

FEDERAL UNIVERSITY OF ITAJUBÁ – UNIFEI  
MECHANICAL ENGINEERING INSTITUTE  
GRADUATE PROGRAM IN MECHANICAL ENGINEERING

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Design, Optimization, and  
Real-Time Structural Health  
Monitoring Using Embedded  
3D-Printed Piezoresistive  
Sensors in Composite Structures

Itajubá/MG

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# Design, Optimization, and Real-Time Structural Health Monitoring Using Embedded 3D-Printed Piezoresistive Sensors in Composite Structures

Dissertation submitted to the Postgraduate Program in Mechanical Engineering, from Mechanical Engineering Institute of the Federal University of Itajubá, as a requirement to obtain the title of Master of Science in Mechanical Engineering.

**Concentration area:** Design, Materials and Processes.

**Supervisor:** Prof. Dr. Guilherme Ferreira Gomes

**Co-supervisor:** Prof. Dra. Marília Sonogo

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*I dedicate this work to my family, whose love and constant support have guided me through every challenge and achievement.*

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*“If you want to go fast, go alone. If you want to go far, go together. If you want to go fast and far, build a team that trusts each other.”*

*–African proverb*

# Abstract

Structural Health Monitoring (SHM) is an essential strategy for ensuring the safety and longevity of critical infrastructure and advanced composite structures. While embedded sensors offer a transformative approach to real-time monitoring by enabling in-situ damage detection, their widespread adoption is hindered by challenges at the sensor-material interface, unoptimized geometric designs, and a critical lack of system-level validation in complex load-bearing components. This thesis presents a comprehensive "Experiment-Model-Optimize-Validate" framework for the development, optimization, and system-level integration of additively manufactured piezoresistive strain sensors. Through a systematic review of the state-of-the-art, the predominance of carbon-based piezoresistive sensors manufactured via Fused Deposition Modeling (FDM) was established, alongside the critical need to balance sensor sensitivity with the mechanical integrity of the host structure. To address this inherent trade-off, a rigorous computational and experimental methodology was developed. A Design of Experiments (DoE) evaluated the influence of geometric parameters (trace width, inter-trace distance, thickness, and end-loops) on sensor performance. Utilizing Gaussian Process Regression (GPR) and a Multi-Objective Particle Swarm Optimization (MOPSO) algorithm, optimal geometries were identified. Experimental validation demonstrated that fully embedded configurations achieved exceptional piezoresistive sensitivity (Gauge Factor  $\approx 59$ ), while a geometrically scaled variant successfully restored the host structure's stiffness to near-native levels ( $\approx 2.18$  GPa) without significant loss of sensitivity. To bridge the gap between laboratory-scale coupon testing and field-ready deployment, the optimized sensing architectures were integrated into a geometrically complex aerospace pylon structure using multi-material FDM. Sensor placement was strategically guided by Finite Element Analysis (FEA) to target critical strain hotspots, and a redundant sensing network was implemented to ensure fault tolerance. System-level testing, validated by full-field Digital Image Correlation (DIC), proved that the embedded sensors exhibited high-fidelity temporal synchronization with mechanical deformation, capturing transient structural events with negligible viscoelastic lag. Furthermore, the redundant architecture successfully maintained monitoring capabilities and diagnosed asymmetrical loading anomalies. Ultimately, this research provides a highly scalable and robust methodology for transitioning 3D-printed embedded sensors from isolated component optimization to integrated, self-sensing structural systems, advancing the technological readiness of real-time SHM in aerospace and civil engineering applications.

**Key-words:** Structural Health Monitoring (SHM), Additive Manufacturing, Fused Deposition Modeling (FDM), Piezoresistive Sensors, Conductive PLA, Multi-Objective Particle Swarm Optimization (MOPSO), Composite Structures, Embedded Sensors.

# Resumo

O Monitoramento da Saúde Estrutural (Structural Health Monitoring - SHM) é fundamental para garantir a segurança e a longevidade de infraestruturas críticas e estruturas de compósitos avançados. Embora sensores embutidos ofereçam uma abordagem promissora para o monitoramento em tempo real por meio da detecção *in-situ* de danos, sua adoção ainda é limitada por desafios relacionados à interface sensor-material, à otimização geométrica e à escassez de validações em nível de sistema. Esta dissertação apresenta uma estrutura integrada de “Experimentar-Modelar-Otimizar-Validar” para o desenvolvimento, otimização e integração de sensores piezoresistivos de deformação fabricados por manufatura aditiva. Uma revisão sistemática identificou a predominância de sensores piezoresistivos à base de carbono produzidos por Modelagem por Deposição Fundida (FDM) e destacou a necessidade de equilibrar a sensibilidade do sensor com a integridade mecânica da estrutura hospedeira. Para enfrentar esse desafio, foi desenvolvida uma metodologia computacional e experimental combinando Planejamento de Experimentos (DoE), Regressão por Processo Gaussiano (GPR) e Otimização por Enxame de Partículas Multiobjetivo (MOPSO). A análise avaliou a influência de parâmetros geométricos, como largura e espaçamento de trilhas, espessura e laços terminais, sobre o desempenho dos sensores. Os resultados experimentais mostraram que configurações totalmente embutidas atingiram elevada sensibilidade piezoresistiva (Gauge Factor  $\approx 59$ ), enquanto uma variante geometricamente escalonada restaurou a rigidez da estrutura hospedeira para níveis próximos aos originais ( $\approx 2,18$  GPa), sem perda significativa de sensibilidade. Para aproximar os resultados laboratoriais de aplicações reais, as arquiteturas otimizadas foram integradas a uma estrutura de pilar aeroespacial geometricamente complexa utilizando FDM multimaterial. O posicionamento dos sensores foi definido por Análise de Elementos Finitos (FEA), enquanto uma rede redundante garantiu tolerância a falhas. Ensaios validados por Correlação Digital de Imagens (DIC) demonstraram sincronização precisa entre as respostas dos sensores e a deformação mecânica, além da capacidade de identificar anomalias de carregamento assimétrico. Em síntese, esta pesquisa estabelece uma metodologia robusta e escalável para a integração de sensores impressos em 3D em estruturas auto-sensoriadas, contribuindo para o avanço do SHM em tempo real em aplicações aeroespaciais e de engenharia civil.

