

Article

Structural Condition Assessment of Steel Anchorage Using Convolutional Neural Networks and Admittance Response

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Abstract: Structural damage in the steel bridge anchorage, if not diagnosed early, could pose a severe risk of structural collapse. Previous studies have mainly focused on diagnosing prestress loss as a specific type of damage. This study is among the first for the automated identification of multiple types of anchorage damage, including strand damage and bearing plate damage, using deep learning combined with the EMA (electromechanical admittance) technique. The proposed approach employs the 1D CNN (one-dimensional convolutional neural network) algorithm to autonomously learn optimal features from the raw EMA data without complex transformations. The proposed approach is validated using the raw EMA response of a steel bridge anchorage specimen, which contains substantial nonlinearities in damage characteristics. A K-fold cross-validation approach is used to secure a rigorous performance evaluation and generalization across different scenarios. The method demonstrates superior performance compared to established 1D CNN models in assessing multiple damage types in the anchorage specimen, offering a potential alternative paradigm for data-driven damage identification in steel bridge anchorages.

Keywords: CNN; strand relaxation; damage identification; EMA; bridge anchorage



Citation: Ho, D.-D.; Kim, J.-T.; Hoang, N.-D.; Tran, M.-H.; Pradhan, A.M.S.; Truong, G.T.; Huynh, T.-C. Structural Condition Assessment of Steel Anchorage Using Convolutional Neural Networks and Admittance Response. *Buildings* **2024**, *14*, 1635. <https://doi.org/10.3390/buildings14061635>

Academic Editor: Nerio Tullini

Received: 3 May 2024

Revised: 17 May 2024

Accepted: 23 May 2024

Published: 3 June 2024



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1. Introduction

The tendon–anchorage subsystem plays a crucial role in transmitting prestress force to the main prestressed structure. The loss of prestressing force (i.e., the strand relaxation) [1,2] and structural damages (i.e., fatigue cracks and corrosion) [3–5] in the anchorage pose a critical risk, capable of precipitating the collapse of the entire structural system. Despite the extensive adoption of prestressing technology in global civil infrastructure, the assessment of abnormal structural conditions in the anchorage zone remains a challenge for engineers and maintenance crews. This is primarily attributed to limited accessibility and the subtle progression of strand relaxation and damage.

Numerous research efforts have been conducted to develop effective tools for evaluating the strand damage in prestressed structures [6–8]. The pioneering researchers have explored the use of global vibration responses, such as natural frequencies of a prestressed

structure, to assess the prestress loss [9,10]. While this global vibration-based technique exhibits promising results, it is more applicable for monitoring stayed cables or external tendons [11–13]. This is because the vibration-based approach relies on low-order modes which are often exhibiting lower sensitivity to local strand looseness damage [14,15]. An alternative approach involves the use of fiber optic sensors (FOSs) for estimating prestress force, wherein the FOSs are inserted into a prestressing strand [16,17]. Nevertheless, the FOS-based method is considered not cost-effective due to the necessity of capturing reflected optical waves with extremely short wavelengths using precise and expensive interrogators [18]. Computer vision and image processing are emerging as a promising and innovative solution for monitoring civil structures, demonstrating effectiveness in identifying visible issues such as cracks, spalling, and corrosion on the surfaces of structures [19–21]. However, this technology faces limitations in detecting invisible progressive damages such as strand relaxation in prestressed anchorages.

In the past decades, the application of the electromechanical admittance (EMA)-based damage detection technique has received considerable attention in structural health monitoring (SHM) [22–24]. This technique involves employing cost-effective, small-sized, high-sensitivity piezoelectric transducers, such as PZT (lead zirconate titanate), to capture EMA signals within a high-frequency range from a host structure. Since the EMA responses contain important information about the dynamic properties of the host structure, the structural integrity can be accessed by monitoring changes in the EMA signatures. Thanks to the short wavelengths generated during PZT excitation, this technology allows for the accurate detection of minor and early structural damages [25,26]. Researchers have implemented the technique for the SHM of prestressed structures. Their approach involves attaching piezoelectric transducers near anchoring zones to capture impedance signals (i.e., the inverse of the admittance), which are sensitive to the relaxation of prestressing tendons [27,28]. Estimating prestress force is commonly accomplished through the regression analysis of impedance features [29–31]. Depending on the local dynamic properties of a host prestressed structure, the frequency band employed for diagnosing prestress loss varies within the range of 10 kHz to 1 MHz [32,33].

Feature extraction and damage diagnosis algorithms have played an important role in EMI-based SHM. Traditional approaches rely on manual feature extractions using common statistical damage indices and trial-and-error searches of optimal frequency bands [25,34] that may lead to erroneous alarms for structural damage and inaccurate severity estimation, which eventually impede the real-time applicability of the EMA technique [35,36]. To overcome these challenges, researchers have increasingly turned to machine learning algorithms for processing EMA responses, with a particular focus on developing convolutional neural network (CNN)-based damage regression/classification models tailored to the EMA technique. Unlike traditional machine learning algorithms, CNN algorithms offer a capability to autonomously extract and learn optimal damage-sensitive features from raw EMA signals [37]. This unique feature empowers CNN-based diagnostic models to function automatically, obviating the need for signal preprocessing and thereby minimizing computational costs and enhancing prediction efficiency [37–39].

To date, various deep learning models have been developed to process EMA signals for monitoring reinforced concrete structures. Ai *et al.* [40] introduced a straightforward 2D CNN to identify compressive stress and load-induced cracking damages in a concrete cubic structure. In a subsequent study, Ai and Cheng [41] divided EMA signatures into sub-range responses, employing a statistical approach to construct the 2D (two-dimensional) input for training and testing the deep learning model. Their experimental findings showed the high accuracy of the proposed 2D CNN model, even in detecting minor damages. Recently, Ai *et al.* [23] presented a 1D (one-dimensional) CNN approach to process raw EMA responses for the automated detection of small-size damages in concrete structures. Li *et al.* [42] integrated the EMA technique with a CNN-based regression model to quantitatively predict and monitor real-time concrete strength development. Ta *et al.* [43] predicted the compressive load of concrete members through the 1D CNN-based deep learning of impedance (an

inverse of admittance) response. These studies have highlighted the effectiveness of CNN models in stress monitoring and damage identification in concrete structures.

Despite previous research efforts, there is a scarcity of research applying CNN algorithms to process impedance/admittance signals from the anchorage area of prestressed structures, with Nguyen *et al.*'s study [44] being the only study to date. However, this research solely focused only on detecting a single damage type, such as prestress loss, while the prestressed anchorage is potentially corroded and cracked during its operational life [3–5]. As of now, a comprehensive diagnostic method to distinguish different types of damage in prestressed anchorage areas is still lacking. Meanwhile, the effectiveness of existing CNN models for multiple damage identification remains questionable. To address these gaps, this paper proposes an approach for automated multi-type damage identification in a prestressed anchorage through the deep learning of raw EMA response. Firstly, the principle of the EMA technique for prestressed anchorage monitoring is outlined. Next, the proposed methodology is described in detail, including the network architecture, training and testing algorithms, data augmentation method, and K-fold cross validation technique. Thirdly, the experiment is conducted on a lab-scaled bridge anchorage under multiple simulated damage types. Finally, the performance of the proposed method is evaluated for detecting multiple damage types in the anchorage specimen. The effectiveness of the proposed method is also demonstrated by comparing its performance with the well-established CNN models in the literature.

As compared with the previous studies, the new contributions of the present work are as follows: (1) This is the first research effort to assess multiple damage types, specifically strand relaxation/damage in prestressed anchorages, based on combining the EMA technique with deep learning. (2) The developed method is automated, autonomously learning optimal features from the raw EMA response without complex transformations, thereby enabling the automated diagnostic process for the EMA-based SHM of prestressed anchorages. (3) In comparison to previous CNN models capable of directly predicting damage from raw EMA data [23,44], the proposed CNN model demonstrates a high accuracy for detecting multiple damage types in the tested prestressed anchorage.

2. The EMA Technique

2.1. The Fundamentals of EMA Response

The EMA technique leverages the piezoelectric effect inherent in piezoelectric transducers. This reversible phenomenon encompasses the generation of an electrical charge through mechanical deformation and, conversely, the induction of mechanical strain through an applied electrical field [25]. The schematic depiction in Figure 1a elucidates the foundational configuration of the EMA technique that is employed for the identification of damage in prestressed anchorages. This methodology entails affixing a PZT transducer to the bearing plate's surface of the anchorage and activating it by an EMA analyzer. The EMA response is then garnered from the host structure within a high-frequency range, often extending into ultrasonic bands.

The data acquisition is achieved by stimulating the transducer with a harmonic voltage $V(\omega)$ using the analyzer. The resulting mechanical deformation of the transducer, induced by the piezoelectric effect, imparts a harmonic force $F(\omega)$ onto the host anchorage, as depicted in Figure 1a. The admittance of this mechanical system characterizes its capacity to react to the stimulating force and is defined as the ratio of the steady-state velocity to the force $F(\omega)$. The obtained EMA response authentically reflects the dynamic attributes of the interconnected transducer–anchorage system. Hence, alterations in the EMA response serve as indicators for identifying structural anomalies in the anchorage, such as strand relaxation and fatigue-induced cracks or corrosion.

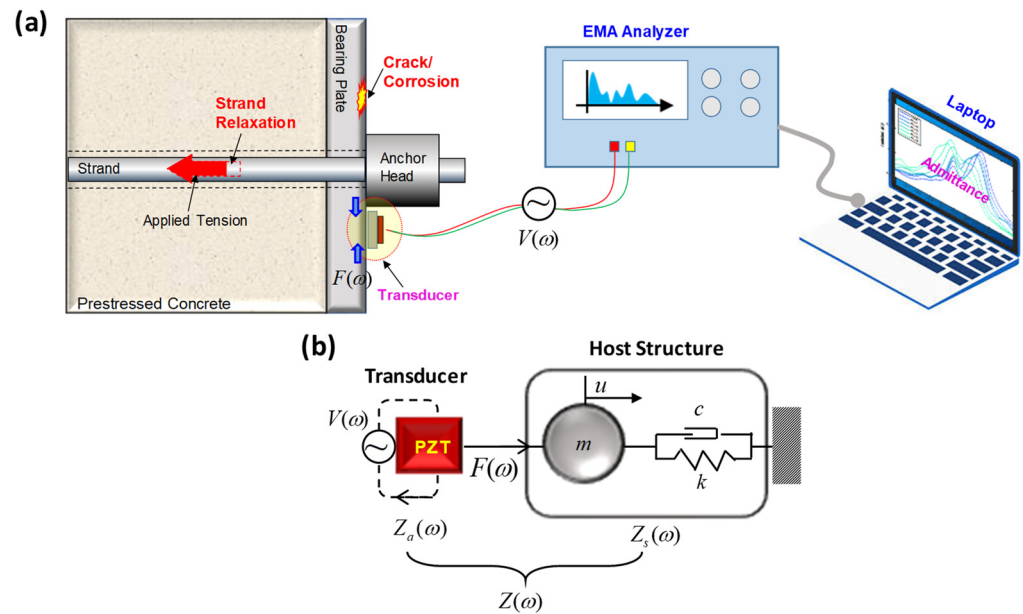


Figure 1. The illustration of the EMA technique for damage identification in a prestressed anchorage structure: (a) The typical EMA setup; (b) The coupled PZT and host structure dynamical system using a simplified model (u : displacement at the PZT driving point).

Based on a theoretical analysis of energy transmission and consumption, Liang *et al.* proposed a one-dof (degree of freedom) model to interpret the interaction between the transducer and the host structure, as presented in Figure 1b [45]. The EMA response of this coupled dynamical system (the transducer–host structure system) can be derived from the mechanical impedance of both the transducer and the host anchorage, supposing the host structure is characterized by common structural variables: mass (m), damping (c), and stiffness (k). The mechanical impedance of the host structure ($Z_s(\omega)$) is determined by the ratio of the induced force ($F(\omega)$) to the velocity of the host structure at the excitation point ($u'(\omega)$), as expressed in Equation (1) [45]:

$$Z_s(\omega) = \frac{F(\omega)}{u'(\omega)} = c + m \frac{\omega^2 - \omega_n^2}{\omega} i \quad (1)$$

Here, i denotes the imaginary unit, ω_n is the host structure's natural frequency, and ω is the swept frequency.

According to the pioneering study by Liang *et al.* [45], the electromechanical impedance of the one-dof system $Z(\omega)$ is a combined function of $Z_s(\omega)$ and $Z_a(\omega)$, as expressed in Equation (2a). The EMA response is computed as an inverse of $Z(\omega)$, as depicted by Equation (2b).

$$Z(\omega) = \left\{ i\omega \frac{w_a l_a}{t_a} \left[\hat{\epsilon}_{33}^T - \frac{1}{Z_a(\omega)/Z_s(\omega) + 1} d_{31}^2 \hat{Y}_{11}^E \right] \right\} \quad (2a)$$

$$Y(\omega) = \frac{1}{Z(\omega)} = \left\{ i\omega \frac{w_a l_a}{t_a} \left[\hat{\epsilon}_{33}^T - \frac{d_{31}^2 \hat{Y}_{11}^E}{Z_a(\omega) / \left[c + m \frac{\omega^2 - \omega_n^2}{\omega} i \right] + 1} \right] \right\} \quad (2b)$$

In Equation (2a), the mechanical impedance of the transducer is $Z_a(\omega)$; the complex Young's modulus of the transducer (no electric field) is denoted as $\hat{Y}_{11}^E$; the complex dielectric constant (no stress condition) is defined by $\hat{\epsilon}_{11}^T$; the one-directional (transverse) piezoelectric coupling constant (no stress field) is expressed by d_{31} ; the width, length, and thickness of the transducer are represented by w_a , l_a , and t_a , respectively.

Equation (2b) theoretically affirms that the resultant EMA response inherently encapsulates the mechanical properties of the host structure (m , c , k). When the host anchor-

age undergoes damage, such as fatigue cracks or corrosion (indicating stiffness or mass changes [46,47]) in the anchorage, the EMA response undergoes variations reflective of the altered mechanical properties. Monitoring such EMA changes facilitates the identification of structural damage in the anchorage. In the case of strand relaxation, the reduced prestress force induces alterations in the stress field of the bearing plate and its contact parameters [48], ultimately manifesting in EMA changes.

