civil Aviation University of China, Tianjin 300300, China

³ School of Safety Science and Engineering, Civil Aviation University of China, Tianjin 300300, China

⁴ AVIC Xi'an Aeronautics Computing Technique Research Institute, Xi'an 710065, China

⁵ School of Computer Science, Northwestern Polytechnical University, Xi'an 710129, China

* Correspondence: wbhe@cauc.edu.cn (W.H.); lixm@swust.edu.cn (X.L.)

Abstract: The accurate identification of dynamic load is important for the optimal design and fault diagnosis of aeronautical structures. Aiming at the identification of dynamic loads on complex or unknown aeronautical structures, a deep convolution neural network (CNN) in the transform domain-based method is proposed. It takes decomposed signals from wavelet transform of several vibration signals as input. A CNN is used for feature extraction, and fully connected layers are used for predicting the decomposed loads in the transform domain. After synthesizing the predicted decomposed components, the loads in the time domain can be obtained. The proposed method could avoid the explicit modeling of the system or transfer functions with complex or unknown structures. Using the data collected on a GARTEUR model, the proposed model is trained and verified. Extensive experimental results with qualitative and quantitative evaluations show the accuracy of this method and the robustness to measurement noise and other unknown load disturbances.

Keywords: dynamic load identification; wavelet transform; transform domain; one-dimensional convolution neural network



Citation: Zhang, X.; He, W.; Cui, Q.; Bai, T.; Li, B.; Li, J.; Li, X. WavLoadNet: Dynamic Load Identification for Aeronautical Structures Based on Convolution Neural Network and Wavelet Transform. *Appl. Sci.* **2024**, *14*, 1928. <https://doi.org/10.3390/app14051928>

Academic Editor: Carmelo Gentile

Received: 23 January 2024

Revised: 12 February 2024

Accepted: 21 February 2024

Published: 27 February 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

In actual flight environments, aerospace structures such as aircraft are often affected by different types of loads, e.g., the impact loads [1] and the dynamic loads [2,3], resulting in a complex mechanical environment. The dynamic load is one of the common forms of load applied to aircraft, which can be caused by the wind or airflows, or the some structure fault like excessive clearances. In the design stage of the aircraft structure, in order to reduce the adverse effect of the vibration caused by different types of loads on the aerospace structure and improve the reliability of the structure, it is necessary to accurately identify the load of the structure. Also, in the case of structural health monitoring, or aerospace structural condition assessment, accurate measurements of loads would also be useful. However, due to the limited measurement conditions, it is usually difficult, if not impossible, to direct measure the dynamic loads that applied to the aircraft structures. On the other hand, while the structural responses caused by the loads are easier to measure, the dynamic loads can be identified by solving the load identification problem, which is an inverse problem to identify the unknown loads from the measured vibration responses.

In the early methods of load identification, the algebraic relationship between the response and the loads can be calculated by directly inverting the transfer function matrix between load excitation and vibration response [4,5]. Unfortunately, load identification often suffers from the ill-conditioned problem [6], weak noises that, when mixed in the

response data, lead to huge errors in the solution. In order to improve the ill-posedness, regularization-based methods [7–11] could be applied to stabilize the solution and to improve the solution disturbance error caused by noise. The truncated singular value decomposition (TSVD) and Tikhonov regularization approaches [7] are two of the commonly used regularization-based methods, in which the selection of optimal regularization parameters is usually important [12]. Choi et al. [13] compares different methods for selecting regularization parameters, namely the ordinary cross validation method, the generalized cross validation (GCV) method and the L-curve method. Recently, the Bayesian inference has been applied to determine the regularization parameter [14], and is used in load identification [10,15]. Pan et al. [9] proposed a method based on matrix regularization for load identification, which uses the Bayesian information content criterion to select regularization parameters. Aucejo and Smet [16] gives the formulation to reconstruct force in a Bayesian framework in the frequency domain.

Besides the regularization-based method, the artificial intelligence-based algorithms, or the intelligent algorithm, would provide another approach to identify the loads, for instance, the support vector machines-based regression method [17], the ensemble learning-based method [18] or the neural network (NN)-based method [19–27]. These approaches implicitly learn the mapping relationship between loads and responses in a data-driven manner, which weakens the dependence on the accurate and time-consuming modeling of structural transfer function and parameter selection in conventional regularization-based methods, and promotes the application of load identification methods in complex or unknown structural applications. Among the intelligent approaches, the NN-based methods are now one of the research topics of load identification methods. In early works, Cao et al. [19] proposed to utilize a fully connected multilayer perceptron (MLP) to identify the loads acting on aircraft wings, and an improved back propagation (BP) algorithm was proposed for network parameter learning. Similar network architectures are used in load identification problems for different structures, e.g., hemispherical metal shells [21] and helicopter weapon pylons [22].

The MLP used in the above-mentioned approaches is a typical but shallow network architecture. With the recent development in deep learning, different other types of network are applied in the problem of load identification, namely the convolutional neural network (CNN), the recurrent neural network (RNN) and the long short-term memory (LSTM)-based RNN. Yang et al. [23] uses the dilated CNN to identify the dynamic loads on a supported beam. Two CNN layer are used for extract features from the vibration responses, and a MLP with two layer would regress the time series loads. Xia et al. [24] propose to use the time delay neural network (TDNN), which is equivalent to a one layer CNN for a sequential input, to identify the dynamic loads for an aircraft rudder model. He et al. [25] apply a CNN with an attention mechanism to identify random loads on aircraft structures under noise disturbance conditions. The attention mechanism can better fuse features extracted by the network and improve the accuracy of load identification; however, the attention module would introduce additional parameters and computing costs. The RNN is used for load identification problems of nonlinear structures in [26]. Trivailo and Carn [20] compare the performances for load identification on different network architecture, including the MLP, the TDNN and the Elman neural network (ENN). The ENN is selected in [20]. The neurons in the ENN are designed with a feed-back branch, which shares some similarities with the RNN. Yang et al. [27] study the dynamic load identification problem using the LSTM network. The LSTM is a variant of RNN with a gated unit, which is useful for the long-term dependencies problem in RNN. The method in [27] is verified by real data from a supported beam.

While the above-mentioned intelligence algorithms mainly focus on the load identification in time domain, in the literature, approaches in other domains like frequency domain [16] and transform domain [28,29] are widely applied in load identification as well, while showing good performances. Experimental results in [29] show that a better identification accuracy can be obtained in the transform domain than that in the frequency

domain using a regularization-based method. In this paper, we tend to address the problem of dynamic load identification with an NN-based method in the transform domain, unlike the time-domain-based NN method [23,25,27]. The network would take the decomposed components of several responses in a time window in the transform domain, e.g., the wavelet domain, as the input. The deep convolution network is designed with weight normalization and batch normalization to extract transform domain features. The network would predict the load in the transform domain based on the extracted features. Similar inputs are also used in [30], in which an LSTM network is applied. While there is similarities between method in [30] and the proposed method, the amount of parameters in the CNN is smaller than that of the LSTM network in [30], which would be useful for the load-identification problem with a small-scale training dataset. The amount of input response signals of the proposed method can be flexible, i.e., a single response signal as the input or multiple responses. The outputs of the proposed approach are different from those in [23]. In [23], an MLP is utilized to regress the time-series of loads. Similar output designs are also used in [31,32], in which the encoder–decoder networks are proposed for feature extraction in predicting the noise-canceling signals. The depthwise separable convolution (DSC) [33] is used in the CNN encoder–decoder architecture in [31] for reducing the amount of parameters. The DSC is also applied in [32], in which a channel attention is designed between the encoder and decoder network for better feature fusion, while a two-layer LSTM helps to learn the temporal representations with the consideration of time delay. In the proposed method, the output is designed to be the prediction of the load at the current time-stamp, rather than a time-series of loads. The output design in the proposed method is based on two considerations. First, since the proposed method is in the wavelet domain, the load signals are decomposed into different components, so to predict all decomposed components of time series of loads, a large MLP or a large encoder–decoder network is required. Second, because we use signals in a time window to predict the load at current time stamp, by sliding the time window along the time axis, the loads can be identified in an online fashion, i.e., a stream of sensor measurements can be inputted into the network to identify the load continuously. The effectiveness of the proposed method is verified by the data collected from the a benchmark structure in the lab. Quantitative comparisons show that more accurate identification results can be obtained from the proposed method would than those from the regularization-based approaches, and those from the time-domain intelligence algorithms, and transform domain intelligence algorithm [30].

The rest of the paper is structured as follows. In Section 2, the proposed load identification method is described. Details of the experimental results are discussed in Section 3. The paper is concluded in Section 4.

2. Proposed Method

Suppose that a dynamic load f is applied to an aerospace structure, time series signal of $f(t)$ in the time domain could be a discrete signal $f(0), f(\Delta t), f(2\Delta t), \dots$, where Δt is a sampling time interval. The load would cause the vibration on the structure and the vibration response are measured at N different measure points on the structure. Suppose that the N measured responses are the acceleration signals, which are relatively easy to measure and widely used in different load identification works [23,25]. Let $a^i(t)$ be the measured discrete acceleration response in the time domain of the i -th measurement point. The goal of load identification is to identify $f(t)$ using $a^i(t), i = 1, 2, \dots, N$.

In the time domain, for a linear vibration system, the relation between the dynamic response $a^i(t)$ and the dynamic response $f(t)$ can be modeled by a convolution of the unit impulse response function $h(t)$. The calculation of the inverse of the response function often suffers ill-posedness, and the accuracy of the identification of the loads would be affected by the noises in the measurements. In the frequency domain or the transform domain, though the conventional relation between the load and the response is replaced by a multiplication, a similar ill-posed problem would happen as well.

2.1. Framework Overview

To alleviate the above-mentioned problem, in this paper, we implicitly model the function from the response to the load in the transform domain using a designed neural network. Figure 1 shows the main framework of the proposed method. There are four modules in the proposed methods in total, including the input module, the feature-extraction module, the prediction module and the output module.

