https://doi.org/10.5755/j02.eie.40795 ELEKTRONIKA IR ELEKTROTECHNIKA, ISSN 1392-1215, VOL. 31, NO. 2, 2025

Damage Identification of Conduit Rack in Offshore Platform Structures Based on a Novel Composite Neural Network

Jiaqiang Yan[1], Yuanchao Qiu[1,*], Renhe Shao[2], Ziqiao Ling[1], Ruixiang Zhang[1]
[1]*College of Engineering, Ocean University of China, Qingdao 266100, China*
[2]*School of Electrical and Electronic Engineering, Huazhong University of Science and Technology, Wuhan 430074, Hubei Province, China*
[*]*yjq0522@126.com; qyc@ouc.edu.cn; M202472412@hust.edu.cn; 21220913088@stu.ouc.edu.cn; 2438019960@qq.com*

***Abstract*—Structural health monitoring (SHM) of offshore jacket platforms is crucial, and currently traditional deep learning methods such as artificial neural networks (ANNs) are widely used in damage identification of offshore conduit rack platform structures, which focusses on mapping feature information caused by damage to structural damage patterns. However, traditional methods have limitations in dealing with the time series data in the feature information. To improve the application of the time series information generated from offshore platform structures in damage modes, we propose a new integrated deep learning network model, which is used to improve the accuracy of the damage mode recognition based on the acceleration information of the conduit rack structure. First, the temporal convolutional network (TCN) breaks through the localisation of traditional convolutional neural networks in modelling the temporal dimension by efficiently extracting the long-term time since of the structural vibration response through an expansive causal convolution mechanism. Second, the bidirectional long short-term memory network (BiLSTM) further extracts the contextual information and global features of the data by extracting feature information in both directions and fusing the before and after correlations of vibration response signals. In addition, we adopt the Newton-Raphson-based optimiser (NRBO) optimisation algorithm for global optimisation of the hyperparameters of TCN and BiLSTM to avoid the subjectivity of manual parameter tuning, which significantly improves the model convergence speed and generalisation performance. Experimentally validated by finite element model simulation and testbed construction, our proposed NRBO-TCN-BiLSTM combined neural network damage identification accuracy is as high as 99 % on average, exceeding existing deep learning methods. The method has a wide range of applications in SHM for offshore platforms.**

***Index Terms*—Composite neural network; Damage identification; Offshore jacket platforms; Structural health monitoring.**

I. INTRODUCTION

A. *Research Background*

The ocean is rich in oil and natural gas resources, and offshore conduit rack platforms are an important part of the oil and gas resource development facilities [1]. The marine environment is complex and variable, and due to the long service cycle, the offshore conduit rack structure is directly exposed to the harsh marine environment and needs to withstand the harsh environmental loads such as wind, waves, ice, and currents for a long period of time, so the conduit rack structure will unavoidably produce various degrees and type of damage, e.g., corrosion, fracture, etc. [2]. As an important part of the offshore conduit rack platform, damage to the conduit rack structure can directly cause serious harm to the platform, resulting in huge economic losses and personnel safety risks [3], [4], therefore, it is very necessary to carry out SHM of the offshore conduit rack structure to ensure the safety and reliability of the offshore conduit rack platform [5].

Accurate damage identification methods are crucial for structural health monitoring (SHM) of marine conduit frame structures; among the traditional damage identification methods, ultrasonic-based acoustic wave methods have been widely used in the field of structural damage identification [6], which use sound waves propagating in the medium to interact with the structure and receive the reflected signals, the ultrasonic method has a higher frequency and shorter wavelength and can accurately locate and detect defects such as tiny cracks, voids, corrosion, and delamination on the surface and inside the structure [7]. In marine environments, where temperature and humidity are highly variable and there are noise disturbances, such as waves and sea breeze, ultrasonic waves usually require clean and well-lubricated structural surfaces to drive the sound waves, and in the case of submerged conduit rack structures, the inspection process is even more difficult and is based on underwater robots, which are measures that can add significant economic costs [8]. The method based on vibration signals is considered one of the most promising methods for structural health inspection, which is used to assess the state of damage of a structure by analysing the vibration response of the structure under dynamic loading and extracting the changes in modal parameters [9]. According to the advantages of the vibration signal that reflects the overall dynamic characteristics of the structure, the parametric method can effectively detect the effect of local damage on the overall stiffness or mass distribution, because it is not necessary to carry out the

Manuscript received 19 November, 2024; accepted 25 February, 2025.

acquisition of damage information at the location of the damage. The parametric method is particularly suitable for offshore conduit rack structures and other large-scale complex structures. Its effectiveness in structural damage monitoring was demonstrated through a series of validation experiments [10]. The disadvantage is that the modal parameters are highly sensitive to environmental factors, and in the marine environment, the severe environmental noise leads to the blurring of the fault characteristics in the modal information, which has a greater impact on the damage identification [11].

Although all of the above methods have been widely used in the field of structural health monitoring and the effectiveness of these methods has been verified in experiments, the influence of harsh environmental factors in the ocean limits the application of these methods in the field of offshore engineering [12], so we need more cutting-edge techniques to be applied in the task of identifying damage to offshore conduit rack platforms.

B. Related Work

With the development and advancement of computer technology, artificial intelligence and machine learning algorithms have been innovated and have made breakthroughs in the fields of automatic driving, speech recognition, large models, and computer vision [13]. Deep learning algorithms have excellent data processing capabilities, so they are widely used in the field of engineering signal processing and have achieved a series of breakthrough results [14]. With excellent feature extraction and data classification capabilities, deep learning methods are increasingly applied to structural damage recognition. Compared to traditional damage recognition methods, deep learning methods do not require manual presetting of modal parameters, and can directly capture sensitive damage feature information that is easily ignored in traditional methods by extracting feature information from structural dynamics signals (acceleration, velocity, and displacement), with good fault tolerance and robustness [15]. The artificial neural network (ANN) is the starting point of neural network development, and many modern neural network techniques are based on its continuous development and innovation [16]. Gifalli *et al.* [17] used ANN models to process and analyse time series information in the kinetic structure to obtain damage features to identify damage patterns. The convolutional neural network (CNN), on the other hand, is based on ANN to better extract the spatial features of the digits through convolutional operations, etc. to improve the recognition accuracy. Bao, T. Fan, Shi, and Yang [18] proposed a one-dimensional convolutional neural network model for damage identification of offshore conduit rack structures, where displacement data obtained from the sensors are preprocessed by the randomised decreasing technique (RDT) and fed into a convolutional neural network to extract key damage features for damage identification of conduit rack structures. Although CNNs have powerful feature extraction capabilities, they cannot effectively capture the time dependence of data when processing the temporal information measured by the sensors. The recurrent neural network (RNN) focusses on processing time series data, but suffers from serious gradient vanishing and gradient explosion problems [19]. Long short-term memory (LSTM) is a special kind of recurrent neural network, which can efficiently capture long-term dependencies in time series information by introducing the gating mechanism and the cell state mechanism [20]. Bao, Fan, Shi, and Yang [21] compare the effectiveness of two deep learning models, CNN and LSTM, in the task of conduit rack structure damage identification, and propose a CNN-LSTM model that enhances the application of time series information while retaining the powerful feature extraction capability, and this integrated deep learning model effectively improves the accuracy of offshore conduit rack structure damage identification. However, LSTM can only capture forward time series information, which has some limitations. Wang *et al.* [22] proposed a CNN-BiLSTM deep learning model, using BiLSTM to simultaneously process time series information in both forward and backward directions, which is capable of fully integrating the upper and lower time series information, and at the same time the model also integrates the squeeze and excitation network attention mechanism, which can evaluate the importance of CNN-extracted features and select damage-sensitive features; the proposed integrated deep learning model has high accuracy in the offshore conduit rack structure identification task.

