Enhancing Structural Health Monitoring in Additive Manufacturing Through Embedded Sensors, Infill Designs and Deep Learning

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ABSTRACT

Additive manufacturing (AM) enables the integration of sensors into complex structures. Embedding sensors within the structure reduces cost, allows precise placement, and protects the sensors from environmental exposure. This study investigates the performance of embedded piezoelectric transducers (PZTs) within polymer plates fabricated via AM, using varied infill patterns to influence surface wave behavior. The Surface Response to Excitation (SuRE) method was employed to excite the structure using multiple pulse width excitation (MPWE) and to monitor the resulting surface wave propagation. Signals captured from the embedded sensors were processed using the Short-Time Fourier Transform (STFT) to generate time-frequency spectrograms, which were then classified using Convolutional Neural Networks (CNNs). This approach enabled accurate estimation of both the location and magnitude of applied loads, achieving classification accuracy above 90%. The results demonstrate the effectiveness of combining embedded sensing, infill-based wave manipulation, and deep learning for structural health monitoring. This method shows strong potential for applications in biomedical, aerospace, and mechanical engineering, particularly where polymer components are used in critical functions.

INTRODUCTION

Embedding sensors within additively manufactured (AM) polymer structures has emerged as a transformative strategy for creating smart components capable of real-time structural health monitoring (SHM) [1], [2], [3]. This technique offers several critical advantages: it reduces overall production costs [4], [5] by eliminating separate sensor installation steps, it enhances reliability through better environmental sealing [6], [7], allows for precise sensor placement [8] within internal geometries, and improves measurement accuracy [6], [9] by minimizing misalignment and vibration effects. Embedded sensors are protected from environmental degradation [7], extend system longevity, and contribute to compact, fully integrated designs. In this study, piezoelectric transducers (PZTs) were embedded into polymer plates fabricated using Fused Filament Fabrication (FFF) [1], [10]. By pausing the print at predetermined layers, we ensured proper bonding, precise placement, and minimal disruption to the mechanical properties of the final part.

Various types of sensors have been successfully embedded into polymer AM structures across a wide range of applications. Thermocouples [2] have been used for temperature monitoring; strain gauges and fiber Bragg gratings (FBGs) [9], [11] for deformation and distributed strain tracking, and piezoresistive and capacitive sensors for force and tactile sensing in soft robotics and wearables [2], [12], [13]. Additionally, conductive inks, carbon nanotubes, and silver nanoparticles have been integrated to fabricate fully printed flexible electronics [4], [8]. The techniques employed for embedding include pause-print-resume strategies [2], [3], [8] , direct ink writing (DIW), and co-printing with multi-material extrusion, allowing researchers to tailor sensor performance for aerospace, biomedical, and automotive applications [14], [6], [15]. Numerous studies have evaluated the durability of embedded sensors under mechanical loads, demonstrating that they maintain signal fidelity and outperform externally mounted sensors in terms of environmental resilience and long-term stability [16], [17]. For example, embedding reduces noise and improves accuracy by eliminating relative motion between the sensor and host structure [6], [9]. Precise sensor positioning has been shown to improve shock detection and localization performance in complex structures such as helmets and UAVs [8]. Economic studies also confirm that embedding sensors lowers material and labor costs while improving system reliability [4], [5].

Several review papers have comprehensively addressed the state-of-the-art in sensor embedding for AM polymers, summarizing current practices, challenges, and future directions [18], [7], [8]. These reviews highlight thermal compatibility issues, alignment tolerances, and degradation under cyclic loading as active areas of research [19], [20]. However, they also confirm the strong momentum and feasibility of embedded SHM systems in polymers, thanks to advances in multi-material AM and functional ink development [2] [8].

Building on this foundation, the present study proposes a computationally efficient SHM framework that combines embedded PZT sensors with time-frequency signal processing and deep learning. Wave responses generated via the Surface Response to Excitation (SuRE) method are analyzed using Short-Time Fourier Transform (STFT) to extract time-frequency features [16], [21] [22] [17]. These features are then classified using Convolutional Neural Networks (CNNs) to localize and categorize applied static loads. By systematically varying internal geometries and infill patterns [23], [24], [10], we also assess how structural heterogeneity affects wave propagation and classification performance [1], [13]. The result is a scalable, interpretable, and field-deployable diagnostic method for real-time SHM in AM polymer parts, suitable for aerospace structures, civil infrastructure, and automotive components.