**Palavras-chaves:** Monitoramento da Saúde Estrutural (SHM), Manufatura Aditiva, Modelagem por Deposição Fundida (FDM), Sensores Piezoresistivos, PLA Condutivo, Otimização por Enxame de Partículas Multiobjetivo (MOPSO), Estruturas Compósitas, Sensores Embutidos.

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# ABBREVIATIONS AND ACRONYMS

|       |                                   |
|-------|-----------------------------------|
| ADC   | Analog-to-Digital Converter       |
| AFP   | Automated Fiber Placement         |
| AgNWs | Silver Nanowires                  |
| AI    | Artificial Intelligence           |
| AM    | Additive Manufacturing            |
| AMS   | Automatic Material System         |
| ANN   | Artificial Neural Networks        |
| CB    | Carbon Black                      |
| CCD   | Central Composite Design          |
| CCF   | Continuous Carbon Fiber           |
| CF    | Carbon Fiber                      |
| CFRP  | Carbon Fiber-Reinforced Polymer   |
| CNT   | Carbon Nanotube(s)                |
| CPC   | Conductive Polymer Composite      |
| DAQ   | Data Acquisition                  |
| DIC   | Digital Image Correlation         |
| DIW   | Direct Ink Writing                |
| DLP   | Digital Light Processing          |
| DoE   | Design of Experiments             |
| EIS   | Electrical Impedance Spectroscopy |
| EMI   | Electromagnetic Interference      |
| FBG   | Fiber Bragg Grating               |
| FDM   | Fused Deposition Modeling         |
| FEA   | Finite Element Analysis           |
| FECA  | Flexible Eddy Current Array       |
| FFF   | Fused Filament Fabrication        |
| FOS   | Fiber Optic Sensor                |
| FSP   | Friction Stir Processing          |
| GA    | Genetic Algorithms                |
| GNPs  | Graphene Nanoplatelets            |
| GPR   | Gaussian Process Regression       |
| IDEX  | Independent Dual Extruder         |
| IoT   | Internet of Things                |

|            |                                                                |
|------------|----------------------------------------------------------------|
| LBS        | Load-Bearing Structure                                         |
| LS         | Laser Sintering                                                |
| MEMS       | Micro-Electromechanical Systems                                |
| MEX        | Material Extrusion                                             |
| MI-MOOP    | Mixed-Integer Multi-Objective Optimization Problem             |
| ML         | Machine Learning                                               |
| MOPSO      | Multi-Objective Particle Swarm Optimization                    |
| MQTT       | Message Queuing Telemetry Transport                            |
| MWCNT      | Multi-Wall Carbon Nanotube                                     |
| NDT        | Non-Destructive Testing                                        |
| NPLC       | Number of Power Line Cycles                                    |
| PA         | Polyamide                                                      |
| PDMS       | Polydimethylsiloxane                                           |
| PHB        | Polyhydroxybutyrate                                            |
| PLA        | Polylactic Acid                                                |
| PMMA       | Polymethylmethacrylate                                         |
| PPy        | Polypyrrole                                                    |
| PS         | Polystyrene                                                    |
| PZT        | Lead Zirconate Titanate                                        |
| RSM        | Response Surface Methodology                                   |
| SCFCCs     | Short Carbon Fiber Conductive Composites                       |
| SHM        | Structural Health Monitoring                                   |
| SLA        | Stereolithography                                              |
| SPS        | Spark Plasma Sintering                                         |
| SWCNT      | Single-Wall Carbon Nanotube                                    |
| TOPSIS     | Technique for Order Preference by Similarity to Ideal Solution |
| TPU        | Thermoplastic Polyurethane                                     |
| UAM        | Ultrasonic Additive Manufacturing                              |
| UTM        | Universal Testing Machine                                      |
| UV         | Ultra-Violet                                                   |
| UWB        | Ultra-Wide Band                                                |
| VPP        | Vat Photopolymerization                                        |
| WSN / WSSN | Wireless Sensor Network / Wireless Smart Sensor Network        |
| WSS        | Wireless Smart Sensor                                          |
| $E$        | Young's modulus / elastic modulus ( $GPa$ )                    |
| $F_t$      | Theoretical engine thrust force ( $N$ )                        |
| $L$        | Sensor gauge length ( $mm$ )                                   |
| $N$        | Number of end loops                                            |
| $R$        | Electrical resistance ( $\Omega$ )                             |

