Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 56-3 (2023) 379–384

Damage Detection of a Pressure Vessel with Smart Sensing and Deep Learning

Yang Zhang[1], Qianyu Zhou[1], Kai Zhou[2], Jiong Tang[1]

1: Department of Mechanical Engineering, University of Connecticut, Storrs, CT 06269, USA

2: Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University, Hung Hom, Hong Kong, China

Abstract: Structural Health Monitoring plays a crucial role in ensuring the safety and reliability of critical infrastructure, including pressure vessels involved in various applications. This research reports the damage detection of a pressure box employed in space habitat that operates in harsh environment where both structural failure and bolt joint loosening may occur. These failure modes are extremely hard to model based on first principles. We explore proper sensing mechanism and the associated inverse analysis algorithm that can elucidate the health condition of the pressure box. It is identified that piezoelectric impedance based active interrogation can provide necessary information for damage detection in such a system. Concurrently, deep learning technique leveraging spatial convolutional neural network is synthesized to analyze the raw data acquired and identify different types of damage. By training the deep learning model on a dataset of healthy and various damage scenarios, we can achieve high accuracy in identifying the presence of damage and its type. This research provides a data-driven methodology for structural damage detection using deep learning and has the potential to be extended to various systems with different failure modes.

Keywords: structural damage detection, deep learning, piezoelectric transducer, pressure vessel.

1. INTRODUCTION

The recent decades have seen a growing use of piezoelectric transducers in Structural Health Monitoring (SHM) of mechanical, infrastructure, and aerospace systems, due to their promising properties such as high bandwidth, good linearity, and being compact and easy to integrate (Park et al, 2003; Wang and Tang, 2009; Zhu et al, 2021; Shi et al, 2022; Xu and Deng, 2022; Zhou et al, 2022; Zhang et al, 2022; Cao et al, 2023). For example, the piezoelectric transducer embedded in a structure can excite the host structure by applying frequency-sweeping harmonic voltage; at the same time, the piezoelectric transducer can collect response measurements based on the two-way electro-mechanical coupling effect. As such, the change of the piezoelectric impedance/admittance signature due to damage can be used as the damage indicator. The physical model-based methods using piezoelectric transduce have embraced great success in structural damage identification. In such approaches, a finite element model is usually built. Then the responses predicted in the parametric space will be compared to the measurements. When the differences between the two are minimized, the structural property changes obtained indicate the damage location and severity. Fan et al (2018) developed a finite element model for a beam using piezoelectric impedance sensing, then the predictions are compared to experimental measurements to formulate a single-objective optimization model to solve for the structural damage. Cao et al (2018) incorporated sparsity of the damage index vector, the l_0 norm, as a separate objective in addition to the original objective of matching the response measurements, into damage identification. Consequently, a multi-objective optimization model is established, which is solved using metaheuristics. In this way, multiple solutions can be obtained as potential damage scenarios. In general, physical model-based damage identification can locate and quantify the damage not only in an accurate way but also in an interpretable manner.

The rapid advancement of computational power and sensing techniques have triggered the fast progress in data-driven analyses with rich datasets which benefit the SHM community. These data-driven approaches can bypass building the physical model and are applicable for complex structures. Deep learning is a type of data-driven methods that involves training artificial neural networks to learn complex patterns in data. In SHM, deep learning can be used to analyze sensor data and detect damage in structures (Zhou et al, 2023). Specifically, by training a deep learning model on a dataset of sensor data from healthy and damaged structures, the model can learn to identify patterns associated with different types of damage. Liu et al (2020) trained a classifier for a frame structure to classify different damage locations where the transmissibility functions are used as inputs and 17 classes are considered as outputs. Deep learning algorithms can be applied to data obtained from piezoelectric transducers to detect and classify different types of damage. For instance, Ai et al (2022) classified the loading conditions using 2D convolutional neural network (CNN) with conductance (real part of admittance) datasets where a piezoelectric transducer is attached to a concrete specimen, and a wide frequency band is swept. Li et al (2021) trained two CNNs for temperature recognition and crack damage quantification under various