MATERIALS AND METHODS

2.1 3D Printing and Embedding Sensors

All test specimens were fabricated using polylactic acid (PLA) filament on the QIDI 3D X-MAX printer, which utilizes the Fused-Filament Fabrication (FFF) method of additive manufacturing. A 0.4 mm nozzle and a uniform layer height of 0.20 mm were maintained throughout the printing process. To embed the piezoelectric transducers (PZTs), the print was manually paused at specific layer heights, allowing each sensor to be affixed at opposite ends of the specimen using adhesive.

Three plates were fabricated for this study, shown in Figure 1, with dimensions and measurements shown in Figure 2.

1. Heterogenous infill pattern: Side A - Honeycomb infill pattern with density of 30%, Side B – Spiral infill pattern with density of 70% (White)
2. Heterogenous infill pattern: Side A – Honeycomb infill pattern with density of 50%, Side B – Spiral infill pattern with density of 50% (Orange)
3. Homogenous honeycomb infill pattern with density of 50% (Black)

2.2 Experimental Setup

Mechanical loading was applied using the Mach-10 TSF Measurement Stand, with force levels of 100 N, 200 N, 300 N, 400 N, and 500 N. To characterize the system’s response, the Surface Response to Excitation (SuRE) technique was employed to capture signal profiles under both baseline and loaded conditions. The testing setup included a signal generator (RIGOL DG1022), an oscilloscope (Tektronix 2 Series Mixed Signal Oscilloscope), and embedded piezoelectric transducers that functioned as actuators and sensors to initiate and record wave propagation through the 3D-printed structure. The experimental setup is illustrated in Figures 3 and 4.

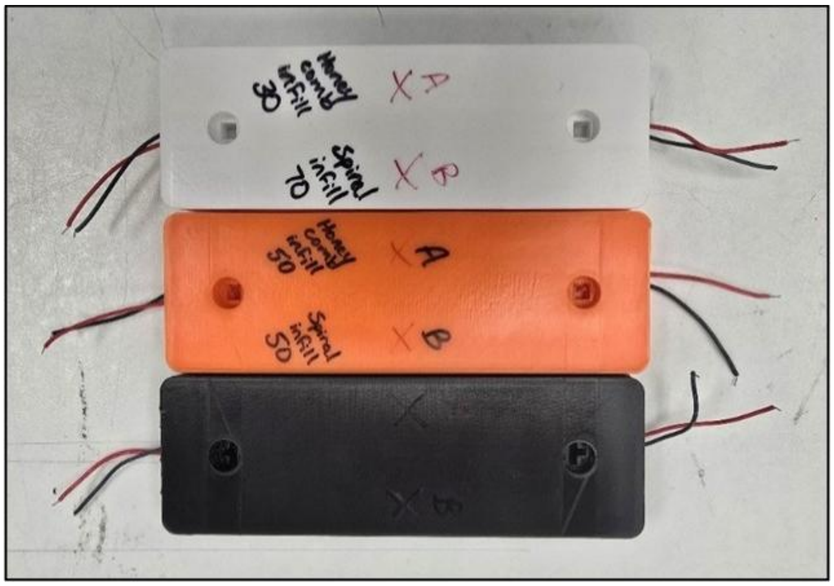

Figure 1: 3D printed polymer specimens with embedded piezoelectric transducers (PZTs) used for load and damage detection via the SuRE method.

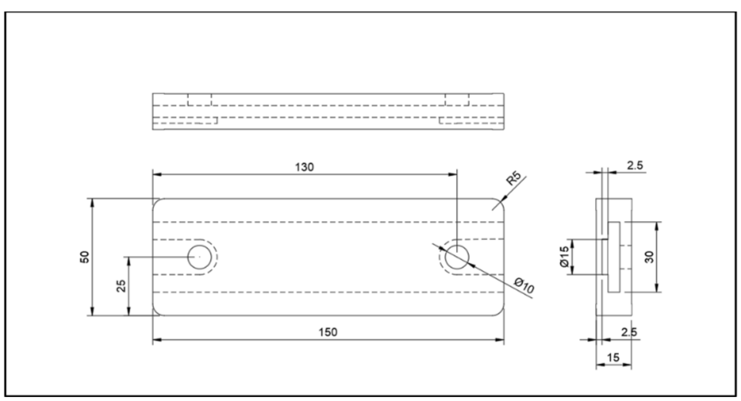

Figure 2: Technical drawing of the IWSHM test specimen used in the structural health monitoring study. The 3D printed plate features embedded piezoelectric transducer cavities and through-holes for alignment or loading, with all dimensions specified in millimeters.