|                         |                                                   |
|-------------------------|---------------------------------------------------|
| $R_0$                   | Baseline electrical resistance ( $\Omega$ )       |
| $\Delta R$              | Change in electrical resistance ( $\Omega$ )      |
| $R^2$                   | Coefficient of determination (linearity)          |
| $t$                     | Trace thickness ( $mm$ )                          |
| $W$                     | Sensor gauge width ( $mm$ )                       |
| $w_1$                   | Trace width ( $mm$ )                              |
| $w_2$                   | Inter-trace distance ( $mm$ )                     |
| $\varepsilon_{\max}$    | Maximum working strain                            |
| $\varepsilon, \epsilon$ | Structural / physical strain                      |
| $\mu$                   | Friction coefficient                              |
| $\nu$                   | Poisson's ratio                                   |
| $\rho$                  | Density ( $kg/m^3$ )                              |
| $d_{33}$                | Piezoelectric coefficient                         |
| $\mu\varepsilon$        | Microstrain                                       |
| $\phi$ -OTDR            | Phase-sensitive Optical Time-Domain Reflectometry |
| C3D10M                  | 10-node modified quadratic tetrahedral element    |

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# 1 Introduction

## 1.1 The Paradigm of Structural Health Monitoring (SHM)

In the modern engineering landscape, the maintenance of structural integrity in critical assets, ranging from aerospace vehicles to civil infrastructure, has evolved from a reactive necessity to a proactive, data-driven discipline. Structural Health Monitoring (SHM) is defined as the process of implementing a damage identification strategy for aerospace, civil, and mechanical engineering infrastructure (18). The core philosophy of SHM lies in its ability to provide real-time, continuous diagnostic information, effectively acting as a “nervous system” for inanimate structures.

The transition toward SHM is driven by the rising demand for safer, more sustainable, and cost-effective operations. By shifting from traditional time-based maintenance to condition-based maintenance (CBM), operators can avert catastrophic failures through early-stage damage detection, such as micro-cracking, fatigue, or corrosion, before they reach critical thresholds. This not only ensures public safety but significantly extends the operational lifespan of assets while reducing the economic burden of unnecessary downtime and structural over-design.

## 1.2 Evolution from NDT to Integrated Sensing

Historically, the safety of structures has relied on Non-Destructive Testing (NDT) techniques, including visual inspection, ultrasonic C-scan, and radiography. While these methods are well-established, they are fundamentally “offline” and periodic, offering only a snapshot of structural health at a specific moment in time. For advanced composite materials, which are increasingly favored in aerospace for their high strength-to-weight ratios, traditional NDT faces significant hurdles. The anisotropic nature of composites leads to complex, internal failure modes, such as delamination and interlaminar cracking, that are often invisible to surface-level inspections.

Conventional sensing technologies, such as metallic foil strain gauges and surface-mounted piezoelectric transducers, have attempted to bridge this gap. However, these “add-on” sensors introduce a new set of vulnerabilities: they are susceptible to environmental degradation, prone to adhesive debonding, and can negatively impact the aerodynamic profile of a component (19). Furthermore, the mechanical mismatch between the rigid sensor and the compliant composite host creates local stress concentrations, potentially initiating the very damage the system was designed to monitor.

### 1.3 Smart Materials and Additive Manufacturing (AM)

The convergence of material science and Additive Manufacturing (AM) has opened a new frontier in SHM: the development of “smart” or self-sensing structures. Unlike traditional sensors, these are monolithically integrated into the structural host during the fabrication process. Additive manufacturing, specifically Fused Deposition Modeling (FDM), allows for the precise deposition of functional materials, specifically conductive polymer composites (CPCs), within the structural geometry.

Materials such as Polylactic Acid (PLA) or Polyether Ether Ketone (PEEK) infused with carbonaceous fillers (carbon nanotubes, graphene, or carbon black) exhibit a piezoresistive response. In these systems, mechanical strain alters the conductive network of the fillers, resulting in a measurable change in electrical resistance. This allows the structural component itself to function as a transducer, providing high-fidelity, in-situ data from the interior of the load path, where damage is most likely to initiate (20, 21).

### 1.4 Scientific Challenges: Optimization and Scalability

Despite the promise of 3D-printed embedded sensors, several critical scientific challenges persist at the intersection of manufacturing and structural mechanics. The electromechanical sensitivity of these sensors, often quantified by the Gauge Factor (GF), is highly dependent on the printing architecture, such as layer height, infill density, and raster orientation. Furthermore, the integration of a sensing element into a load-bearing member inherently risks degrading the host’s mechanical properties, creating a conflict between sensing performance and structural integrity.

Current literature has largely focused on laboratory-scale coupons, often neglecting the complexities of system-level deployment. Transitioning this technology to application-relevant components, such as aerospace pylons or wind turbine blades, requires a multidisciplinary approach. This involves not only the optimization of the sensor geometry to maximize sensitivity while maintaining stiffness but also the implementation of redundant sensor architectures to ensure fault tolerance in harsh operational environments.

### 1.5 Thesis Motivation and Scope

This research is motivated by the need to bridge the gap between material characterization and real-world structural application. This thesis proposes a systematic, multi-objective optimization framework for 3D-printed embedded sensors, moving beyond simple signal compensation to a full-scale structural validation. By leveraging statistical Design of Experiments (DoE), Finite Element Analysis (FEA), and Digital Image Correlation (DIC),

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this work demonstrates the feasibility of a truly integrated, self-monitoring structural system that is robust, scalable, and optimized for next-generation engineering applications.

## 2 Research Aim and Objectives

### 2.1 Research Aim

The primary aim of this research is to develop, optimize, and experimentally validate a comprehensive framework for the system-level integration of additively manufactured piezoresistive sensors into complex, load-bearing structures to achieve reliable, real-time Structural Health Monitoring.