The aforementioned studies have unequivocally demonstrated that the integration and refinement of models have led to a remarkable augmentation in the accuracy of damage identification for offshore jacket structures. However, in the relentless pursuit of improved precision and efficiency, continuous exploration in research remains imperative. With the escalating complexity of the identification tasks of structural damage propelled by time series information, traditional models have increasingly manifested limitations in processing long sequences and capturing global features.

With the increasing number of structural damage identification tasks driven by time series information year by year, temporal convolutional neural networks have gradually gained attention in the field of structural health monitoring [23]. Compared to CNN, the temporal convolutional neural network (TCN) adopts the core mechanism of causal convolution and dilated convolution, which can effectively process time series information, capture global features, and can be parallelised for computation to improve training efficiency [24]. At the same time, it effectively combines the advantages of BiLSTM that can process time series information in both directions and make full use of context information.

C. Contribution and Novelty

This paper proposes an integrated TCN-BiLSTM deep learning model, which can effectively process the time series information collected by the sensors to accurately identify offshore conduit rack damage. To avoid overfitting during model training, we use the Newton-Raphson-based optimiser (NRBO) optimisation algorithm to globally find the optimal hyperparameters of the TCN and BiLSTM, avoiding the subjectivity of manual parameter tuning, and significantly improving the model convergence speed and generalisation performance [25]. Finally, we carry out experimental validation through simulation of finite element models and testbed construction. After several experimental validations, as well as data analysis, our NRBO-TCN-BiLSTM model has an accuracy of up to 99 % in the task of structural damage identification of conduit racks, which exceeds the existing deep learning methods. This method has a wide application prospect in the structural health inspection of offshore platforms.

D. *Paper Organisation*

This paper is organised as follows. Section II introduces the proposed methodology and principles. In Section III, we build a model of the offshore conduit rack structure using MATLAB code and validate the simulation data using the proposed neural network model. In Section IV, we build a testbed based on the simulation model for experimental evaluation to validate the validity of the methodology, and in Section V, we summarise and draw conclusions.

II. METHODS

To improve the ability to accurately identify damage to offshore conduit rack structures using time series information from feature information and to improve the service life and safety of offshore conduit rack platforms, we propose a novel integrated deep learning neural network, which combines two types of neural networks, the temporal convolutional network (TCN) and the BiLSTM, and is capable of effectively processing time series information for damage identification of offshore conduit rack platforms. To avoid overfitting during model training, we use the Newton-Raphson-based optimiser optimisation algorithm to globally find the optimal hyperparameters of the TCN and BiLSTM. The framework of our approach is shown in Fig. 1.

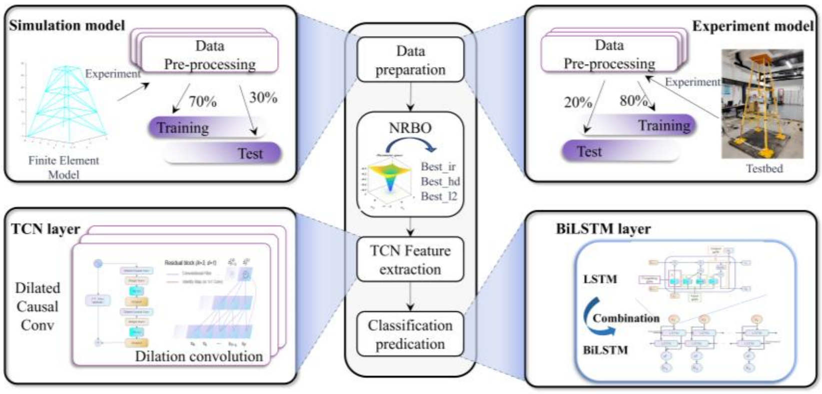


Fig. 1. Schematic diagram of the system flow.

The framework flow of the proposed research method is as follows.

Data Preparation: Use MATLAB code to construct a finite element model of the offshore conduit rack structure, get the data after damage, preprocess the data and divide them into training and testing sets, build a real conduit rack test bed based on the finite element model, get the data after simulating the damage conditions, and divide the data and training sets after the same preprocessing.

TCN Layer: The TCN model efficiently extracts local features from vibration signals through dilated causal convolution stacking.

BiLSTM Layer: The BiLSTM model is time-dependent from both positive and negative directions to enhance global feature extraction capability under complex damage conditions. The mapping relationship between damage patterns and feature information is also constructed.

NRBO: There are multiple hyperparameters in the training process of the proposed integrated deep learning model, and we use the latest Newton-Raphson-based optimiser optimisation algorithm to perform parameter optimisation for the number of hidden layer units, the initial learning rate of the model training, and the L2 regularisation coefficient of the BiLSTM.

A. *Data Preparation*

In our overall workflow, we need to collect two parts of the data. One part is to establish the finite element model of the offshore conduit rack structure through finite element modelling and simulate different damage conditions in the finite element model to get the vibration information of the finite element model under different damage modes. The other part of the data comes from the test rig we built in the laboratory, which is similar to the simulation model to obtain the vibration information of the structure under different damage modes. The data-related processing flow is shown in Fig. 2.

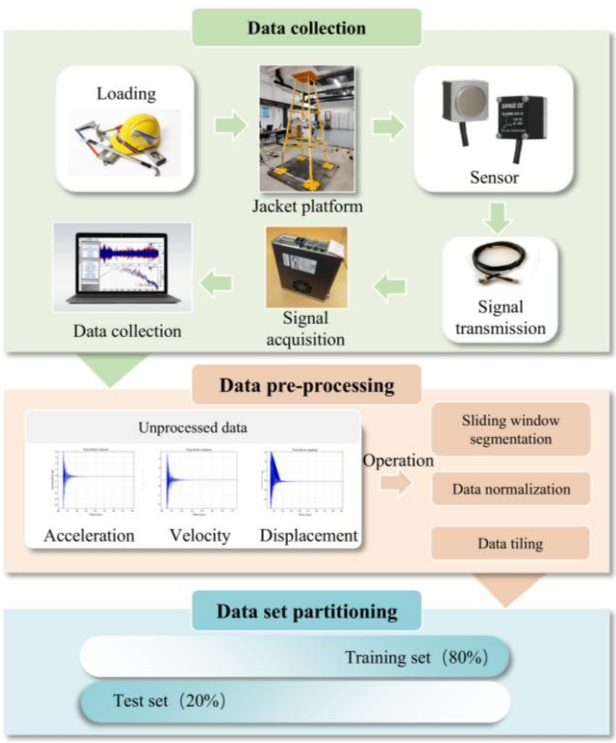


Fig. 2. Data-related processing flows.

After obtaining the vibration signal data under different damage modes from the test bench experiment and the finite element simulation model, we need to preprocess the data to enhance the usability of the data. In deep learning models, common data processing methods include data transposition, data segmentation, data cleaning, data labelling, and data normalisation. In the process of integrating deep model training, we need to split the data set proportionally into training set and test set to evaluate the effectiveness of our model.

In the data preprocessing process, we use overlapping segmentation to maximise the use of the data (1)

$$X_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}, \tag{1}$$

where x_{norm} is the normalised data, x is the original data, and x_{max} and x_{min} are the maximum and minimum values in the original data. The data normalisation process can effectively solve the problem of data scale inconsistency and improve the stability of the deep learning model, while the consistent range of features facilitates the visual analysis of the model effect.

After normalising the data for training, we have to convert the normalised data from matrix to cell array to meet the requirements of the subsequent inputs of the composite neural network model.

B. Model Architecture

The novel composite neural network model that we propose is mainly composed of the TCN layer and the bidirectional long short-term memory (BiLSTM) layer.

TCN is a deep learning architecture specifically designed for modelling temporal data, which overcomes the limitations of recurrent neural networks (RNNs) in terms of long-range-dependent learning and training efficiency by improving the temporal adaptation capability of traditional convolutional neural networks (CNNs). The core design of TCN has three parts which are causal convolution, inflationary convolution, and residual linking. The network architecture of TCN is shown in Fig. 3.