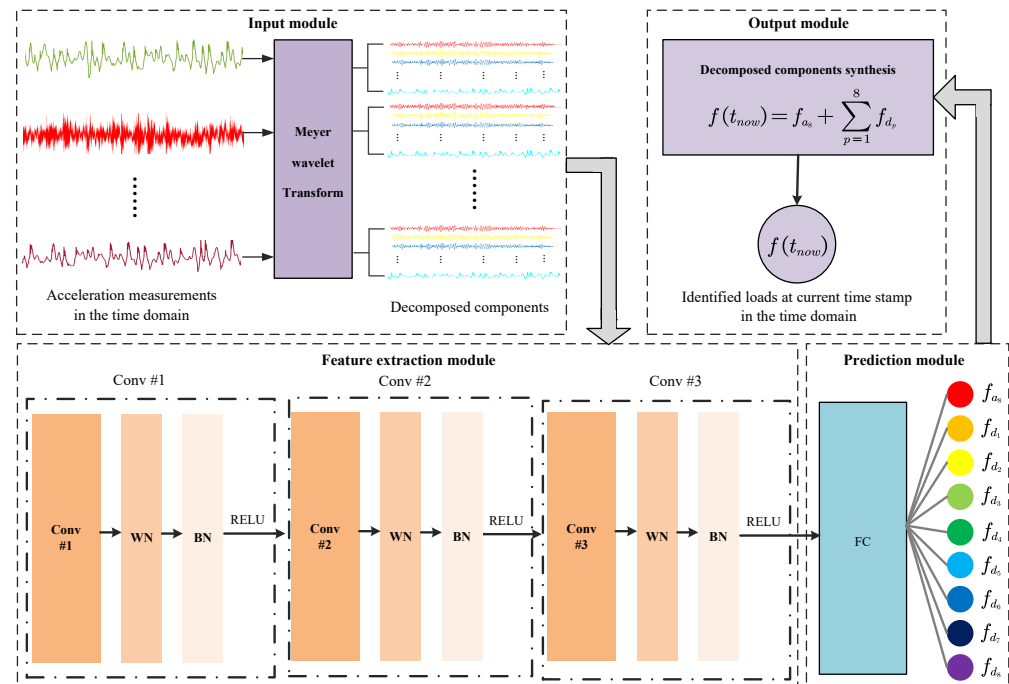


Figure 1. The framework sketch of the proposed method. The input module takes the acceleration measurements from N different measurement points in the time domain as the input. For each acceleration measurement, a wavelet transform is applied and 9 decomposed components are input to the feature-extraction module, in which the convolutions are utilized. The prediction module would make use of the extracted features in the transform domain, and predict the 9 decomposed components of the load at current timestamp in wavelet domain. In the output module, the predicted decomposed components are transformed back to the time domain to obtain the load at current time.

In the input module, the response in time domain, i.e., $a^i(t), i = 1, 2, \dots, N$ for N different acceleration measurement points in a certain time window are transformed into wavelet domain using Meyer wavelet. In total, 9 of 16 decomposed components of the wavelet are used in the network for each $a^i(t), i = 1, 2, \dots, N$. In the feature-extraction module, the convolutions designed with batch normalization and weight normalization would extract the data-driven features in the wavelet domain. In the prediction module, the learned wavelet domain features are used for predict the load in the wavelet domain, i.e., the 9 decomposed components. Finally, in the output module, the load in wavelet domain is transformed back to the time domain. Details of the proposed network is given in Section 2.2.

2.2. Network Details

In this subsection, we describe the details of the different modules in the proposed approach, namely the input module, the feature extraction module, the prediction and the output module.

2.2.1. Input Module

Using transform domain analysis methods such as wavelet transform, the time domain signals of vibration and load can be analyzed in the transform domain. In particular, the

Meyer wavelet proposed by the mathematician Yves Meyer is suitable for analyzing the local characteristics of the signal. At the same time, the Meyer wavelet can also describe the details of the signal in different frequency ranges. It is suitable for analyzing signals with different frequency contents. The basis function of the Meyer wavelet is given by

$$\Psi(\omega) = \begin{cases} \frac{1}{\sqrt{2\pi}} \sin\left(\frac{\pi}{2} \nu\left(\frac{3|\omega|}{2\pi} - 1\right)\right) e^{j\omega/2} & \text{if } 2\pi/3 < |\omega| < 4\pi/3 \\ \frac{1}{\sqrt{2\pi}} \cos\left(\frac{\pi}{2} \nu\left(\frac{3|\omega|}{4\pi} - 1\right)\right) e^{j\omega/2} & \text{if } 4\pi/3 < |\omega| < 8\pi/3 \\ 0 & \text{otherwise} \end{cases}, \quad (1)$$

where $\nu(\cdot)$ is an auxiliary function. By truncating the high-frequency or low-frequency part of the basis function $\Psi(\omega)$ in the frequency domain, the low-pass filter and high-pass filter of the Meyer wavelet in the frequency domain can be obtained. After inversely transforming the two types of filters in the frequency domain to the time domain, The low-pass filter coefficient $h(t)$ and high-pass filter coefficient $g(t)$ of Meyer wavelet can be obtained.

In this paper, the 8-order Meyer wavelet is utilized to perform transform domain decomposition on the time domain signals of response. Take the time domain response $a^i(t)$ for measurement point i as an example, by filtering $a^i(t)$ with low-pass filter $h(t)$ and high-pass filter $g(t)$, the low-frequency components of $a^i(t)$, $a_{a_1}^i$, and the high-frequency components $a_{d_1}^i$ can be obtained, respectively. The scale of $a_{a_1}^i$ and that of the $a_{d_1}^i$ are the same as that of $a^i(t)$. Then, a down-sampling is applied on the low-pass and high-pass filtered signals, i.e., $a_{a_1}^i$ and $a_{d_1}^i$, and low-pass and high-pass filtering is applied to obtain the low-frequency component $a_{a_2}^i$ and high-frequency component $a_{d_2}^i$ at a lower scale. Repeat the down-sampling and filtering, the low-frequency component $a_{a_1}^i, a_{a_2}^i, \dots, a_{a_8}^i$ and the high-frequency component $a_{d_1}^i, a_{d_2}^i, \dots, a_{d_8}^i$ at 8 different scales can be obtained.

For each response measurement $a^i(t), i = 1, 2, \dots, N$, the low frequency components at the 8-th scale $a_{a_8}^i$, and all 8 high frequency components $a_{d_1}^i, a_{d_2}^i, \dots, a_{d_8}^i$ are used for feature extraction. Therefore, for N measurement, there are $9 \times N$ components are input to the feature extraction module, with $1 \times N$ for low frequency components and $8 \times N$ for high frequency components. Figure 2 gives an example of the original acceleration measurement signal and the decomposed components.

Considering the fact that the load at current timestamp t_{now} , $f(t_{now})$, would affect the response at t_{now} and those of the future timestamps $t_{now} + \Delta t, t_{now} + 2\Delta t, \dots$, where Δt is the sampling time interval, responses in a time window $[t_{now}, t_{now} + M\Delta t]$ are used for the identification of $f(t_{now})$, where M is the size of the time window. We assume that the contribution of the response outside the time window, e.g., response at time $t_{now} + (M + 1)\Delta t$ would be minor. Therefore, the dimension of the input module would be $(9 \times N, M)$, where N is the number of response measurement points, M the size of time window.

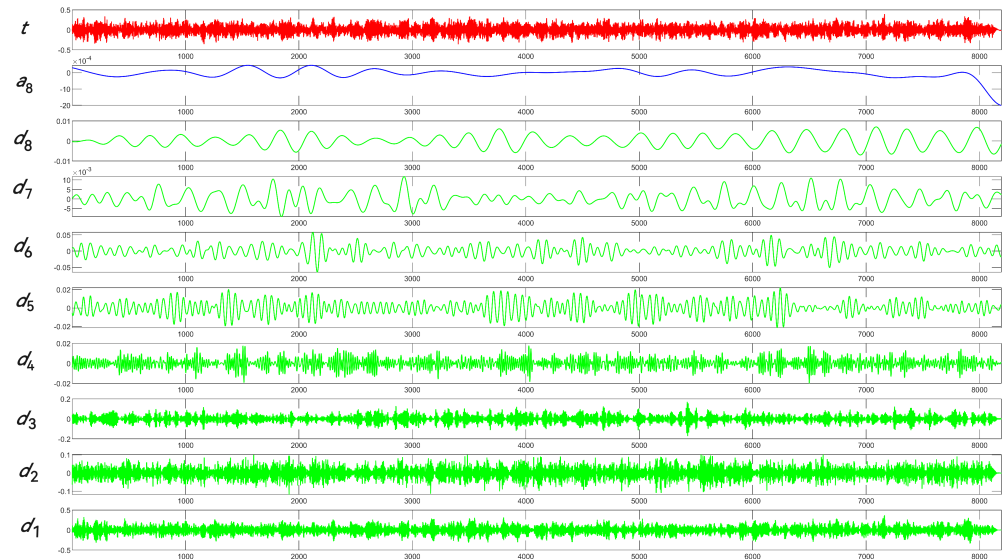


Figure 2. An example of a signal in time domain, together with the corresponding 1 low frequency component and 8 high frequency components. The signal in time domain is a Gaussian white noise, which is shown in red in the first row. The low frequency component a_8 is shown in blue curve in the second row. The high frequency components, namely d_1 to d_8 , are shown in the green curves. All 9 components are input to the following feature extraction module in the network.

2.2.2. Feature-Extraction Module

Based on the input of decomposed components from different measurement points in the pre-defined time window, this module would make use of the neural network to learn features in each component. In particular, a convolution neural network is applied. The CNN is exclusively applied in the 2D image feature extraction [34–36], and also is useful for 1D signals like sound waves [37], electrocardiogram [38] and accelerations [23,25].

The input and output of the CNN are both the feature maps with $I \in \mathbb{R}^{F_{in} \times D_{in}}$ and $O \in \mathbb{R}^{F_{out} \times D_{out}}$, respectively. In the proposed method, the input of the feature extraction module would be the decomposed components in the dimension of $(9 \times N, M)$, i.e., 9 channels of decomposed components. The $(9 \times N, M)$ decomposed components in the previous module can be regarded as a special feature map. $O^{d_{out}} \in \mathbb{R}^{F_{out}}$, $1 \leq d_{out} \leq D_{out}$ is a slice vector in O , and $I^{d_{in}} \in \mathbb{R}^{F_{in}}$, $1 \leq d_{in} \leq D_{in}$ is a slice vector in I . In the CNN network, the convolutional kernel $Q \in \mathbb{R}^{W \times D_{in} \times D_{out}}$ is defined, with $w^{d_{in}, d_{out}} \in \mathbb{R}^L$ being the one-dimensional convolutional kernel, $1 \leq d_{in} \leq D_{in}$, $1 \leq d_{out} \leq D_{out}$. L is the length of the one-dimensional convolutional kernel. The convolutional kernels applied in this network would slide along only one direction. $O^{d_{out}}$ is calculated by

$$O^{d_{out}} = a(z^{d_{out}}) = a\left(\sum_{d_{in}=1}^{D_{in}} w^{d_{in}, d_{out}} \otimes I^{d_{in}} + b^{d_{out}}\right), \quad (2)$$

where $b^{d_{out}}$ is a scalar bias, $\otimes$ the operator of cross-correlation, $a(\cdot)$ a activation function. The value of each element in the kernel, i.e., the weight in the kernel, and the bias are learnable. In order to increase the receptive field of the convolution kernel without increasing the number of parameters or introducing additional computational costs, $D_{dil} - 1$ zero values can be inserted in the conventional kernel $w^{d_{in}, d_{out}}$, where D_{dil} is the dilation rate.