2.2. Traditional Identification Metrics

In practical scenarios, the EMA response is routinely captured across a broad frequency spectrum [25,32]. The traditional extraction of EMA features demands manual intervention, necessitating the judicious selection of damage-sensitive sub-bands for effective damage identification [32,35]. Established metrics, such as Root Mean Square Deviation (RMSD) and Cross-Correlation Deviation (CCD), have been widely accepted in quantifying damage within the EMA technique [49,50]. Typically, these damage indices approach zero in the absence of structural impairment, escalating beyond zero upon the onset of damage.

The RMSD damage index is formulated in Equation (3) [50]:

$$\text{RMSD} = \sqrt{\frac{\sum_{i=1}^N [Y^*(\omega_i) - Y(\omega_i)]^2}{\sum_{i=1}^N [Y(\omega_i)]^2}} \quad (3)$$

In Equation (3), $Y(\omega_i)$ is the EMA signal at the healthy state for the i th frequency, $Y^*(\omega_i)$ is the EMA signal at the unknown state, and N is the quantity of swept frequencies.

The CCD damage index is defined by Equation (4) [49]:

$$\text{CCD} = 1 - \frac{1}{N-1} \frac{\sum_{i=1}^N (Y(\omega_i) - \bar{Y})(Y^*(\omega_i) - \bar{Y}^*)}{\sigma_Y \sigma_{Y^*}} \quad (4)$$

In Equation (4), $\bar{Y}$ and $\bar{Y}^*$ are the means of the EMA signatures, respectively; σ_Y and σ_{Y^*} are the respective standard deviations.

Ensuring effective damage classification hinges on the judicious choice of EMA features. Notably, an EMA feature that is deemed effective for a specific host structure may not exhibit similar efficacy for others. The RMSD and CCD indices, characterized by distinct sensitivities, underscore this variability. While the CCD index manifests heightened sensitivity to the horizontal shift (i.e., frequency change) and diminished sensitivity to the vertical shift (i.e., amplitude change) in the EMA spectrum, the RMSD index is responsive to both shifts [51,52]. Consequently, the appropriateness of a damage metric correlates strongly with the evolving trend of the EMA data. Employing an unsuitable EMA feature may lead to suboptimal performance in damage detection and severity estimation. Moreover, the manual feature extraction process imposes a substantial computational burden, impeding the transition towards automated operations within the EMA technique.

3. The Proposed Method

This section introduces an automated method for strand relaxation and damage diagnosis in prestressed anchorages by integrating the EMA technique with a 1D CNN structural condition classification model. The proposed scheme directly processes raw EMA responses, autonomously extracting features and predicting structural conditions. By leveraging the 1D CNN's inherent capabilities for feature extraction, the method eliminates the need for manual feature extraction and data preprocessing steps [53,54].

The flowchart of the proposed relaxation/damage identification approach is shown in Figure 2. It comprises following stages. (1) Data collection: a dataset of EMA signals is collected from a transducer deployed on a prestressed anchorage subjected to various scenarios of strand relaxation and damage. (2) Data augmentation: data augmentation is performed by injecting white Gaussian noises into the measured raw EMA signals. This

step broadens the dataset, accounting for variations induced by diverse environmental conditions. (3) K-fold cross-validation: the resulting noise-contaminated EMA data are partitioned into training and validation datasets using K-fold cross-validation. This ensures a rigorous evaluation of the proposed method's performance and generalization across different scenarios. (4) 1D CNN model design: the architecture of the 1D CNN classification model is meticulously designed for identifying structural conditions related to strand relaxation and damage. Hyperparameters are determined to optimize model performance. (5) Training and evaluation: the initiated 1D CNN model undergoes training using the augmented dataset. The model is rigorously tested using the K-fold cross-validation approach, and its accuracy and generalization capability are thoroughly evaluated.

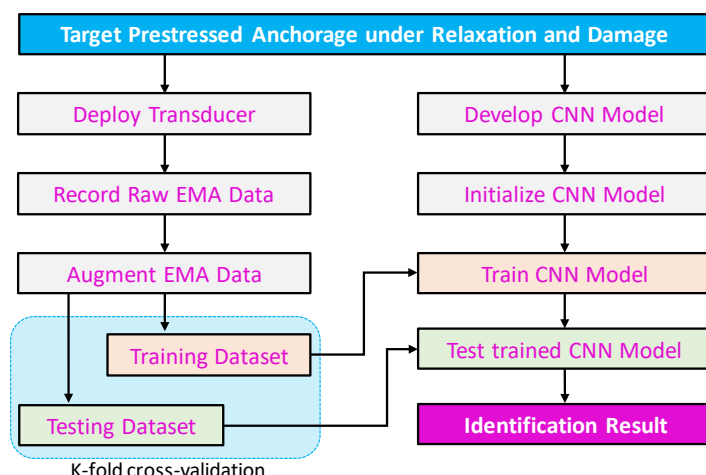


Figure 2. The illustration of automated damage identification process for a target anchorage.

The proposed scheme can overcome the shortcomings of conventional EMA feature extraction techniques induced by the non-consistent pattern of damage characteristics and facilitate the automated damage identification in a target prestressed anchorage.

3.1. 1D CNN Model

The autonomous 1D CNN-based model is designed for multi-type damage identification in prestressed anchorages. The network architecture, detailed in Figure 3, is designed based on established models [44,55], to enable effective learning and the prediction of structural conditions of a target anchorage. The proposed network is composed of 12 layers, each serving a specific role in information processing. The input layer accepts raw EMA responses, and subsequent layers (including convolution, batch normalization, ReLU (rectified linear unit) activation, maxpooling, and fully connected layers, and a classification output layer) contribute to the implicit feature extraction and classification process. Detailed layer properties are outlined in Table 1.

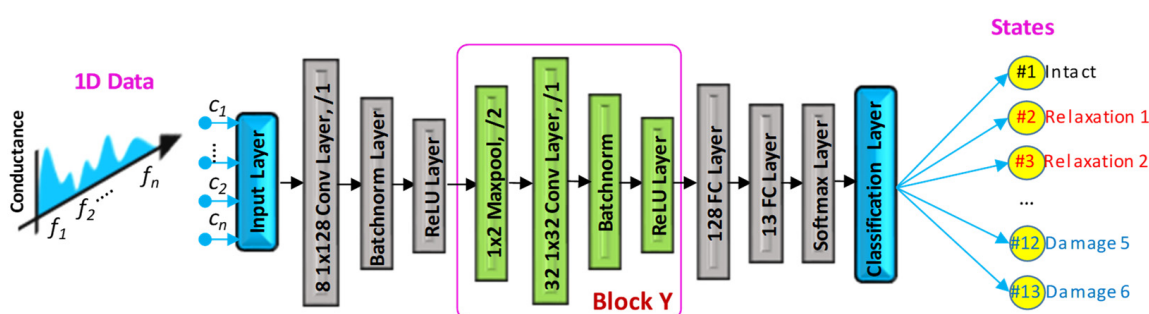


Figure 3. The proposed CNN model for automated identification of multi-type damage in a pre-stressed anchorage.

Table 1. The layer information of the proposed CNN model (kernel size: channel $\times$ height $\times$ width).

Layer	Operator	Output Shape	Kernel Size	Stride	Layer	Operator	Output Shape	Kernel Size	Stride
1	Input	1×901	-	-	7	Batch Normalization	32×451	-	-
2	Convolution	8×901	$8 \times 1 \times 128$	1	8	ReLU	32×451	-	-
3	Batch Normalization	8×901	-	-	9	Fully Connected	1×128	-	-
4	ReLU	8×901	-	-	10	Fully Connected	1×13	-	-
5	Maxpooling	8×451	1×2	2	11	Softmax	1×13	-	-
6	Convolution	32×451	$32 \times 1 \times 32$	1	12	Output	1×13	-	-

Input Layer

The input to the CNN model is a 1D EMA signal of size $1 \times N$, where $N = 901$ represents the number of frequency points in the EMA signal. To ensure the consistent distribution of inputs and facilitate error backpropagation, data normalization is applied to each 1D EMA sample in the input layer. The zero-center normalization method is employed, as expressed in Equation (5):

$$\text{norm}Y(\omega) = \frac{Y(\omega) - \bar{Y}}{\sigma_Y} \quad (5)$$

where $\text{norm}Y(\omega)$ and $Y(\omega)$ are the normalized and the original EMA signals, respectively, $\bar{Y}$ is the mean of the original signal, and σ_Y is the corresponding standard deviation.

Convolutional Layer

During convolution, the kernels slide over the 1D input pattern with a specified stride (s) to learn features. Each 1D convolutional layer utilizes C channels of filters (kernels) of dimension $1 \times Q$, where Q is the temporal window covered by the filter. The mathematical notation for a 1D convolutional layer is expressed as follows [56]:

$$y_r = f\left(\sum_{q=1}^Q w_q x_{r,q} + b\right) \quad (6)$$

where y_r is the output of the unit r of the filter feature map of size R ; x is the 1D input portion overlapping to the filter; w is the connection weight of the convolutional filter; b is the bias term; and $f(\cdot)$ is an activation function. In the process of convolution, the use of the ‘same’ zero padding is employed to extend the input, ensuring the inclusion of information from the input’s borders. This specific padding method is designed to maintain the exact size of both the input and output when the stride (s) is set to 1.

Batch Normalization Layer

During the training phase, the batch normalization layer normalizes and zero-centers the input based on the entire batch, which is the set of instances utilized for computing the loss and gradient during the learning process. This comprehensive normalization allows the model to learn the optimal scaling of the input, contributing to more efficient training. The batch normalization layer functions differently during the testing phase. Instead of utilizing batch-wide statistics, it relies on the precomputed mean and variance obtained during training. This ensures consistent normalization and zero-centering procedures, aligning with the learned characteristics of the model. Further technical details can be referred to the comprehensive explanation provided in reference [56].

ReLU Layer

The ReLU layer serves to rectify negative values in the output of the preceding layer by mapping them to zero, while preserving positive values. This layer plays a pivotal role in minimizing computational costs and enhancing the efficiency of the training process. For a given input value, x is the input value, and the ReLU operation is mathematically expressed as follows [57]:

$$\text{ReLU}(x) = \max(0, x) \quad (7)$$

This operation effectively introduces non-linearity into the model, enabling the network to learn complex relationships within the data. The rectification of negative values contributes to the sparsity of activations, fostering a more efficient learning process and promoting the network's ability to capture intricate patterns in the data.

Maxpooling Layer

The maxpooling layer applies a kernel to the output of the preceding layer with a specified stride (s), selecting the maximum value for each position within the kernel's sliding window. Zero-padding is employed to prevent the loss of crucial information at the input borders. For an input sequence v of length K , the 1D maxpooling layer, characterized by a window size of $1 \times F$ and a stride s , systematically identifies the maximum value within each window, generating an output sequence k . Mathematically, this process is represented as follows [58]:

$$k_i = \max_{j=(i-1)s+1}^{is+F} v_j \quad (8)$$

where k_i represents the output at the position i in the resulting sequence. The incorporation of such a layer not only effectively reduces the dimensionality of the input but also aids in error propagation during the backpropagation phase, contributing to the overall convergence of the neural network. This size reduction renders the representation space invariant to small translations of the input, enabling the network to recognize specific patterns at different locations within the feature map.

Fully Connected Layer

A fully connected layer operates by performing a matrix multiplication between the input and a weight matrix, followed by the addition of a bias vector. In each fully connected layer, every unit is connected to all units in the preceding layer, and the computation of each unit activation $y_j^{(l)}$ is expressed as follows:

$$y_j^{(l)} = f\left(\sum_{i=1}^I w_{ji}^{(l)} x_i^{(l-1)} + b_j^{(l)}\right) \quad (9)$$

Here, I represents the number of units in the previous layer, l denotes the current layer, $w_{ji}^{(l)}$ is the weight of the connection between unit j of this layer and unit i in the previous layer, and $b_j^{(l)}$ is the bias term of unit j . The activation function $f(\cdot)$ introduces non-linearity, allowing the network to capture complex relationships in the data. This fully connected layer facilitates the learning of intricate patterns and features through the adjustment of weights and biases during the training process.

Softmax Layer

For classification tasks, a typical configuration involves appending a softmax layer and subsequently, a classification output layer after the final fully connected layer. The softmax layer employs a softmax function to compute probabilities $\hat{y}_m$ for each of the M classes [59]:

$$\hat{y}_m = \frac{e^{a_m}}{\sum_{m=1}^M e^{a_m}} \quad (10)$$

Here, a_m represents the conditional probability of the sample given class m , effectively representing the output of the last fully connected layer. The role of this softmax layer is to encode the probabilities associated with each class.

Output Layer

The output of the network is of size $1 \times M$, where M is the number of predicting structural conditions for the target anchorage. In this study, $M = 13$, encompassing the 'intact' state (healthy), six 'relaxation' states, and six 'damage' states. Subsequently, the classification output layer takes the probabilities obtained from the softmax layer and assigns each input to one of the M mutually exclusive classes, corresponding to the M predicting structural conditions of the target anchorage. This assignment is based on the highest probability, providing a clear classification outcome [60]. To quantify the discrepancy between the predicted probabilities and the actual labels, the layer employs cross-entropy loss, a measure commonly used in classification tasks.

3.2. Network Training and Performance Measurement

During the training phase, the classification layer employs cross-entropy loss to quantify the disparity between the predicted probability distribution and the actual probability distribution [61]. The cross-entropy loss between two probability distributions is computed using the following formula [62]:

$$\text{loss} = - \sum_{m=1}^M (y_m^* \log \hat{y}_m) \quad (11)$$

where y_m^* represents the true probability for class m and $\hat{y}_m$ is the corresponding predicted probability.

To minimize the categorical cross-entropy loss and iteratively update the parameters of the CNN, the SGDM (stochastic gradient descent with momentum) optimization algorithm is employed. The hyperparameters are configured with a mini-batch size of eight, momentum of 0.9, learning rate of 0.001, learning rate drop factor of 0.1, and a learning rate drop period of 20. The training process spans 35 epochs. To enhance the learning process and augment the generalization capability of the machine learning model, the training data are shuffled at the commencement of each training epoch. This practice aids in mitigating overfitting and contributes to the robustness of the trained model.

The performance of the 1D CNN model is assessed through the examination of the confusion matrix and the accuracy metric. The confusion matrix displays the instance frequencies of true classes along the rows and predicted classes along the columns [63]. For a specific class, the accuracy metric is calculated as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (12)$$

Here, TP (true positive) represents instances correctly predicted by the algorithm for the given class, FP (false positive) denotes instances not belonging to the class mistakenly classified as belonging to it, TN (true negative) signifies instances correctly predicted as not belonging to the class, and FN (false negative) indicates instances of the class mistakenly classified as not belonging to it.