### 2.2 Research Objectives

To achieve the overarching aim, the following specific objectives were established:

1. **To critically evaluate the state-of-the-art** in embedded sensor technologies for composite structures, identifying the prevailing integration processes, active sensing materials, and specific performance limitations related to sensor-host interactions and long-term durability.
2. **To optimize the geometric design of 3D-printed piezoresistive strain sensors** using a statistical Design of Experiments (DoE) and Multi-Objective Particle Swarm Optimization (MOPSO), balancing the conflicting objectives of maximizing strain sensitivity while preserving the elastic modulus of the host structure.
3. **To develop a methodology for the targeted integration** of the optimized sensors into a complex structure using Finite Element Analysis (FEA) to identify critical strain hotspots and multi-material FDM to achieve monolithic encapsulation.
4. **To experimentally validate the electromechanical performance, dynamic tracking fidelity, and fault tolerance** of a redundant embedded sensor network within a representative load-bearing pylon structure, utilizing full-field Digital Image Correlation (DIC) as a ground-truth measurement.

### 3 Advances in Embedded Sensor Technologies for Structural Health Monitoring of Composite Structures: A Comprehensive Review

Structural Health Monitoring (SHM) is critical for ensuring the safety and reliability of advanced composite structures. While embedded sensors offer a transformative approach to real-time monitoring, a critical challenge lies at the sensor-material interface, where integration processes and environmental factors govern long-term system performance. This review adds to existing knowledge by providing a focused, critical analysis of the specific challenges and advancements related to the integration and in-situ performance of embedded sensors in composites. A systematic literature search of the Web of Science and Scopus databases was conducted, focusing on peer-reviewed articles from the last five years related to embedded sensors, composites, and SHM. From an initial pool of over 1300 articles, 93 were selected for in-depth analysis based on specific inclusion criteria, focusing on experimental findings and novel integration techniques. The analysis reveals a clear predominance of piezoresistive sensors, particularly those using carbon-based nanomaterials, due to their excellent compatibility with composites and suitability for additive manufacturing. Key advancements in sensor integration via 3D printing (FDM, DIW, SLA) are identified, alongside significant challenges, including process-induced defects, thermal mismatch, and signal degradation from environmental factors like moisture and temperature. The findings indicate that while sensor technology has advanced, the reliability of the entire SHM system is often limited by the sensor-material interface. The move towards multifunctional, wireless, and self-powered sensors is a clear trend, but long-term durability and the inability to repair embedded sensors remain significant barriers to widespread adoption. This review concludes that future research must prioritize the development of robust, resilient sensor materials and standardized testing protocols. Integrating advanced materials like metamaterials and leveraging machine learning for predictive data analysis are crucial next steps to creating truly autonomous and reliable SHM systems for composite structures.

#### 3.1 Introduction

Structural Health Monitoring (SHM) is a process through which the structural integrity and operational health status of structural members is monitored in real-time in order to

avert failures in service. This objective is achieved through early detection of damages, and taking proactive measures to curtail its advancement (18). This technology finds a very useful application in the civil engineering structures, aerospace, automobile and marine industries where safety, performance and reliability are very important. Successful implementation of any SHM system goes a long way in prolonging the assets' lifespan, reducing downtime and associated costs (22).

In any SHM process, components such as sensors, data acquisition devices, some analytical tools for analyzing and interpretation of acquired data are combined together, to monitor the integrity of the infrastructures. For example, in the field of civil engineering, the structural integrity of skyscrapers and bridges are monitored against failures, thereby ensuring public safety. The same applies to aerospace and automobile industries, where the air and road worthiness of airplanes and automobiles respectively, are monitored against damages such as cracks, fatigue, corrosion etc. (23). This gives room for shift from routine maintenance strategies, to condition based, thereby optimizing resources and reducing unnecessary interruptions. The structure of a typical SHM system is explained graphically by Figure 3.1.

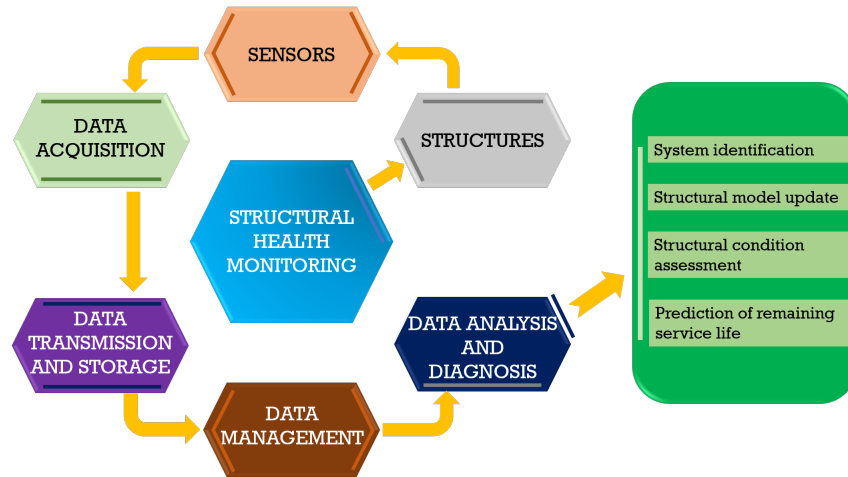


Figure 3.1 – Schematic diagram of a typical Structural Health Monitoring (SHM) process (adapted from (1)).