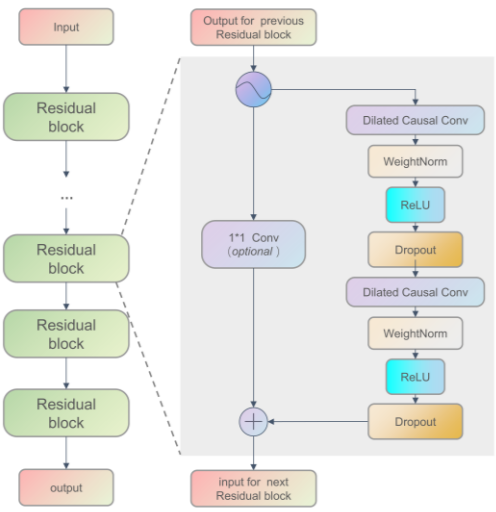


Fig. 3. TCN network.

While causal convolution preserves temporal causality by linearly stacking convolutional layers to capture long-range dependencies, this approach inevitably leads to increased model complexity. In TCN, dilated convolution overcomes this trade-off by exponentially expanding the receptive field with fewer layers, thus maintaining modelling efficiency while avoiding excessive parameter accumulation. The dilation convolution gradually increases the receptive field through an exponentially expanding dilation factor (dilation factor), which effectively captures long-range temporal dependencies. The schematic diagram of dilation convolution is shown in Fig. 4.

The output sequence $\hat{\boldsymbol{y}} = [\hat{y}_0, \hat{y}_1, \ldots, \hat{y}_T]$ of the expansion convolution operation F for the input x can be expressed as in (2)

$$\hat{y}_t = \sum_{i=0}^{K-1} k_i \cdot x_{t-d \cdot i}, \tag{2}$$

where d is the dilation factors, K is the convolution kernel size (filter size), valid for $t - d \cdot i \geq 0$, otherwise handled by zero padding.

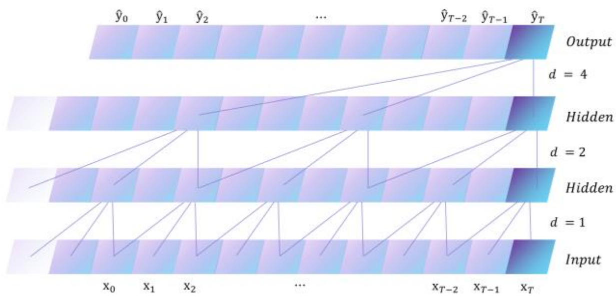


Fig. 4. Dilation convolution.

The third core introduces a cross-layer residual block to alleviate the problem of gradient vanishing in deep networks and improve the feature reuse capability of the model. The residual block allows deep learning networks to transfer information across layers, preventing information loss that may occur due to too many layers. A residual block contains two layers of convolution and nonlinear mapping, and WeightNorm and Dropout are also added in each layer to regularise the network. A 1*1 convolutional layer is also applied after the convolutional layer to perform a dimensionality reduction operation to ensure consistency of the input and output.

After introducing the TCN layer, we will introduce the BiLSTM layer. BiLSTM is a modified RNN specifically designed to process sequence data. BiLSTM is able to capture bidirectional dependencies in sequences by combining the outputs of both forward and backward LSTM networks. BiLSTM is able to capture bidirectional dependencies in sequences by combining the outputs of both forward and backward LSTM networks.

LSTM overcomes the problem of gradient vanishing and gradient explosion in traditional RNNs when processing long sequences by introducing gate mechanisms (input gate, forget gate, and output gate). A single LSTM is shown in Fig. 5.

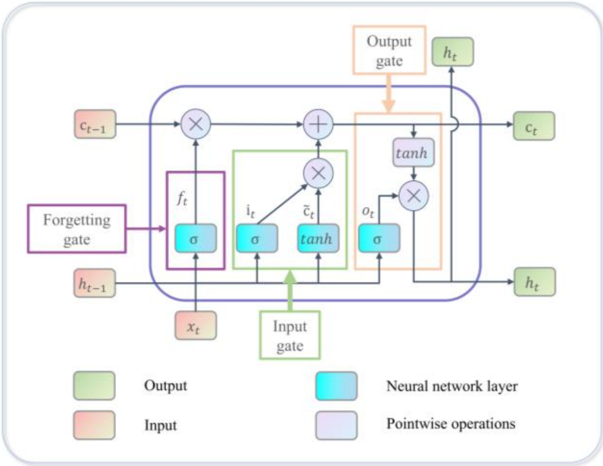


Fig. 5. LSTM network architecture.

From the figure, it can be seen that the three gates, the input gate, the output gate, and the forgetting gate, work together to flow and update the information in LSTM. σ and *tanh* are two different activation functions; σ function uses sigmoid function, which is used to compress the data into the range of $[0, 1]$, and $tanh$ denotes hyperbolic tangent activation function which is used to normalise the data into the range between $[-1, 1]$. Compared to the hidden layer of RNN, LSTM has an extra cell state c_t,the inputs in the graph are the input x_t, the hidden layer state h_{t-1}, and the cell state c_{t-1} at time *t*, and the outputs are the hidden layer state h_t and the cell state c_t.

The input gate is responsible for deciding which information to input into the cell state, the σ function is responsible for selecting the updated parts, and the *tanh* function computes the candidates for generating the updated information:

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right), \tag{3}$$

$$\tilde{c}_t = tanh\left(W_c \cdot [h_{t-1}, x_t] + b_c\right), \tag{4}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t, \tag{5}$$

where $W_i$and W_c are weight coefficients, b_i and b_c are bias constants, and c_t is the current state vector;

$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right), \tag{6}$$

$$h_t = o_t \cdot tanh(c_t), \tag{7}$$

where h_t is the output information at the current time, W_o is the weight coefficient, and b_o is the deviation constant.

The forgetting gate is responsible for deciding to discard that old information from the cell state while retaining the valid information. The inputs to the oblivion gate are h_{t-1} and x_t. A value between 0 and 1 is output via the sigmoid function, with 0 indicating complete discard and 1 indicating complete retention

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right), \tag{8}$$

where h_(t - 1) is the output of the previous moment, x_t is the input of the current moment, W_f is the weight coefficient, and b_f is the deviation constant.

Through the gate mechanism, LSTM can effectively capture long-term dependencies in the classification process and solve the problems of gradient explosion and gradient vanishing to some extent [26].

BiLSTM networks represent an important advance in deep learning. It can enhance the LSTM architecture by processing data in both forward and reverse directions simultaneously. This dual processing approach allows the network to access both past and future contextual information, enriching the model's understanding and interpretation of sequences. In BiLSTM, two independent LSTM layers are used: one processes the sequence from the beginning to the end and analyses the future information of the input data, while the other processes the sequence in the opposite direction to analyse the past information of the input data. The outputs of these two layers are then combined at each time step, usually by concatenation or summation, to produce a single output that effectively reflects both past and future information. The model is shown in Fig. 6:

$$\overrightarrow{h_t} = \overrightarrow{LSTM}\left(h_{t-1}, x_t, c_{t-1}\right), t \in [1, T], \tag{9}$$

$$\overleftarrow{h_t} = \overleftarrow{LSTM}\left(h_{t+1}, x_t, c_{t-1}\right), t \in [1, T], \tag{10}$$

$$H_t = \left[\overrightarrow{h_t}, \overleftarrow{h_t}\right], \tag{11}$$

where T is the time series length and H_t represents the output at the current time.