All training and testing experiments in this study are conducted on a desktop computer equipped with an Intel Core i7-8700 CPU running at 3.2 GHz, 32 GB DDR4 memory, and a GeForce GT 1030 GPU. The 1D CNN is implemented in the Matlab environment.

3.3. Data Augmentation Method

The EMA signals are susceptible to diverse influences, including material degradation and temperature variations [64–66]. Comprehensive experimentation that incorporates all these factors can pose significant challenges in terms of both feasibility and cost. As a pragmatic alternative to address the complexities associated with realistic measurement conditions, data augmentation emerges as a viable solution. One widely adopted technique for data augmentation involves the introduction of Gaussian noise into the recorded EMA signals [44,67]. This method offers flexibility by employing two adjustable parameters,

namely mean zero and standard deviation, allowing for the injection of noise at varying levels. The formulation for the injection of noise into the EMA signal is expressed by the following equation:

$$Y_{noisy}(\omega) = Y(\omega) + \epsilon(\omega) \quad (13)$$

Here, $Y(\omega)$ denotes the measured EMA signal, $Y_{noisy}(\omega)$ represents the corresponding noise-contaminated signal, and $\epsilon(\omega)$ corresponds to the added white Gaussian noise vector.

3.4. K-fold Cross Validation Approach

The efficacy of deep learning models hinges significantly on the accessibility and quality of available data, with imbalances in datasets leading to diminished accuracy during training [68]. To mitigate this challenge, our study leverages a specialized K-fold cross-validation method known as stratified shuffle-split cross-validation [69]. The K-fold cross-validation process, detailed in Figure 4, partitions the measured raw EMA signals into five distinct folds ($K = 5$). Each fold undergoes random division, allocating 80% of the data to the training set and 20% to the evaluation set. Following this, an evaluation of the individual performance of each fold is conducted, and the average performance is amalgamated to characterize the overall proficiency of the K-folds.

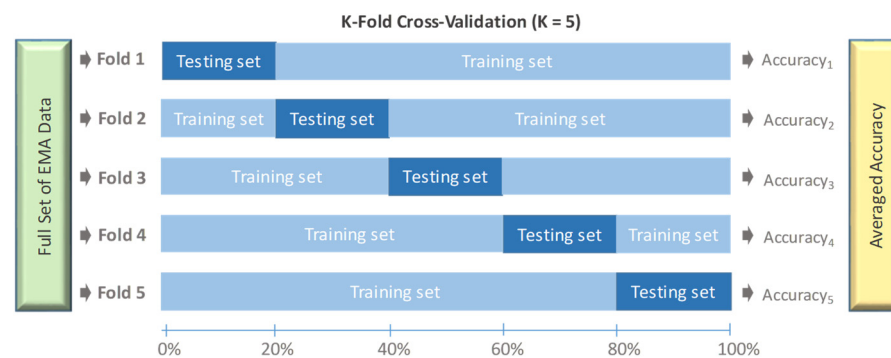


Figure 4. The illustration of K-fold cross-validation used in this study ($K = 5$).

The K-fold cross-validation process for evaluating the 1D CNN model involves two key stages: ‘data collection and preparation’ and ‘model training and evaluation’. In the first stage, raw EMA signals and their corresponding structural condition of the target anchorage (i.e., the strand relaxation and damage) are collected and used to form the deep learning datasets. These datasets undergo categorization into training and evaluation folds through the K-fold cross-validation method. Moving to the next stage, the 1D CNN classification model is instantiated. Training fold datasets, comprising EMA datasets and associated structural conditions, are used to train the 1D CNN model, while evaluation fold datasets assess the model’s performance on previously unseen data.

4. Experimental Investigation in Lab-Scaled Bridge Anchorage

4.1. Experimental Setup

The experimental investigation focuses on a prestressed reinforced concrete girder, with detailed dimensions available in a prior study [44]. The girder, featuring a T-shaped cross-section with a length of 6.4 m, is prestressed using a mono strand comprising seven wires with a diameter of 15.2 mm. The strand is anchored at both ends using anchor heads (45 mm diameter) and steel bearing plates (10 mm thickness). The real experimental setup is illustrated in Figure 5. The girder is configured as simply supported and undergoes prestressing using a hydraulic jack installed at the live end. Prestress force measurements are facilitated by a load cell and a digital indicator. In the healthy state (i.e., the intact), the girder is prestressed by a load of 14 tons.

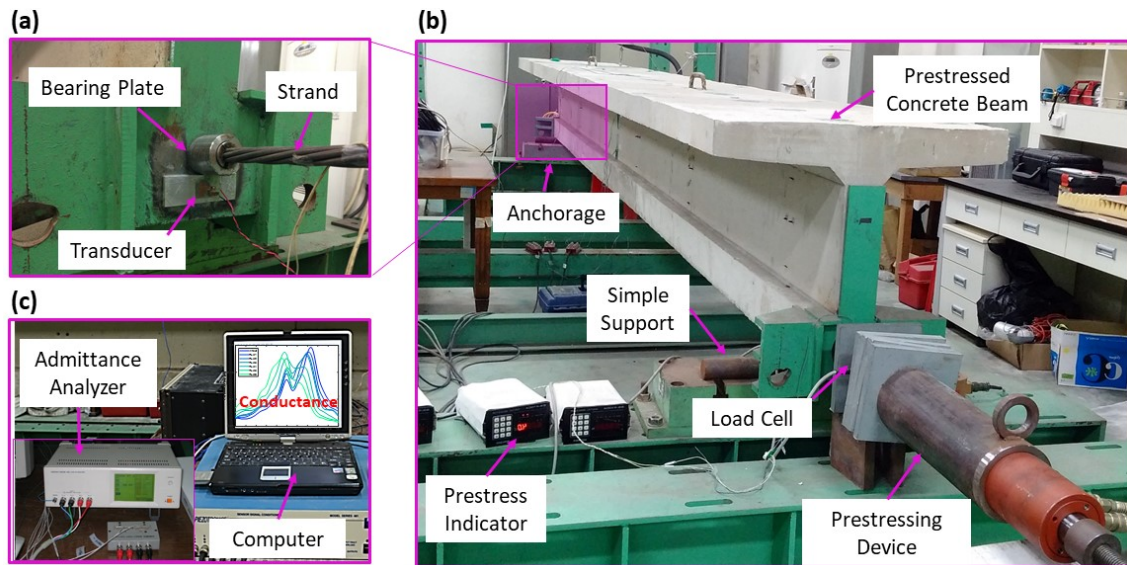


Figure 5. The experimental setup of the lab-scaled bridge anchorage: (a) Prestressed anchorage (b) Reinforced concrete girder (c) EMA analyzer.

Sensor placement is critical to secure the capability of detecting structural damage [70]. To capture strong EMA responses from the bridge anchorage, a piezoelectric transducer is strategically mounted on the bearing plate via an aluminum base, employing the mountable PZT-interface technique [71]. This deployment enhances the sensitivity of the transducer to mechanical changes in the anchorage. Through magnifying a weak EMA signature in the rigid anchorage, it effectively diminishes the necessity for high-performance EMA analyzers [29]. Moreover, this approach contributes to maintain the repeatability of the EMA signatures [72,73].

The designed aluminum base, measuring 33 mm in width and 100 mm in length, features two outer bonded sections with a thickness of 5 mm and a middle unbonded section of 4 mm thickness. The transducer, fabricated from a PZT-5A patch with dimensions of 20 mm width, 20 mm length, and 0.51 mm thickness, records EMA signals using an admittance analyzer (HIOKI 3532). The frequency sweep spans from 10 kHz to 55 kHz, encompassing 901 data points with a 50 Hz interval. This range is specifically chosen to capture robust resonant responses, crucial for effective damage identification, following the previous recommendations [29,74]. Environmental conditions are controlled to ensure data consistency, with laboratory temperature regulated using air conditioners to mitigate the potential effects of temperature variations on the EMA signal.

4.2. Strand Relaxation and Simulated Damage Tests

In this study, a series of experimental tests were conducted on a prestressed bridge anchorage under varying prestress forces and simulated damages induced by added masses. This method of simulating damage allows for the representation of stiffness or mass changes in the anchorage, mimicking the effects of cracks or corrosion, without damaging the test structure [32,75,76]. The history of strand relaxation and simulated damage tests for the test anchorage is shown in Figure 6. In brief, the experiment encompasses fourteen sequential testing cases corresponding to thirteen structural conditions of the test anchorage. For each of the testing cases, five EMA samples are repeatedly measured.

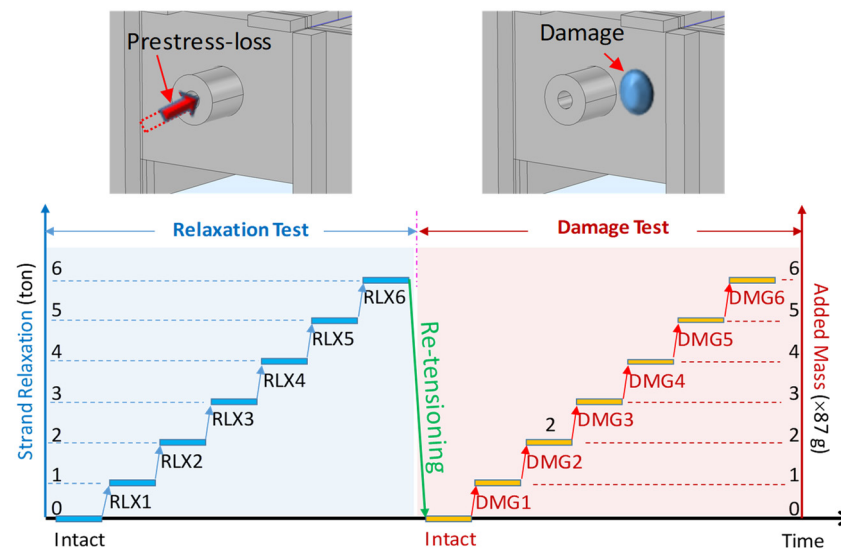


Figure 6. History of strand relaxation and simulated damage for the bridge anchorage.

At first, the girder was prestressed up to 14 tons to simulate the first intact state. Afterwards, the strand relaxation test was conducted. Specifically, the prestress forces were reduced from 14 to 8 tons with a ton decrement for simulating relaxed states of the prestressing strand (RLX1 to RLX6). Next, the girder was re-tensioned to 14 tons to simulate the second intact state. Then, the damage test was performed. Simulated damages involve the addition of masses at a single location (DMG 1 to DMG3) or multiple locations (DMG4 to DMG6), introducing complexities reflective of real-world structural damages. The corresponding labels and descriptions which categorize the thirteen structural conditions of the anchorage are presented in Table 2.

Table 2. The structural condition of the test bridge anchorage during the strand relaxation and simulated damage tests.

Test Case	Prestress Force (ton)	Damage by Added Mass ($\times 87$ g)	Description of Structural Condition	Label
1	14	0	Healthy state	Intact
2	13	0	1 ton relaxation	RLX1
3	12	0	2 ton relaxation	RLX2
4	11	0	3 ton relaxation	RLX3
5	10	0	4 ton relaxation	RLX4
6	9	0	5 ton relaxation	RLX5
7	8	0	6 ton relaxation	RLX6
8	14 (re-tension)	0	Healthy state	Intact
9	14	1	1 mass block at one location	DMG1
10	14	2	2 mass blocks at one location	DMG2
11	14	3	3 mass blocks at one location	DMG3
12	14	4	4 mass blocks at two locations	DMG4
13	14	5	5 mass blocks at two locations	DMG5
14	14	6	6 mass blocks at two locations	DMG6

The locations of added masses on the prestressed bridge anchorage during the simulated damage test are depicted in Figure 7. The simulated damages were assumed to close the anchor head where the stress was highly concentrated under the prestress load. A typical mass block has a cylindrical form with dimensions measuring 10 mm in height and 40 mm in diameter, possessing a weight of 87 g. The masses were magnetically affixed to the surface of the bearing plate on the tested anchorage. In the testing cases DMG1–DMG3, three mass blocks were sequentially added to the bearing plate just above the anchor head. Afterwards, three other blocks, respectively, were attached to the bearing plate on the right side of the anchor head to simulate the testing cases DMG4–DMG6.

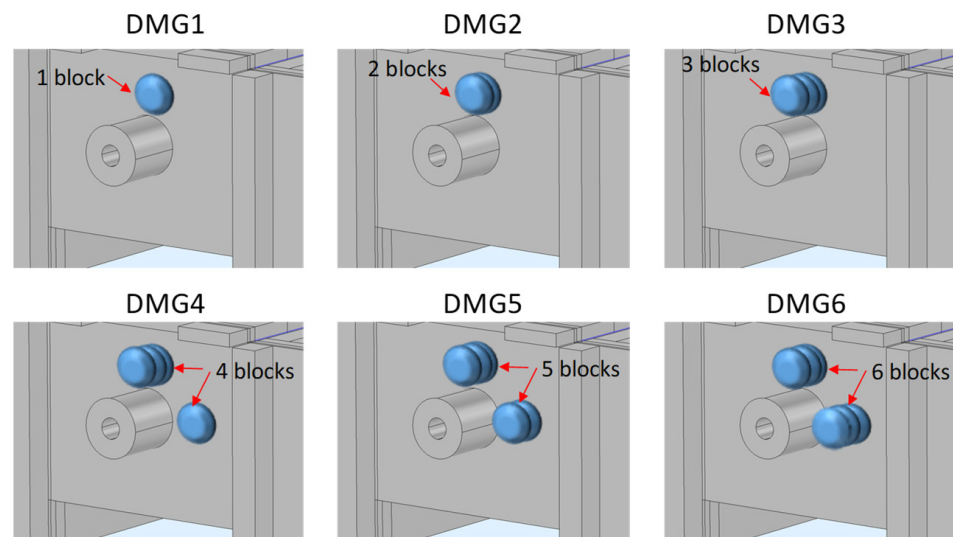


Figure 7. The locations of added masses on the bridge anchorage during the simulated damage test.