As shown in Figure 1, in this module, there are 3 conventional layers in total, namely Conv #1, Conv #2 and Conv #3. The length of the kernel (kernel size) in all three layers are set to 8. The output dimension D_{out} for the three layers, which is also the filter numbers, are set to 32. In order to increase the receptive field for deeper layers, D_{dil} of the three layers is set to 1, 2 and 4, for Conv #1, Conv #2 and Conv #3, respectively. The stride in all 3 layers is set to 1. Table 1 give the details of the configurations of the three layers.

Table 1. Configurations of the conventional layers in the feature extraction module. There are in total 3 layers. While the kernel size, the stride and the filter numbers are set to be the same for all 3 layers, the dilation rate are different for a larger receptive fields for deeper layers.

Layers	Kernel Size	Filter Number	Dilation Rate	Stride
Conv #1	8	32	1	1
Conv #2	8	32	2	1
Conv #3	8	32	4	1

In order to improve the training efficiency and performance of the network, in each conventional layer, the network is regularized with batch normalization (BN) and weight normalization (WN). The BN is applied to $z^{d_{out}}$ in Equation (2), i.e., $(\sum_{d_{in}=1}^{D_{in}} w^{d_{in},d_{out}} \otimes I^{d_{in}} + b^{d_{out}})$. Suppose that the mean and variance of $z^{d_{out}}$ for a small batch of training data is μ and σ^2 , the BN is defined as

$$BN(z^{d_{out}}) = \frac{z^{d_{out}} - \mu}{\sqrt{\sigma^2 + \epsilon}}, \quad (3)$$

where ϵ is a pre-defined small constant. The BN would the convolved output to a standard normal distribution with a mean of 0 and a variance of 1. The WN, on the other hand, is to normalize the weight in the kernel vector $w^{d_{in},d_{out}}$. The WN would decompose the weight vector into its direction $\frac{w^{d_{in},d_{out}}}{\|w^{d_{in},d_{out}}\|}$ and its magnitude $\|w^{d_{in},d_{out}}\|$, and use the decoupled weight direction and weight magnitude to replace the original weight vector to be a new learnable parameters in the network.

For the activation function in the three conventional layer, the ReLU function is applied, which is expressed as

$$ReLU(x) = \max(0, x). \quad (4)$$

2.2.3. Prediction and Output Module

The output of the previous module would be a feature map $O \in \mathbb{R}$. In the prediction module, the feature map O would be firstly flatten to a 1D vector $v_{in} \in \mathbb{R}^{\times 1}$. v_{in} is then connected to a fully connected (FC) layer, with a hidden layer of 160 neurons. The output of the FC layer is designed with 9 neurons, i.e., a vector $v_{out} \in \mathbb{R}^{9 \times 1}$, representing the 8 high-frequency components of loads $f_{d_1}, f_{d_2}, \dots, f_{d_8}$ and 1 low-frequency component f_{a_8} . Here, we only predict the load at current time stamp t_{now} . The relation between v_{out} and v_{in} is given by

$$v_{out} = a(W_{FC}v_{in} + b_{FC}), \quad (5)$$

where W_{FC} is the weight matrix in the FC layer, b_{FC} the bias vector. The values of elements in W_{FC} and those of b_{FC} are learnable. The activation function $a(\cdot)$ in this layer is also the ReLU function (Equation (4)).

The prediction module would learn a mapping from the learnt feature maps of the decomposed components of the responses to the decomposed representations of the load. In the output module, the decomposed representations are transformed back to the time domain using

$$f(t_{now}) = f_{a_8} + \sum_{p=1}^8 f_{d_p}, \quad (6)$$

where $f(t_{now})$ is the predict load at time stamp t_{now} in the time domain. It is noteworthy that the proposed method would take the responses in a time window to identify the load at a certain time stamp. When sliding the time window to a new time interval, the load at another time stamp would be identified, which make it possible for the propose method to meet the online identification demands by a overlapped moving time window.

2.3. Model Training Details

To train the parameters in the proposed network, a proper loss function is needed. For a training set of synchronized “load-response” data, the loads at a certain time stamp t_i can be decomposed into 8 high-frequency components and 1 low-frequency components using the procedures in Section 2.2.1. Let $v_{truth}^i \in \mathbb{R}^{9 \times 1}$ be the vector of the ground truth load at time t_i . The loss is defined as the mean square error (MSE) between the predicted load v_{out}^i at time t_i and v_{truth}^i ,

$$L_i = \|v_{out}^i - v_{truth}^i\|_2, \quad (7)$$

where $\|\cdot\|$ is the L2 norm. The mini-batch gradient descent using Adam optimization is applied for network parameter learning. For a training batch that containing B load samples, the total loss is $L = \sum_{i=1}^B L_i$. The learning rate is 1.0×10^{-4} , and the batch size is set to 1024. To reduce the model over-fitting, during the training of the three conventional layers, i.e., Conv1D #1 to Conv1D #3, a dropout [39] is applied with a dropout probability of 0.2.

3. Experimental Results

In this section, we discuss the experimental results of the proposed approach. First, the procedures for collecting network work training and testing data is described in Section 3.1. The quantitative evaluation metrics, as well as the quantitative evaluation results on differently designed experiments, are given in Section 3.2. An ablation on the design of wavelet-based NN is discussed in Section 3.3.

3.1. Equipment and Procedures for Data Collection

In order to demonstrate the performances of load identification under real conditions and collect data for network training, a self-build GARTEUR aircraft model [40] is set up. The self-build GARTEUR model is similar with that in [25], which comprises six 2024-T3 aluminum beams with rectangular cross-sections, namely the fuselage, wings, vertical tail, horizontal tail and wingtip ballast plates. The elastic modulus, the Poisson’s ratio and the density of the model is given in Table 2. As shown in Figure 3, the model has a wingspan of 2 m, a fuselage length of 1.5 m, and a total weight of 43.34 kg. Throughout all experiments, the deformation of the self-build GARTEUR model remains within the elastic deformation range, making the system behave as an elastic system that adheres to Hooke’s law, which is also similar to that in [25]. A modal experiment is conducted using PolyMAX [41]. For the GARTEUR model, the modal data is between 6.062 Hz (mode 1) to 140.024 Hz (mode 14).

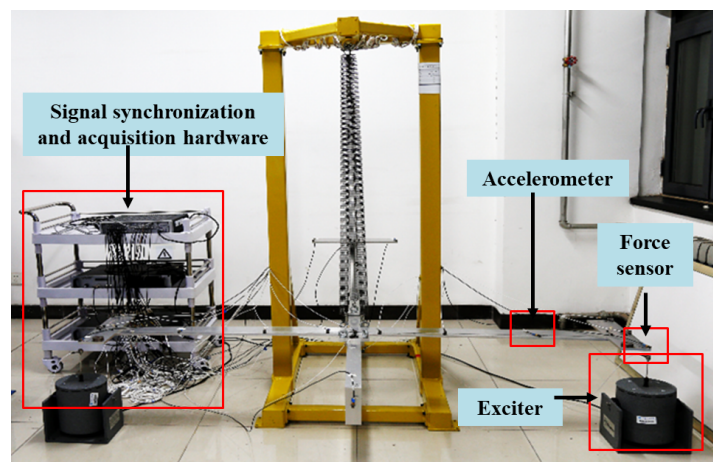


Figure 3. The equipment used for data collections. A self-build GARTEUR model is utilized for the structures. The force sensor that attached on the exciter would provide the ground truth values for the loads, while the accelerometers on attached on the GARTEUR model would measure the response signals. All signals are synchronized and captured by the LMS SCADAS III from Siemens (Leuven, Belgium).

Table 2. The elastic modulus, the Poisson’s ratio and the density of the self-build GARTEUR model.

Elastic Modulus	Poisson’s Ratio	Density
73 GPa	0.33	2780 kg/m ³

In order to collect the synchronized “load-response” data on the above-mentioned GARTEUR model, the vibration exciter, force sensor and the accelerometers are attached on the GARTEUR model. To evaluate the proposed approach under different response position configurations, in the experiments, two configurations of the accelerometers position are designed, namely the symmetrical distribution and the asymmetrical distribution. Figure 4 shows the sketch of the positions of the exciter and the accelerometers under the two configurations. For the symmetrical distribution, the vibration exciter with an attached force sensor is placed at the triangle point on Figure 4a. In the meanwhile, the acceleration response data are captured at six different positions, which are shown as the circle points on Figure 4a. As for the asymmetrical case, the exciter is placed at a different position, which is also shown as a triangle point on Figure 4b. To verify the identification performance under different numbers of measurement points, in this scenario, four accelerometers are used, which are placed on the circle points on Figure 4b. The Siemens LMS SCADAS III, which is from the Siemens LMS, Leuven, Belgium, is utilized for the temporal synchronization of the load and response signals.

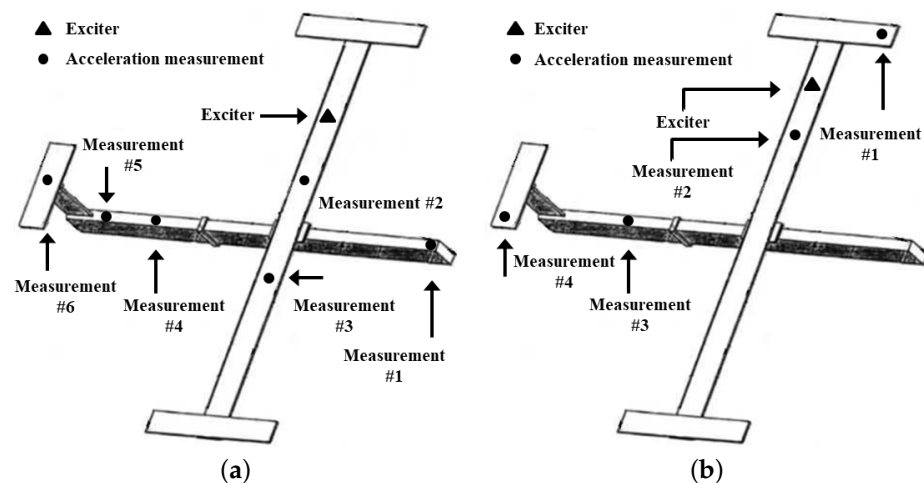


Figure 4. Two different distributions of the accelerometer positions. For the first distribution, 6 accelerometers are symmetrically placed on the GARTEUR model. For the other distribution, 4 accelerometers are asymmetrically distributed. (a) Symmetrical distribution of the accelerometers. (b) Asymmetrical distribution of the accelerometers.