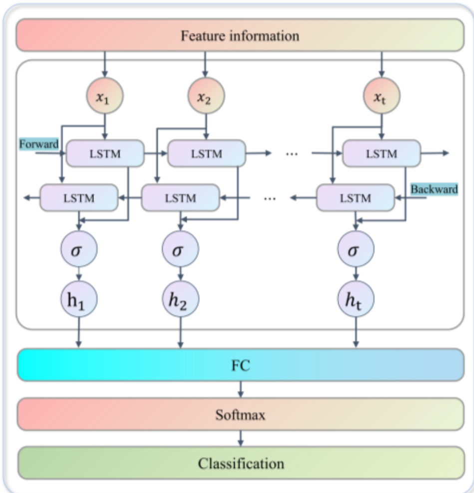


Fig. 6. BiLSTM network architecture.

C. Optimisation

The Newton-Raphson-based optimiser (NRBO) is a novel metaheuristic algorithm, and the proposed NRBO defines search paths by exploring the search domain using several sets of vectors and two operators, and applying the NRM to discover the search region.

The Newton-Raphson search rule (NRSR) enhances the search capability of the NRBO based on the Newton-Raphson method and improves the convergence speed so that better search space locations can be reached faster. It speeds up the search process by calculating the first- and second-order derivatives of the function to update the solution location.

The purpose of the trap avoidance operator (TAO) is to help the NRBO to avoid local optimal solutions. It avoids the algorithm from falling into local optimality by changing the way the solution is updated to add randomness and diversity.

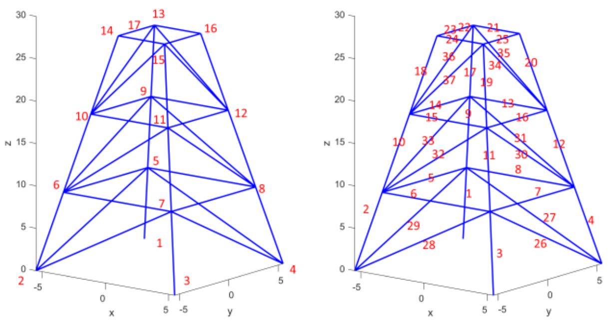
The composite neural network model brings not only high performance, but also more complex parameters. We use the NRBO optimisation algorithm to optimise the number of hidden units best_hd of BiLSTM, and we also perform a parameter search for the initial learning rate best_ir and regularisation coefficients best_l2 for model training.

III. FINITE ELEMENT SIMULATION

A. Finite Element Model

In the finite element experiments, based on the knowledge of MATLAB structural dynamics, we used the MATLAB code to construct the finite element model of the offshore conduit rack structure. The conduit rack structure adopts the Euler-Bernoulli beam unit theory, as shown in Fig. 7. The constructed offshore conduit rack structure has 17 nodes, each node has six degrees of freedom, and it is composed of the node-to-node connection shelf subunits, respectively, which constitute 37 units.

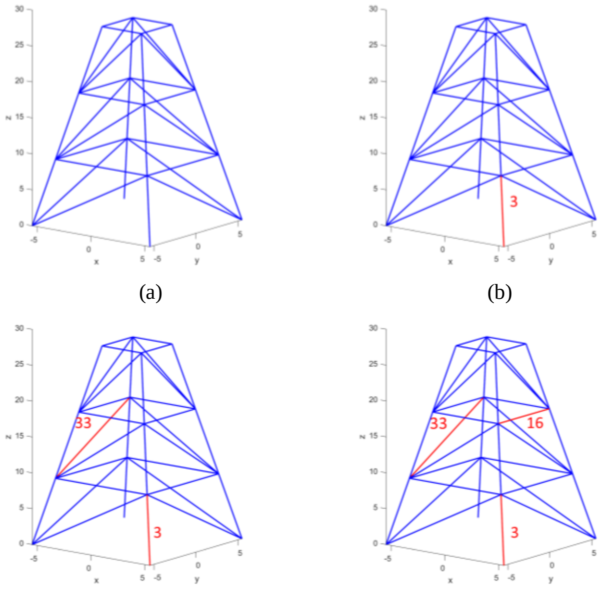
The conduit rack material is made of Q235 steel with circular cross-section, the mass density of Q235 steel is $7850\,kg/m^3$, Poisson's ratio is 0.3, and modulus of elasticity is $210\,GPa$. The structure of the conduit rack consists of four layers, with a height of $27.42\,m$, i.e., the height of each layer is $9.14\,m$, and the information about the lengths of conduit racks from the top to the bottom is $3.66\,m$, $6.10\,m$, $8.52\,m$, and $10.98\,m$, and each circular fittings unit is a hollow round tube with the outer diameter of $0.178\,m$ and inner diameter of $0.16\,m$.



(a) (b)

Fig. 7. (a) Nodal position; (b) Unit rod number.

In the offshore conduit rack structure generated by the MATLAB code modelling, we use the method of reducing the modulus of elasticity of the unit rods to simulate the damage of the structure in the marine environment, so we designed a model of the offshore conduit rack structure in four different damage modes, namely, no damage, single rod damage, double rod damage, and multiple rod damage, and we try to use different rod numbers to simulate damage, namely, main brace and diagonal brace, to simulate a more realistic and comprehensive damage situation. Damage location information is shown in Fig. 8. And the work conditions design is shown in Table I.



(a) (b)

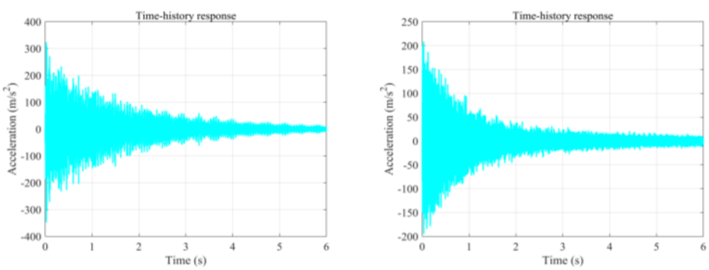
(c) (d)

Fig. 8. Design for damage conditions: (a) No damage condition; (b) Single damage condition; (c) Two damage conditions; (d) Multiple damage conditions.

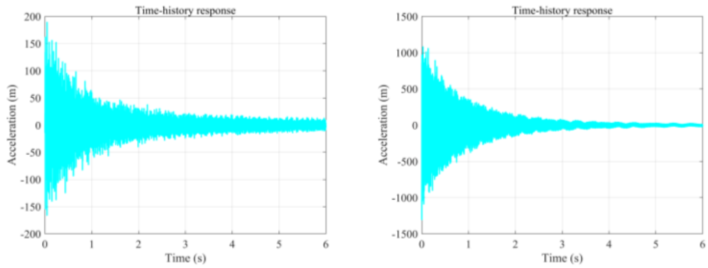
TABLE I. DESIGN FOR DAMAGE CONDITIONS.

Damage condition	**Location**	**Degree of damage (reduction in modulus of elasticity)**
1	0	0
2	3	50 %
3	3 & 33	70 %, 50 %
4	3 & 33 & 16	70 %, 50 %, 50 %

After completing the design of the finished condition, we start to collect the characteristic information of the model after simulating the damage; we design to apply the impulse load in the direction of the second degree of freedom at the 17^{th} node and at the same time calculate the acceleration information of each degree of freedom of the finite element model of the conduit rack structure under different damage modes, and the acceleration calculation method that we adopt is the centre-difference method. The coordinates of the seventeenth node are $(0,\ 1.83, 27.42)$, which is the midpoint of the bar. We show the vibration response of the finite element model for the four degrees of freedom (DOF) of the system under the undamaged condition in Fig. 9.



(a) (b)



(c) (d)

Fig. 9. Vibration response diagram: (a) DOF - 48; (b) DOF - 50; (c) DOF - 60; (d) DOF - 72.

Based on what the image shows, we find that the amplitude waveform is a gradual convergence trend, which is due to the structure's own damping, we use the sliding window technique to segment the taken vibration data set, with a time window of 0.08 s and a time step of 0.0002 s. A total of 1,000 data samples are generated, of which 70 % is used as a training set, and the remaining 30 % is used for the performance testing and validation.