4.3. Analysis of Changes in EMA Response

4.3.1. EMA Response versus Strand Relaxation

Figure 8 presents the conductance spectra corresponding to different levels of strand relaxation in the tested anchorage. The EMA spectra reveal three distinct resonant zones, known for encapsulating crucial structural information. As depicted in Figure 8a–c, these resonances exhibit discernible variations during the strand relaxation test, rendering them well-suited for damage monitoring and assessment through the proposed model.

Across varying states of strand relaxation from the intact to RLX6 conditions, the conductance resonances consistently display progressive shifts towards lower frequencies. This observed trend aligns coherently with established experimental and numerical findings [77], elucidating the influence of prestress fluctuations on the behavior of the bearing plate. Each resonant band demonstrates clear translations of the conductance peaks. For instance, in Figure 8b, a substantial peak around 12.75 kHz undergoes a reduction in amplitude, while a lower peak near 12.45 kHz undergoes an increment. Similarly, Figure 8c reveals a diminished amplitude in the primary conductance peak at 31.3 kHz, alongside an opposing trend in the lower peak at 31.05 kHz. In Figure 8d, the third resonant band exhibits analogous translations, particularly evident in the peaks above 45 kHz showing significant amplitude reductions, while those below this threshold manifest an inverse trend. These observed peak shifts in conductance reflect alterations in the contact damping of the bearing plate induced by prestress variations [78].

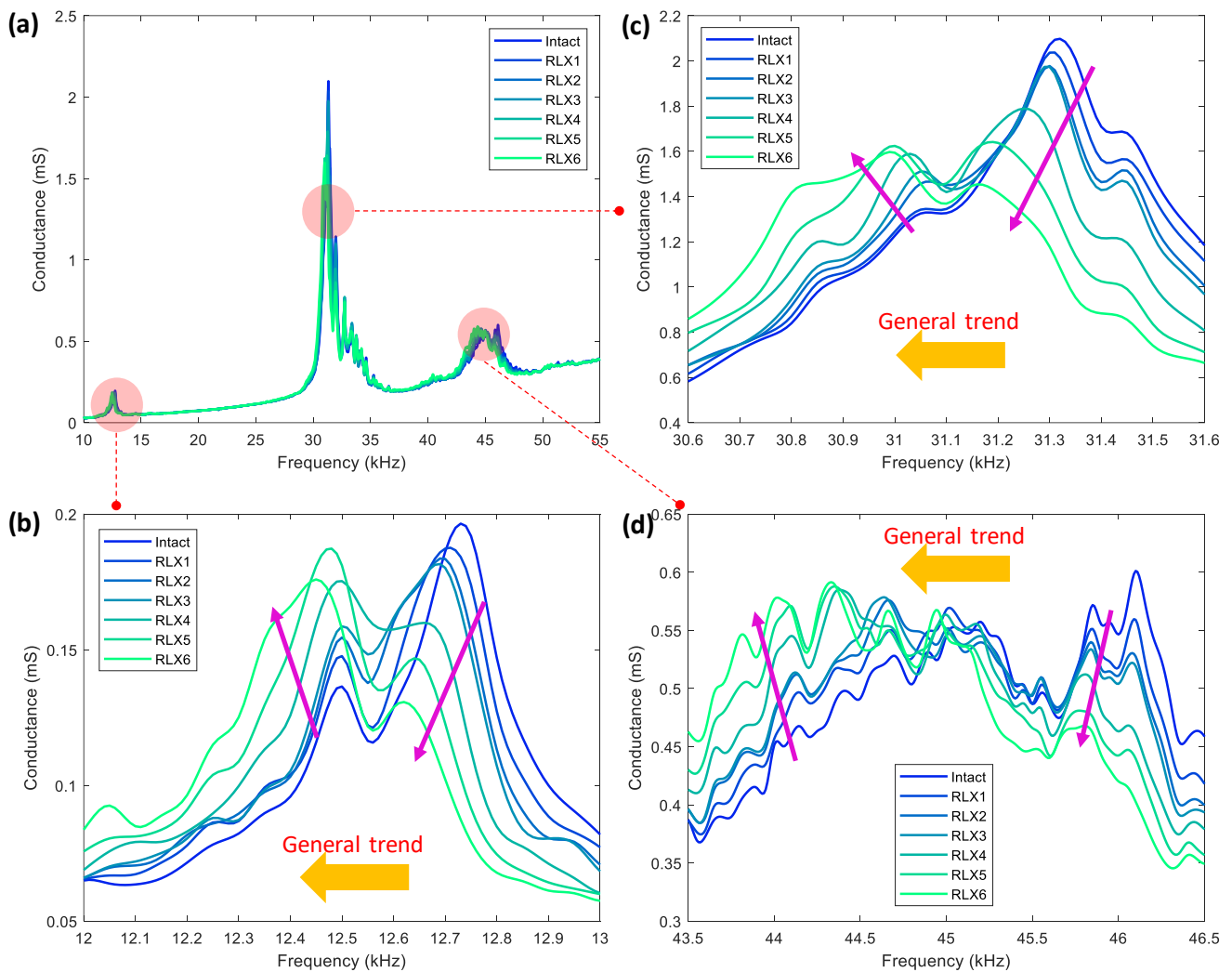


Figure 8. The EMA samples during the strand relaxation test: (a) 10–55 kHz; (b) 1st resonance; (c) 2nd resonance; and (d) 3rd resonance.

4.3.2. EMA Response versus Structural Damage

The impact of structural damage on the conductance spectra was further investigated. Figure 9a presents the conductance spectra across various damage states of the test anchorage. The EMA spectra of three resonances are zoomed in Figures 9b and 9c, respectively. Generally, the conductance resonances exhibit distinguishable shifts, from the intact to DMG6 states; these are responsible for reduced modal stiffness or increased modal mass. For the single damage location cases (DMG1–DMG3), when the mass blocks are placed on the opposite side of the anchor head compared to the position of the transducer, the conductance response only slightly varies. In these tests, the waves generated by the transducer could be heavily scattered by the anchor head on the path to reach the damaged location. When other mass blocks are placed on the right side of the anchorage, the space between the transducer and the damage has no obstacles, resulting in notable leftward shifts in conductance for the testing cases DMG3 → DMG4.

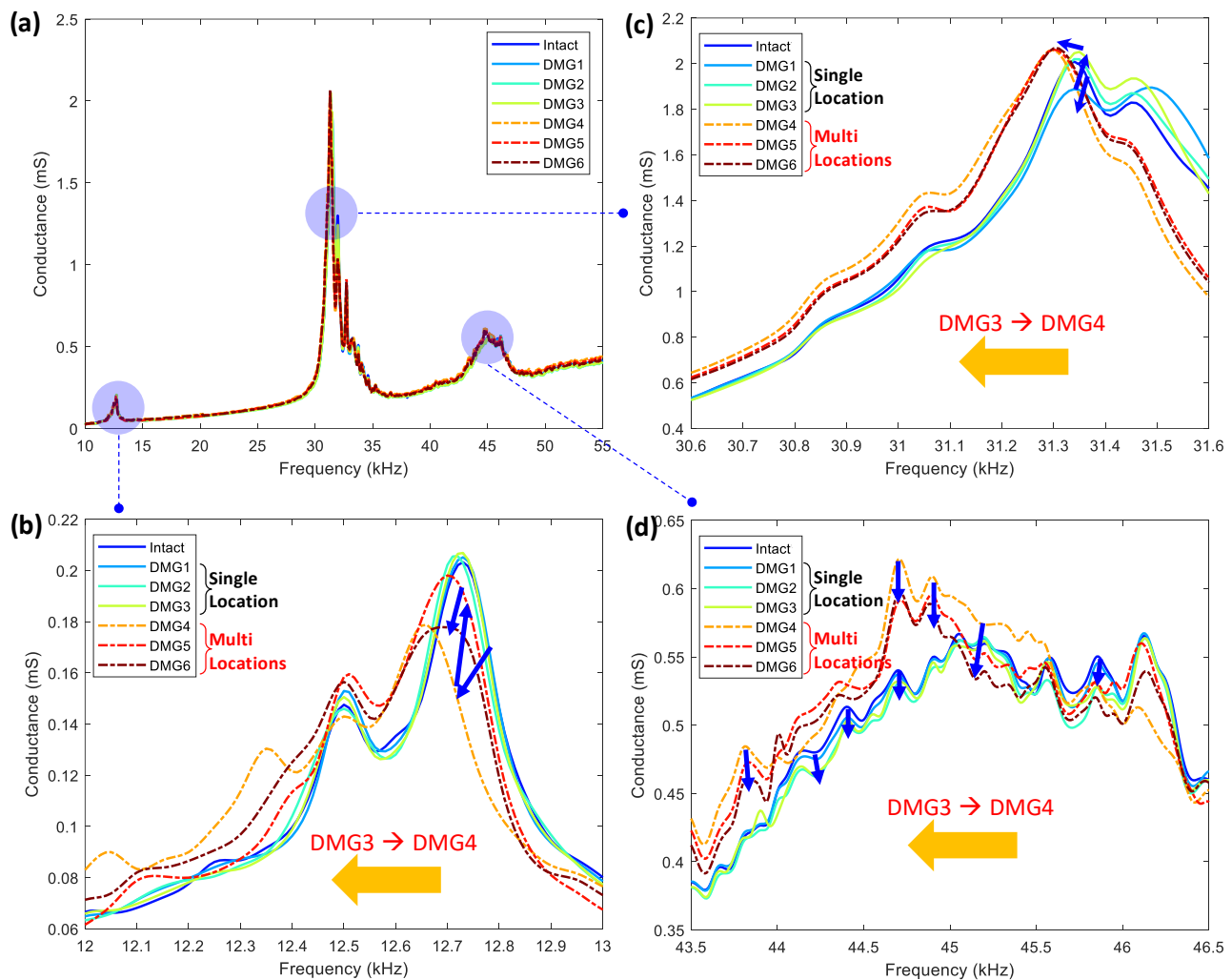


Figure 9. The EMA samples during the damage test: (a) 10–55 kHz; (b) 1st resonance; (c) 2nd resonance; and (d) 3rd resonance.

As compared with the strand relaxation cases, the conductance shifts in the simulated damage cases are more complex due to the presence of multi damage locations. No consistent shift trends can be observed from three resonances. For example, as depicted in Figure 9b, the peak near 12.75 kHz undergoes an amplitude reduction and leftward shift in the cases DMG3 → DMG4. In the cases DMG4 → DMG5, this peak presents an inversely leftward shift and increased amplitude. Then, this peak again exhibits a reduced amplitude in the case DMG6. Regarding the second resonance in Figure 9c, the main conductance peak at 31.35 kHz shows reduced amplitude while the lower peak at 31.45 shows an increased tendency for the intact → DMG1 cases. For the cases DMG1 → DMG3, the peak at 31.35 kHz undergoes an increment in conductance amplitude while the peak at 31.45 shows fluctuations in amplitude. For the last resonance shown in Figure 9c, it is clearly observed that the increment of mass weight added at single locations in the test cases DMG1 → DMG3 and DMG4 → DMG6 generally leads to downward shifts in the conductance spectrum. The conductance shifts during the damage test are found to be heavily non-linear. The next section will investigate the quantification of these nonlinearities and the quantitative relaxation severity estimation using statistical metrics. This examination aims to unveil distinctive patterns associated with damage scenarios and assess their potential for effective damage identification.

4.3.3. EMA Responses of Intact States

The EMA responses of intact states are analyzed, specifically comparing the conductance spectra of two different intact cases in the strand relaxation and damage tests, as illustrated in Figure 10. The second intact state is achieved by re-tensioning the strand to the prestress level of the first intact state (i.e., 14 tons) after the strand relaxation test. Despite having the same prestress force and no added mass (i.e., damage), noticeable gaps are observed in the second spectrum compared to the first spectrum.

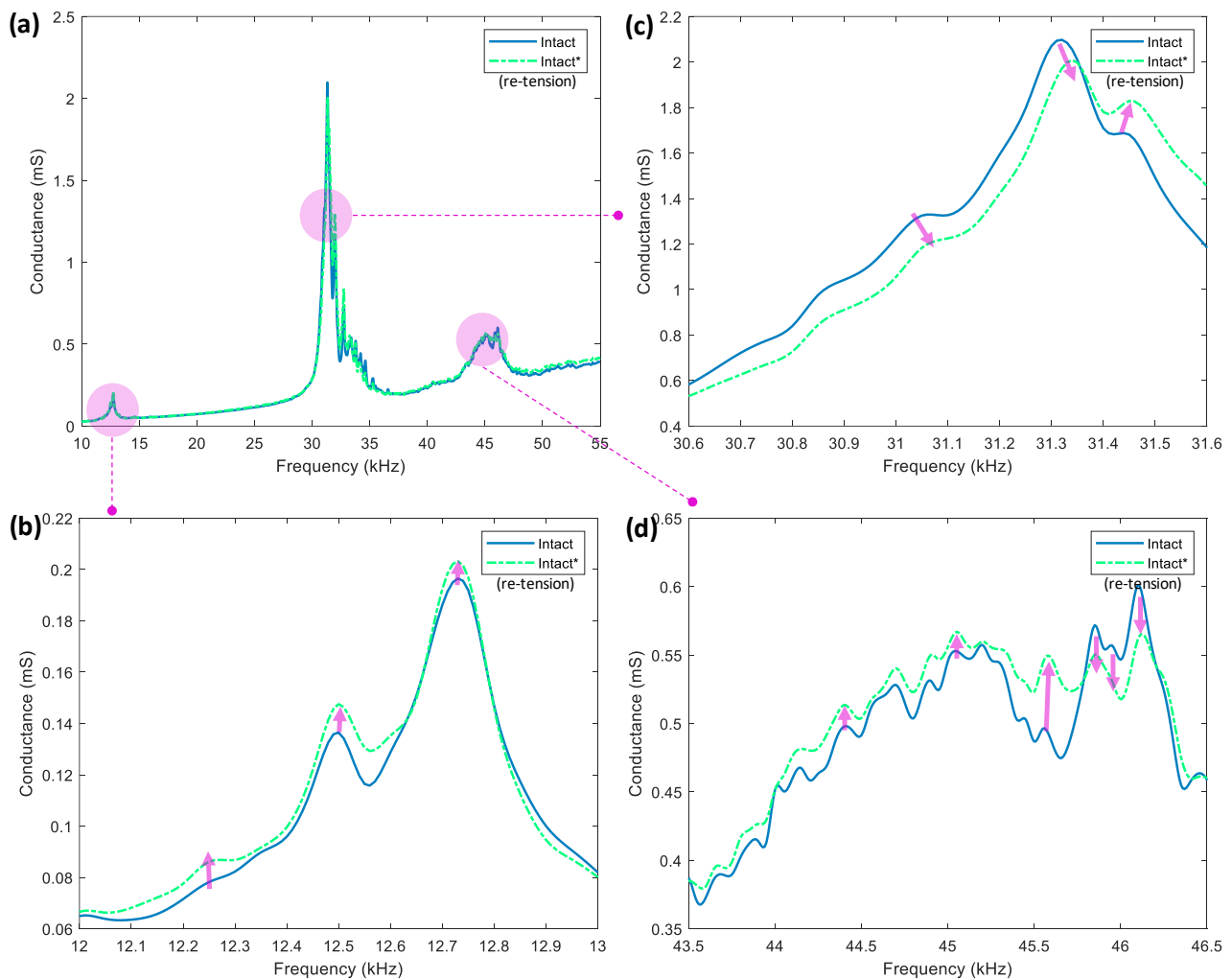


Figure 10. Comparison of the EMA samples of the two intact states: (a) 10–55 kHz; (b) 1st resonance; (c) 2nd resonance; and (d) 3rd resonance. (* superscript indicates the second intact state after re-tension).