Composite materials are advanced material developed to substitute the traditional metals and alloys for some of their unique characteristics such as high strength to weight ratio, corrosion resistance among others. These materials have found tremendous applications, especially in the aerospace industry. However, unlike other metals, composites due to their anisotropic nature, exhibit different failure modes such as fiber fracture, delamination, cracks and fiber debonding (23). These made them susceptible to subtle failure. Hence, composite materials are too difficult to monitor using the traditional SHM systems. This challenge is what gave birth to embedded sensing technology in SHM systems (24). These embedded sensors serve as transformative tools for the monitoring of composite structures. Unlike traditional sensors, which are mounted on the surfaces of the



structures inform of add-ons, and rely on indirect measurements, the embedded sensors are integrated into the structure (18). In this way, they can be able to monitor in real-time the condition of the structure. They can be used to directly measure localized stresses, vibrations, and therefore can be able to detect damages at their early stages (24).

While numerous reviews have covered SHM broadly, a unique scientific problem persists at the sensor-material interface. The integration of a foreign sensing element into a composite host creates a complex interplay of mechanical, thermal, and chemical interactions that governs the long-term reliability and accuracy of the entire monitoring system. The unique contribution of this manuscript is its focused, critical analysis of the advancements and challenges specifically related to the *integration* and *in-situ performance* of embedded sensors in composite structures. We synthesize recent findings on additive manufacturing for sensor embedding, evaluate the impact of environmental factors from a mechanistic perspective, and identify key research gaps in durability and system-level design that must be addressed to advance the field.

Subsequent advancements in the embedded sensor technology gave rise to piezoelectric sensors, piezoresistive sensors, ultrasonic sensors, and fiber optic sensors (22). These advanced sensors embedded in composites significantly improved the capabilities of SHM systems. Wireless communication technologies are combined with these advanced sensors to make SHM systems more effective and efficient with the least interference (25). The introduction of self-sensing (embedded sensors) into the technology of SHM represented shift in the philosophy of structural health monitoring process (22). The emergence of embedded sensors not only enhance the process of SHM, but clears the way for the emergence of smart sensor technologies that are smarter and data driven into various engineering industries. The role of these embedded sensors in SHM keeps becoming more and more critical, as the demand for more efficient, sustainable, and safer infrastructure keep rising (24).

This paper probes the progress made so far and developments in SHM implementation in composite structures, emphasizing their impact in the field, technological advancements and key milestones reached. It explores some highly advanced embedded sensors with a special focus on strain sensors, focusing mainly on their integration with composite structures and their capabilities in real-time damage detection. The review also analyzes factors affecting sensor performance, including environmental impacts such as moisture, temperature fluctuations, along with mechanical factors such as sensor-material compatibility and long-term reliability. In addition, it presents real-world applications and experimental results showcasing the performance of embedded sensors for the monitoring of composite structures. Lastly, the review summarizes the findings, identifies research gaps, and proposes future research directions to improve SHM systems and sensor technologies.

This review focuses specifically on SHM in composite structures. It is limited to a

detailed examination of FBG sensors, carbon fiber sensors, and their role in SHM systems, providing insights into how environmental factors, such as moisture and temperature fluctuations, influence sensor performance and the structural integrity of composites. Similarly, case studies are limited to SHM applications in aerospace, civil engineering, and other critical industries using composite materials. The review excludes SHM systems for metallic or homogeneous structures, generalized sensor technologies not related to composites, and purely destructive testing methods. By integrating historical, technological, and practical insights, this review aims to advance the understanding and application of embedded sensor technologies for SHM in composite structures.

This manuscript is organized into six main sections to provide a comprehensive and focused review of advancements in embedded sensor technologies for SHM of composite structures. Section 2 provides a condensed overview of traditional inspection methods and their limitations, establishing the critical need for the advanced embedded sensors that are the focus of this review. Section 3 details the evolution of SHM technologies, covering the key technological enablers and the variety of sensors used in modern systems. Section 4 offers a deep dive into advanced sensor technologies, with a thematic restructuring that covers key sensor modalities, integration processes and their associated challenges, and advanced system-level architectures. Section 5 explores the critical factors that affect embedded sensor performance, such as environmental and loading conditions. Section 6 presents case studies and experimental findings from recent literature, demonstrating the real-world application and performance of these technologies. Finally, Section 7 concludes the review by summarizing key findings, identifying existing research gaps, and proposing future research directions to enhance SHM systems.

## 3.2 The Need for Advanced SHM: A Brief Overview of Traditional Methods

For decades, the integrity of structures was assessed using a range of traditional, largely manual, Non-Destructive Testing (NDT) methods. Techniques such as visual inspection, acoustic emission, infrared thermography, and X-ray radiography formed the bedrock of structural assessment (26). Visual inspection is inexpensive but limited to surface-level defects and highly dependent on inspector expertise (27). More advanced methods like acoustic and ultrasonic testing allowed for the detection of internal flaws but often required skilled technicians for interpretation (28). Other methods like eddy current testing are highly effective for conductive materials but have limited applicability for non-conductive polymer matrix composites.

While indispensable, these traditional methods have significant limitations when applied to advanced composites. Their anisotropic nature and complex internal failure modes (e.g., delamination) are difficult to detect with conventional NDT. These techniques are often

labor-intensive, require structural downtime, are prone to human error, and struggle to detect damage before it reaches a critical stage. This created a critical need for a paradigm shift from periodic, offline inspections to continuous, real-time monitoring. This necessity drove the evolution towards the advanced, sensor-based SHM technologies that form the core of this review (29). A summary comparison is provided in Table 3.1.