B. *Network Training*

Our proposed model is the NRBO-TCN-BiLSTM attention model, and our model training is done on the Window 11 platform using MATLAB2024b running with 32 GB of RAM, and the hardware of our experimental platform contains an RTX 3061Ti GPU, an Intel Core i7-12700 CPU.

We use the NRBO optimisation algorithm to optimise the number of hidden units best_hd of BiLSTM, and we also perform a parameter search for the initial learning rate best_ir and regularisation coefficients best_l2 for model training. We use Adma optimiser for the training process, and the fitness curves for multiple parameter-seeking iterations of training are shown in Fig. 10.

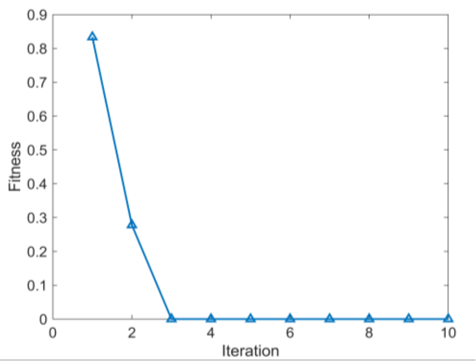


Fig. 10. The fitness in model training.

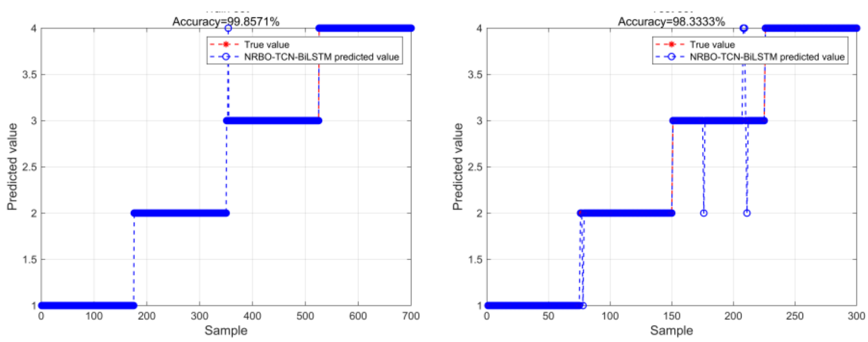
From the fitness curve we can see that the value of the fitness function stabilises after the third iteration, which represents that we get the optimal hyperparameters in the integrated deep network. At the same time, we also specify the other parameters of the network and input the above parameters into the training network to get our training network parameter settings as in Table II.

TABLE II. TRAINING PARAMETER SETTINGS.

Parameter	**Settings**
NumFilters	64
DropoutFactor	0.005
FilterSize	5
NumBlocks	4
Best_hd	9
Best_ir	0.0023
Best_l2	0.007

According to the above parameter settings, we train the model and evaluate the effectiveness of our model by the accuracy of the training model in the training set and test set as well as the confusion matrix as shown in Fig. 11, from which it can be seen that the accuracy of our proposed model for damage pattern recognition in the training set is 99.8571 %, and the accuracy for the test set of data has reached 98.9796 %. This is a very good result for all deep learning networks used for the recognition of structural damage of offshore conduit racks.

To highlight the performance of the proposed model, the confusion matrix for damage pattern recognition is provided in Fig. 12. This matrix shows the classification results for the four types of damage condition data obtained from the finite element simulation. The detailed classification results will be accounted for in the confusion matrix, which we obtained using the finite element data test in Fig. 12.



(a) (b)

Fig. 11. Accuracy: (a) Train data; (b) Test data.

Fig. 12. Confusion matrix: (a) Train data; (b) Test data.

In the confusion matrix, to evaluate the effectiveness of the model, we plan three indicators through the results of the confusion matrix, which are Precision, Recall, and F1 score, and the detailed formula is as follows:

$$Precision = \frac{TP}{TP + FP}, \tag{12}$$

$$Recall = \frac{TP}{TP + FN}, \tag{13}$$

$$F1 = \frac{2 * Precision * Precision}{Precision + Recall}. \tag{14}$$

Combined with the accuracy rate, we can use these four metrics to evaluate the effectiveness of our model and, at the same time, compare it with other common deep learning models used for structural damage recognition to demonstrate the superiority of our proposed model. We calculated four metrics for the proposed NRBO-TCN-BiLSTM model on finite element simulation data, Accuracy = 0.9833, Precision = 0.9836, Recall = 0.9833, and F1 Score = 0.9835. As in Fig. 13, we compare our model with four deep learning models, CNN, TCN, BiLSTM, and CNN-BiLSTM, based on the four evaluation metrics above.

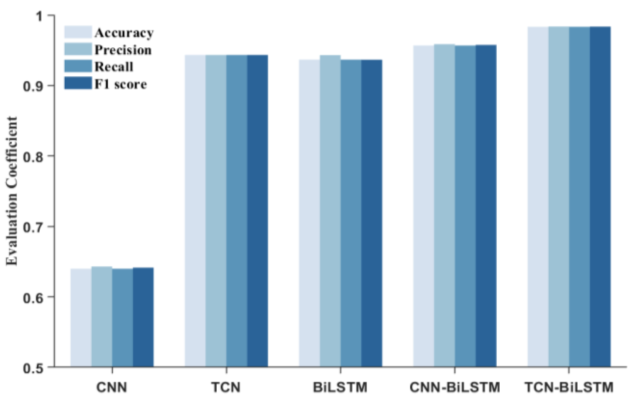


Fig. 13. Evaluation.

We can observe that the use of only a convolutional neural network (CNN) yields the least favourable results. On the other hand, using theTCN or BiLSTM network alone also demonstrates remarkable performance in the damage recognition task. This might be attributed to their excellent capabilities in handling time series information.

The CNN-BiLSTM model takes advantage of CNN's powerful feature extraction ability and BiLSTM's ability to capture contextual information bidirectionally. It performs quite well, with an average accuracy of around 0.95.

In particular, our proposed TCN-BiLSTM model outperforms the others. All of its evaluation indexes exceed 0.98, showcasing its outstanding performance.

C. Experimental Model

Referring to the indexes of the finite element model constructed in the MATLAB code, we built a new test bed of the conduit rack structure onboard in the laboratory to collect real data to evaluate the effectiveness of our proposed method.

To be closer to our finite element simulation model, we also used Q235 steel to build our conduit rack structure, which still has a circular cross-section, a mass density of 7850 kg/m^3, a Poisson's ratio of 0.3, and an elasticity modulus of 210 GPa. As shown in Fig. 14(a), the structure of the conduit rack is still in a four-storey structure, but due to the constraints of the real conditions, the structure is altered a little bit. The height of the conduit rack structure is 2.00 m, the length of the main support is 0.65 m, the outer diameter of the rod is 0.032 m, the inner diameter is 0.026 m, the side length information of the conduit rack from top to bottom is 0.25 m, 0.26 m, 0.44 m, and 0.61 m, respectively, and the length of the diagonal strut is 0.84 m, and the length of the cross brace and the diagonal strut is 0.016 m for the outer diameter and 0.0136 m for the inner diameter of each circular pipe fitting unit. 0.0136 m inner diameter hollow circular pipe. Our node information is shown in Fig. 14(b). The damage location information is shown in Fig. 15. And the working condition design is shown in Table III.

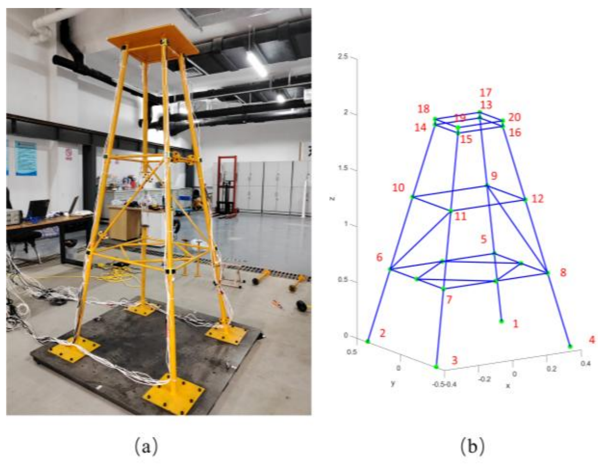


Fig. 14. Jacket structure: (a) Experimental model; (b) Node position.

