


# IMPACT LOAD IDENTIFICATION METHOD FOR AIRCRAFT RUDDER PLANES BASED ON NARX NEURAL NETWORK

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## Abstract

Accurate identification of impact loads has great influence on the safe and reliable operation of practical engineering structures. To ensure the reliability of structural design, designers need to accurately know the effect of impact loads acting on structures, such as load amplitude and duration, so as to effectively reduce or even eliminate the adverse effects of impact loads on structural performance. Taking aircraft rudder plane model as the research object, this paper investigates the application of the Nonlinear Autoregressive with Exogenous Inputs (NARX) neural network in impact load identification. The recurrent neural network, which is widely used in the field of deep learning, is introduced into the research on impact load identification. By combining the "memory" characteristic of recurrent neural networks with the solution principle of impact response, the goal of impact load identification is achieved.

**Keywords:** load identification, deep learning, NARX neural network, inverse problem, aircraft rudder plane

## 1. General Introduction

Aircraft rudder planes are the core executive components of flight control systems. By deflecting to alter the aerodynamic shape of wings or empennages, they realize aircraft attitude adjustment and trajectory control, and their structural integrity directly determines flight safety. Under the actual service conditions, rudder plane structures will inevitably suffer various instantaneous and high amplitude impact loads. Characterized by short duration, high load peak, and strong randomness, such loads are far beyond the influence of conventional aerodynamic loads, and are easy to cause the deformation, fatigue cracks, or even instantaneous failure of rudder plane structures.

However, direct measurement of impact loads faces significant technical bottlenecks in practical research. On the one hand, the extremely short duration of impact makes it difficult for conventional force sensors to accurately capture the time-domain waveform of loads. On the other hand, direct installation of force sensors on the surface of rudder planes can easily change the mass distribution and boundary conditions of the structure, thus interfering with the true dynamic response of the structure. Therefore, dynamic load identification technology, which infers the magnitude and distribution of impact loads based on structural dynamic responses, has become the core means to solve this problem, and it is also a research hotspot in the field of structural dynamics inverse problems.

Dynamic load identification is an ill-posed problem in structural dynamics inverse problems. Small errors in structural responses can lead to significant deviations in load identification results. The core difficulty of impact load identification is that there is a strong nonlinear mapping relationship between impact loads and structural responses. Traditional model driven methods rely on accurate structural dynamic models, while the material parameters and boundary constraint stiffness of the actual model in engineering are difficult to accurately determined, which is easy to lead to deviations in identification results. In addition, impact response signals are often accompanied by noise interference, which further exacerbates the ill-posedness of the inverse problem.

Dynamic load identification belongs to the second type of inverse problem of structural dynamics, which was first proposed in the aviation field around the 1970s. There is an ill-posed problem in

solving this kind of inverse problem. For this reason, many methods have been proposed. A new kind of time-domain dynamic load identification method using the implicit Newmark-β method and the improved basis function were proposed [1]. This method considered the unknown initial conditions and solves the problem that load identification methods may be sensitive to initial conditions. In the case that most load identification methods need to know the excitation location of the load in advance, Li et al. [2] came up with a sparse Bayesian framework to simultaneously identify both location and time history of the load, which considered the uncertainty of input load and response measurement, and then reconstructed the global response of the structure. Through numerical simulation and experimental verification, the results demonstrated that their method exhibits precise response reconstruction and load identification capabilities. Aiming at single-point and multi-point loads identification, Chang et al. [3] proposed an implicit Landweber method, and verified the effectiveness and robustness of the method through simulation and transonic wind tunnel tests of a spacecraft model. He et al. [4] proposed a method that can identify structural-acoustic coupled system with random sound pressure load. In their study, the adaptive selection of regularization parameters helped addressing the ill-posedness problem in dynamic load identification while mitigating error amplification.