Table 3.1 – Comparative analysis of SHM and NDT Methodologies.

| Method Category                       | Examples                                                    | Pros                                                                                                                                                          | Cons                                                                                                                                                    |
|---------------------------------------|-------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>Traditional NDT</b>                | Visual Inspection, Ultrasonic C-scan, X-Ray, Eddy Current   | Well-established; good for detecting manufacturing defects or significant surface damage.                                                                     | Labor-intensive; requires downtime (offline); prone to human error; poor for detecting incipient or internal damage in composites.                      |
| <b>Advanced SHM (Surface-Mounted)</b> | Surface-mounted strain gauges, PZT transducers.             | Provides real-time operational data; more sensitive to in-service changes than traditional NDT.                                                               | Intrusive to aerodynamics/aesthetics; can be damaged by environment; adhesive bonds can degrade; alters local stress fields.                            |
| <b>Embedded Sensor Technologies</b>   | Embedded FBGs, Piezoresistive carbon fibers, embedded PZTs. | In-situ monitoring from within the material; protected from external environment; highly sensitive to internal damage initiation; enables "smart structures". | Inaccessible for repair/replacement; integration process can introduce defects (voids, stress concentrations); potential material compatibility issues. |

While invaluable for quality control and post-manufacturing inspection, these traditional NDT techniques are fundamentally limited by their inability to provide real-time, in-situ data during a structure's operational life. They offer snapshots in time, often requiring the component to be taken out of service, and are generally insensitive to incipient damage. This critical gap in continuous, life-cycle monitoring necessitates a paradigm shift towards integrated sensing technologies capable of reporting on the structural state from within. The following sections will explore these embedded technologies, which directly address the limitations of their traditional counterparts.

### 3.3 The Evolution of Structural Health Monitoring Technologies

Building upon the limitations identified in Section 3.2, embedded sensor technologies represent a paradigm shift in SHM philosophy, from surface attachment to internal integration. This transition is not merely technological but conceptual, as it redefines the sensor - structure relationship from external observation to internal participation, thereby improving signal fidelity and environmental robustness. An overview of the various processes

for SHM is presented in Figure 3.2, and a historical evolution for aerospace monitoring is illustrated in Figure 3.3.

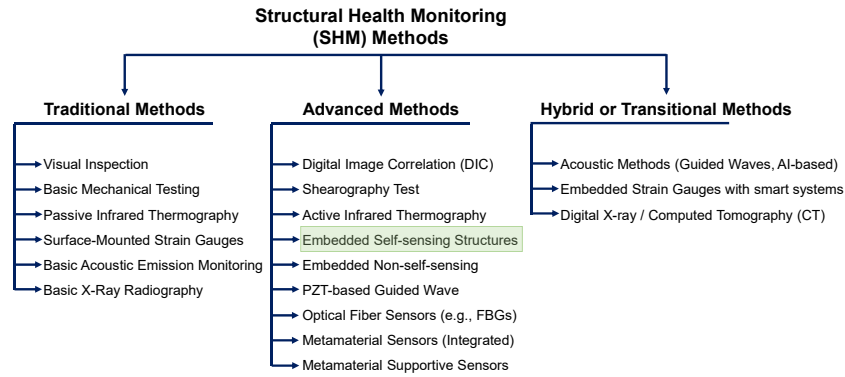


Figure 3.2 – Overview of Structural Health monitoring (SHM) Systems processes

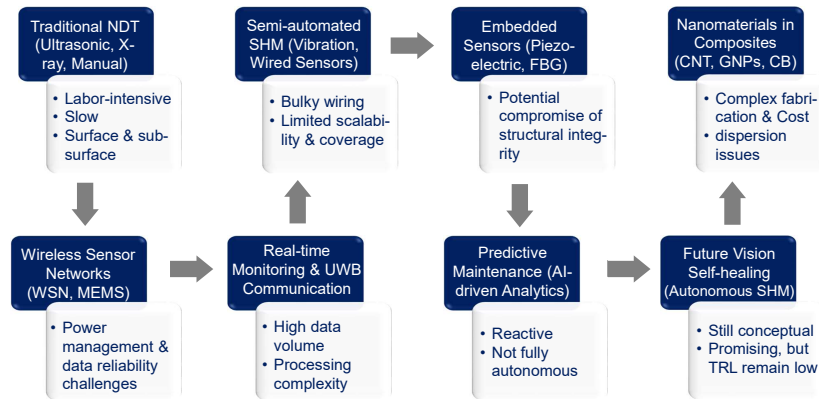


Figure 3.3 – Historical Evolution of Structural Health Monitoring

Initially, SHM relied on traditional manual and auto-manual defect detection methods. While these approaches were effective, they had several limitations, including labor intensity, slow detection processes, and reliance on inspector expertise. Additionally, they were often restricted to surface and subsurface damage detection. Over time, SHM systems evolved with the introduction of advanced sensors capable of continuous structural monitoring, localized damage detection, and faster, more accurate assessments.

A major milestone in SHM development was the integration of sensors into composite materials. Traditional methods relied on external probes, which could compromise structural integrity. However, advancements in material science led to the development of multifunctional composites with self-sensing capabilities, eliminating the need for separate sensing devices. Nanocomposites incorporating carbon nanotubes (CNT), graphene, and carbon black have significantly enhanced structural performance while enabling functionalities such as strain detection, damage localization, and ultrasonic wave detection (30, 31). Embedding these nanomaterials into composite structures has allowed the material itself to act as both a structural element and a sensing device.