The sampling frequency is set to 2048 Hz, which is more than 10 times of the frequency of the 14th mode of the structure. For four sinusoidal loads, 4 s of response signals are captured. For random loads on symmetrically distributed sensors, the duration of the signals is 16 s, while that of the random loads on asymmetrically distributed sensors is 8 s. For each signal, a proportion of 70% data is used for NN training, and 30% of the data are used for quantitative evaluation. It should be noted that the proposed method is a supervised learning-based method, so the training data are important for the algorithm performance. When applying the approach to unknown structures without the training data prior, there could be a domain gap that would affect the algorithm’s performance. Such problems can be further addressed using unsupervised learning techniques like auto-encoder [42] or generative adversarial network [43]. The two works in [42,43] are both based on vibration data. The use of unsupervised learning techniques would reduce the dependence on training data for the algorithms.

3.2. Experimental Results

In this subsection, the quantitative evaluation of the proposed approach on different types of dynamic loads are given. The quantitative metrics utilized in the experiments are the root mean square error (RMSE) and the correlation coefficient (CC). Suppose that $Q_i, i = 1, 2, \dots, N_Q$, is identified loads at timestamp i , and N_Q is the total time. $\hat{Q}_i, i = 1, 2, \dots, N_Q$ is the ground truth values of the loads. The RMSE is given by

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N_Q} (Q_i - \hat{Q}_i)^2}. \quad (8)$$

The metric CC is given by

$$CC = \frac{1}{N_Q - 1} \sum_{i=1}^{N_Q} \left(\frac{Q_i - \mu_Q}{\sigma_Q} \right) \left(\frac{\hat{Q}_i - \mu_{\hat{Q}}}{\sigma_{\hat{Q}}} \right), \quad (9)$$

where μ_Q and σ_Q are the mean value and standard deviation of the identified loads, respectively. $\mu_{\hat{Q}}$ and $\sigma_{\hat{Q}}$ are those of the ground truths of the loads, respectively. A lower RMSE or higher CC would reflect better identification results of the load.

3.2.1. Experiment 1: Quantitative Analysis and Comparison on Random Loads

In this experiment, random loads are applied on the GARTEUR model, and the proposed approach is quantitatively evaluated. For the case of symmetrically distributed sensors, the data in [25] is adopted, in which the signals for random excitation is Gaussian white noise. Similar Gaussian white noise random excitations are also applied for the asymmetrically distributed sensors. The Siemens LMS Test.lab [44] is used for random signal generation.

To validate the effectiveness of the proposed method, quantitative comparative analyses are conducted between regularization based methods and data-driven methods for load identification. Two regularization-based load identification methods are selected, namely the TSVD regularization and Tikhonov regularization-based method. For the data-driven method, two approaches in the time domain, namely the TDNN-based approach [24], one-dimensional CNN with attention mechanism (1D-att-CNN)-based approach [25], and one approach in the wavelet domain, the wavelet-LSTM [30], are compared.

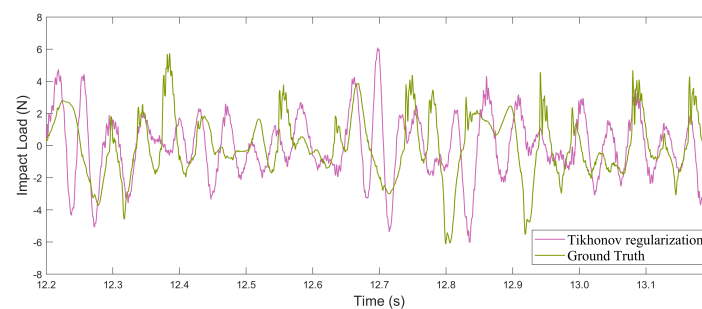
In the comparative experiments, the regularization parameters for TSVD and Tikhonov methods were obtained using the GCV method [45]. For the TDNN method [24], a three-layer shallow network was employed with the input being the time-domain vibration signal within a time window. The 1D-att-CNN method [25] used the described network structure with the input being the time-domain vibration signal within a time window, and the network structure consisted of two layers of stacked attention-based one-dimensional convolutional layers and one fully connected layer. For the wavelet-LSTM method [30], the network input was the 8th-order Meyer wavelet decomposition within a time window, consistent with the input of the proposed method. The network was designed with two layers of LSTM and one fully connected layer, with 128 neurons in the LSTM layer. To ensure fairness in the comparison, the time window for the original input of the neural network-based methods, including the proposed method, is set to 256. The learning rate and number of training epochs are set to be the same for all data-driven approaches. Table 3 provides quantitative comparison results of load identification for the proposed algorithm and the other comparative methods.

From Table 3, it can be observed that, compared to the regularization-based methods, the four data-driven methods yield better identification results. For the case of symmetrical sensor distribution, the proposed method outperforms the other three data-driven load identification methods in terms of both the RMSE and CC metrics. For the asymmetrical ones, the proposed method is the second best in terms of RMSE metric and the best in terms

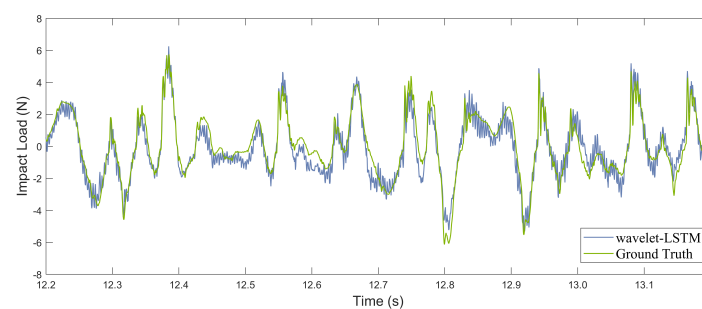
of the CC metric. The comparisons between the performances of different sensor distributions shows that the regularization-based method would be sensitive to the sensor positions, while the propose method would give a relative stable identification result, with the CC metric near 0.97 for both sensor distributions. Figure 5 gives the the detailed comparisons for different approaches with respect to the ground truth loads with symmetrical sensor distribution. The comparisons show the identified random loads with respect to the ground truth values for time stamp 12.2 s to 13.2 s. From Figure 5, it can be seen that the three data-driven-based methods (Figure 5b–d) would outperform the regularization-based method (Figure 5a). Figure 5b shows that the wavelet-LSTM [30] approach would output more oscillating identification results. The time domain method [25] and the proposed method would output good identification results. However, the proposed method outperforms the time domain method [25] in terms of RMSE and CC.

Table 3. Load identification performances evaluations and comparisons on random loads. The random loads are configured to be the Gaussian random loads. The proposed approach is evaluated in two different sensor distributions. As for the comparisons, two regularization-based methods, two data-driven methods in the time domain and one data-driven method in the transform domain are selected.

Sensor Distribution	Method	RMSE	CC
Symmetric	TSVD regularization	1.9392	0.6385
	Tikhonov regularization	1.6975	0.6436
	TDNN	1.5566	0.6547
	1D-att-CNN	0.7517	0.9232
	wavelet-LSTM	0.8643	0.8967
	ours	0.4824	0.9702
Asymmetric	TSVD regularization	8.1759	0.0974
	Tikhonov regularization	7.8381	0.1088
	TDNN	2.9995	0.7756
	1D-att-CNN	0.8211	0.9701
	wavelet-LSTM	2.5022	0.8456
	ours	1.0579	0.9710



(a)



(b)

Figure 5. Cont.

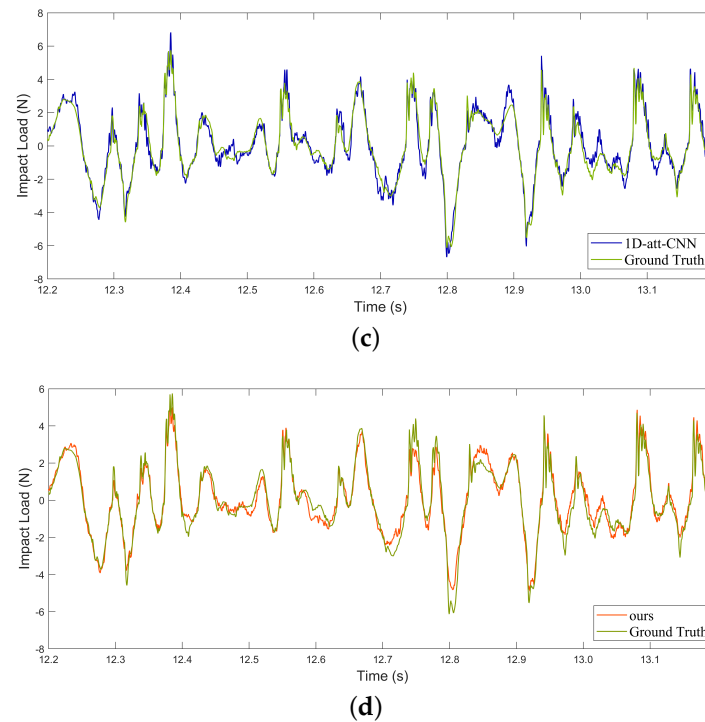


Figure 5. The detailed comparisons of the identified random loads with respect to the ground truth values with different approaches. In this comparison, the symmetrical sensor distribution is utilized. 1 regularization method (a), 1 wavelet based data-driven method (b) and 1 time domain data-driven method (c) are compared with the proposed approach. (a) Comparisons of the estimated loads using Tikhonov method with respect to the ground truth values. (b) Comparisons of the estimated loads using wavelet-LSTM method with respect to the ground truth values. (c) Comparisons of the estimated loads using 1D-att-CNN method with respect to the ground truth values. (d) Comparisons of the estimated loads using the proposed method with respect to the ground truth values.

3.2.2. Experiment 2: Quantitative Analysis and Comparison on Sinusoidal Loads

To further verify the identification performances on different types of dynamic loads, in this experiment, the proposed approach is quantitatively evaluated on the different sinusoidal loads using the above two metrics. Quantitative comparisons between the performances proposed approach and those of the performances of other approaches are also provided.

For the sinusoidal loads, two loads are evaluated on the symmetrically distributed sensors and the asymmetrical ones, respectively. In particular, $F_{sin1} = 5 \sin(20\pi t)$ and $F_{sin2} = 5 \sin(30\pi t)$ are applied to the symmetrical distribution, while $F_{sin3} = 4 \sin(20\pi t)$ and $F_{sin4} = 4 \sin(30\pi t)$ are applied to the asymmetrical one. Table 4 gives the quantitative evaluation on different sinusoidal loads when accelerometer sensors are symmetrically and asymmetrically distributed.

Table 4. Load identification performances evaluations on sinusoidal loads. In the experiments, different sensor distributions and sinusoidal signals with different frequency are considered. In each experiment, identification results with very high CC are obtained.