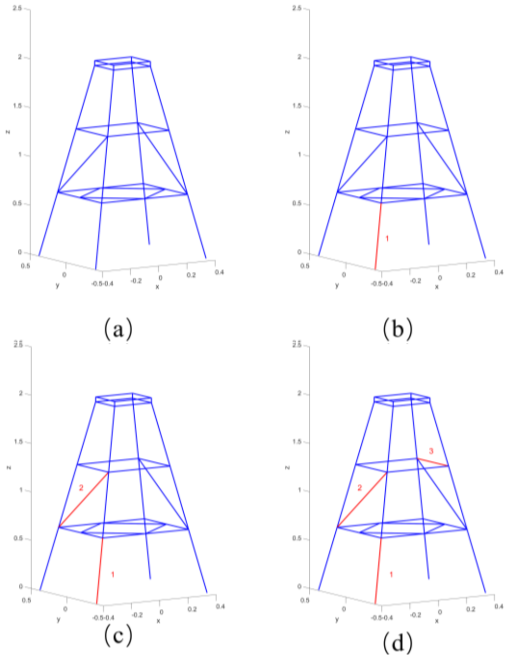


Fig. 15. Location of damage in the experimental model: (a) No damage condition; (b) Single damage condition; (c) Two damage conditions; (d) Multiple damage conditions.

TABLE III. DESIGN FOR DAMAGE CONDITIONS IN THE EXPERIMENTAL MODEL.

Damage condition	**Location**	**Degree of damage (Outer diameter of replacement rod)**
1	0	0
2	1	0.02 m
3	1 & 2	0.02 m, 0.01 m
4	1 & 2 & 3	0.02 m, 0.01 m, 0.01 m

D. *Real-World Testbed Specifics*

The experimental environment is shown in Fig. 16. The acceleration sensor is the Model2220 capacitive accelerometer, which is an integrated accelerometer featuring low power consumption, low noise, and low cost. The signal acquisition device employs the Cronos PL data acquisition system, which can provide high-resolution and low-noise measurements. Acceleration data are measured by the acceleration sensor and transmitted through the signal transmission cable to the signal acquisition device. Finally, the high-performance computer preprocesses the data to generate the sample data required for training of the neural network model.

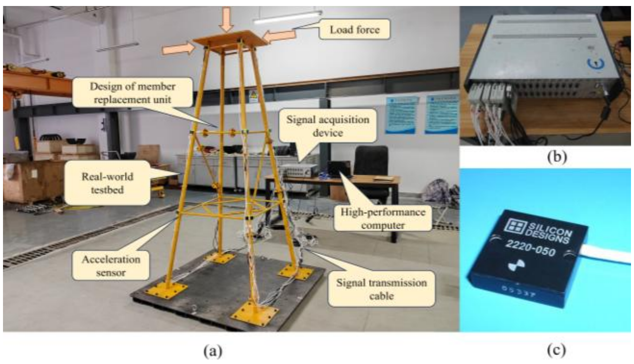


Fig. 16. Physical model test bench: (a) Physical modelling experimental setup; (b) Signal collector; (c) Acceleration sensor.

As shown in Fig. 17, in the physical model experiment, this study simulates the damage of the members by replacing the members. Therefore, in the design of the damage conditions, it is necessary to calculate the outer diameter of the replaced members to achieve a reduction in stiffness. We will introduce the specific damage simulation data in Table III.

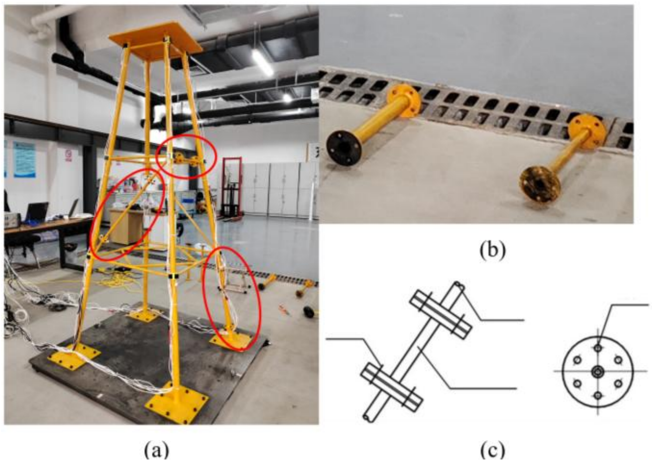


Fig. 17. Experimental rod replacement design: (a) Replacement rod unit locations; (b) Replacement rod unit; (c) Rod connection design.

In the experiment, to comprehensively extract the vibration information of the structure, we placed accelerometers on the x-axis and the y-axis at node numbers 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, and 16, and the accelerometers were connected to the signal collector, which was modelled as CRONOS PL 64-DCB8, and the frequency of the collected signals was 1000 hz in the experimental process. During the experiment, we applied the load force to the top plate from the x-axis and the y-axis to simulate the wind wave load on the conduit rack.

We use the sliding window technique to segment the taken vibration data set with a time window of 0.4 s and a time step of 0.001 s. A total of 988 data samples are generated, of which 80 % are used as a training set, and the remaining 20 % are divided into a test set for performance testing and validation. The acceleration signals we obtained for one of the three degrees of freedom are shown in Fig. 18.

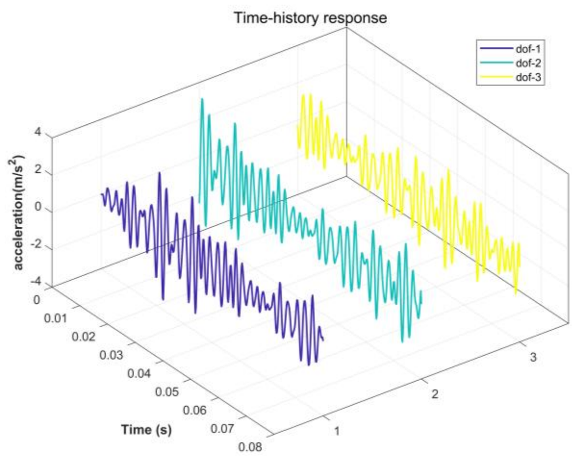


Fig. 18. Acceleration signals.

E. *Network Training*

We use the NRBO optimisation algorithm to optimise the number of hidden units best_hd of BiLSTM, as well as the parameter seeking optimisation of the initial learning rate best_ir and the regularisation coefficient best_l2 for model training. We use Adma optimiser for the training process, and the fitness curves of training with multiple parameter seeking iterations are shown in Fig. 19.

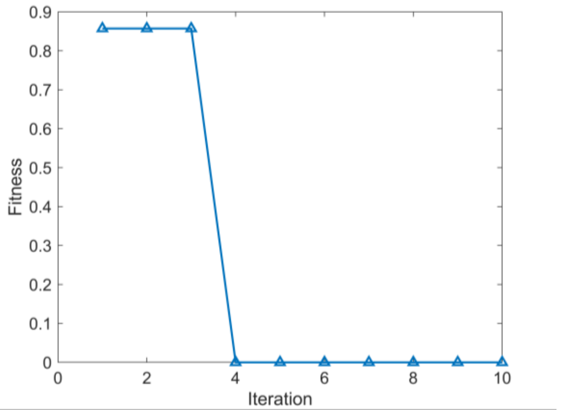


Fig. 19. Fitness of model training using real data.