Rapid progress in electronics and computing has further propelled the adoption of embedded sensors in SHM systems. Wireless sensor networks (WSNs) have replaced traditional wiring, enabling seamless sensor integration and improving flexibility, scalability, and reliability (32). Additionally, the advent of micro-electromechanical systems (MEMS) has led to the development of small, low-power sensors that can be embedded in composite materials without compromising structural integrity (33). These low-power sensors have addressed one of the key challenges in SHM: efficient power management.

A significant advantage of modern SHM systems is their ability to acquire real-time data, allowing continuous structural health monitoring. This capability provides immediate feedback, facilitating the early detection of damage and swift intervention. Real-time data analysis supports quicker decision-making, preventing further structural deterioration. Wireless communication technologies, particularly Ultra-Wide Band (UWB), have played a crucial role in transmitting large volumes of data with minimal energy consumption. These wireless systems reduce the need for direct access to monitored structures, making SHM more adaptable and less intrusive.

The focus of SHM has also shifted toward predictive maintenance, moving away from scheduled inspections that may not align with a structure's actual condition. Predictive maintenance leverages continuous monitoring and real-time data analysis to determine when maintenance is necessary. This approach reduces unnecessary repairs while minimizing the risk of undetected damage or failure. As SHM technologies continue to advance, they enhance safety, reliability, and cost-effectiveness in structural maintenance.

In summary, the evolution of SHM technologies has transitioned from manual inspection techniques to advanced sensor-based systems incorporating real-time data acquisition, wireless communication, and predictive maintenance. Advances in material science, electronics, and computing have enabled the seamless integration of sensors into composite structures, providing efficient, cost-effective, and non-intrusive monitoring solutions. As these technologies continue to develop, SHM systems will become increasingly reliable and widely adopted in industries such as aerospace, civil engineering, and automotive sectors.

### 3.3.1 The Role of Technology in Enhancing SHM

The advancement of technology has played a crucial role in enhancing SHM systems. Innovations such as compact sensors, fiber optic sensors, and smart materials have significantly improved composite structure monitoring, addressing challenges related to their unique properties, including anisotropy and sensitivity to environmental factors. Technological breakthroughs have transformed SHM systems, particularly through the development of miniaturized sensors, fiber optics, and smart materials. Miniaturized sensors enable efficient monitoring without significantly increasing weight, making them especially valuable

in industries like aerospace. Their small size allows for high accuracy and seamless integration into structures, providing comprehensive data on material behavior (26, 29).

Fiber optic sensors represent another significant advancement, excelling in measuring strain, temperature, and displacement with high precision. Their resistance to electromagnetic interference makes them ideal for industrial environments and aerospace applications. Additionally, their ability to monitor large areas over long distances enhances their effectiveness in composite structure monitoring (29, 34). Smart materials, such as self-sensing composites, have further revolutionized SHM. Carbon fiber-reinforced polymers (CFRP) infused with nanoparticles like carbon nanotubes or graphene possess inherent sensing capabilities, allowing them to detect damage such as strain or cracks without external sensors. This capability is crucial for monitoring complex or hard-to-reach structural components. Smart materials also enable real-time data acquisition, improving safety and durability (26, 34). Addressing the unique challenges of composite structures is another critical aspect of SHM advancements. Composite materials, particularly fiber-reinforced polymers, exhibit anisotropic properties, meaning their mechanical characteristics vary depending on direction. This presents challenges for damage detection. However, the inclusion of nanoscale fillers like carbon nanotubes and graphene enhances SHM sensitivity, improving damage detection across various orientations (26, 29, 34).

Environmental sensitivity is another challenge, as composite materials are susceptible to variations in temperature, humidity, and pressure, which can impact sensor accuracy and system reliability. To mitigate these issues, advancements in fiber optic sensors and miniaturized electronics have improved resilience to harsh environmental conditions. Fiber optics provide resistance to electromagnetic interference, while miniaturized sensors are designed to function effectively in extreme conditions without affecting structural performance. Additionally, smart materials can adapt to environmental fluctuations, ensuring consistent and reliable data collection (26, 29, 34). In conclusion, technological innovations in miniaturized sensors, fiber optics, and smart materials have significantly enhanced SHM systems. These advancements address the unique challenges posed by composite materials, including their anisotropic nature and environmental sensitivity. As a result, SHM systems have become more precise, reliable, and efficient, making them highly adaptable for monitoring composite structures across various industries.

### 3.3.2 The Overview of SHM Systems

The successful deployment of SHM systems requires the effective integration of several key components that function seamlessly. These components include sensors, data acquisition and transmission systems, and data processing and management systems, each playing a crucial role in ensuring the overall functionality of SHM systems. Sensors serve as the core elements in SHM, monitoring structural health by detecting parameters such as strain, stress, cracks, and deformations. They can also measure shifts in material properties like



conductivity, piezoelectricity, or capacitance, which indicate potential damage. Additionally, sensors track environmental factors such as temperature, humidity, and pressure, which can influence material performance. Various sensor types, including piezoelectric sensors, strain gauges, accelerometers, and fiber optic sensors, are either externally attached or embedded within structures to provide continuous monitoring and a comprehensive assessment of structural integrity over time (18, 26).