However, when using traditional physics-based models in dynamic loads identification, those methods often suffer from noise disturbance, ill-posedness of matrices, and difficulties in constructing frequency response function matrices. To address these issues, scholars have conducted extensive researches on data-driven methods for dynamic load identification [5]. Early in 1998, Cao et al. [6] adopted Artificial Neural Network (ANN) to identify the dynamic loads on an aircraft wing model by simplifying wing structure as cantilever beam, and the nonuniform distributed aerodynamic loads acting on the wing model were approximated by a group of concentrated loads. It was proved that the ANN can identify aerodynamic loads effectively, and the well-trained ANN model has very fast convergence rate and high precision for the load identification on the cantilever beam. Subsequently, many scholars performed researches on load identification problem using deep learning technology [7][8]. Yang et al. [9] developed an innovative approach of dynamic load identification using deep Dilated Convolution Neural Network (DCNN). They used this method to identify several types of loads on simply supported beams, and analyzed the dynamic systems with uncertain model parameters. It is found that this method is suitable for systems with uncertain parameters. In their study, the inverse model between excitation and response was directly constructed by using the black box model of neural network to avoid solving the model parameters. In 2021, Xia et al. [10] proposed a reverse sequence dynamic load identification approach by adopting conventional recurrent neural networks (RNNs) based on impulse response functions. The feasibility of their method was validated by identifying multi-point random concentrated dynamic loads and distributed dynamic loads. In 2022, Aiming at accurately identifying stationary random loads in broad frequency band, Yang et al. [11] proposed a feature extraction method for stationary random signals using wavelet transform, and thus established the identification method for stationary random loads using Long Short-Term Memory (LSTM) neural networks.

In engineering applications, especially for large and complex structures, it is difficult to establish an accurate dynamic model of structural. Therefore, researchers are committed to developing a dynamic load identification method based on neural network, which does not depend on the dynamic model of structural.

The Nonlinear Autoregressive with Exogenous Inputs (NARX) neural network has inherent structural characteristics that are highly compatible with the core requirements of impact load identification. Equipped with output feedback loops, this network can predict the impact load at the current moment by adopting historical time-series data of structural responses, and such a structural feature is well consistent with the dynamic coupling law between impact loads and structural responses. The instantaneous response of a structure is governed not only by the impact load input at the current time, but also closely associated with the structural vibration state excited by previous impact loads. By capturing the temporal correlation between historical responses and real-time loads, the network can effectively reproduce the dynamic evolution process of the coupled system of impact loads and structural responses. Under impact excitation, structures may produce nonlinear mechanical behaviors including local plastic deformation and modal coupling, and traditional linear modeling methods are incapable of accurately describing the complex nonlinear mapping relationships

between them. Relying on the nonlinear mapping ability of multilayer perceptrons, the NARX neural network can directly explore and learn the nonlinear correlations between the time series of impact responses and impact loads from simulation and experimental data. As a typical data-driven model-free identification method, it does not depend on accurate analytical models of structural dynamics, and effectively makes up for the limitations of traditional model-driven methods in solving nonlinear problems. Meanwhile, with the aid of data fitting and weight parameter optimization during training, the NARX neural network can suppress the adverse effects of noise within a certain range. Compared with conventional methods for solving inverse problems in structural dynamics, this network presents better identification stability and ensures the reliability of impact load identification results under noisy conditions.

Taking an aircraft rudder plane model as the research object, this paper carried out simulation and experimental research on impact load identification based on the NARX neural network.

## 2. Methodology

### 2.1 NARX Neural Network

NARX neural network is a kind of neural network based on autoregressive model, which has strong time series modeling capability and is particularly suitable for prediction and time series analysis. Its core concept is to map the input sequences to the output sequences through regression analysis, while using previous outputs and current inputs to predict the current output. This characteristic enables the NARX neural network to perform well in capturing dynamic relationship in time series data, which is highly compatible with the requirements of impact load identification. The NARX neural network consists of input layer, hidden layer, and output layer. It is trained using the backpropagation algorithm, and continuously optimizes the weights and parameters of the network by minimizing prediction errors. The model structure is shown in Figure 1.