Sensor Distribution	Load	RMSE	CC
Symmetric	$5 \sin(20\pi t)$	0.5830	0.9999
Symmetric	$5 \sin(30\pi t)$	0.3361	1.0000
Asymmetric	$4 \sin(20\pi t)$	0.3572	0.9999
Asymmetric	$4 \sin(30\pi t)$	0.4451	0.9999

From Table 4, it can be seen that in both cases of symmetrically and asymmetrically distributed sensors, sinusoidal loads of different frequencies can be well identified, with all CC metrics of almost 1. To further evaluate the proposed method, we choose 1 regularization based method, namely the TSVD regularization method, and 1 data-driven method, the attention based 1D-CNN [25] for quantitative comparisons. Table 5 gives the comparison results. It can be seen that the two data-driven method would outperform the regularization based method. The 1D-CNN [25] method obtains a better RMSE metric than the proposed method; however, the CC metric for both 1D-CNN [25] and our method are almost 1. Figure 6 gives the identified loads from 0 s to 5 s for F_{sin1} (symmetrically distributed sensors) from different approaches, respectively. It can be seen that the 1D-CNN [25] method and the proposed method output similar identification results.

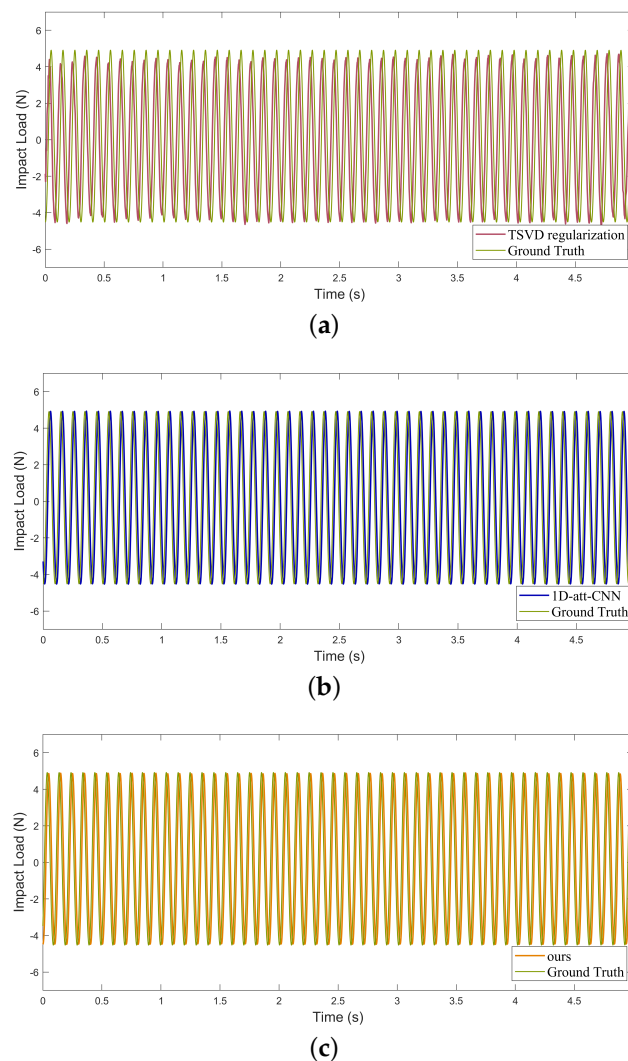


Figure 6. The detailed comparisons of the identified sinusoidal loads with respect to the ground truth values with different approaches. In this comparison, the symmetrical sensor distribution is utilized. The load is $F_{sin1} = 5\sin(20\pi t)$. One regularization-based method and one data-driven method are compared. It can be seen that the proposed method would output similar identification results to those of the 1D CNN based method [25]. (a) Comparisons of the estimated sinusoidal loads using TSVD regularization method with respect to the ground truth values. (b) Comparisons of the estimated sinusoidal loads using 1D-att-CNN method with respect to the ground truth values. (c) Comparisons of the estimated sinusoidal loads using the proposed method with respect to the ground truth values.

Table 5. Load identification performances comparisons on sinusoidal loads. For comparison, 1 regularization-based method, namely the TSVD regularization method, and 1 neural network-based method [25] are utilized for comparisons.

Sensor Distribution	Load	Method	RMSE	CC
Symmetric	$5 \sin(20\pi t)$	TSVD	1.3486	0.9163
		1D-att-CNN	0.1421	1.0000
		ours	0.5830	0.9999
	$5 \sin(30\pi t)$	TSVD	1.0771	0.9565
		1D-att-CNN	0.2218	1.0000
		ours	0.3361	0.9999
Asymmetric	$4 \sin(20\pi t)$	TSVD	0.9681	0.9500
		1D-att-CNN	0.1581	1.0000
		ours	0.3572	0.9999
	$4 \sin(30\pi t)$	TSVD	0.7061	0.9814
		1D-att-CNN	0.1909	1.0000
		ours	0.4451	0.9999

3.2.3. Experiment 3: Experiments on Additional Sensor Measurement Noises

Under real flight conditions, vibration signals measured from the accelerometers are inevitably subject to measurement noise. In this experiment, we tend to evaluate the robustness of the proposed approach under the presence of measurement noise in vibration measurements. Though the acceleration measurements in the previous experiment in Sections 3.2.1 and 3.2.2 are from real accelerometers, these signals already contain some inherent measurement noise; in this experiment, additional noises are added to the acceleration measurements.

In particular, we choose to use the data in Section 3.2.1, i.e., the random excitation. Gaussian noise with a mean of 0 and a standard deviation corresponding to 0–30% of the vibration amplitude, i.e., the maximum value of the random excitations, which is further added to the random vibration signals collected on the experimental setup. Table 6 gives the quantitative analyses and comparisons of the identification results under different strengths of measurement noises.

To compare the quantitative results, we choose the second-best approach in Section 3.2.1, namely the 1D-att-CNN [25] approach, for comparisons. From Table 6, it can be seen that for both cases of symmetrical and asymmetrical sensor distributions, the proposed method outperforms in terms of both metrics when the additional measurement noise exists. Figure 7 shows the changes in the RMSE and CC metrics when the noise strengths increase. From Figure 7b, it can be seen that for symmetrical sensor distributions, the CC metric of approach in [25] would decrease dramatically from 0.9232 when no additional measurements noised to 0.2794 when 30% of the measurement noise. In the meantime, the proposed would remain above 0.75 at all noises strengths, which indicates more consistent identification results. For asymmetrical sensor distributions, though the approach in [25] can obtain a lower RMSE than that of the proposed approach when no additional measurement noises exists, when noises are added, the proposed approach outperforms in terms of the two metrics. Once again, the proposed would remain above 0.75 in CC at all noises strengths, which shows the robustness of the proposed method on additional measurements noises.

Table 6. Load identification performances evaluations and comparisons with additional sensor measurement noises. The evaluated loads are the random loads in Section 3.2.1. Extra Gaussian noise with different noise strength are added on the acceleration measurements. We choose to compare the proposed approach with the second-best algorithm in Section 3.2.1.

Sensor Distribution	Noise Strength	Method	RMSE	CC
Symmetric	0%	1D-att-CNN	0.7517	0.9232
		ours	0.4824	0.9702
	10%	1D-att-CNN	1.5608	0.6070
		ours	0.9217	0.8798
Asymmetric	0%	1D-att-CNN	1.8461	0.3677
		ours	1.1425	0.8142
	30%	1D-att-CNN	1.8545	0.2794
		ours	1.2456	0.7699
Asymmetric	0%	1D-att-CNN	0.8211	0.9701
		ours	1.0579	0.9710
	10%	1D-att-CNN	1.8808	0.8375
		ours	1.8564	0.8791
Asymmetric	20%	1D-att-CNN	2.5385	0.6902
		ours	2.3807	0.8022
Asymmetric	30%	1D-att-CNN	2.5211	0.6809
		ours	2.4250	0.7977

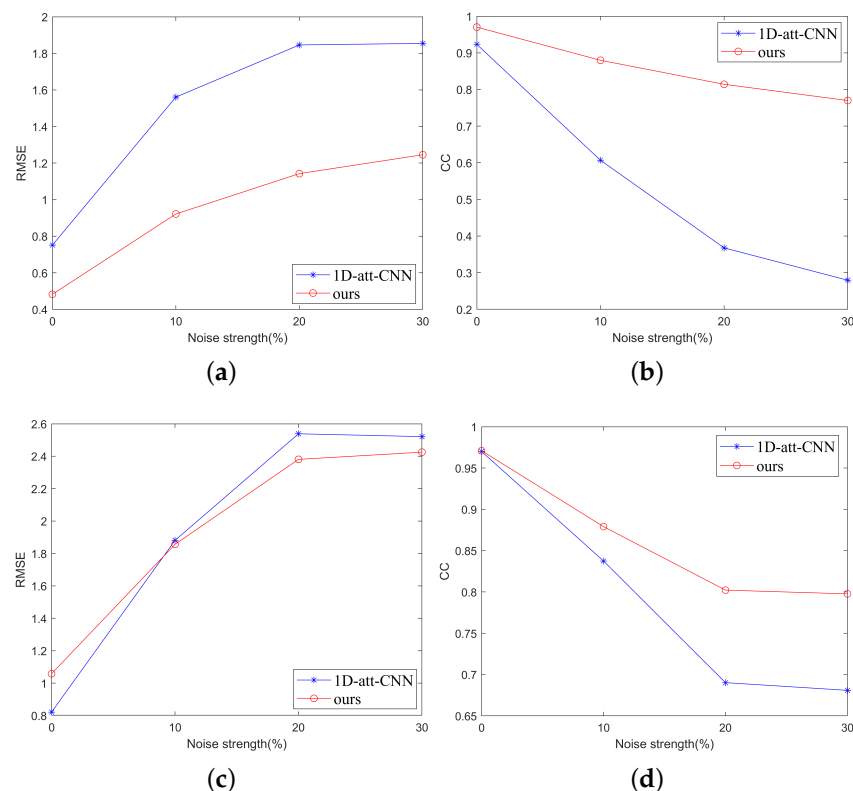


Figure 7. The comparisons of the RMES and CC metrics of different approach under different additional measurement noise strengths. The first row gives the results for symmetrical sensor distribution, while the second row gives those of the asymmetrical sensor distribution. (a) The RMSE for symmetrical distribution under different noise strength. (b) The CC for symmetrical distribution under different noise strength. (c) The RMSE for asymmetrical distribution under different noise strength. (d) The CC for asymmetrical distribution under different noise strength.