10.1016/j.ifacol.2023.12.053

temperatures respectively. In this effort, the piezoelectric transducer is attached to a concrete block and the conductance datasets are collected, and the Orthogonal Matching Pursuit (OMP) algorithm is utilized to augment the datasets. Furthermore, Oliveira et al (2018) applied multiple piezoelectric transducers for classifying different structural damage cases in a plate structure. Zhang et al (2022) leveraged 1D CNN to conduct damage identification using piezoelectric impedance where, a tunable inductor is introduced into the circuit to enrich the dataset. Both structural damage and bolt loosening are considered. The trained neural network can not only locate the damage in a beam structure but also pinpoint the damage types. The results show the promising application of piezoelectric transducer in structural identification. Na (2021) utilized piezoelectric transducer-based technique with probabilistic neural networks (PNN) to identify torque loss of bolts on three bolted structure specimens. Here, small-sized transducers are attached to the caps of the bolts. To train the neural network model, the electromechanical impedance measurements are acquired.

It is worth noting that bolt joints are commonly used as fasteners in engineering structures. Loosened bolts often cause abnormal structural function. Therefore, bolt loosening can be considered as one damage type. It is, however, extremely difficult to establish first-principle based model to relate bolt joint loosening with dynamic responses. In this research, we use deep learning combined with piezoelectric impedance sensing to monitor the health for a pressure box employed in space habitat, which works in harsh and extreme environmental conditions. By continuously monitoring the structural health of the pressure box, potential damage caused by meteorite impact and bolt joint loosening can be detected and repaired. The goal in this research is to synthesize deep learning technique to identify the types of damage scenarios based on experimental data. By training a deep learning model with a dataset of healthy and damaged pressure boxes, the model can learn to identify patterns and features associated with different types of damage.

The rest of the paper is organized as follows. Section 2 outlines the problem setting and the data acquisition system using piezoelectric transducer. Section 3 elaborates the proposed spatial neural network architecture and systematic case studies. Section 4 gives the concluding remarks.

2. PRESSURE BOX DAMAGE DETECTION PROBLEM FORMULATION

2.1 Measurement system

The experimental setup is shown in Figure 1. A piezoelectric transducer is bonded to the top surface of the lid of a pressure box using MG Chemicals 8331D-14G silver conductive epoxy. To minimize the influence of the thickness of bonding layer, the resin layer is kept at smaller than 0.15 mm. The lid part is fastened to the main body of the pressure box using 32 bolts. Both structural damage of the top lid and bolt joint loosening are to be identified. A piezoelectric transducer is bonded to the top lid to excite the pressure box and sense the response. The lid part is made of aluminum material with Young's modulus of 72 GPa and density of 2850 kg/m^3. The geometric dimensions are thickness 12.7 mm, length 824.23 mm and width 469.9 mm. The piezoelectric transducer has a length of 70 mm, width of 28.575 mm and thickness of 3.175 mm.

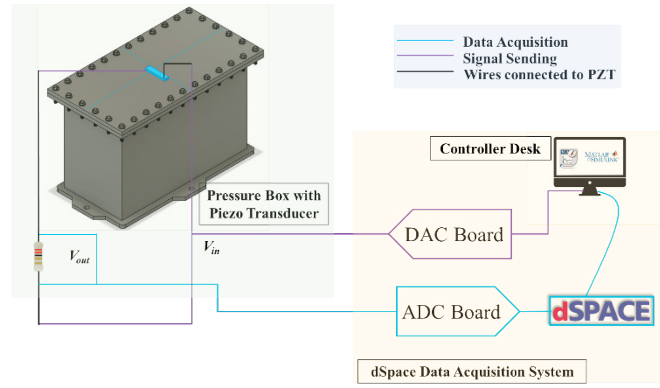

Figure 1. Pressure box and measuring system and Simulink model.