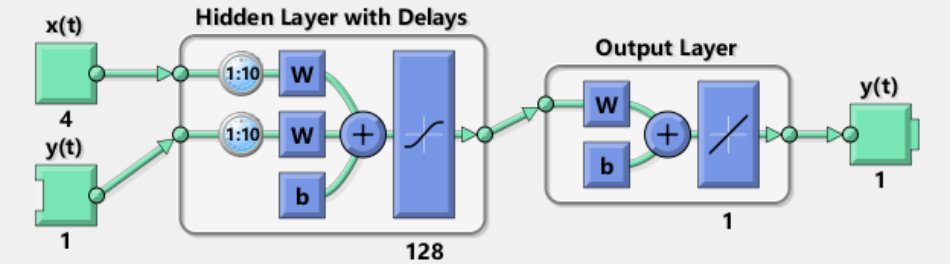



Figure 1 – Schematic diagram of the NARX neural network structure.

The process of applying the NARX neural network for impact load identification can be divided into the following steps:

(1) Data acquisition: obtain load-response data of the aircraft rudder plane model under single point impact load through finite element simulation or experiment, which are used as input-output data for neural network training.

(2) Network initialization: set the number of neurons in the input layer, hidden layer, and output layer, and randomly initialize the weights and biases of the network.

(3) Forward propagation: calculate the output values of the hidden layer and output layer according to the input data and network structure until the final prediction results are obtained.

(4) Loss calculation: calculate the error loss between the prediction results and actual labels in the validation set to evaluate the performance of the network.

(5) Back propagation: update the weights and biases of the network through the backpropagation algorithm based on the loss calculation results to reduce prediction errors.

(6) Iterative optimization: repeat the processes of forward propagation and back propagation to continuously optimize the network performance until the preset training target is achieved. Finally, the identification results of the impact loads acting on the structure by the neural network are obtained through the test set.

In the research scenario of this paper, the inputs and outputs of the NARX network are clearly defined as follows:

- Exogenous inputs: the time-series impact response data measured at key points of the aircraft rudder plane model. In this study, acceleration time-history curves are selected and collected

by sensors installed at the free end and the middle section of the rudder plane model.

- Feedback inputs: historical load prediction values derived from the network output layer, which serve to capture the temporal correlation characteristics of impact loads.
- Model output: the time-series curve of the target impact load.

The network is trained with response-load sample datasets acquired from drop hammer impact simulations and experiments. On this basis, a nonlinear mapping relationship from structural response signals to impact loads can be established, which enables the accurate identification of unknown impact loads.

Time delay refers to the process of delaying input data or signals for a certain period of time in a network model, and then performing calculations and processing. In NARX neural networks, time delay is an important component that can help the network better capture long dependencies and periodic features in time series data. The time delay of NARX neural network has the following characteristics:

(1) Adaptive: The network can automatically select the appropriate time delay value based on the characteristics of the data, avoiding the tedious process of manually setting the delay.
(2) Nonlinear: The delay process of NARX neural network adopts a nonlinear mapping function, which enables the network to better adapt to the characteristics of complex data patterns.
(3) Scalability: The time delay is not limited to a fixed delay value and can be extended according to the distribution of data, improving the network's fault tolerance and generalization ability.

While the impact of time delay on NARX neural networks is mainly reflected in the following two aspects:

(1) Feature extraction: Time delay can help NARX neural networks capture long-term dependencies and periodic features in time series data, thereby better extracting features from input data.
(2) Model performance: Reasonable time delay can improve the training efficiency and prediction accuracy of NARX neural network, while also enhancing the network's generalization ability and robustness.

The designed NARX neural network model for aircraft rudder plane impact load identification has 128 neurons in the hidden layer, with the Sigmoid function as the neuron activation function. The time delay coefficient is set to 10, indicating that the previous 10 groups of data in the sequence are involved in the training of the current moment. The output layer is a fully connected layer, and the activation function of output layer neurons is the tanh function.