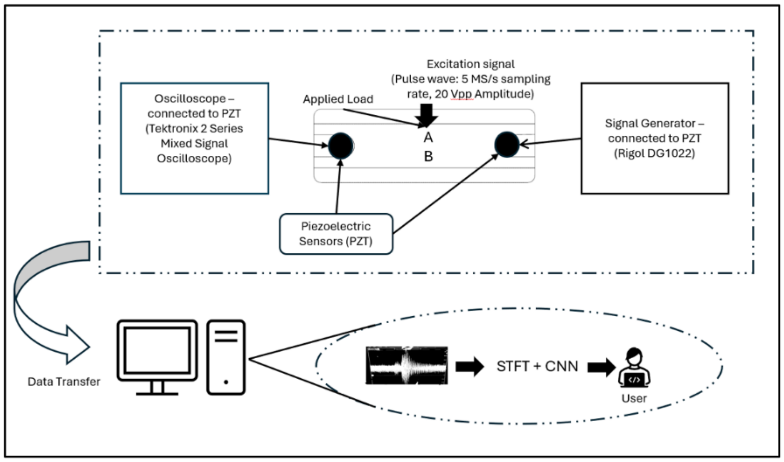

Figure 3: Schematic of experimental setup

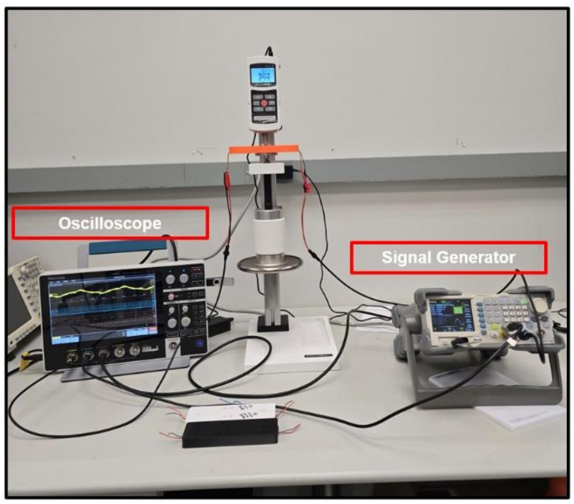

Figure 4: Experimental setup for load monitoring using the SuRE method.

2.3 Embedded Sensor Monitoring and Deep Learning Techniques

This study utilizes the Surface Response to Excitation (SuRE) technique to perform structural health monitoring on 3D-printed polymer components embedded with piezoelectric transducers (PZTs). A pulse waveform with a fixed frequency of 1 kHz, a sampling rate of 5 MSa/s, and a peak-to-peak amplitude of 20 V was used as the excitation signal. In contrast to typical SuRE applications that rely on frequency sweeps to detect physical damage based on size, this work focuses on load monitoring, where the concern is the magnitude and location of applied force rather than geometric defects. Since load changes have no characteristic length, the wavelength constraints associated with damage detection do not apply.

The propagating pulse interacts with internal features of the material, such as the infill structure. Embedded PZT sensors capture the resulting wave response, generating voltage signals that are processed using the Short-Time Fourier Transform (STFT) to extract time-frequency information. These results are then converted into spectrograms, which serve as input to a Convolutional Neural

Network (CNN). The CNN is trained to identify both the location and magnitude of applied loads based on the spectrotemporal characteristics of the signal. This method provides a real-time, non-destructive means of assessing structural response without the need for external instrumentation. An overview of this process is shown in Figure 5.

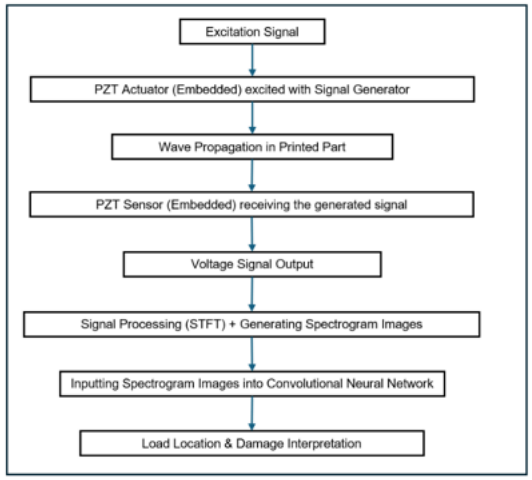

Figure 5: Diagram of Embedded Sensor Monitoring Approach

2.4 Classification Methods

In this study, we implemented a Convolutional Neural Network (CNN). The process seen in Table 1 as the primary classification method to identify both the location and magnitude of applied mechanical loads on 3D-printed polymer specimens. Raw time-domain signals collected from embedded PZT sensors were first processed using the Short-Time Fourier Transform (STFT) to generate spectrograms, which captured the time-frequency characteristics of each excitation response. These spectrograms served as 2D input images to the CNN, allowing the model to extract spatial and temporal patterns associated with different load cases.