2.2 Data acquisition

The piezoelectric impedance measurement is facilitated through a small resistor connected in series with the transducer. The dSpace data acquisition system is used in this research. As shown in Figure 1, the ControlDesk 6.2 controls the measurement process where a Simulink model is built so that it can generate command voltage to excite the transducer and acquire the measurements from the transducer due to the two-way electromechanical effects. The voltage generated will pass through the DAC Board and be applied across the circuit. The system measures the voltage across the resistor and passes the measurements through ADC Board to the ControlDesk. A chirp signal is used here since it can cover a wide frequency range, in which the frequency increases (up-chirp) linearly with time. The frequency range is set as from 1,000 Hz to 5,000 Hz within 20 seconds. The sampling rate is 10,000 Hz with measuring time set as 180 seconds. The gain in signal generation model is adjustable so that different voltage levels can be applied to the transducer. Here in this research, we take it as 0.5 V.

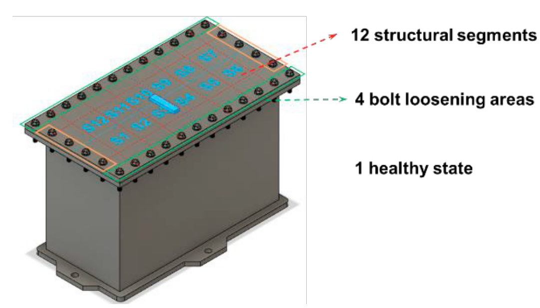

Figure 2. Pressure box and damage case settings.

The lid part, as shown in Figure 2, is divided into structural damage and bolt l oosening areas. The bolt loosening areas include two long edges and two short edges. The four corner bolts belong to the two long edges. This is because when we compare the signals from corner bolt loosening case to signals from long and short edges respectively, the results show that the corner bolt loosening has nearly the same responses to that from long edges. Additionally, we add mass blocks with an average weight of 334 g to the lid to emulate the structural damage scenarios. By this, we can conduct SHM without altering the boundary conditions and changing the lid. One example measurement is shown in Figure 3. It is obvious that there are 4 cycles when chirp signal is applied within the measuring time, i.e., the basic shape repeats 4 times, as marked in the plot. Each measurement contains 1,960,000 data points. For the sake of computational efficiency, each measurement will be sliced into 4 slices equally sized, named as S1-S4, shown in Figure 3.

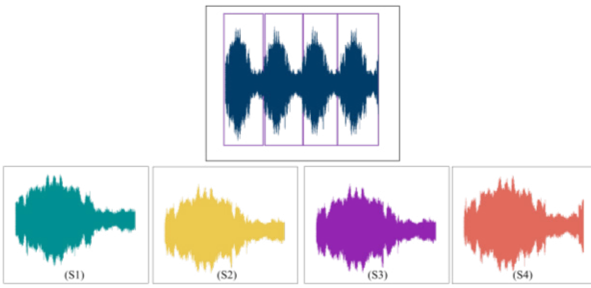

Figure 3. Measurement example and slices.

3. DEEP LEARNING FOR DAMAGE DETECTION

3.1 Spatial Convolutional Neural Network

Convolutional Neural Networks (CNNs), originally designed for image processing, have demonstrated unparalleled prowess in capturing spatial hierarchies and intricate patterns within data. Their unique ability to recognize and learn spatial features makes them an indispensable tool, especially when data can be represented or transformed into a spatial format. While sequential data is traditionally processed using Recurrent Neural Networks (RNNs) due to their capacity to capture temporal dynamics, there are scenarios where the spatial representation of such data offers richer insights. In our endeavor, we have found that transforming our 1D pressure box signals into a 2D spatial format can unveil complex spatial relationships, making CNNs an apt choice for classification. This decision to employ a spatial CNN underscores our belief in leveraging the best of both spatial and sequential data paradigms to achieve superior results.

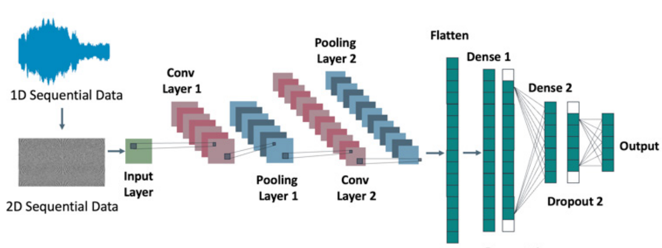

Figure 4. Illustration of spatial convolutional neural network.