3.2.4. Experiment 4: Experiments under Unknown Excitation Source Disturbance Conditions

For real aerospace structures, multiple loads could be applied simultaneously at different positions. Besides the load to be identified, i.e., the target load, the other additional loads could introduce extra disturbances to the identification problem. To further validate the robustness of the proposed method under such disturbance conditions, in this experiment, an extra vibration exciter is attached on the GARTEUR model. Figure 8 gives the locations of the target exciter (for target loads), disturbance exciter (for disturbance loads) and the accelerometers for both symmetrical distribution and the asymmetrical distribution.

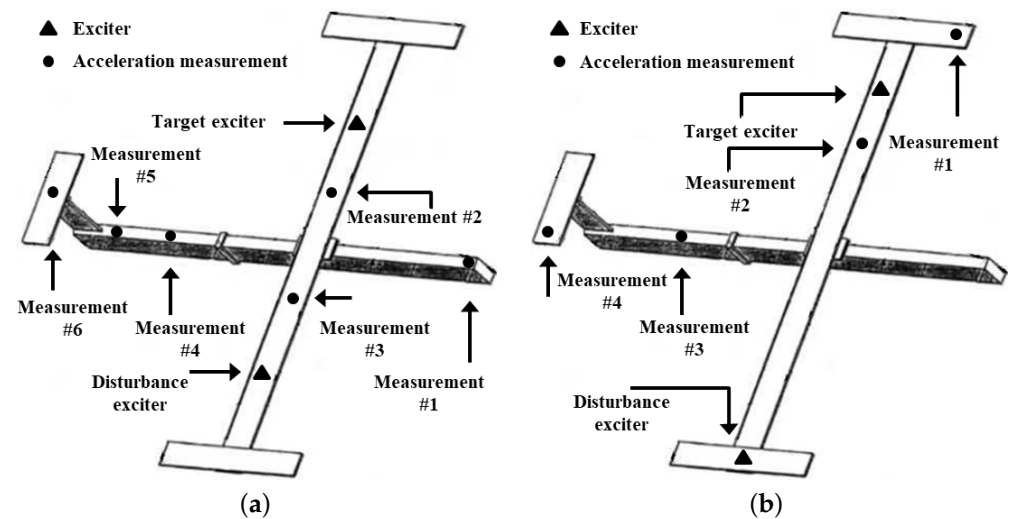


Figure 8. Two different distributions of the accelerometer positions, with disturbance exciters. One extra exciter is placed at a different location in each scenario, which would provide the disturbance loads with different amplitudes. (a) Symmetrical distribution of the accelerometers, together with the disturbance exciter. (b) Asymmetrical distribution of the accelerometers, together with the disturbance exciter.

As for the loads, in the experiment, the target load is the Gaussian white noise random load described in Section 3.2.1. The disturbance load, on the other hand, is configured as a Gaussian white noise random load with amplitudes of 0%, 40% and 100% relative to that of the target load. Table 7 and Figure 9 give the quantitative analyses and comparisons in different sensor distributions.

Similar to Section 3.2.3, the comparisons are with the 1D-att-CNN method [25]. Table 7 and Figure 9 show that in various disturbance conditions, our proposed method outperforms in both RMSE and CC metrics. From Figure 9a,b, it can be seen that for symmetrical sensor distribution, the performance of time domain method [25] would decrease more than the proposed method when stronger disturbance occurs. Though the RMSE in Figure 9c is lower for [25] than ours when there is no disturbance, when the disturbance is stronger, our method outperforms. This indicates that our method can achieve superior identification results and reflects its robustness in the presence of other dynamic load disturbances.

Table 7. Load identification performances evaluations and comparisons under unknown excitation source disturbance conditions. The evaluated loads are also the random loads in Section 3.2.1. An extra vibration exciter is applied on the GARTEUR model, performing Gaussian random excitations with different amplitudes. Once again, the proposed approach is compared with the second-best algorithm in Section 3.2.1.

Sensor Distribution	Disturbance Amplitude	Method	RMSE	CC
Symmetric	0%	1D-att-CNN	0.7517	0.9232
		ours	0.4824	0.9702
	40%	1D-att-CNN	1.0261	0.8599
		ours	0.7915	0.9221
	100%	1D-att-CNN	1.2517	0.7628
		ours	1.0468	0.8432
Asymmetric	0%	1D-att-CNN	0.8211	0.9701
		ours	1.0579	0.9710
	40%	1D-att-CNN	3.4922	0.6465
		ours	1.8053	0.9180
	100%	1D-att-CNN	3.7184	0.6311
		ours	2.0576	0.8994

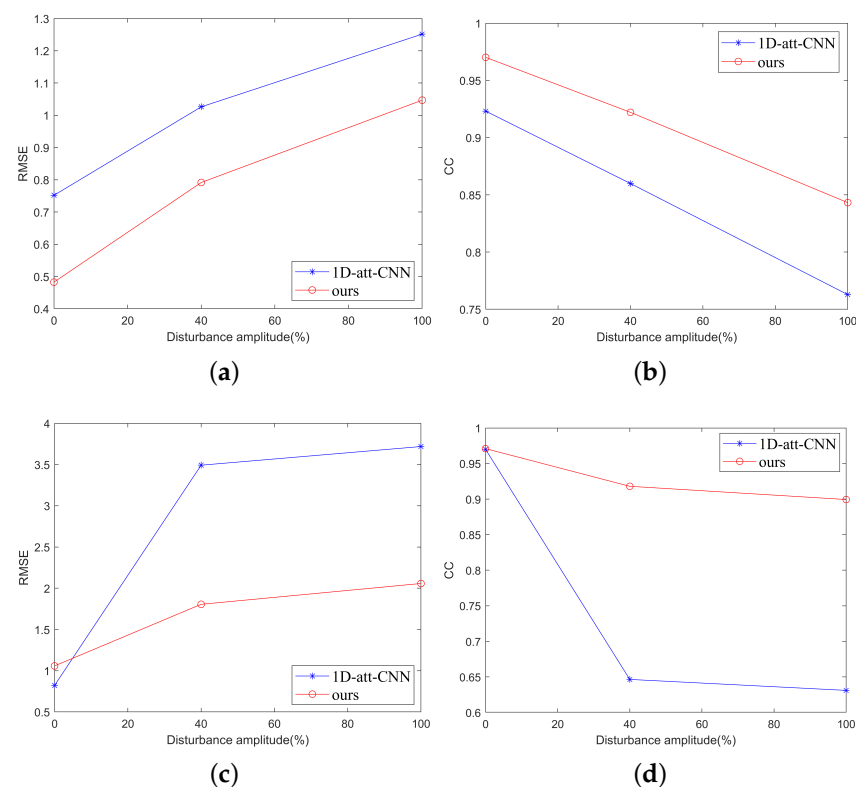


Figure 9. The comparisons of the RMES and CC metrics of different approach under different disturbance conditions. The first row gives the results for symmetrical sensor distribution, while the second row gives those of the asymmetrical sensor distribution. (a) The RMSE for symmetrical distribution under different disturbance conditions. (b) The CC for symmetrical distribution under different disturbance conditions. (c) The RMSE for asymmetrical distribution under different disturbance conditions. (d) The CC for asymmetrical distribution under different disturbance conditions.

3.2.5. Experiment 5: Experiment on Vibration Data from Finite Element Models

To further verify the performances of the proposed method on different structures, experiments on finite element models are conducted. In the experiment, three structures are used, namely a plate, a simply supported beam and a spatial truss structure. Figure 10 gives the sketches of the three models.

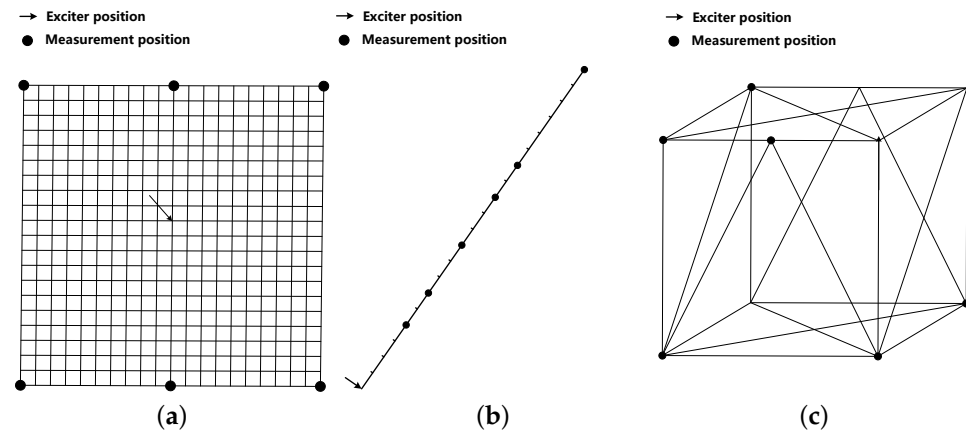


Figure 10. The three model used in the experiment, which are the plate, the simply supported beam and the spatial truss structure. In the figure, the arrow shows the position of the applied random loads, while the circles show the positions of the accelerometers. (a) The plate model used in the experiment. (b) The simply supported beam model used in the experiment. (c) The spatial truss structure model used in the experiment.

The material of the three models is set to be the same of the GARTEUR model, which is the 2024-T3 aluminum. The plate is modeled using the quad4 unit, with a size of $1000\text{ mm} \times 1000\text{ mm} \times 10\text{ mm}$. The simply supported beam is modeled using the beam unit. The length of the beam is 2000 mm and the cross-sectional size of the beam is $10\text{ mm} \times 10\text{ mm}$. For the spatial truss structure, the size is $1000\text{ mm} \times 1000\text{ mm} \times 1000\text{ mm}$, the nodes are located at the middle-point of bars, the spatial truss structure is modeled using bar unit. In Figure 10, the arrow indicates the position of the excitation and the circles indicate the positions of accelerometers. The load is set to be the same with the random loads in Experiment 1 for the asymmetrical sensor distribution. For the plate and the simply supported beam, the load is applied along the direction that perpendicular to the plate and the simply supported beam, respectively. For the spatial truss structure, the load is applied along the axis of the bar.

Based on the data collected from the above finite element models, the performances of the proposed method are further evaluated. We also compare the proposed method with the time domain data-driven method in [25]. Table 8 gives the quantitative comparisons.

Table 8. Quantitative comparisons on the performances based on vibration data from the finite element models.

Structure	Method	RMSE	CC
plate	1D-att-CNN	2.0326	0.8303
	ours	0.8993	0.9762
simply supported beam	1D-att-CNN	2.1473	0.7965
	ours	0.6768	0.9864
spatial truss structure	1D-att-CNN	1.7968	0.8492
	ours	1.2056	0.9620

From Table 8, it can be seen that, for all the three structures, identification results with the CC metric that are larger than 0.95 can be obtained from the proposed method. In the meantime, the proposed method would outperform the time domain method in [25] in terms of both the RMSE and CC metrics. The results are also coincident with the verification results in the other experiments.