The CNN architecture was trained on labeled spectrograms corresponding to known load magnitudes and positions. Through multiple convolutional and pooling layers, the network learned hierarchical features that differentiated between subtle variations in signal behavior. The final fully connected layers mapped these features to discrete output classes representing each load condition. This approach offers a robust, automated framework for classifying structural responses based on internal wave behavior—without requiring manual feature engineering.

Layer Name	**Output Size**	**Block Structure**	**Repeat**
Conv1	112x112	7x7, 64, stride 2	1
Conv2_x	56x56	[1x1,64 >3x3,64 > 1x1, 256]	3
Conv3_x	28x28	[1x1,128 >3x3,128 > 1x1, 512]	4
Conv4_x	14x14	[1x1,256 >3x3,256 > 1x1, 1024]	6
Conv5_x	7x7	[1x1,512 >3x3,512 > 1x1, 2048]	3

Avg pool	1x1	Global average pooling	-
fc	1x1	Fully connect + SoftMax	-

Table I: CNN Framework used for SHM (Input Size 224x224x3)

RESULTS

Specimen	**Location**	**Load**	**Accuracy**
50% Honeycomb		0 Newtons	100%
	Left/Right	100 Newtons	98.18% / 95.45%
	Left/Right	200 Newtons	100% / 90%
	Left/Right	300 Newtons	73.64% / 91.82%
	Left/Right	400 Newtons	94.55% / 90%
	Left/Right	500 Newtons	95.45% / 96.36%
50% Honeycomb / 50% Spiral		0 Newtons	100%
	Left/Right	100 Newtons	87.27% / 100%
	Left/Right	200 Newtons	95.45% / 90.91%
	Left/Right	300 Newtons	89.09% / 100%
	Left/Right	400 Newtons	88.18% / 70.91%
	Left/Right	500 Newtons	91.82% / 97.27%
30% Honeycomb / 70% Spiral		0 Newtons	100%
	Left/Right		90.91% / 95.45%
	Left/Right		96.36% / 95.45%
	Left/Right		73.64% / 99.09%
	Left/Right		90.91% / 96.36%
	Left/Right		93.64% / 91.82%

Table II: CNN Performance for each specimen. (Baseline – no load, Left – Point A, Right – Point B)

In this study, surface response data were collected across 11 load conditions, including a baseline (no load) and applied forces of 100 to 500 N on both point A and point B of the specimen. Each condition was measured 20 times, yielding 220 original samples per specimen. To improve model generalization and increase the training volume, data augmentation was applied to the spectrogram images, effectively expanding the dataset with transformed variants of the original signals.

Following augmentation, the dataset was randomly divided 50/50, with 50% used for training and the remaining 50% used for testing. This ensured a balanced evaluation while preserving sufficient diversity during training.

For the first specimen, the consistent structure and balanced infill density offered a stable propagation medium for surface waves, enabling the CNN to classify loading conditions with high accuracy. In the second specimen, although classification remained strong (Table II), slight confusion arose between adjacent load levels, suggesting subtle wave behavior changes at the interface between different infill zones. Nevertheless, CNN exhibited adaptability and robustness to moderate internal heterogeneity. The third specimen, which combined 30% honeycomb and 70% spiral infill, reached an accuracy of 93.39%. As illustrated in Table II, misclassifications were more frequent at the 300 N honeycomb region, with predictions dispersing toward nearby load levels. The reduced infill density and intricate internal geometry likely increased damping and wave dispersion, reducing the clarity of the extracted frequency-domain features used for classification.

CONCLUSION

This study explored the effectiveness of using embedded piezoelectric transducers (PZTs) within 3D-printed polymer structures for structural health monitoring via the Surface Response to Excitation (SuRE) method. A 1 kHz pulse waveform with a 20 V peak-to-peak amplitude was applied to the surface, and the resulting wave propagation was captured by the embedded sensors. The collected voltage signals were processed using Short-Time Fourier Transform (STFT) to generate spectrograms, which were then used as inputs to a Convolutional Neural Network (CNN) designed to classify both the location and magnitude of the applied mechanical loads.

The results demonstrated that the CNN model effectively identified varying load conditions and sensor locations with high accuracy. The spectrograms provided rich time-frequency features that enabled the model to distinguish subtle variations in the response signals associated with different load magnitudes. This indicates that the approach is well-suited for interpreting complex internal interactions in additively manufactured structures without requiring external sensing hardware.

Based on these findings, we recommend the implementation of embedded PZTs for real-time, non-destructive load monitoring in 3D-printed components. The integration of signal processing techniques like STFT with deep learning models such as CNNs offers a scalable and automated solution for internal structural assessment. This method holds strong potential for applications in smart manufacturing, condition-based maintenance, and adaptive structural systems.

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