Here we apply the spatial convolutional neural network (S-CNN) and train with the time-series data. The network architecture consists of multiple layers of 2D convolutional and pooling operations, followed by fully connected layers and drop out layers. Each convolutional layer applies a set of filters to the input, and the resulting feature maps are down sampled through pooling operations to reduce the dimensionality of the data. The fully connected layers then combine the extracted features to make the prediction for our structural health monitoring. Figure 4 presents the diagram of the model architecture for spatial convolutional neural network. The following sub-sections will elaborate on each layer in detail.

3.2 Data Preprocessing

The entire 1D time-series data of a test sample is acquired and subsequently segmented evenly into four slices to facilitate further analysis, as Figure 3 presents. Each slice is then subjected to resampling to reduce its dimensionality. Specifically, the proposed resampling algorithm performs a Fourier transform to convert the signal into the frequency domain, interpolates the signal by zero-padding, and then performs an inverse Fourier transform to return the signal back to the time domain with the new number of samples. This resulting resampled signal is a lower-resolution representation of the original signal, while preserving the overall structure and essence of the original data. The resampled data is then reshaped into a 2D time-series data format without normalization, which is deemed suitable for subsequent 2D convolutional operations. Segmentation and resampling steps are carried out to enable the extraction of relevant features, and to enhance the interpretability of the results obtained from the convolutional neural network model. These steps are essential to be integrated into the proposed model structure to ensure the quality and accuracy of the analysis.

3.3 Convolutional Neural Layer

Convolutional neural networks have been demonstrated with superior performance in a wide range of machine learning tasks, particularly in image-based classification. This is achieved through the mechanism of feature extraction in convolutional layers, which involves sliding a window over the input to capture local, translatable features.

The convolutional layers are essential components of the network that extract representative and identical features while preserving as many local details as possible from the entire input. These local features, obtained from different locations in the input by sliding the inspection window and performing the convolution operation at every stride, are combined to produce a 3D feature map. Each 3D local feature map is then transformed into a 1D vector and reassembled into a 3D output feature map, representing a wealth of local details and features.

To achieve a comprehensive understanding of the input, progressively abstract patterns and knowledge must be learned from the local feature maps produced by the previous layers. Local features alone cannot provide a complete picture of the input, and combinations of features must be discovered to capture more complex patterns. The deeper layers of the network generate more global patterns comprised of the local features, rendering relevant knowledge and features spatially hierarchical. This allows the convolutional neural network to observe and evaluate sample images from multiple perspectives, enabling it to effectively classify and analyze complex input.

3.4 Fully Connected Layer

In the spatial convolutional neural network, the fully connected layer is the final layer of the network, responsible for transforming the feature maps produced by the convolutional and pooling layers into a form that can be used for classification. The fully connected layer is composed of a set of nodes, each of which is connected to every node in the previous layer. These connections are represented by a matrix of weights, which are learned during the training process using backpropagation. The inputs to the fully connected layer are flattened versions of the output feature maps from the previous convolutional and pooling layers. This flattening process allows the fully connected layer to treat each element of the feature map as a separate input, and to learn relationships between these inputs and the target output. Each node in the fully connected layer computes a weighted sum of its inputs, using the learned weights and biases. The result is passed through an activation function, the rectified linear unit, to introduce nonlinearity into the model. The output of the fully connected layer can be interpreted as a probability distribution over the possible classes for prediction reference.

After the fully connected layer, a dropout layer is added to the neural network architecture to further reduce overfitting. The fully connected layer can have a large number of parameters, making it particularly susceptible to overfitting, and the dropout layer can help to mitigate this problem by introducing stochasticity and reducing the co-adaptation of neurons in the layer. During training, the dropout layer randomly drops out a percentage of the nodes in the layer, which encourages the remaining nodes to learn more robust and generalizable features. This helps to prevent overfitting and improve the performance of the neural network on unseen data. In our practice, the dropout layer is applied after the fully connected layer but before the final output layer of the network, and the probability of dropout is set to 0.2. Dropout has been shown to be an effective regularization technique in improving the performance and generalization of the proposed model.