## 2.2 Inverse Problem of Impact Load Identification

For a linear time-invariant system, assuming initial conditions $y(0)=0$ and $\dot{y}(0)=0$, the system response $y(t)$ can be described by the convolution relationship between the input excitation $f(t)$ and the unit impulse response function $h(t)$:

$$y(t)=h(t)\otimes f(t)=\int_{o}^{t}h(t-\tau)f(\tau)d\tau \tag{1}$$

Where $\otimes$ represents the convolution operation; $\tau$ represents the time shift factor and satisfies $t>\tau$; $y(t)$ represents the system response, such as acceleration, velocity, displacement, strain or other physical quantities that are easy to measure.

Eq. (1) describes a positive problem, that is, solving the response of the known system excitation and transfer function is known. For the load identification problem, an inverse problem analysis method needs to be applied to determine the unknown excitation force acting on the structure. By discretizing Eq. (1) in time domain, the following matrix form can be obtained:

$$Y_s=H_sF \tag{2}$$

$F$, $Y_s$, $H_s$ are the impact load vector, impact response vector and transfer function matrix after discretization in time domain. The transfer function matrix Hs is usually ill-posed and has a large condition number. Therefore, the solution obtained by directly inverting Eq. (2) to identify the impact load is usually unstable and has a very large error. While the neural network method can solve such problems more accurately. Based on this, this article uses the NARX neural network to identify the impact load is a very suitable method.

## 3. Simulation of Impact Load Identification

Taking the aircraft rudder plane model shown in Figure 2 as the research object. The finite element model of the aircraft rudder plane is established in the finite element software for dynamic simulation, which is shown in Figure 3.

Firstly, the modal analysis of the aircraft rudder plane model is carried out. The first four natural frequencies of the model are measured by experiments as 9.490Hz, 33.691Hz, 83.330Hz and 99.151Hz. The modal analysis of the finite element model established above shows that the first four modal frequencies of the finite element model are 9.491Hz, 33.445Hz, 83.333Hz and 99.152Hz. The comparison error between the two is less than 1%.

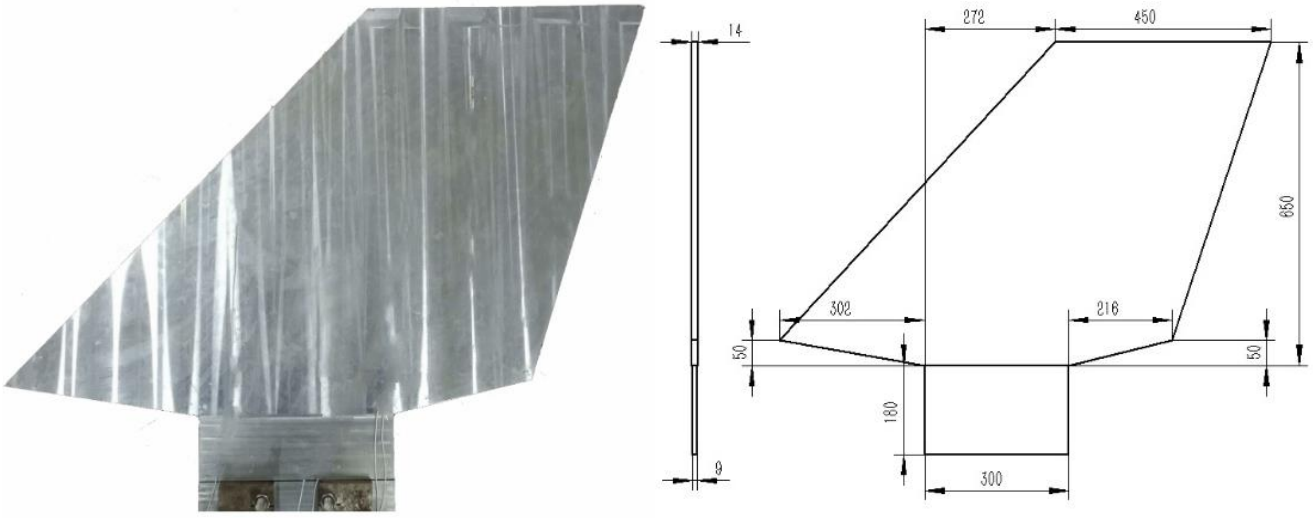



Figure 2 – Geometric dimension of the rudder plane model.