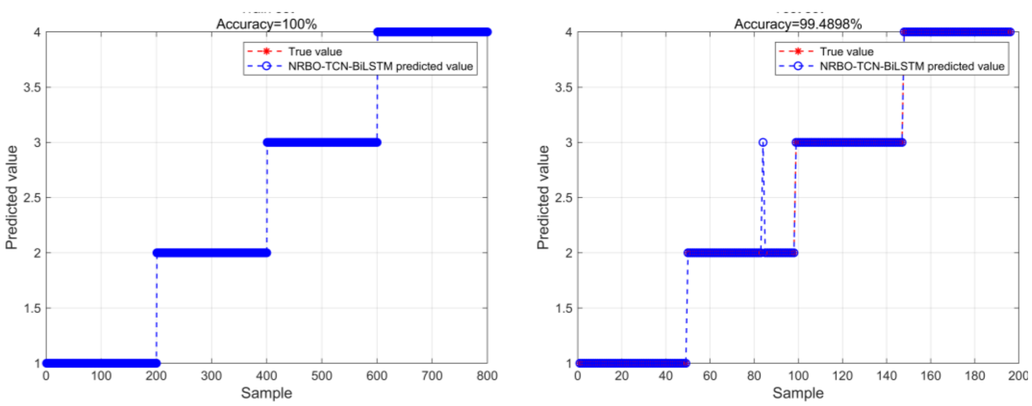
From the fitness curve in Fig. 19, we can see that the value of the fitness function stabilises after the 4th iteration, which represents that we get the optimal hyperparameters in the integrated deep network. At the same time, we also specify the other parameters of the network and input the above parameters into the training network to get our training network parameter settings as in Table IV.

TABLE IV. TRAINING PARAMETER SETTINGS.

Parameter	Settings
NumFilters	64
DropoutFactor	0.005
FilterSize	5
NumBlocks	4
Best_hd	40
Best_ir	0.001
Best_l2	0.003

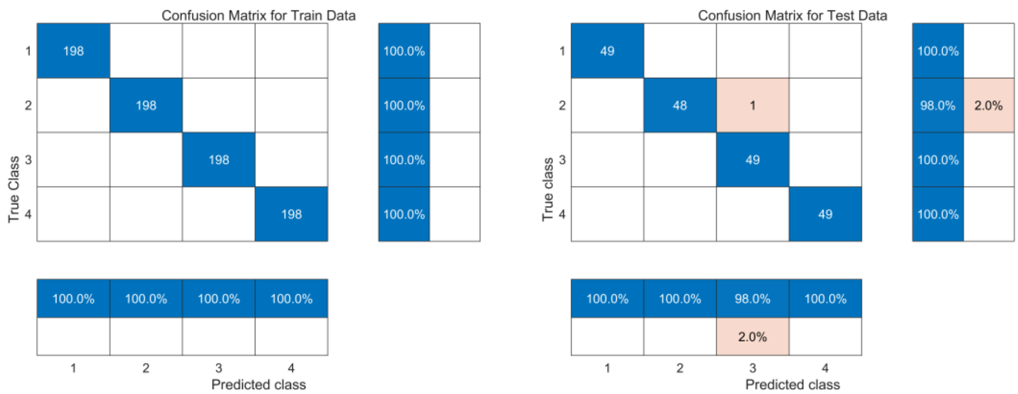
According to the above parameter settings, we train the model and evaluate the effectiveness of our model by the accuracy of the training model in the training set and test set, as well as the confusion matrix as shown in Fig. 20, from which it can be seen that the accuracy of our proposed model for damage pattern recognition in the training set is 100 % and the accuracy for the test set of data has reached 98.9796 %. This is a very excellent result for all deep learning networks used for damage recognition of offshore conduit rack structures.

However, analysing only the accuracy of the model is not sufficient to evaluate its performance. The confusion matrix is a summary of the prediction results of a classification problem, and it is also a commonly used visualisation tool for analysing the performance of deep learning models. We also obtain the confusion matrix as in Fig. 21.



(a) (b)

Fig. 20. Accuracy obtained from real data: (a) Train data; (b)Test data.



(a) (b)

Fig. 21. Confusion matrix obtained from real data: (a) Train data; (b) Test data.

We calculated the four metrics of the proposed NRBO-TCN-BiLSTM model on finite element simulation data with an accuracy of 0.9949, Precision = 0.9950, Recall of 0.9949, and an F1 score of 0.9949. To highlight the effectiveness of our proposed integrated deep learning model, we compared our model with the CNN, TCN, BiLSTM, and CNN-BiLSTM models based on the above four evaluation metrics, as shown in Fig. 22. Performance evaluations of different models are shown in Table V.

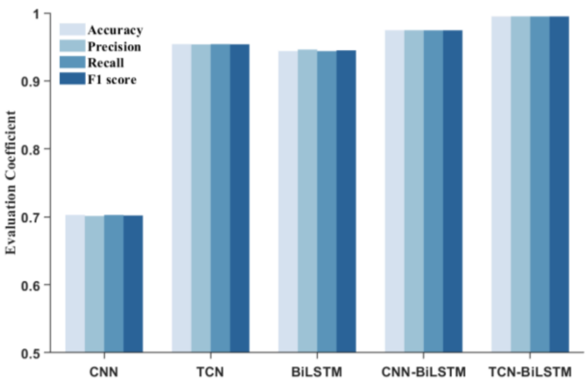


Fig. 22. Model evaluation.

TABLE V. PERFORMANCE EVALUATIONS OF MODELS.

Model	Accuracy	Precision	Recall	F1
CNN	0.7027	0.7013	0.7027	0.7020
TCN	0.9541	0.9538	0.9541	0.9539
BiLSTM	0.9439	0.9461	0.9439	0.9450
CNN-BiLSTM	0.9745	0.9746	0.9745	0.9745
TCN-BiLSTM	0.9949	0.9950	0.9949	0.9949

The integrated neural network model we proposed performs the best among the three methods. Its accuracy on the test set is 29.22 % higher than that of the CNN model, 4.08 % higher than that of the TCN model, and 5.10 % higher than that of the BiLSTM model. The reason might be that the integrated neural network model can fully exploit the advantages of subnetworks and play a complementary role in performance. Therefore, in identifying structural damage, compared to using each technology separately, the integrated model has better capacity and capability.

In the integrated neural network, the TCN-BiLSTM model we proposed has 2.04 % higher accuracy than the CNN-BiLSTM model. After multiple experiments, the accuracy rate of damage classification of our neural network model is above 99 % on average.

IV. CONCLUSIONS

In the study of the identification of structural damage identification from offshore conduit rack platforms, integrated deep learning models show significant advantages, which can effectively combine the advantages of composed models and make up for the shortcomings of individual models. The inflated causal convolution of the TCN enlarges the sensory field, efficiently extracts the long time series features of vibration signals, and overcomes the limitations of the localisation of traditional CNNs. BiLSTM bidirectionally handles time series data, fuses contextual information, and enhances the ability to express global features. NRBO effectively improves the convergence speed and generalisation performance of the model. NRBO effectively improves the model convergence speed and generalisation performance. Our proposed NRBO-TCN-BiLSTM achieves a damage recognition accuracy of more than 98 % in finite element simulation data, and all other evaluation indexes are above 0.98 , while the accuracy is improved to more than 99 % and other evaluation indexes are higher than 0.99 in tests on real data. At the same time, we experimentally validate the network in finite element simulation and real experiments and demonstrate the network's strong adaptability under different sources of data source conditions with strong adaptability and damage pattern discrimination reliability. The bidirectional processing of time series features by the BiLSTM module complements effectively with the multiscale feature extraction capability of the TCN module, which significantly improves the accuracy of the nonlinear mapping between structural response and damage states.

In the future, we look forward to adding multisensor data to the model to further improve the damage identification accuracy for complex time series data, as well as adding embedded devices to the model to improve the ability of online monitoring, and we consider that there is no added attention mechanism to the model, which may be improved in the future for our proposed deep learning integrated neural network model.