3.5. Implementation

Two cases considered here, namely measuring time with 60s and 200s, in order to establish the significance of periodic features in the response that can capture the damage information. In the former case, we obtained 585,000 time-series data points, which correspond to a single instance of a 60s response, as marked in Figure 3. We repeated this procedure nine times across three distinct states. Subsequently, we partitioned each response into 18 equally sized pieces, leading to 54 independent training samples for each classification class, with each segment being considered as an autonomous input to the ensuing feature extraction process.

For the latter scenario, we obtained 1,960,000 time-series data points, which correspond to a singular occurrence of a 200s response. Similarly, we repeated this data collection process twelve times across three disparate states and partitioned each response into four non-overlapping slices to preserve all the periodic features, resulting in a total of 48 independent training samples for each classification category. Ultimately, we trained our proposed spatial convolutional neural network using the Adam optimizer, with a learning rate of 0.00001, for 40 epochs. All training procedures were performed on a workstation equipped with a single CUDA-compatible NVIDIA RTX A4000 graphics processing unit. The neural network model is summarized in Table 1.

Table 1 Summary of S-CNN

Sequence	Layer (Size)
1	Input (490,000,)
2	Resample (35,000,)
3	Conv2D (32, 3×3)
4	MaxPooling2D
5	Conv2D (64, 3×3)
6	MaxPooling2D
7	Flatten
8	Dense (5000,)
9	Dropout (0.2)
10	Dense (512,)
11	Dropout (0.2)
12	Dense (64,)
13	Dropout (0.2)
14	Dense (3,)

3.6 Result and discussion

For comparison, here the Root Mean Square Error (RMSE) is first discussed to show its effectiveness in structural damage detection. RSME provides a quantitative measure of deviation between the predicted and actual structural response. By creating a baseline model representative of a healthy structure's behavior, the RMSE can be calculated using new observations to capture differences indicative of damage. Essentially, an elevated RMSE, beyond a predetermined threshold, can signal potential structural abnormalities, such as damage or bolt loosening. Here the baseline is determined based on the healthy measurements. Three baseline cases are considered randomly with 1, 8 and 24 measurements out of the total 48 healthy measurements. The baseline is averaged if there are multiple measurements used. Then the RMSEs obtained are shown in Figure 5. Two conclusions can be drawn from the figure: 1) different baselines can lead to various damage detection results; 2) RMSEs for the healthy state and structural damage case are close to each other, rendering it hard to distinguish the two. To avoid the determination of baseline and achieve an efficient damage detection, the CNN method is discussed below as an alternative method for damage detection.

The proposed spatial convolutional neural network is designed to better extract and recognize the local spatial features from sequential data by reshaping 1D sequential data into a 2D format. Additionally, the preprocessing techniques embedded in the model structure can be customized for specific cases to augment and downsample data. However, in practice, a dilemma arises in that higher sampling frequency is preferred to reconstruct responses in higher resolution, but this demands more time to present all the recurring sets of periodic features. Consequently, the data points describing the response signal will increase exponentially, potentially causing millions of data points to crash the model training due to the prohibitively large computation load, which cannot be performed on current workstations. Moreover, the workflow is designed to be realized in real-time. To overcome this challenge, we propose two strategies for data processing.

In the first case, a single recurring set of periodic features is included in one emulation of 60s, and we employ data augmentation techniques by slicing the response into 18 pieces, with each piece consisting of 32,500 time-series data points. This strategy guarantees that the training sample pool includes all the recurring sets of periodic features but presents them in different samples. In the latter case, four recurring sets of periodic features can be observed in one emulation of 200s, and we can preserve one recurring set of periodic features in one training sample by partitioning the response into 4 pieces. However, we need to downsample the training sample of 490,000 points into 35,000 points for model training.

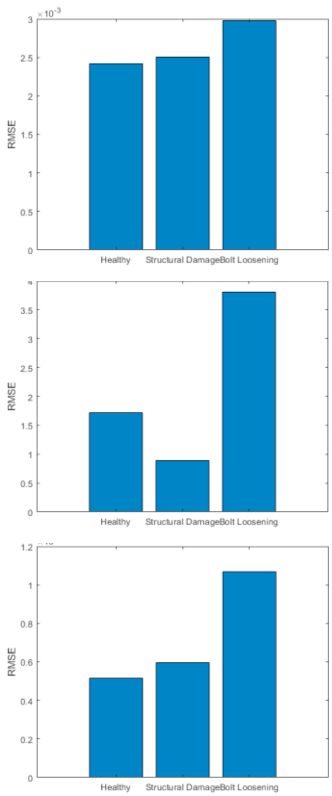

Figure 5. RMSEs from different baselines.