In Figure 10b, amplitude shifts are observed in the conductance peaks of the first resonant band. Similarly, Figure 10c shows that in the second resonant band, the conductance peaks tend to shift to the right, with a significant peak undergoing an additional amplitude reduction. The behavior of the peaks in the final resonance band, presented in Figure 10d, is diverse, with some shifting upward and others shifting downward.

The observed differences between the two EMA signals belonging to two different intact states can potentially impact the accuracy of damage diagnosis. Despite having identical structural conditions, the deviations in the conductance spectra suggest non-linear behaviors in the EMA responses. These nonlinearities may introduce variations in the identified structural conditions, potentially influencing the effectiveness of traditional damage diagnosis algorithms.

4.4. Quantitative Evaluation of Strand Relaxation and Damage

This section quantitatively evaluates the strand relaxation and damage via using the traditional damage indicators RMSD and CCD. Figure 11a presents the RMSD-based quantitative evaluation results derived from the conductance signatures in the entire spectrum (i.e., 10–55 kHz). It can be seen that the RMSD metric exhibits consistent growth with relaxation development from the intact to RLX6 states. After reaching the peak (about 27%), the RMSD amplitude shows a turning point of sharp decline at the intact* state when the strand is re-tensioned to the initial prestress level (14 tons). However, the RMSD of the second intact state is still significant (about 10%) as compared with the first intact state due to the nonlinearity in the EMA behavior after re-tensioning, as explained in Section 4.4. The RMSD slightly increases when a mass block is added to the bearing plate in DMG1; afterward, it remains stable even when the damage becomes more severe in the cases DMG2–DMG3 due to ignorable variations in the conductance spectrum. In the cases DMG4–DMG6, the RMSD tends to decrease when more damage locations are simulated to the bearing plate.

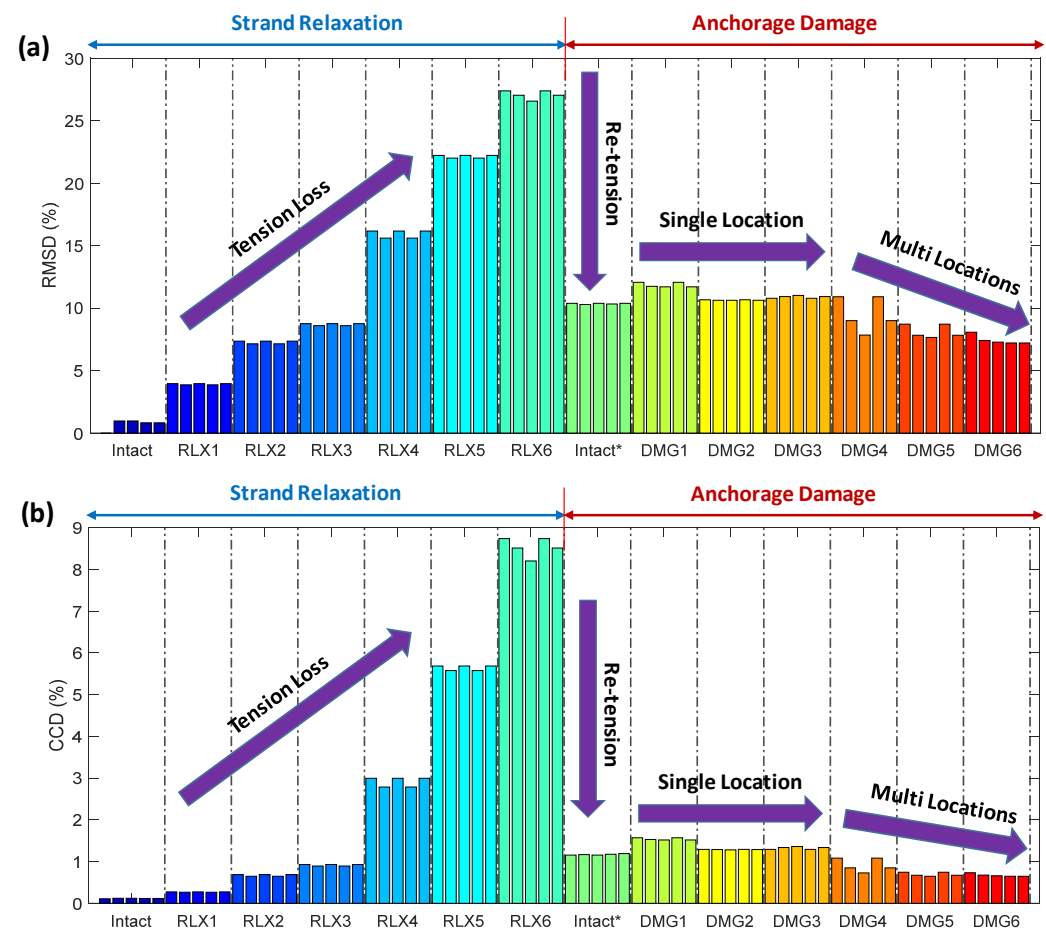


Figure 11. The quantitative evaluation of relaxation and damage in the test anchorage using the entire spectrum: (a) RMSD metric; (b) CCD metric (intact*: the intact state after re-tension).

The CCD metric also shows similar tendencies with additional nonlinearities, as shown in Figure 11b. In particular, the CCD metric nonlinearly increases with the relaxation severity from the first intact state to the RLX6 state. The CCD metric changes slowly from the intact state to RLX3 but quickly for the cases RLX3–RLX6. The metric significantly drops when the girder is prestressed up to the initial healthy state (i.e., intact*), but it is still significant as compared to the metric of the first intact state.

The presence of nonlinearities in the EMA response contributes to corresponding nonlinear variations in RMSD and CCD metrics, potentially leading to incorrect damage detection results [35,79]. The nonlinear effects become evident in the changing EMA baseline when re-tensioning the prestressing strand. Consequently, the interpretation of the second intact state becomes challenging, as illustrated in Figure 11a,b, where it may be misconstrued as a relaxation state (i.e., RLX3). The sensitivity of EMA signals to damage is influenced by factors like wave scattering and attenuation. Due to wave scattering from the anchor head, detecting added mass blocks in DMG1–DMG3 becomes challenging, leading to minimal changes in EMA response and subsequently inconspicuous variations in the RMSD and CCD metrics. Interestingly, the damage state DMG6 is found to be less severe than the DMG1 state due to the nonlinear change in conductance, manifesting as reductions in the RMSD and CCD metrics.

From the preceding discussions, it becomes evident that there is a need for a more reliable feature extraction approach capable of minimizing the nonlinearities in EMA behaviors. The traditional RMSD and CCD metrics provide only general information about structural integrity, making it challenging to interpret the extent of damage accurately. Hence, an advanced feature extraction method that can automatically identify damage-sensitive EMA features across the entire spectrum is crucial for ensuring the accuracy of relaxation and damage identification results.

5. Performance Evaluation of the Proposed Method

5.1. Data Preparation

For each of the fourteen strand testing cases as described in Table 2, five EMA samples were repeatedly measured. In each sample, 901 data points were collected from the 901 frequency points ranging from 10 to 55 kHz (0.05 kHz interval). Consequently, a databank of 63,070 data points corresponding to thirteen structural conditions of the test anchorage (i.e., intact, DMG1–DMG6, RLX1–RLX6) were obtained.

The EMA signatures in real applications are altered by external disturbances such as noise conditions. For data augmentation and the consideration of realistic situations as explained in Section 3.3, each of the EMA signals is respectively injected by a random white Gaussian noise with a standard deviation ranging from 0% to 5% (0.5% interval) of the signal amplitude. As a result, a databank of 770 EMA signals with 693,770 data points of the thirteen anchorage conditions are created for training and testing the proposed damage identification model. Figure 12a–c illustrate the sample noise-contaminated EMA signal for the intact, RLX6, and DMG6 states, respectively. It is evident that the introduction of additional noises has modified the original signal to some extent. The higher the noise percentage, the more noticeable the amplitude changes in the signal.

The stratified shuffle–split technique [69] (K-fold cross-validation as presented in Section 3.4) was utilized to randomly split the obtained databank into five fold datasets (Fold 1–Fold 5). Each of the five folds consists of the evaluation set (20%) of randomly selected 154 EMA signals and the training dataset (80%) of the remaining 616 EMA signals. Figure 13 presents the distribution of the testing EMA samples of the evaluation set in each fold. The implementation of the stratified shuffle–split technique ensures that each fold has a representative distribution of the target structural conditions and the distinctiveness of each split dataset for the training and evaluation of the proposed 1D CNN.

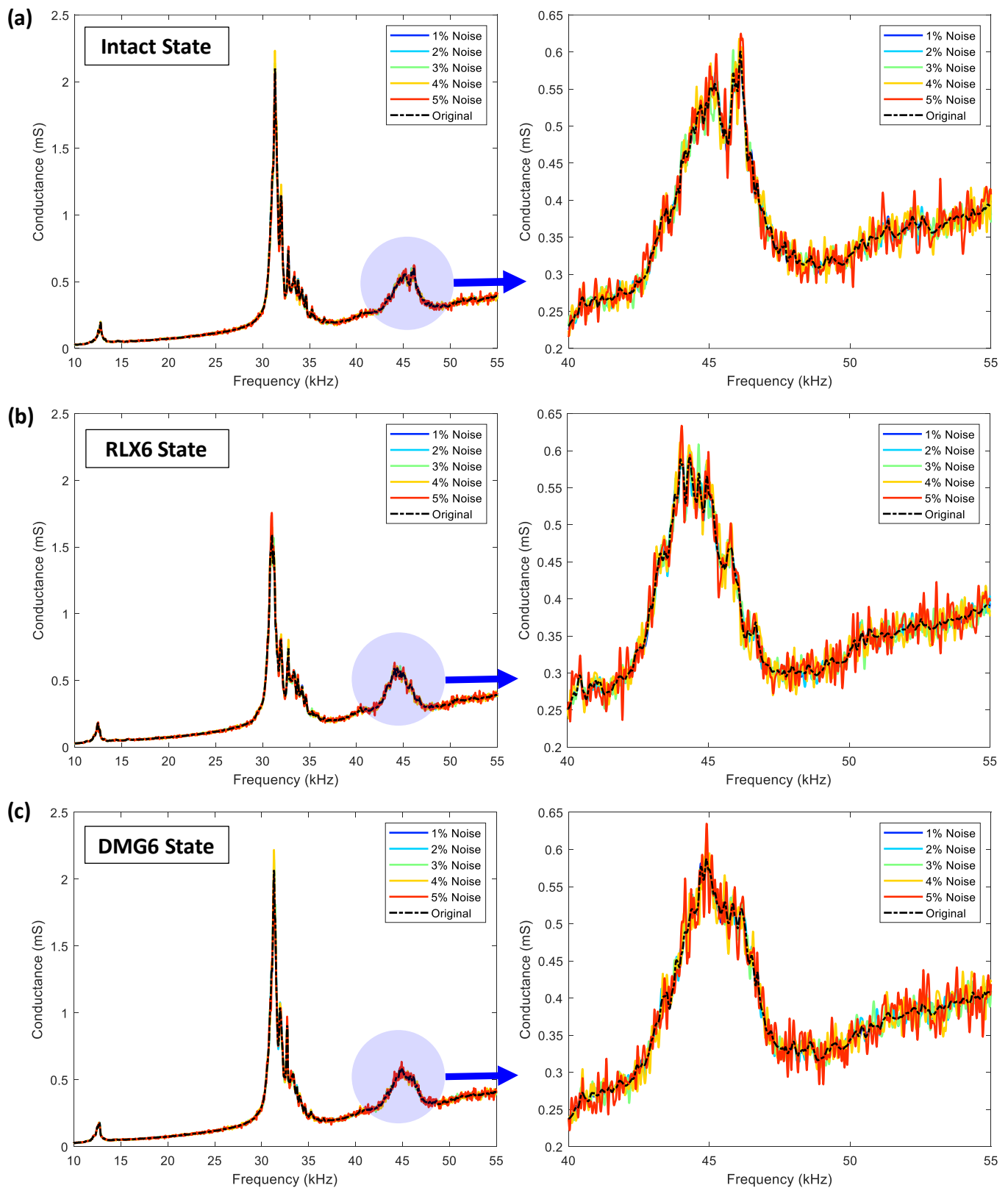


Figure 12. Data augmentation by introducing white Gaussian noises into the EMA signals: (a) the noise-contaminated EMA signal of the intact state; (b) the noise-contaminated EMA signal of the RLX6 state; and (c) the noise-contaminated EMA signal of the DMG6 state.