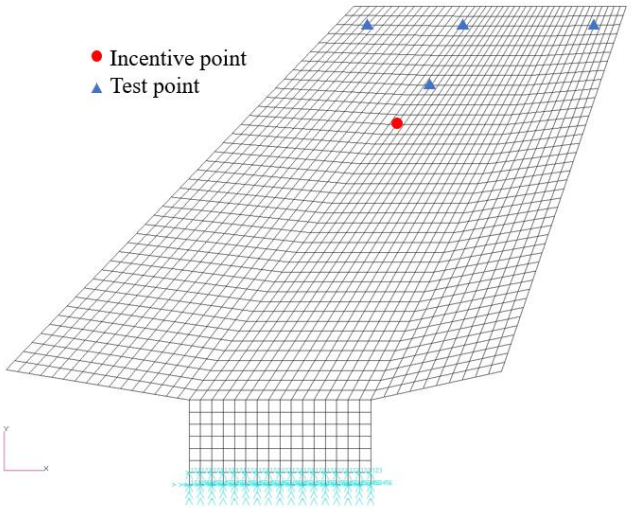



Figure 3 – The finite element model of the aircraft rudder plane model and the location of the excitation point and test points.

The time series response data of each measuring point under the single point impact load condition were obtained to form the input-output data set of the neural network. All data were randomly divided into 80% as the training set, 15% as the cross validation set, and 5% as the test set, so as to improve the identification performance of the neural network.

Considering that practical engineering structures are subjected to random load excitations while bearing impact excitations, this paper takes the impact loads formed by superimposing random signals and half-sine wave signals as a special type of impact load for identification research, which is defined as burr-contained impact load. In addition, the impact loads acting on engineering structures are not limited to single impact forms, and consecutive double impacts or triple impacts also commonly occur in practice. Correspondingly, they are defined as double-peak impact load and triple-peak impact load in this study respectively.

Then establish a NARX neural network model and use it to identify the impact load on the rudder

plane model. The first layer of NARX neural network is the sequence input layer, which inputs the acceleration response data of the test points on the rudder plane. The second layer is the NARX layer, which is the time recurrent neural network layer. The third layer is the activation function layer to increase the non-linear expression ability and improve its fitting effect. The fourth layer is a fully connected layer, and each node of the fully connected layer is connected to all the nodes of the previous layer, which is used to integrate the features extracted from the front. The output layer is the regression layer, which is used to fit data. The structure of NARX neutral network is shown in Figure 4.

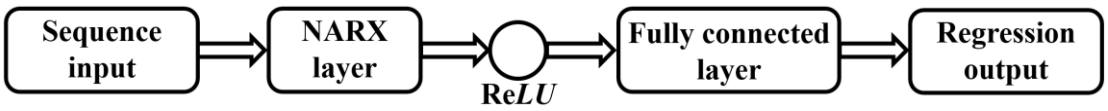



Figure 4 – Structure of NARX neural network model.

After designing the neural network model, use the input and output data obtained earlier to train the NARX neural network.

The well-trained NARX neural network is tested with the aforementioned test sets respectively to acquire the identified time histories of impact loads. These identified results are compared with the real time histories of impact loads in the test sets. Furthermore, the peak values of both datasets in each test group are extracted to calculate the relative errors, and the specific identification results are illustrated in Figure 5.