We hope to obtain the damage sample data of the actual offshore platform jacket structure to test the effectiveness and robustness of the method proposed in this paper. Additionally, we aim to verify whether the composite network model presented in this paper holds practical significance in engineering applications.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

REFERENCES

[1] M. Zhang, N. Tsoulakos, P. Kujala, and S. Hirdaris, "A deep learning method for the prediction of ship fuel consumption in real operational conditions", *Engineering Applications of Artificial Intelligence*, vol. 130, art. 107425, 2024. DOI: 10.1016/j.engappai.2023.107425.

[2] J. Leng *et al.*, "Damage detection of offshore jacket structures using structural vibration measurements: Application of a new hybrid machine learning method", *Ocean Engineering*, vol. 288, part 2, art. 116078, 2023. DOI: 10.1016/j.oceaneng.2023.116078.

[3] H. Lin, H. Luan, A. M. Uzdin, S. Zhang, L. Wei, and L. Yang, "A CFD-FEA coupled model for simulating dynamic response of offshore jacket platform under earthquake considering wind, wave, current and aftershock loads", *Ocean Engineering*, vol. 300, art. 117481, 2024. DOI: 10.1016/j.oceaneng.2024.117481.

[4] H. Lin, S. Zhang, A. M. Uzdin, L. Wei, Q. Fan, and L. Yang, "Numerical study on hydrodynamic characteristics, wave forces and dynamic responses of offshore jacket platform under tsunami-like solitary waves", *Ocean Engineering*, vol. 318, art. 120147, 2025. DOI: 10.1016/j.oceaneng.2024.120147.

[5] S. Huang, D. Yu, W. Bai, X. Guo, and J. Dai, "Experimental and numerical analysis of seismic performance of jacket platforms subjected to onshore and offshore earthquakes", *Engineering Structures*, vol. 311, art. 118177, 2024. DOI: 10.1016/j.engstruct.2024.118177.

[6] S. Zhao, G. Li, and C. Wang, "Bridge cable damage identification based on acoustic emission technology: A comprehensive review", *Measurement*, vol. 237, art. 115195, 2024. DOI: 10.1016/j.measurement.2024.115195.

[7] D.-K. Pyun, R. P. Palanisamy, and A. T. Findikoglu, "Large-area inspection of defects in metal plates using multi-mode guided acoustic waves and sparse sensor networks", *Ultrasonics*, vol. 141, art. 107322, 2024. DOI: 10.1016/j.ultras.2024.107322.

[8] W. Zhang, K. Zhu, Z. Yang, Y. Ye, J. Ding, and J. Gan, "Development of an underwater detection robot for the structures with pile foundation", *Journal of Marine Science and Engineering*, vol. 12, no. 7, pp. 1051, 2024. DOI: 10.3390/jmse12071051.

[9] R. R. Rabi, M. Vailati, and G. Monti, "Effectiveness of vibration-based techniques for damage localization and lifetime prediction in structural health monitoring of bridges: A comprehensive review", *Buildings*, vol. 14, no. 4, p. 1183, 2024. DOI: 10.3390/buildings14041183.

[10] D. C. Nguyen, M. Salamak, A. Katunin, G. Poprawa, and M. Gerges, "Vibration-based SHM of railway steel arch bridge with orbit-shaped image and wavelet-integrated CNN classification", *Engineering*

Structures, vol. 315, art. 118431, 2024. DOI: 10.1016/j.engstruct.2024.118431.

[11] Y. Zhang, J. Ding, Y. Li, Z. Ren, and K. Feng, "Multi-modal data cross-domain fusion network for gearbox fault diagnosis under variable operating conditions", *Engineering Applications of Artificial Intelligence*, vol. 133, part C, art. 108236, 2024. DOI: 10.1016/j.engappai.2024.108236.

[12] A. Entezami, H. Sarmadi, and B. Behkamal, "Removal of freezing effects from modal frequencies of civil structures for structural health monitoring", *Engineering Structures*, vol. 319, art. 118722, 2024. DOI: 10.1016/j.engstruct.2024.118722.

[13] M. Ozkan-Okay *et al.*, "A comprehensive survey: Evaluating the efficiency of artificial intelligence and machine learning techniques on cyber security solutions", *IEEE Access*, vol. 12, pp. 12229–12256, 2024. DOI: 10.1109/ACCESS.2024.3355547.

[14] T. Subba and T. Chingtham, "Comparative analysis of machine learning algorithms with advanced feature extraction for ECG Signal Classification", *IEEE Access*, vol. 12, pp. 57727–57740, 2024. DOI: 10.1109/ACCESS.2024.3387041.

[15] J. Zhang, X. Lei, P.-w. Chan, and Y. Dong, "Integrating physics-informed machine learning with resonance effect for structural dynamic performance modeling", *Journal of Building Engineering*, vol. 84, art. 108627, 2024. DOI: 10.1016/j.jobe.2024.108627.

[16] A. B. Naeem *et al.*, "Heart disease detection using feature extraction and artificial neural networks: A sensor-based approach", *IEEE Access*, vol. 12, pp. 37349–37362, 2024. DOI: 10.1109/ACCESS.2024.3373646.

[17] A. Gifalli *et al.*, "Fault detection and normal operating condition in power transformers via pattern recognition artificial neural network", *Applied System Innovation*, vol. 7, no. 3, p. 41, 2024. DOI: 10.3390/asi7030041.

[18] X. Bao, T. Fan, C. Shi, and G. Yang, "One-dimensional convolutional neural network for damage detection of jacket-type offshore platforms", *Ocean Engineering*, vol. 219, art. 108293, 2021. DOI: 10.1016/j.oceaneng.2020.108293.

[19] T. Das and S. Guchhait, "A hybrid GRU and LSTM-based deep learning approach for multiclass structural damage identification using dynamic acceleration data", *Engineering Failure Analysis*, vol. 170, art. 109259, 2025. DOI: 10.1016/j.engfailanal.2024.109259.

[20] Chencho, J. Li, and H. Hao, "Structural damage quantification using long short-term memory (LSTM) auto-encoder and impulse response functions", *Journal of Infrastructure Intelligence and Resilience*, vol. 3, no. 2, art. 100086, 2024. DOI: 10.1016/j.iintel.2024.100086.

[21] Bao, T. Fan, C. Shi, and G. Yang, "Deep learning methods for damage detection of jacket-type offshore platforms", *Process Safety and Environmental Protection*, vol. 154, pp. 249–261, 2021. DOI: 10.1016/j.psep.2021.08.031.

[22] M. Wang *et al.*, "Structural health monitoring on offshore jacket platforms using a novel ensemble deep learning model", *Ocean Engineering*, vol. 301, art. 117510, 2024. DOI: 10.1016/j.oceaneng.2024.117510.

[23] R. Gu, S. Zhang, J. Zhu, X. Shu, H. Zhu, and Y. Li, "Damage identification for UAV composite propeller blades based on transmissibility probabilistic distance and attention bidirectional temporal convolutional network", *Measurement*, vol. 241, art. 115751, 2025. DOI: 10.1016/j.measurement.2024.115751.

[24] W. Wu, J. Gao, A. Wei, and S. Guan, "Damage identification method for jacket platform based on dual-channel model", *Digital Signal Processing*, vol. 156, part B, art. 104827, 2025. DOI: 10.1016/j.dsp.2024.104827.

[25] R. Sowmya, M. Premkumar, and P. Jangir, "Newton-Raphson-based optimizer: A new population-based metaheuristic algorithm for continuous optimization problems", *Engineering Applications of Artificial Intelligence*, vol. 128, art. 107532, 2024. DOI: 10.1016/j.engappai.2023.107532.

[26] J. Zhou *et al.*, "An integrated CSPPC and BiLSTM framework for malicious URL detection", *Scientific Reports*, vol. 15, no. 1, p. 6659, 2025. DOI: 10.1038/s41598-025-91148-z.