The underlying principle behind these two strategies is that they both fulfill the requirement for a sufficient amount of training data and input dimension limitation, while also accounting for differences in the number of sampling points. In order to ensure a fair comparison, the complete set of recurring periodic features is included in the training sample for both strategies. However, the distinction lies in the fact that in the first case, the single recurring sets of periodic features are distributed across different training samples, while in the latter case, they are presented in a single sample following the downsampling process.

To evaluate the performance of our trained network, we employ an independent test set, distinct from the data utilized during the training phase. This methodology is adopted to guarantee an impartial assessment of the network's capability to generalize across novel data instances. Consequently, the reported accuracy values in our result table reflect the model’s proficiency on this separate test set. Furthermore, to address the evaluation of different strategies, accuracy is selected as the primary metric. It provides a clear and universally recognized gauge of a strategy’s efficacy in correctly discerning the inherent fault patterns within the signal. A strategy’s effectiveness is directly proportional to its accuracy score, with a higher score signifying an enhanced aptitude for fault pattern recognition and classification.

Table 2 Performance comparison

Parameter	**Case 1**	**Case 2**
Training data	38 × 3	34 × 3
Testing data	16 × 3	14 × 3
Model	S-CNN	S-CNN
Training Sample	54 × 3	48 × 3
Training Sample Size	32,500	490,000
Downsample	N/A	35,000
Epochs	40	40
Accuracy	0.5306	0.9318

It is evident from Table 2 that Case 2 exhibits a significantly higher classification rate of 0.9318 compared to Case 1. Based on these results, we can conclude that including all recurring sets of periodic features in a single training sample is necessary for accurately representing response signals. Furthermore, the downsampling process does not significantly affect data representation in terms of model training. To further analyze the recognition capabilities of the model on the three classes, we plot a confusion matrix for both cases in Figure 6. Our findings suggest that the model performs exceptionally well in recognizing healthy status but struggles in distinguishing bolt loosening and structural damage. In Case 1, the model tends to classify most damage samples as structural damage and fails to detect the subtle differences for damage scenarios embedded in the response signals. However, including all recurring sets of periodic features in one training significantly improves model training by providing the complete picture of identical features in every training sample for each class. Consequently, the model can capture the interconnections between the features instead of learning them locally and independently.

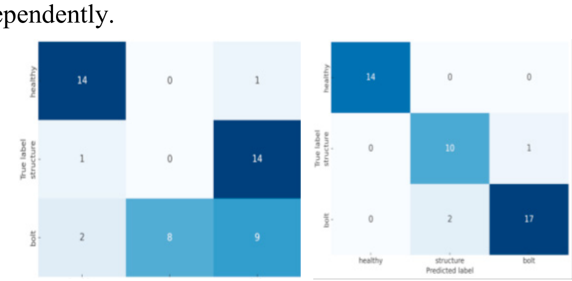

Figure 6. Confusion matrices for two cases: (a) Case 1; (b) Case 2.

4. CONCLUSION

In this study, a spatial neural network is proposed to realize structural damage detection for a pressure vessel, which is integrated with a piezoelectric transducer. The time series datasets are obtained using dSpace measuring system and fed to train the neural network. Two cases with distinct measurements are systematically studied and compared. The results show that the proposed data measuring strategy with periodic features and spatial neural network can identify the damage types with high accuracy.

ACKNOWLEDGMENT

This research is supported by a Space Technology Research Institutes grant (number 80NSSC19K1076) from NASA's Space Technology Research Grants Program.

REFERENCES

Ai, D., Mo, F., Han, Y. and Wen, J. (2022). Automated identification of compressive stress and damage in concrete specimen using convolutional neural network learned electromechanical admittance. *Engineering Structures*, 259, p.114176.