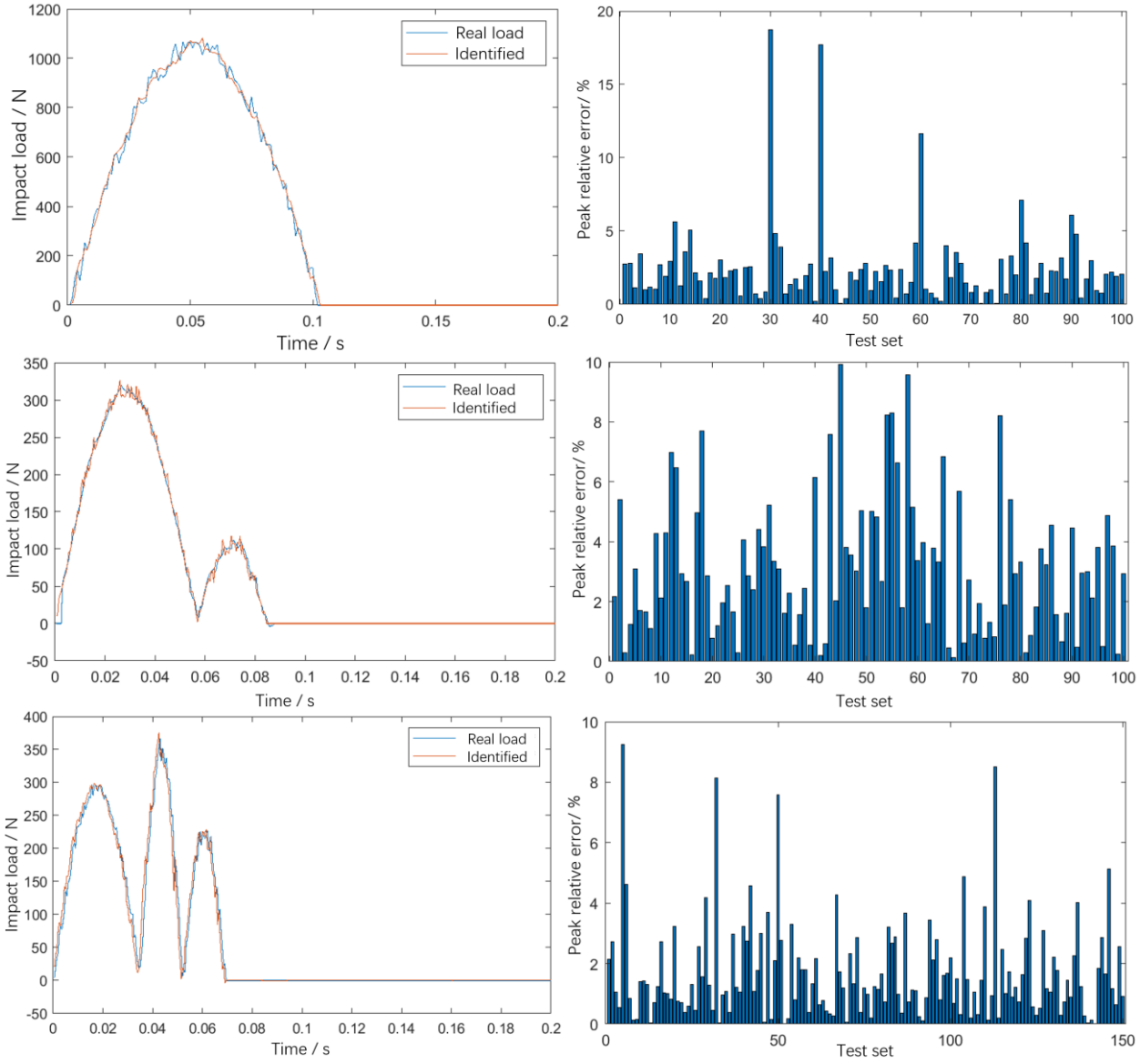



Figure 5 – Comparison of time-history identification results and peak relative errors of the test set.

In the figures, the blue curves represent the real impact load, while the red curves stand for the identified impact load. It can be observed that the identified waveform hardly produces phase shift or bandwidth deviation, and most burr features of the real impact load can be well fitted. It can be seen from the load time history comparison diagrams, the method proposed in this paper can effectively identify the time history curves of single-peak, double-peak, and triple-peak impact loads with burrs, and the average peak relative error is all below 5%, which can achieve good identification effect.

## 4. Experimental verification

This section carries out experimental investigations on impact load identification of the aircraft rudder plane model introduced in Section 3.