Figures 11–13 give the detailed comparisons of the identified random load with respect to the ground value using data from the plate, simply supported beam and the spatial truss structure, respectively. The identified loads in time 2.8 s to 5.8 s are shown in the three figures. From the figures, it can be seen that the identified loads from the proposed method are more coincident to the ground truths than those from the method in [25].

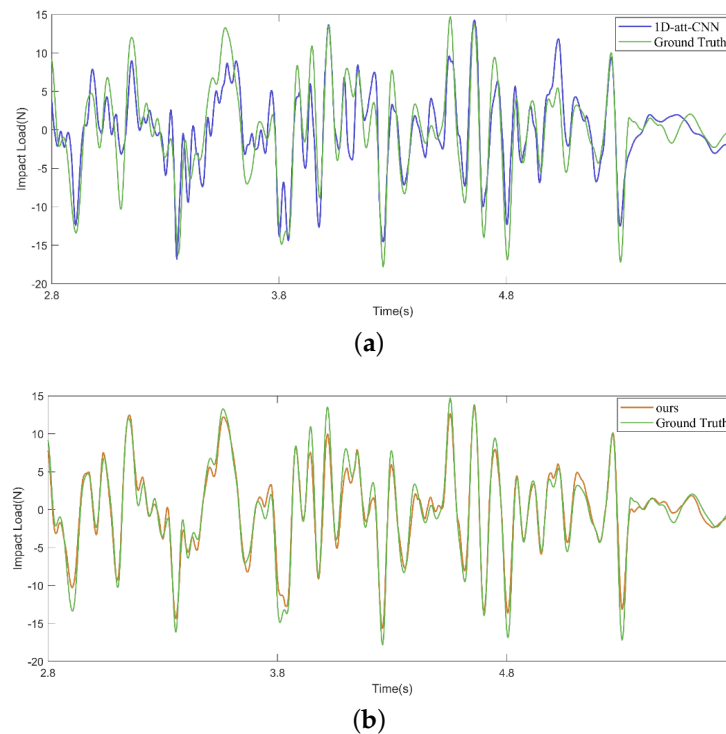


Figure 11. The detailed comparisons of the identified random loads with respect to the ground truth values using the vibration data from the plate structure. **(a)** Comparisons of the estimated loads using 1D-att-CNN method with respect to the ground truth values. **(b)** Comparisons of the estimated loads using the proposed method with respect to the ground truth values.

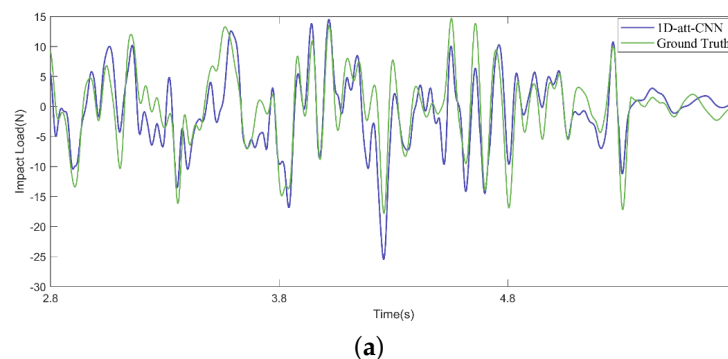


Figure 12. *Cont.*

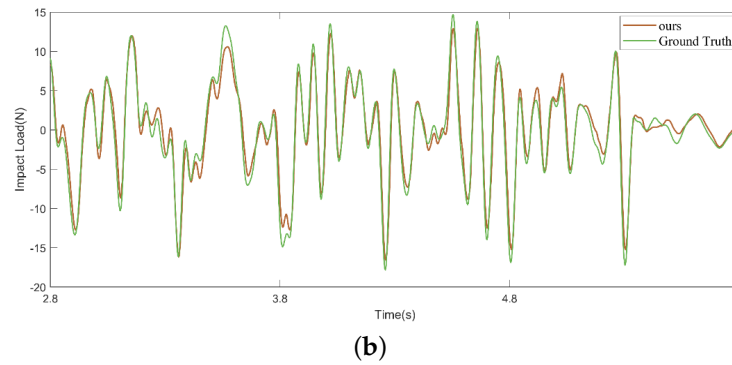


Figure 12. The detailed comparisons of the identified random loads with respect to the ground truth values using the vibration data from the simply supported beam structure. **(a)** Comparisons of the estimated loads using 1D-att-CNN method with respect to the ground truth values. **(b)** Comparisons of the estimated loads using the proposed method with respect to the ground truth values.

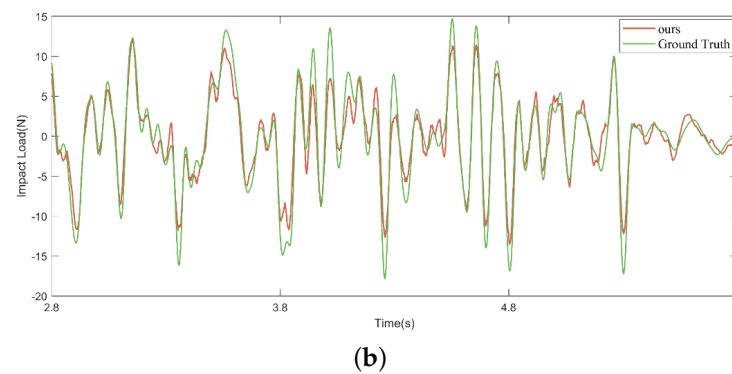
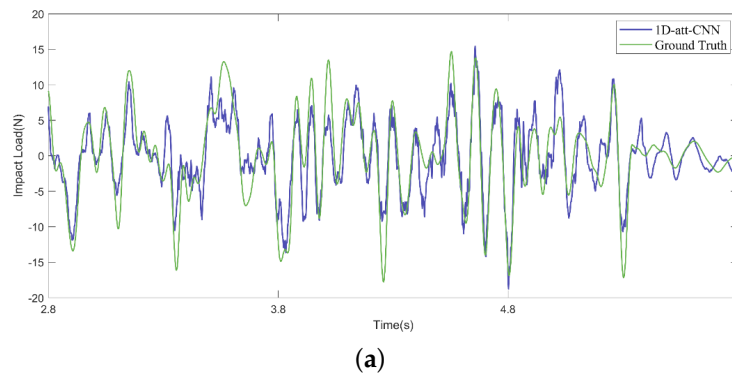


Figure 13. The detailed comparisons of the identified random loads with respect to the ground truth values using the vibration data from the spatial truss structure. **(a)** Comparisons of the estimated loads using 1D-att-CNN method with respect to the ground truth values. **(b)** Comparisons of the estimated loads using the proposed method with respect to the ground truth values.

3.2.6. Experiment 6: Experiments on Algorithm Repeatability

To further verify the repeatability of the proposed method, we select Experiment 3 (Section 3.2.3) and conduct extra runs of the experiment. The sensor distribution is set to be symmetrical, and the noise strength is set to be 10%. The performance metric reported in the submission is $RMSE = 0.9217$ and $CC = 0.8798$. Four extra runs of the experiment are conducted. Table 9 shows the quantitative evaluation results from five different runs.

In the Table 9, the unit of the $RMSE$ is N . The standard deviation of the $RMSE$ is $0.0251N$, and the standard deviation of the CC is 0.007 . It can be seen that similar performances can be obtained from the proposed method and a certain level of repeatability of the proposed method could be demonstrated.

Table 9. Quantitative evaluation results on extra runs of the experiment of additional sensor measurement noises.

Sensor Distribution	Noise Strength	Run No.	RMSE	CC
Symmetric	10%	1	0.9217	0.8798
		2	0.9007	0.8873
		3	0.9552	0.8743
		4	0.8903	0.8925
		5	0.9260	0.8836

3.3. Ablation Study

In this subsection, an ablation is performed to find the quantitative comparisons for the load identification results when from the input of the high- and low-frequency components using wavelet transform and those from the input in the time domain. We choose to use the random loads data in Section 3.2.1 when accelerometers are symmetrically distributed, i.e., the sensor distribution in Figure 4a, in this ablation. For the case of “time-domain”, the acceleration measurements in the time domain of all six sensors are set to be the input of the network, while for the case of “ours”, the proposed method is applied. Despite the difference in network inputs, the other details on network design and network training would remain the same. Table 10 shows the quantitative comparisons on the metrics.

Table 10. Ablations on network input in different domain. The effectiveness of the usage of wavelet transform is evaluated using random load with symmetrical sensor distribution. For the case of “time-domain”, the acceleration measurements are directly input to the network, while in the case of “ours”, the proposed method is evaluated.

Sensor Distribution	Case	RMSE	CC
Symmetric	time-domain	0.6247	0.9470
	ours	0.4824	0.9702

From the comparisons in Table 10, it can be seen that by using the decomposed components as the network input, the proposed approach would obtain a better load identification results in terms of a higher CC and a lower RMSE. The feature extraction in the decomposed components would be helpful for the load identification. However, it should be noted that the computational loads of the proposed method are larger than those of the method using time domain inputs.

4. Conclusions

In this paper, a novel approach for dynamic load identification on aerospace structures based on a deep convolutional network in the transform domain is proposed. The proposed approach first applies wavelet transform to the vibration signals in time domain on aerospace structures. The decomposed components are input to the designed one-dimensional convolutional network to extract the transformed domain features of the vibration signals, and subsequently predict the representation of the load in the transform domain. The proposed method avoids the explicit modelling structural transfer functions while achieving higher identification accuracy than the conventional regularization-based method. Results from ablation studies indicate that using decomposed components in the transformed domain helps the network refine its learning of signal features in different frequency ranges, leading to excellent results in random load identification. Additionally, the proposed method demonstrates a certain level of robustness to measurement noise and unknown vibration disturbances.

In our future work, we seek to further improve the robustness of the identification approach on various types of noises or disturbances, while exploring the optimal measurement position on aerospace structures for load identification. The architecture of the network can be further optimized for a lower amount of parameters using techniques like

DSC [31–33]. Since the proposed method is a supervised data-driven method, there would be a domain gap problem when applying it to unknown structures, using the unsupervised learning method, which would reduce the dependence on training data; this is a direction worth exploring further.

Author Contributions: Conceptualization, X.Z.; data curation, T.B. and B.L.; formal analysis, X.Z. and Q.C.; investigation, X.Z. and W.H.; methodology, X.Z. and W.H.; project administration, X.L.; software, X.Z., T.B., B.L. and J.L.; supervision, Q.C., X.L.; visualization, T.B.; writing—original draft, X.Z.; writing—review and editing, W.H., Q.C. and X.L. All authors have read and agreed to the published version of the manuscript.