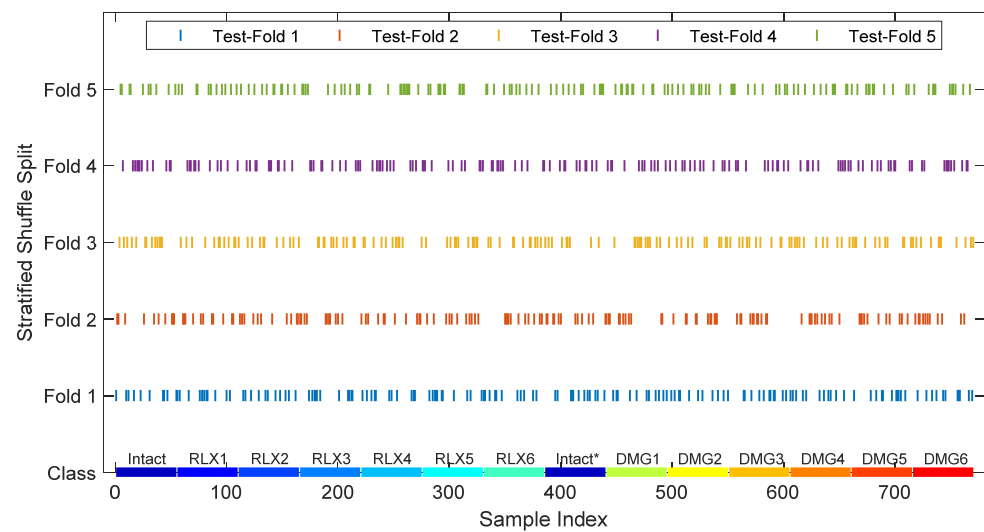


Figure 13. The distribution of the testing samples in each fold generated by the stratified shuffle-split technique.

5.2. Relaxation and Damage Prediction Using the Proposed 1D CNN

Figure 14 presents the outcomes of the proposed deep learning model for strand relaxation and damage identification in the test bridge anchorage. As shown in Figure 14a, a gradual reduction in loss across training iterations is observed for the five folds. After over 2500 iterations, all training losses of the folds become negligible, indicating the stable convergence of the 1D CNN model. The model's performance through training accuracy is depicted in Figure 14b. A consistent upward trend in accuracy over iterations is observed for all five folds. After 2695 iterations, the training accuracies approach near-perfection. The model's testing accuracy across five different fold splits is notably high, varying between 96.75% and 99.35%, as observed in Figure 14c. The trained 1D CNN model demonstrates promising outcomes for relaxation and damage identification, with an average testing accuracy across five folds reaching 98.05%.

Figure 15 presents the average confusion matrix across five folds for the relaxation and damage prediction by the proposed 1D CNN. The matrix encapsulates the nuanced probabilities associated with 13 distinct structural conditions of the test anchorage (intact, RLX1–RLX6, and DMG1–DMG6), where the horizontal axis signifies the true class and the vertical axis denotes the predicted class. Notably, the proposed network achieves remarkable testing accuracy, particularly evidenced by the high probability of the diagonal elements and minimal off-diagonal values. The accuracy for predicting the strand relaxation varies between 90.9% and 100% while the damage identification accuracy ranges from 96.4 to 100%. Despite the remarkable accuracy, few misclassifications for identifying the strand relaxation states are still observed. There exists a 1.8% misclassification rate where instances of RLX2 are inaccurately predicted as RLX1. An additional 7.3% of RLX2 instances are misclassified as RLX3, whereas 3.6% of RLX3 samples are misclassified as RLX2. This suggests an overlap in the characteristics of RLX1–RLX3.

The achieved outcomes affirm the effectiveness of our proposed 1D CNN model in accurately identifying various structural conditions within the bridge anchorage. The model shows the ability to autonomously process raw EMA datasets and learn optimal EMA features for accurate damage classification, even in the presence of nonlinearity within damage characteristics and variations in intact states. Thus, the model successfully overcomes the limitations inherent in traditional RMSD and CCD-based damage prediction approaches.

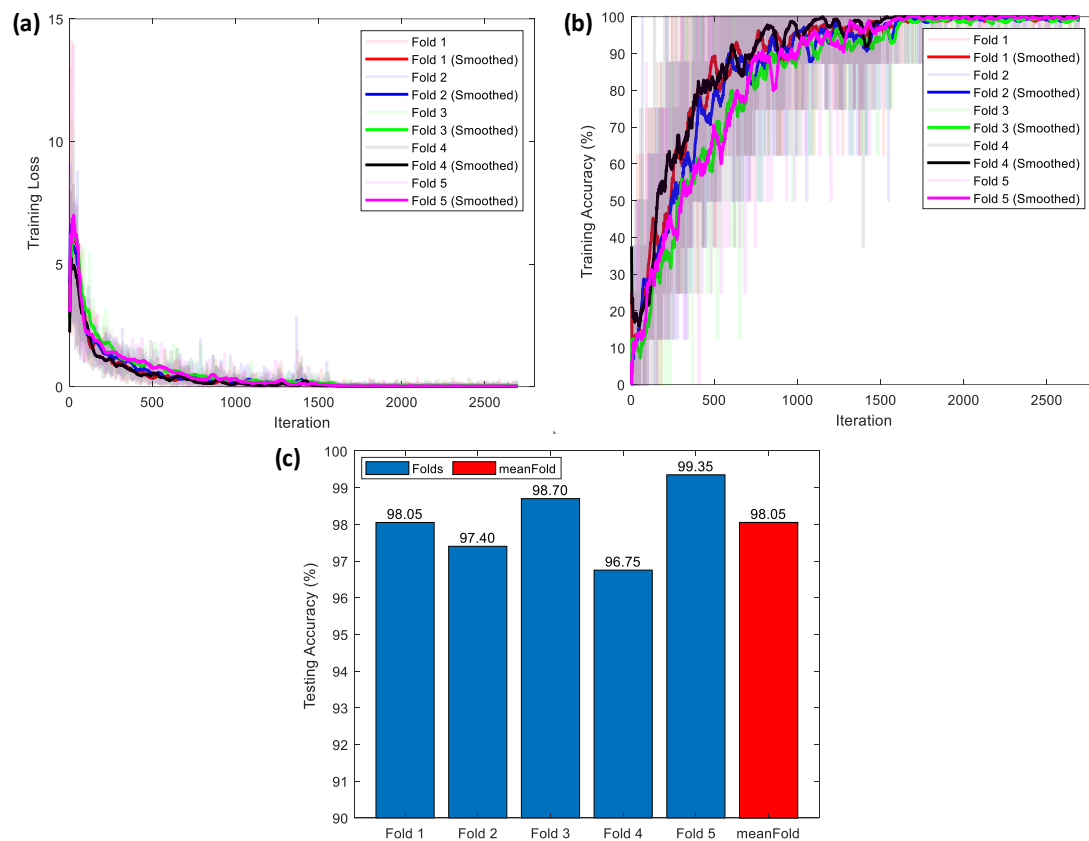


Figure 14. The training and evaluation results of the proposed 1D CNN-based damage identification method: (a) training loss, (b) training accuracy, and (c) testing accuracy across five folds ('meanFold' indicates the average accuracy).

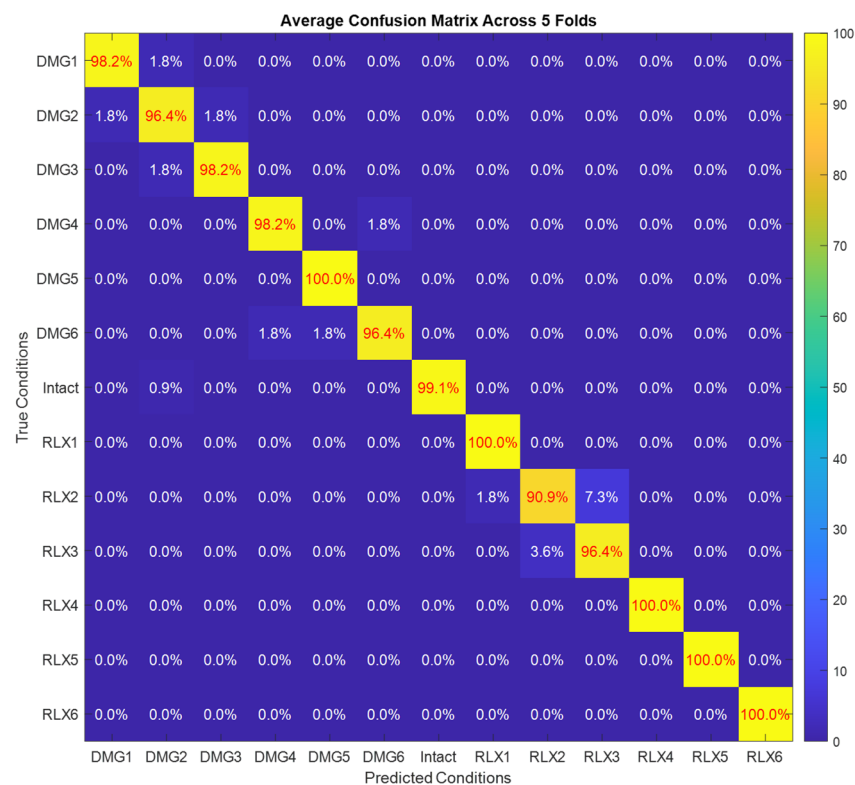


Figure 15. The average classification probability matrix across five folds for the relaxation and damage prediction by the proposed 1D CNN-based damage identification method.

5.3. Comparison with Other 1D CNN Models

In this section, the performance of the proposed model with four well-established 1D networks are compared, including the 1D CNN model proposed by Nguyen *et al.* (2022) [44], and the CNN160, CNN320, and CNN640 models proposed by Ai *et al.* (2023) [23]. The four models were trained and validated using the same training and validation sets of the five folds via the K-fold cross-validation method. The training algorithm and training parameters are set following the method described in Section 3.2. Figure 16 presents the comparison of the average testing accuracy across the five folds between this study and the previous studies. The comparative assessment of testing accuracies across multiple deep learning models reveals the superior performance of the proposed method, as evidenced by the highest testing accuracy. In contrast, the 1D CNN model reports a testing accuracy of 88.96%, while the CNN160 model and the CNN320 both attain slightly higher accuracies at 89.35% and 88.96%, respectively. The CNN640 model, although showing competence, registers a testing accuracy of 87.27%. The obtained result showcases the proposed network's efficacy in accurately identifying thirteen structural conditions (strand relaxation and damage states) within the test bridge anchorage. The detailed results of the relaxation and damage identification by the four well-established models are presented in the following sections.

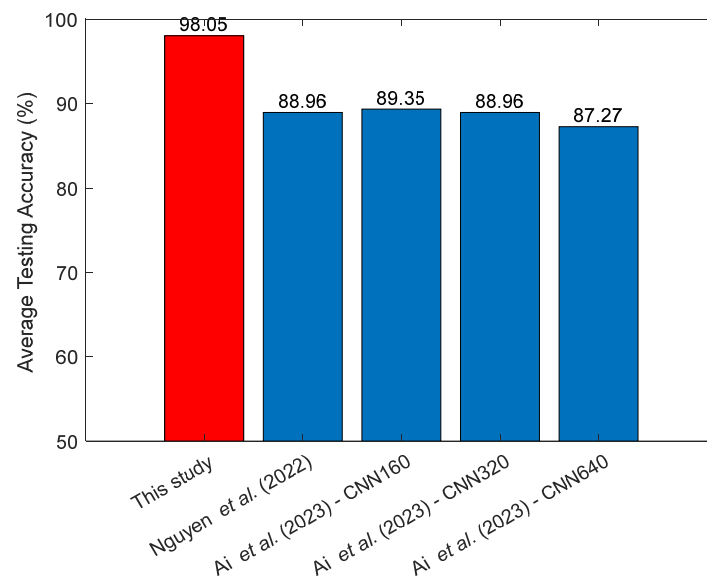


Figure 16. Comparison of the average testing accuracy across five folds between the proposed method in this study with other methods in literature [23,44].

5.3.1. Results by Nguyen's Prediction Model

The 1D CNN model proposed by Nguyen *et al.* (2022) [44] was implemented for strand relaxation and damage identification in the test bridge anchorage. The network architecture of the model was initially designed to process the 501×1 signals and have a single output [44]. Therefore, to fit with the prepared EMA databank, the dimension of the input layer was expanded to 901×1 while the dimension of the output layer was extended to 13×1 , corresponding to the thirteen structural conditions of the anchorage.

Figure 17 illustrates the training process and damage prediction outcomes of the 1D CNN model developed by Nguyen *et al.* (2023) [44]. In Figure 17a, there is a gradual decline in loss observed across training iterations for the five folds. After 2772 iterations, all training losses reach negligible levels, indicating the stable convergence of the 1D CNN model. The testing performance of the model is depicted in Figure 17b, showing a testing accuracy ranging between 80.52% and 94.16% across five different fold splits, with an average testing accuracy of 88.96%.

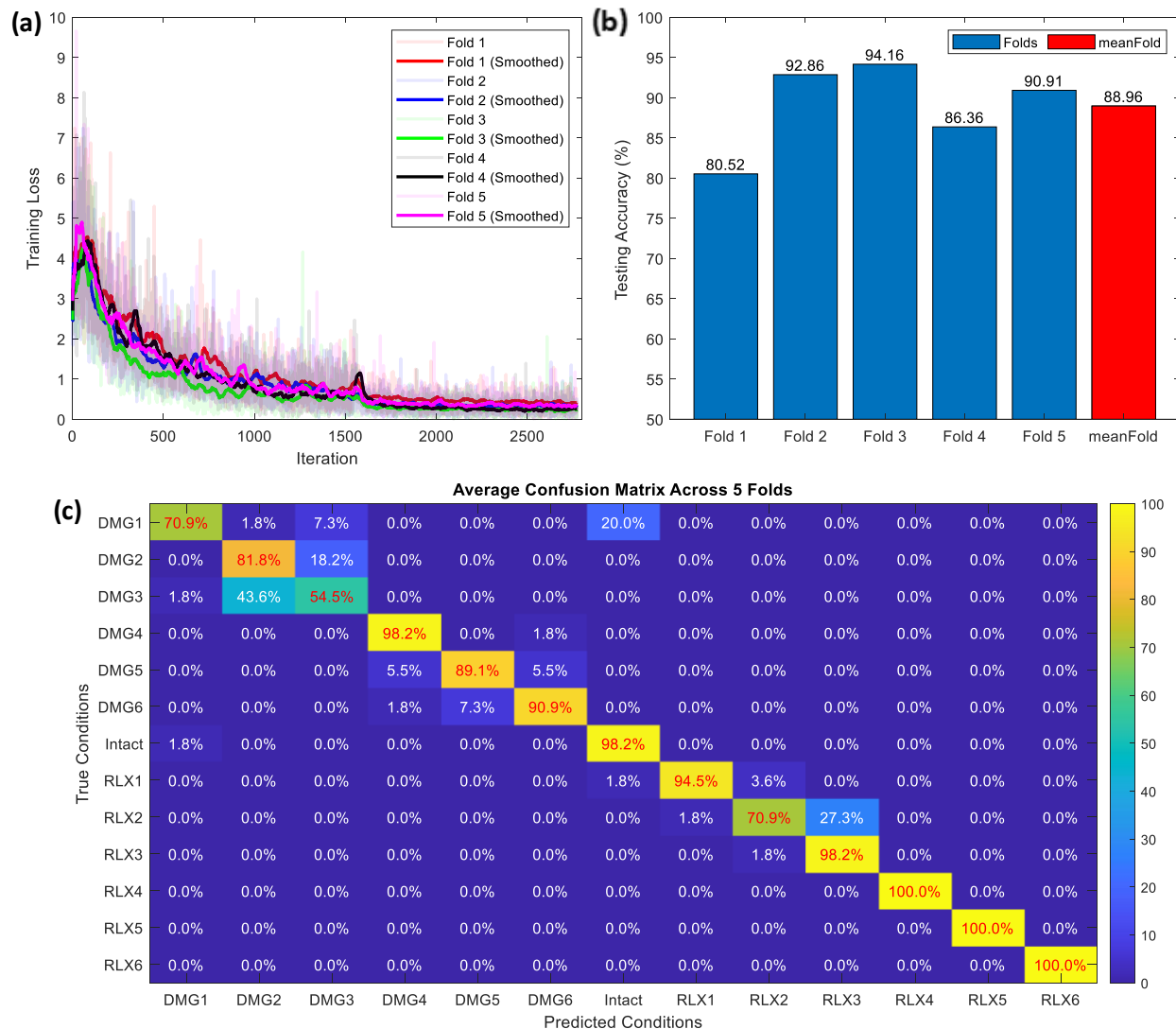


Figure 17. The training and evaluation results for the relaxation and damage prediction across five folds of the CNN model developed by Nguyen *et al.* (2022) [44]: (a) training loss, (b) testing accuracy across five folds, and (c) the average classification probability matrix across five folds.