The aircraft rudder plane model was horizontally fixed on the test bench with its root rigidly supported. The PCB 086C04 force hammer was used to apply impact excitation to the test piece, and the sensitivity of the force sensor equipped on the impact hammer is 11.28 mV/N. Select four response measuring points on the upper surface of the cantilever plate to measure the acceleration response signal. The adopted acceleration sensor is PCB 333B30 with a sensitivity of 100 mV/g, which is attached to the upper surface of the control surface model using beeswax. A multi-functional signal acquisition instrument of model SIRID-8×STGM-8×AO developed by DEWESoft is utilized for signal collection. The layout of excitation points and test points of the model, as well as the site of the impact excitation experiment, are shown in Figure 6.

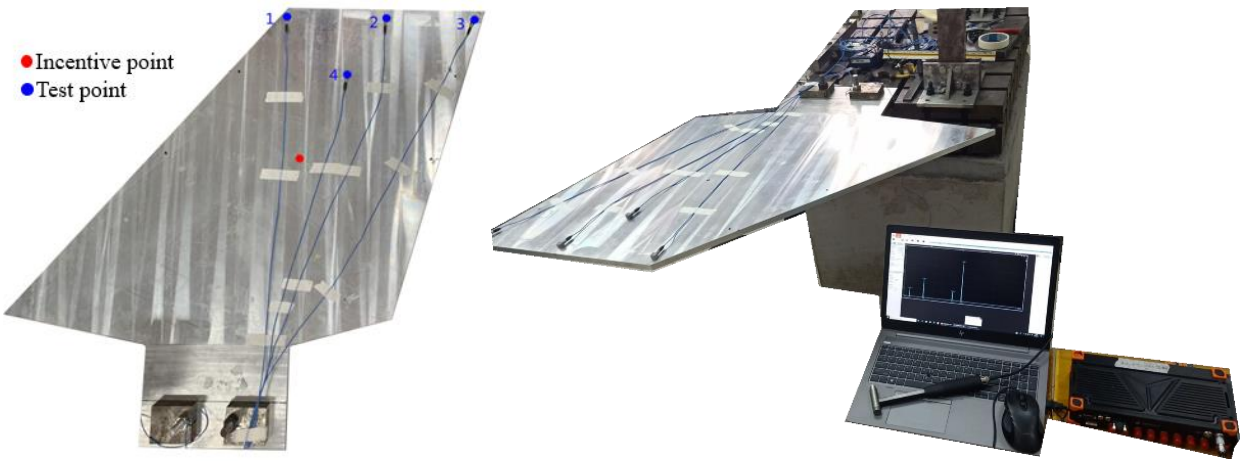



Figure 6 – Excitation point and test points layout of the model and impact excitation experiment site.

The acceleration response data of the aircraft rudder plane model under the impact of the force hammer were obtained through experiments as the training data of the neural network model for training. Then, the trained neural network and the acceleration response data under the impact excitation were used to identify the real impact load. A total of 250 sets of load-response data are acquired. Among them, 200 sets are selected for neural network training, and the remaining 50 sets are used for identification verification, so as to test the identification performance of the network and carry out error analysis. After the completion of neural network training, the trained NARX neural network was tested using the test set to obtain the identified impact load data. The identified data were compared with the real impact load data of the test set, and the peak values of both were extracted from each group of test sets to calculate the relative errors. The specific results are shown as follows:

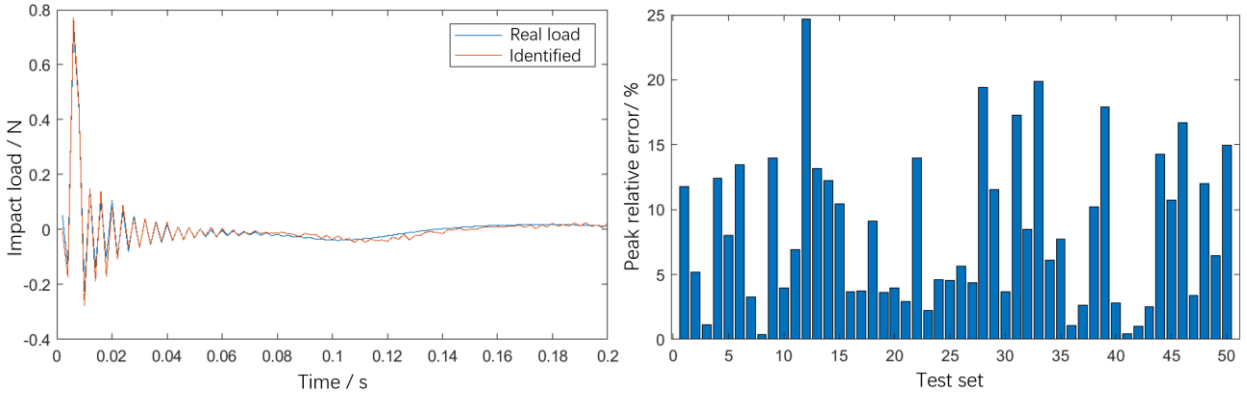



Figure 7 – Comparison of time-history identification results and peak relative errors of the test set.

The identification results show that the method proposed in this paper can effectively identify the peak values and waveforms of impact loads acting on the rudder plane model in both simulation and experiment. In the experimental cases, the average peak relative error of impact load identification in the test set is 8.29%. At the same time, the time-history reconstruction of impact load is quite accurate. These results demonstrate the application advantages of the method, indicating its potential for promotion to engineering practice, and providing a novel data-driven solution for impact load identification of aerospace structures.

## 5. Conclusion

In this study, the NARX neural network is adopted to train and test the datasets of impact loads and corresponding structural responses acting on the aircraft rudder plane model. The time history identified results obtained from the NARX neural network for each group of test samples are compared with the real impact loads. Combined with the quantitative analysis of peak relative errors and qualitative analysis of randomly selected single-group waveform comparisons, the identification results are evaluated from the perspectives of peak error and phase deviation.

The identification results demonstrate that the NARX neural network achieves satisfactory performance in identifying impact loads acting on the aircraft rudder plane model, with the average peak relative error of all identified results less than 10%. In addition, the comparison between time-domain data of identified and real impact loads verifies that the proposed network can accurately reconstruct the waveform characteristics of real impact loads.

Apart from methodological innovation, this research also possesses prominent practical engineering significance, which is summarized as follows:

(1) Breaking the linear assumption and model dependence limitations of traditional load identification methods

Traditional model-driven methods usually regard structures as linear elastic models and rely on high-precision finite element models. In contrast, the NARX neural network is free from predefined structural dynamic models and can directly process nonlinear response data generated in impact events. It establishes a universal framework for impact load identification of strongly nonlinear structures and enriches the solution theories for data-driven inverse problems in structural dynamics.

(2) Providing a lightweight solution for on-site impact load monitoring of aircraft rudder planes

In practical engineering applications, the impact load monitoring of aircraft rudder planes is restricted by limited sensor installation space and computing resources. Benefiting from its lightweight structural features, the NARX network can be embedded into miniaturized data acquisition devices. By collecting vibration response signals at key positions of rudder planes, it realizes online real-time impact load identification and provides early warnings against foreign object impacts, abrupt variations of aerodynamic loads and other abnormal events during flight.

(3) Promoting the interdisciplinary integration of neural networks and impact dynamics of aeronautical structures

By introducing the NARX neural network into the field of impact load identification for aircraft rudder planes, this study constructs a complete technical chain covering experimental data acquisition, network training optimization and inverse load identification, which provides a typical

research paradigm for the interdisciplinary combination of aeronautical structural dynamics and machine learning. Furthermore, the training and verification strategies of the NARX network based on the control surface model can be extended to the impact load identification research of other aeronautical structures such as wings and fuselages, offering a replicable technical route for anti-impact design and structural health monitoring of aeronautical structures.

The limitation of impact load identification method based on neural network is that there are no rules to determine the network structure, and the parameters of network also need to be optimized. However, due to the strong nonlinear fitting ability of neural network, it provides an effective way to the large-scale complex structure and non-linear structure impact load identification problem, which is difficult to be solved by traditional methods, so this method has prospect in engineering applications.

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