Chen, Z. and Sun, H. (2021). Sparse representation for damage identification of structural systems. *Structural Health Monitoring*, 20(4), 1644-1656.

Cao, P., Shuai Q., and Tang J. (2018). Structural damage identification using piezoelectric impedance measurement with sparse inverse analysis. *Smart Materials and Structures*, 27(3), 035020.

Cao, P., Zhang, Y., Zhou, K. and Tang, J. (2023). A reinforcement learning hyper-heuristic in multi-objective optimization with application to structural damage identification. *Structural and Multidisciplinary Optimization*, 66(1), p.16.

De Oliveira, M.A., Monteiro, A.V. and Vieira Filho, J. (2018). A new structural health monitoring strategy based on PZT sensors and convolutional neural network. *Sensors*, 18(9), p.2955.

Fan, X., Li, J. and Hao, H. (2018) Impedance resonant frequency sensitivity based structural damage identification with sparse regularization: experimental studies. *Smart Materials and Structures*, 28(1), 015003.

Liu, T., Xu, H., Ragulskis, M., Cao, M. and Ostachowicz, W. (2020). A data-driven damage identification framework based on transmissibility function datasets and one-dimensional convolutional neural networks: Verification on a structural health monitoring benchmark structure. *Sensors*, 20(4), p.1059.

Li, H., Ai, D., Zhu, H. and Luo, H. (2021). Integrated electromechanical impedance technique with convolutional neural network for concrete structural damage quantification under varied temperatures. *Mechanical Systems and Signal Processing*, 152, p.107467.

Lizhe Tan, Jean Jiang, *Digital Signal Processing: Fundamentals and Applications* (Third Edition), Academic Press, 2019, Chapter 2, Pages 13-58, ISBN 9780128150719

Na, W.S. (2021). Bolt loosening detection using impedance based non-destructive method and probabilistic neural network technique with minimal training data. *Engineering Structures*, 226, p.111228.

Park, G., Sohn, H., Farrar, C.R. and Inman, D.J. (2003) Overview of piezoelectric impedance-based health monitoring and path forward. *Shock and vibration digest*, 35(6), 451-464.

Shi, Binkai, Maosen Cao, Zijian Wang, and Wieslaw Ostachowicz. (2022). A directional continuous wavelet transform of mode shape for line-type damage detection in plate-type structures. *Mechanical Systems and Signal Processing*,167, 108510.

Vieira Filho, J., Baptista, F.G. and Inman, D.J. (2011). Time-domain analysis of piezoelectric impedance-based structural health monitoring using multilevel wavelet decomposition. *Mechanical Systems and Signal Processing*, 25(5), 1550-1558.

Wang, X. and Tang, J. (2009). Damage identification using piezoelectric impedance approach and spectral element method. *Journal of Intelligent Material Systems and Structures*, 20(8), 907-921.

Xu, C. and Deng, M. (2022). Lamb wave imaging based on multi-frequency sparse decomposition. *Mechanical Systems and Signal Processing*, 174, 109076.

Zhang, Y., Zhou, K. and Tang, J. (2022). Structural damage identification using inverse analysis through optimization with sparsity. *In Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems* 2022 (Vol. 12046, pp. 36-40). SPIE.

Zhang, X., Wang, H., Hou, B., Xu, J. and Yan, R. (2022) 1D-CNN-based damage identification method based on piezoelectric impedance using adjustable inductive shunt circuitry for data enrichment. Structural Health Monitoring, 21(5), 1992-2009.

Zhu, J., Qing, X., Liu, X. and Wang, Y. (2021). Electromechanical impedance-based damage localization with novel signatures extraction methodology and modified probability-weighted algorithm. Mechanical Systems and Signal Processing, 146, 107001.

Zhou, K., Zhang, Y. and Tang, J. (2022). Order-Reduced Modeling-Based Multi-Level Damage Identification Using Piezoelectric Impedance Measurement. *IFAC-PapersOnLine*, 55(27), 341-346.

Zhou, K., Diehl, E. and Tang, J. (2023). Deep convolutional generative adversarial network with semi-supervised learning enabled physics elucidation for extended gear fault diagnosis under data limitations. *Mechanical Systems and Signal Processing*, 185, p.109772.