Funding: This work is supported in part by the Natural Science Foundation of China under Grant 62201479, in part by the Natural Science Foundation of Sichuan Province under Grant 2023NSFSC1388, in part by the Key Laboratory of Medicinal and Edible Plant Resources Development of Sichuan Education Department, Chengdu University under Grant 10Y202201.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Park, J.; Ha, S.; Chang, F.K. Monitoring impact events using a system-identification method. *AIAA J.* **2009**, *47*, 2011–2021. [\[CrossRef\]](#)
2. Li, Y.; Mulani, S.B.; Fei, Q.; Wu, S.; Zhang, P. Vibro-acoustic analysis under stationary and non-stationary random excitations with KLE/FEM/BEM. *Aerosp. Sci. Technol.* **2017**, *66*, 203–215. [\[CrossRef\]](#)
3. Zheng, Y.; Wu, S.; Fei, Q. Distributed Dynamic load identification on irregular planar structures using subregion interpolation. *J. Aircr.* **2021**, *58*, 288–299. [\[CrossRef\]](#)
4. Bartlett, F.; Flannelly, W. Model verification of force determination for measuring vibratory loads. *J. Am. Helicopter Soc.* **1979**, *24*, 10–18. [\[CrossRef\]](#)
5. Uhl, T. The inverse identification problem and its technical application. *Arch. Appl. Mech.* **2007**, *77*, 325–337. [\[CrossRef\]](#)
6. Karlsson, S. Identification of external structural loads from measured harmonic responses. *J. Sound Vib.* **1996**, *196*, 59–74. [\[CrossRef\]](#)
7. Turco, E. Tools for the numerical solution of inverse problems in structural mechanics: Review and research perspectives. *Eur. J. Environ. Civ. Eng.* **2017**, *21*, 509–554. [\[CrossRef\]](#)
8. Jacquelin, E.; Bennani, A.; Hamelin, P. Force reconstruction: Analysis and regularization of a deconvolution problem. *J. Sound Vib.* **2003**, *265*, 81–107. [\[CrossRef\]](#)
9. Pan, C.; Ye, X.; Zhou, J.; Sun, Z. Matrix regularization-based method for large-scale inverse problem of force identification. *Mech. Syst. Signal Process.* **2020**, *140*, 106698. [\[CrossRef\]](#)
10. Jiang, J.; Tang, H.; Mohamed, M.S.; Luo, S.; Chen, J. Augmented tikhonov regularization method for dynamic load identification. *Appl. Sci.* **2020**, *10*, 6348. [\[CrossRef\]](#)
11. Wang, L.; Liu, J.; Xie, Y.; Gu, Y. A new regularization method for the dynamic load identification of stochastic structures. *Comput. Math. Appl.* **2018**, *76*, 741–759. [\[CrossRef\]](#)
12. Park, Y.; Reichel, L.; Rodriguez, G.; Yu, X. Parameter determination for Tikhonov regularization problems in general form. *J. Comput. Appl. Math.* **2018**, *343*, 12–25. [\[CrossRef\]](#)
13. Choi, H.G.; Thite, A.N.; Thompson, D.J. Comparison of methods for parameter selection in Tikhonov regularization with application to inverse force determination. *J. Sound Vib.* **2007**, *304*, 894–917. [\[CrossRef\]](#)
14. Jin, B.; Zou, J. Augmented tikhonov regularization. *Inverse Probl.* **2008**, *25*, 025001. [\[CrossRef\]](#)
15. Luo, S.; Jiang, J.; Zhang, F.; Mohamed, M.S. Distributed Dynamic Load Identification of Beam Structures Using a Bayesian Method. *Appl. Sci.* **2023**, *13*, 2537. [\[CrossRef\]](#)
16. Aucejo, M.; De Smet, O. On a full Bayesian inference for force reconstruction problems. *Mech. Syst. Signal Process.* **2018**, *104*, 36–59. [\[CrossRef\]](#)
17. Wang, J.; Wang, C.; Lai, X. MIMO SVM based uncorrelated multi-source dynamic random load identification algorithm in frequency domain. *J. Comput. Inf. Syst.* **2015**, *11*, 198–207.
18. Guo, C.; Jiang, L.; Yang, F.; Yang, Z.; Zhang, X. An intelligent impact load identification and localization method based on autonomic feature extraction and anomaly detection. *Eng. Struct.* **2023**, *291*, 116378. [\[CrossRef\]](#)

19. Cao, X.; Sugiyama, Y.; Mitsui, Y. Application of artificial neural networks to load identification. *Comput. Struct.* **1998**, *69*, 63–78. [CrossRef]
20. Trivailo, P.; Carn, C. The inverse determination of aerodynamic loading from structural response data using neural networks. *Inverse Probl. Sci. Eng.* **2006**, *14*, 379–395. [CrossRef]
21. Chen, G.; Li, T.; Chen, Q.; Ren, S.; Wang, C.; Li, S. Application of deep learning neural network to identify collision load conditions based on permanent plastic deformation of shell structures. *Comput. Mech.* **2019**, *64*, 435–449. [CrossRef]
22. Gao, Y.; Yu, X.; Chen, L.; Huang, D. Impact Load Identification Algorithm of Helicopter Weapon Pylon Based on Time-Domain Response Signal. *Aerospace* **2022**, *9*, 388. [CrossRef]
23. Yang, H.; Jiang, J.; Chen, G.; Zhao, J. Dynamic load identification based on deep convolution neural network. *Mech. Syst. Signal Process.* **2023**, *185*, 109757. [CrossRef]
24. Xia, P.; Yang, T.; Xu, J.; Wang, L.; Zhichun, Y. Reversed time sequence dynamic load identification method using time delay neural network. *Acta Aeronaut. Astronaut. Sin.* **2021**, *42*, 224452.
25. He, W.; Zhang, X.; Feng, Z.; Leng, Q.; Xu, B.; Li, X. Random Dynamic Load Identification with Noise for Aircraft via Attention Based 1D-CNN. *Aerospace* **2023**, *10*, 16. [CrossRef]
26. Zhou, J.; Dong, L.; Guan, W.; Yan, J. Impact load identification of nonlinear structures using deep Recurrent Neural Network. *Mech. Syst. Signal Process.* **2019**, *133*, 106292. [CrossRef]
27. Yang, H.; Jiang, J.; Chen, G.; Mohamed, M.S.; Lu, F. A Recurrent Neural Network-Based Method for Dynamic Load Identification of Beam Structures. *Materials* **2021**, *14*, 7846. [CrossRef]
28. Doyle, J.F. A wavelet deconvolution method for impact force identification. *Exp. Mech.* **1997**, *37*, 403–408. [CrossRef]
29. Li, Z.; Feng, Z.; Chu, F. A load identification method based on wavelet multi-resolution analysis. *J. Sound Vib.* **2014**, *333*, 381–391. [CrossRef]
30. Yang, T.; Yang, Z.; Liang, S.; Kang, Z.; You, J. Feature extraction and identification of stationary random dynamic load using deep neural network. *Acta Aeronaut. Astronaut. Sin.* **2022**, *43*, 225952.
31. Cha, Y.J.; Mostafavi, A.; Benipal, S.S. DNoiseNet: Deep learning-based feedback active noise control in various noisy environments. *Eng. Appl. Artif. Intell.* **2023**, *121*, 105971. [CrossRef]
32. Mostafavi, A.; Cha, Y.J. Deep learning-based active noise control on construction sites. *Autom. Constr.* **2023**, *151*, 104885. [CrossRef]
33. Chollet, F. Xception: Deep learning with depthwise separable convolutions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Honolulu, HI, USA, 21–26 July 2017; pp. 1251–1258.
34. Bhatt, D.; Patel, C.; Talsania, H.; Patel, J.; Vaghela, R.; Pandya, S.; Modi, K.; Ghayvat, H. CNN variants for computer vision: History, architecture, application, challenges and future scope. *Electronics* **2021**, *10*, 2470. [CrossRef]
35. Zhou, Z.; Zhang, X.; Ran, L.; Han, Y.; Chu, H. DSC-GraspNet: A Lightweight Convolutional Neural Network for Robotic Grasp Detection. In Proceedings of the 2023 9th International Conference on Virtual Reality (ICVR), Xianyang, China, 12–14 May 2023; pp. 226–232.
36. Zhong, L.; Zhang, X.; Ran, L.; Han, Y.; Chu, H. Visual SLAM for Dynamic Environments Based on Static Key-Points Detection. In Proceedings of the 2023 9th International Conference on Virtual Reality (ICVR), Xianyang, China, 12–14 May 2023; pp. 93–99.
37. Oord, A.v.d.; Dieleman, S.; Zen, H.; Simonyan, K.; Vinyals, O.; Graves, A.; Kalchbrenner, N.; Senior, A.; Kavukcuoglu, K. Wavenet: A generative model for raw audio. *arXiv* **2016**, arXiv:1609.03499.
38. Acharya, U.R.; Oh, S.L.; Hagiwara, Y.; Tan, J.H.; Adam, M.; Gertych, A.; San Tan, R. A deep convolutional neural network model to classify heartbeats. *Comput. Biol. Med.* **2017**, *89*, 389–396. [CrossRef]
39. Srivastava, N.; Hinton, G.; Krizhevsky, A.; Sutskever, I.; Salakhutdinov, R. Dropout: A simple way to prevent neural networks from overfitting. *J. Mach. Learn. Res.* **2014**, *15*, 1929–1958.
40. Balmes, E.; Wright, J.R. GARTEUR group on ground vibration testing: Results from the test of a single structure by 12 laboratories in Europe. In Proceedings of the International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Sacramento, CA, USA, 14–17 September 1997; American Society of Mechanical Engineers: New York, NY, USA, 1997; Volume 80401, p. V01AT03A004.
41. Peeters, B.; Van der Auweraer, H.; Guillaume, P.; Leuridan, J. The PolyMAX frequency-domain method: A new standard for modal parameter estimation? *Shock Vib.* **2004**, *11*, 395–409. [CrossRef]
42. Wang, Z.; Cha, Y.J. Unsupervised deep learning approach using a deep auto-encoder with a one-class support vector machine to detect damage. *Struct. Health Monit.* **2021**, *20*, 406–425. [CrossRef]
43. Soleimani-Babakamali, M.H.; Sepasdar, R.; Nasrollahzadeh, K.; Sarlo, R. A system reliability approach to real-time unsupervised structural health monitoring without prior information. *Mech. Syst. Signal Process.* **2022**, *171*, 108913. [CrossRef]
44. Siemens-Simcenter. Simcenter Testlab, Formerly Called LMS Test.Lab. 2022. Available online: <https://community.sw.siemens.com/s/article/simcenter-testlab> (accessed on 12 December 2023).
45. Hansen, P.C. Regularization tools version 4.0 for Matlab 7.3. *Numer. Algorithms* **2007**, *46*, 189–194. [CrossRef]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.