In Figure 17c, the average confusion matrix across five folds reveals noteworthy distinctions in the predictive performance of the model concerning strand relaxation and damage identification. Specifically, the accuracy for predicting strand relaxation fluctuates between 70.9% and 100%, while the accuracy for damage identification ranges from 54.5% to 90.9%. A comparative analysis with our developed model indicates a higher incidence of misclassifications in this model, particularly concerning the identification of damages within the anchorage region. As depicted in Figure 17c, only 54.5% of DMG3 instances are accurately predicted while a significant 43.6% of DMG3 samples are erroneously classified as DMG2. In contrast, for DMG2, 81.8% are correctly predicted, while the remaining 18.2% of DMG2 instances are misclassified as DMG3. Notably, 20% of DMG1 instances are erroneously categorized as intact (non-damaged). These outcomes underscore the model's challenges in effectively distinguishing between EMA signals representing DMG1–DMG3 states due to inherent overlaps in their characteristics. Additionally, the model exhibits confusion in distinguishing between RLX2 and RLX3. Notably, 27.3% of RLX2 instances are misclassified as RLX3.

5.3.2. Results by Ai's Prediction Models

The evaluation of the CNN160, CNN320, and CNN640 models, as introduced by Ai *et al.* (2023) [23], was conducted for strand relaxation and damage identification within the bridge anchorage. These three models were purposefully crafted to process resonant EMA data with varying dimensions. The CNN160 features an input layer of dimensions 160×1 , while the CNN320 and CNN640 boast input layers of dimensions 320×1 and 640×1 , respectively. In this study, frequency ranges encompassing EMA resonances, aligning with the input size of each network, were selected, following the guidelines laid out in [23]. Specifically, the CNN160, CNN320, and CNN640 models were configured to utilize the EMA data in the frequency ranges of 29–36.95 kHz (160 data points), 30.5–46.45 kHz (320 data points), and 23–54.95 kHz (640 data points), respectively. This strategic alignment ensures the optimal integration of the selected frequency ranges with the network architectures, enhancing their efficacy in capturing resonant features for structural condition assessment in the anchorage.

Figure 18a–c depicts the training loss and evaluation results for the relaxation and damage prediction across five folds of the three networks, respectively. For all models, a substantial reduction in loss is observed across the first 2000 training iterations for the five folds. Subsequently, the loss exhibits a more gradual decrease over the remaining iterations, converging for all folds after 7700 iterations. The CNN160 model achieves an average testing accuracy of 89.35%, ranging from 86.36% to 95.45% across five folds (Figure 18a). The CNN320 model attains an average testing accuracy of 88.96%, varying between 82.47% and 95.45% (Figure 18b). Meanwhile, the CNN640 model demonstrates an average testing accuracy of 87.27%, ranging from 82.47% to 91.56% (Figure 18c). Observably, among the three models, there is little variation in average testing accuracy, with the CNN160 model demonstrating slightly superior accuracy compared to the other two models. This outcome aligns well with findings from a previous study [23], indicating good agreement with existing research.

Figure 19a–c shows the average confusion matrix across five folds for the CNN160 model, the CNN320 model, and the CNN640 model, respectively. For all models, a higher occurrence of misclassifications is observed in the identification of damages in the anchorage compared to strand relaxation conditions. Similar to the prediction results of Nguyen's model presented in Section 5.3.2, these three models encounter challenges in effectively distinguishing between EMA signals representing DMG1–DMG3 conditions of the anchorage.

For the CNN160 model (Figure 19a), the accuracy for predicting damage conditions fluctuates between 34.5% and 96.4%, while the accuracy for strand relaxation conditions ranges from 94.5% to 100%. Notably, for DMG2, 49.1% of instances are misclassified as DMG3, with an additional 12.7% mistakenly categorized as DMG1, whereas 14.6% of the DMG3 samples are erroneously classified as DMG2. For DMG6, 18.2% of instances are misclassified as DMG5; conversely, 14.6% of DMG5 samples are erroneously classified as DMG6. Moreover, 10.9% of DMG4 instances are incorrectly identified as DMG5.

The CNN320 model (Figure 19b) exhibits inferior classification results for DMG1–DMG3 compared to the CNN160 model overall. Notably, the diagnostic accuracy for DMG2 is particularly concerning, reaching only 27.3%. A noteworthy 60% and 9.1% of DMG2 instances are misclassified as DMG3 and intact, respectively. Furthermore, the accuracy of diagnosing DMG1 also diminishes, with nearly 9% of DMG1 cases being misclassified. Among the three models, the CNN640 model (Figure 19c) yields the least reliable results. Notably, a significant portion of instances are misclassified, including 16.4% of DMG1, 60% of DMG2, and 12.7% of DMG3 instances, which are erroneously categorized as intact, DMG3, and DMG2, respectively.

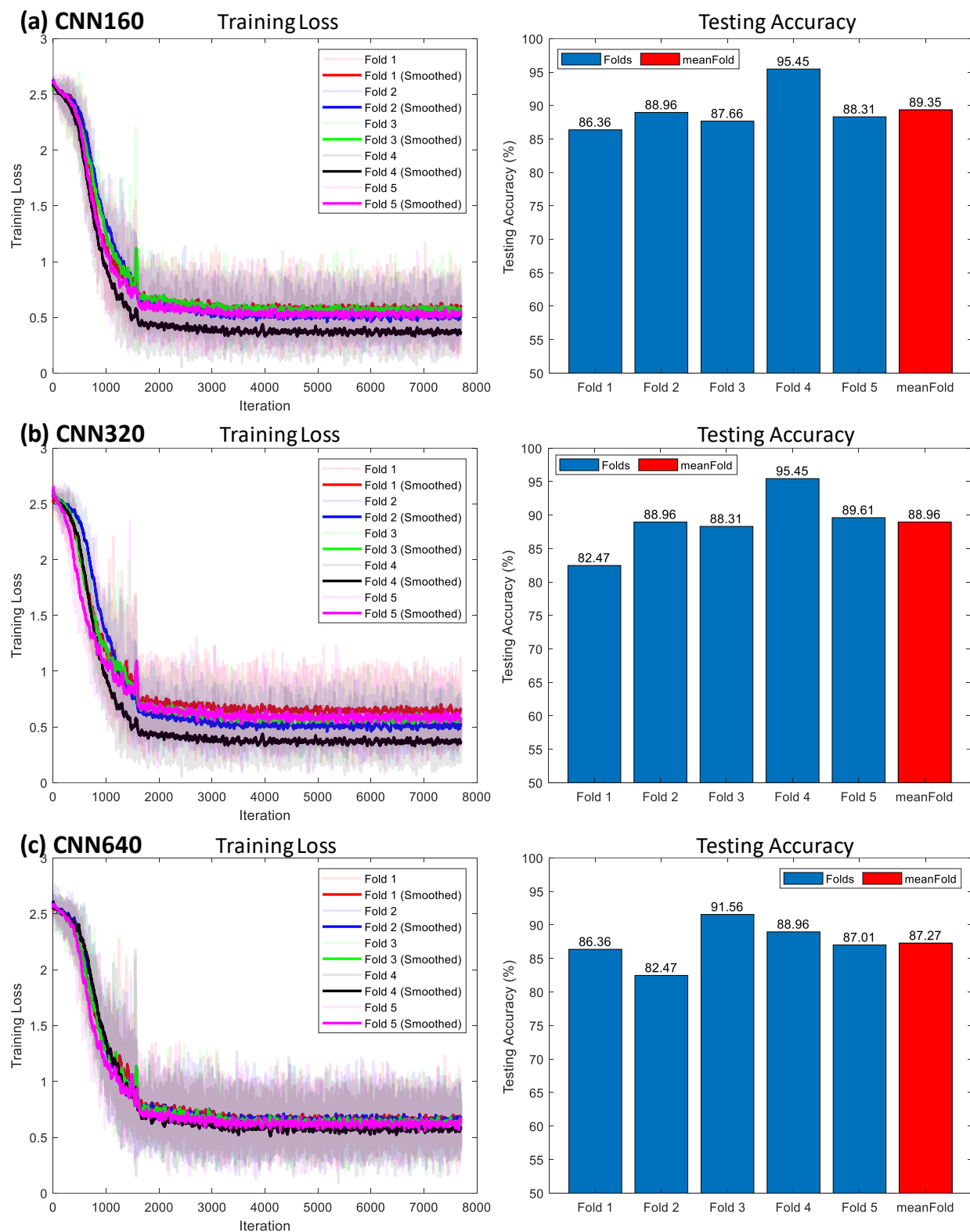


Figure 18. The training loss and evaluation results for the relaxation and damage prediction across five folds of the CNN models proposed by Ai *et al.* (2023) [23]: (a) the CNN160 model, (b) the CNN320 model, and (c) the CNN640 model.

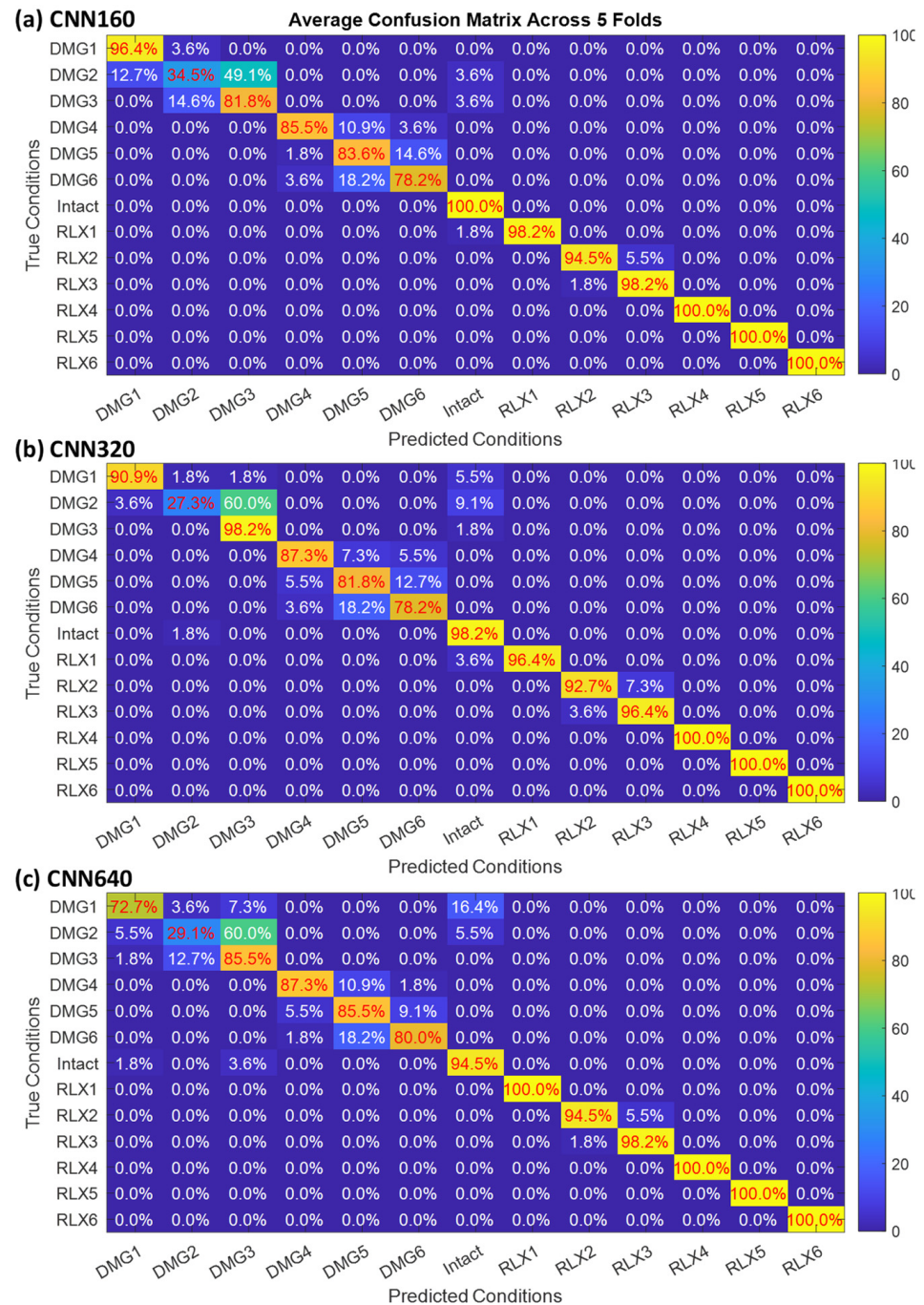


Figure 19. The average classification probability matrix across five folds for the relaxation and damage prediction of the CNN models proposed by Ai *et al.* (2023) [23]: (a) the CNN160 model, (b) the CNN320 model, and (c) the CNN640 model.

5.4. Comparison of Network Architectures

5.4.1. Databank and Network Architectures

The EMA signatures captured using PZT sensors in practical scenarios are inevitably influenced by external disturbances, including varying noise conditions [65,66]. To evaluate the impact of noise on the accuracy of the proposed 1D CNN model, a training set without noise and a validation set with introduced noise were configured. The training set encompasses all seventy measured EMA samples corresponding to thirteen structural conditions of the test anchorage (Intact, DMG1–DMG6, RLX1–RLX6). For the construction of the validation set, these 70 samples underwent augmentation with Gaussian white noises,

ranging from 1% to 5% (in 1% increments) of the EMA amplitude. This noise injection, as outlined in Section 3.3, results in an evaluation set comprising 350 EMA samples, totaling 315,350 data points.

A robust damage diagnostic model should provide accurate predictions even in the presence of noise influences. For the purpose of model selection, four distinct network architectures with increasing complexity, denoted as Model 1 to Model 4, are proposed and their performance is assessed using the aforementioned training and validation sets. The 1D CNN model presented in Section 3.1 is opted as Model 2. Model 1 is crafted by reducing the depth of Model 2, which is achieved by eliminating Block Y from the sequential layers, as illustrated in Figure 2. On the other hand, Model 3 and Model 4 are constructed by incrementally adding one and two additional Block Y to Model 2, respectively.

5.4.2. Prediction Results by Different Network Architectures

Models 1–4 were trained with the training set without noise and tested using the validation set with injected noise. Figure 20a presents the comparison of the training loss of the four models. The loss exhibits a significant reduction during the first 250 iterations and then remains stable over the remaining iterations. After 800 iterations, the loss of all models converges well. The model's performance through training accuracy is depicted in Figure 20b. A consistent upward trend in accuracy over iterations is observed for all models. Among the four models, Model 2 shows the best training loss and training accuracy during the training process.

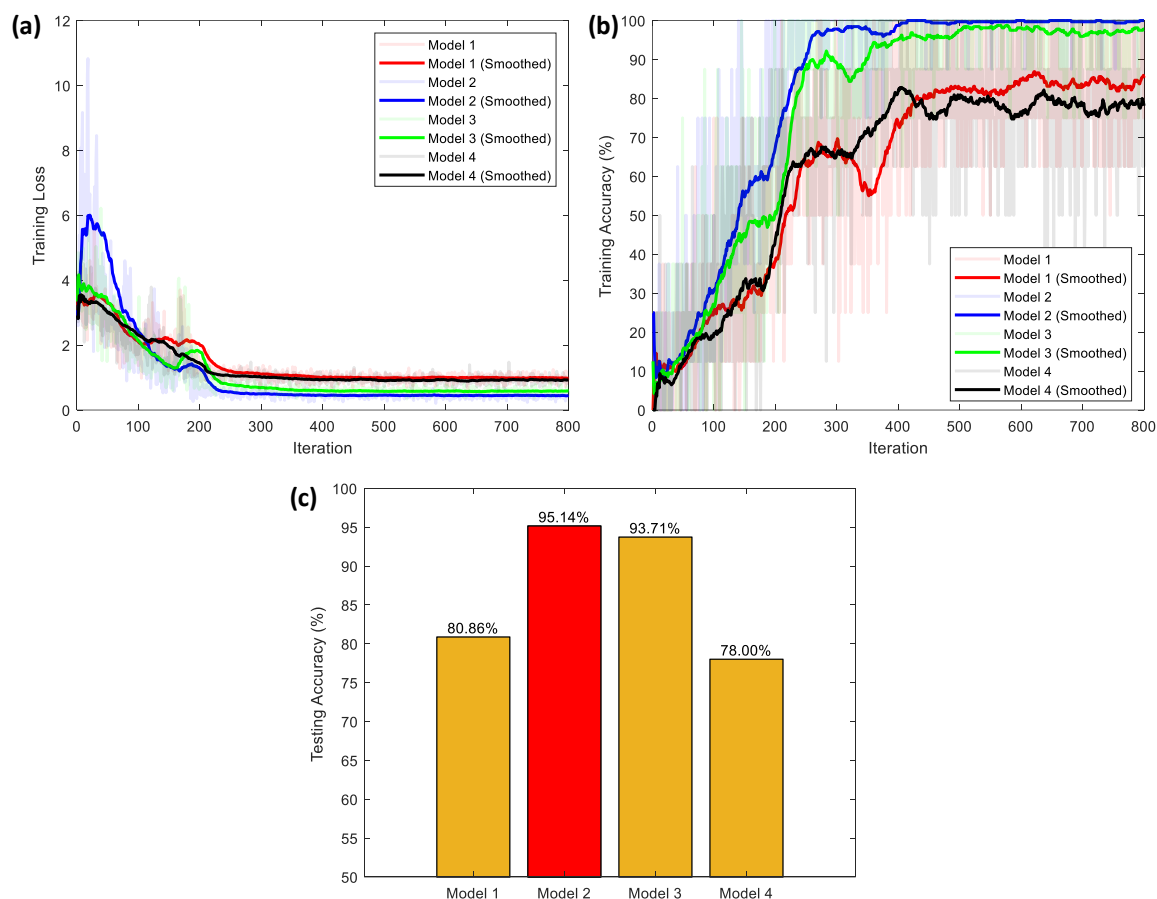


Figure 20. Comparison of four network architectures (Models 1–4) for the relaxation and damage prediction: (a) training loss, (b) training accuracy, and (c) testing accuracy.

Figure 20c compares the testing accuracy of the four models. Observing the results, it is evident that as the model complexity increases from Model 1 to Model 4, there is a

discernible impact on the testing accuracy. Model 2 stands out with the highest accuracy at 95.14%, showcasing an improvement in accuracy as complexity grows. However, as the complexity further increases from Model 2 to Model 4, there is a gradual decline in accuracy, indicating a phenomenon of overfitting. These findings underscore the importance of considering model complexity in achieving optimal diagnostic accuracy.

Analyzing the confusion charts of Models 1–4 reinforces the above comparison results. As depicted in Figure 21a, Model 1 completely fails to accurately predict DMG2 and achieves only a 16% accuracy when predicting DMG1 states. For DMG2, over 80% of DMG2 samples are misclassified as DMG3, and the remaining 20% are erroneously predicted as intact. Regarding DMG1, 40% of DMG1 instances are misclassified as DMG3, and 44% are mistakenly categorized as intact. Model 1 also struggles with classifying DMG5 and DMG6, achieving an accuracy of only 52% when predicting DMG5, with the remaining 48% misclassified as DMG6. Overall, Model 1 predicts strand relaxation conditions fairly accurate but exhibits poor performance in predicting damage conditions in the bridge anchorage.

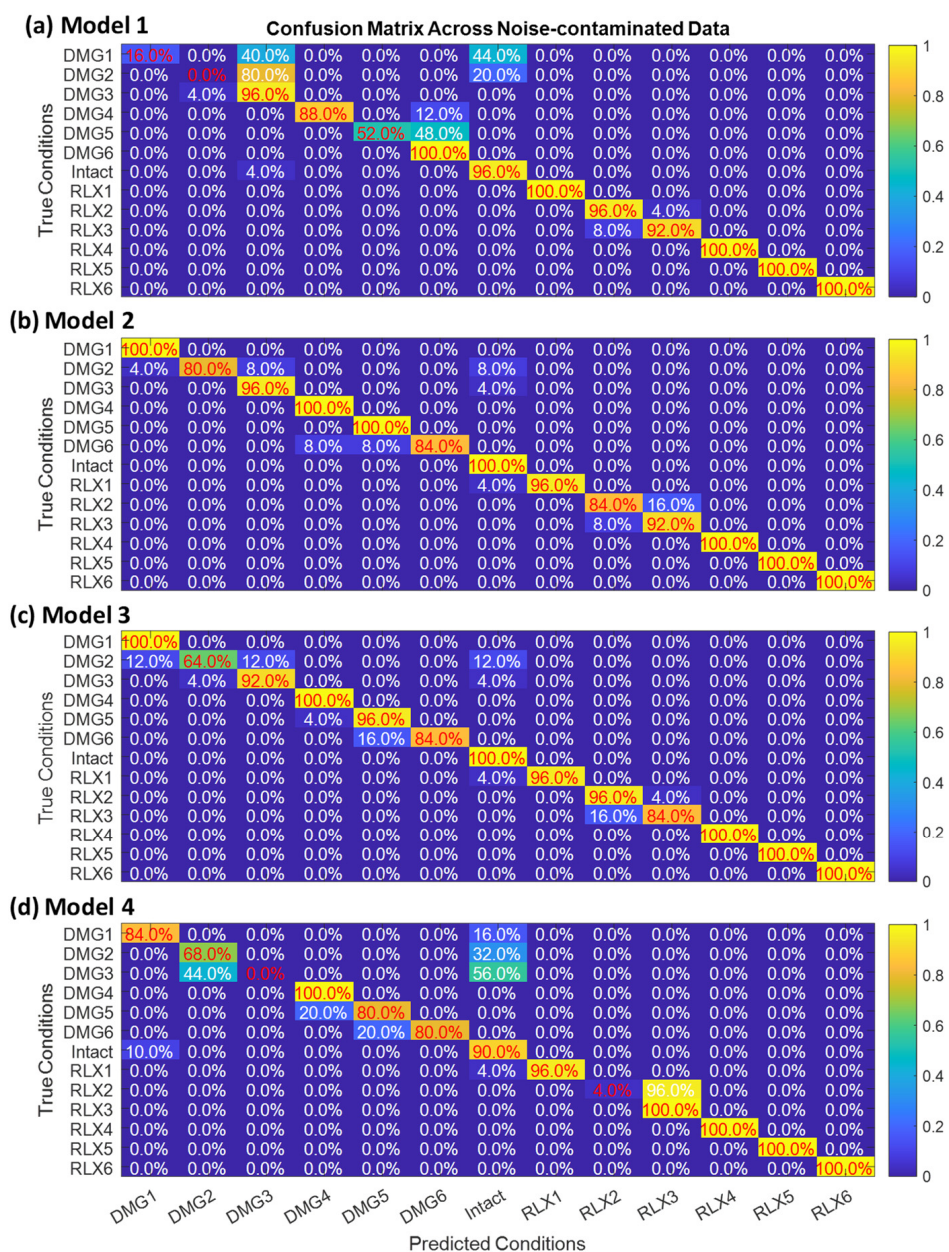


Figure 21. The classification probability matrix for the relaxation and damage prediction by different network architectures: (a) Model 1, (b) Model 2, (c) Model 3, and (d) Model 4.

As the network's complexity increases, the classification probability for damage classification has improved. In particular, Model 2 predicts damage conditions in the anchorage fairly accurately, as depicted in Figure 21b. Although the accuracy in diagnosing DMG6 and RLX2 has decreased, the overall accuracy of Model 2 remains high. As demonstrated in Figure 21c, when the complexity of the network architecture increases from Model 2 to Model 3, the model encounters difficulties in classifying DMG2, with accuracy decreasing from 80% to 64%. About 36% of DMG2 instances are misclassified as DMG1, DMG3, and intact. Furthermore, with the increased depth of the network in Model 4, the accuracy has significantly decreased. As shown in Figure 21d, Model 4 faces challenges in distinguishing between DMG1–DMG3 and intact, as well as RLX2 and RLX3.

Conclusively, Model 2 demonstrates high accuracy even when predicting strand relaxation and damage conditions of the anchorage using noisy EMA signals. Therefore, Model 2 is proposed as the optimal network architecture for multi-damage identification in the tested anchorage specimen in this investigation.

6. Conclusions

This study developed an automated method for the identification of various anchorage damage types through the 1D CNN-based deep learning of raw EMA responses. The accuracy of our method was further compared with well-established 1D CNN models. The following concluding remarks can be drawn, as follows:

- The analysis of EMA signals from the test anchorage revealed significant nonlinear behaviors in responses under different damage conditions and varying intact states after tendon re-tensioning. These nonlinearities introduced variations in identified structural conditions, potentially affecting traditional damage diagnosis metrics' effectiveness.
- The developed 1D CNN model exhibited the ability to effectively learn optimal features from raw EMA data with substantial nonlinearities in damage characteristics, demonstrated by accurate damage identification results, therefore addressing the limitations of traditional EMA feature extraction metrics.
- The results demonstrated the method's superiority over established 1D CNN models in assessing thirteen structural conditions (strand relaxation and damage states) within the test bridge anchorage, with a remarkable average testing accuracy of 98.05% across five folds.
- Among different network architectures, Model 2 with 12 layers demonstrated the highest accuracy, even when predicting strand relaxation and damage conditions using noisy EMA signals. Therefore, Model 2 emerges as the optimal network architecture in the context of this investigation.
- This study represents one of the first efforts to diagnose multiple structural conditions in bridge anchorages. The proposed method exhibits excellent accuracy and efficiency, offering a great potential for data-driven damage identification in prestressed structures.

Future studies are still needed to enhance the performance of the CNN-based anchorage damage identification approach and to expand its application scope. Firstly, this study simulates added masses as the representation of the bearing plate's damage and future research efforts should focus on more realistic damage simulation. Secondly, as this is a preliminary exploration for the feasibility of using CNNs for detecting multiple types of anchorage damage, it focuses only on the identification of singular structural condition scenarios. Future investigations should focus on the detection of combined or complex strand relaxation and structural damage states. Thirdly, the effectiveness of the proposed method shall be further investigated for an in situ and full-scaled multi-tendon anchorage subsystem.

Author Contributions: Conceptualization, T.-C.H., G.T.T. and D.-D.H.; methodology, J.-T.K., N.-D.H., T.-C.H. and D.-D.H.; validation, J.-T.K., N.-D.H., T.-C.H., D.-D.H., G.T.T., A.M.S.P. and M.-H.T.; writing—original draft preparation, T.-C.H., D.-D.H. and G.T.T.; writing—review and editing, J.-T.K., N.-D.H., T.-C.H., D.-D.H., G.T.T., A.M.S.P. and M.-H.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data are available upon request.

Acknowledgments: We acknowledge Ho Chi Minh City University of Technology (HCMUT), VNU-HCM for supporting this study.

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

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