Data acquisition and transmission systems play a vital role in gathering and transferring sensor data to a central processing unit for analysis. These systems include signal conditioning units, which refine raw signals by amplifying or filtering them for clarity, and analog-to-digital converters (ADCs), which convert analog sensor signals into digital data for further processing. Many modern SHM systems incorporate wireless technologies such as Wi-Fi, Bluetooth, or UWB to enhance data transmission efficiency, especially for large-scale structures where extensive wiring is impractical. Once the data is collected and transmitted, it undergoes processing and analysis to extract meaningful insights. Signal processing techniques are applied to reduce noise, enhance signal quality, and identify patterns indicative of structural issues. The processed data is then visualized through graphical representations such as heat maps, strain plots, or damage maps, allowing engineers to interpret the structure's health efficiently. Real-time monitoring dashboards further facilitate continuous observation. Additionally, advanced predictive models powered by AI and machine learning can forecast a structure's remaining useful life based on current data trends, aiding in proactive maintenance and risk mitigation. In conclusion, SHM systems rely on three interdependent components: sensors for data collection, data acquisition and transmission systems for efficient data transfer, and data processing and management systems for interpretation and decision-making. These components work synergistically to monitor structural integrity, ensuring enhanced safety, longevity, and cost-effectiveness in various applications (18, 26).

### 3.3.3 Types of Sensors used in SHM

Various types of sensors are utilized in SHM, particularly for composite structures. A comparative summary is provided in Table 3.2. Among the widely employed sensors, strain gauges play a crucial role in measuring deformation or strain within a composite structure. These mechanical sensors detect elongation or compression of the material, translating these changes into variations in electrical resistance proportional to the strain. By providing continuous monitoring of strain distribution, strain gauges offer valuable insights into structural behavior under stress, particularly in critical areas such as load-bearing sections and joints, where potential failure points may emerge (26, 35). Different strain gauge designs have been commercially available for different SHM applications. The two basic designs are those with out-of-plane terminals, more suitable for embedded sensing applications as demonstrated in Figure 3.4(a), and those with in-plane terminals

for surface mounting as demonstrated in Figure 3.4(b). The choice is usually motivated by the different factors.

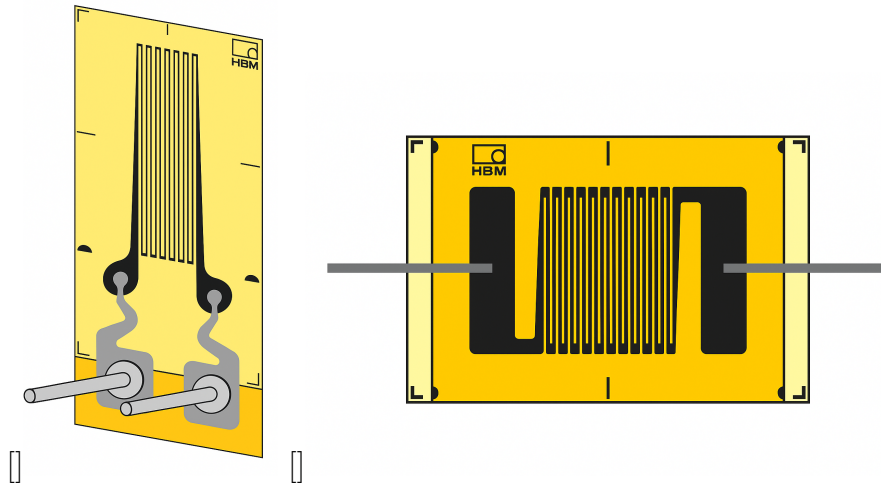


Figure 3.4 – Strain gauge designs (a) Strain gauges with out-of-plane terminals (Embedded LI66) (b) Strain gauges with in-plane terminals (Conventional LY21 Strain Gauge) for surface mounting (2).

Piezoelectric sensors, specifically lead zirconate titanate (PZT) sensors, are another key category used in SHM. These sensors function based on the piezoelectric effect, wherein mechanical stress generates an electrical charge, allowing them to convert mechanical energy into electrical signals. Known for their high sensitivity, rapid response times, and robust mechanical properties, PZT sensors are effective in real-time condition monitoring applications, including motion state recognition and equipment vibration monitoring. Recent advancements have led to the development of flexible PZT sensors that maintain high sensitivity while conforming to various surfaces, enhancing their applicability in emerging technologies. However, concerns regarding the environmental impact of lead-based materials in PZT sensors have prompted research into sustainable alternatives that preserve their desirable sensing characteristics (36, 37, 38).

Fiber Bragg Grating (FBG) sensors, a type of optical sensor, have garnered significant attention for SHM applications due to their precision in measuring strain and temperature. These sensors operate by reflecting specific wavelengths of light that shift in response to strain or temperature variations. Their resistance to harsh environmental conditions, including extreme temperatures and electromagnetic interference, makes them highly suitable for monitoring composite structures in demanding environments where other sensors may struggle to provide reliable data (26, 35).

Ultrasonic sensors, frequently employed in SHM, utilize high-frequency sound waves to detect internal flaws in composite materials. These waves travel through the material and reflect back upon encountering defects such as cracks or voids, allowing for the assessment of damage location and severity. Their ability to detect both surface and sub-



surface damage makes them highly effective for comprehensive condition monitoring of composite structures (26, 35). Another innovative approach involves carbon fiber sensors, which can be directly embedded within composite materials to facilitate real-time structural health monitoring. These sensors, often composed of carbon fibers or carbon nanotubes, leveraging their inherent electrical properties to detect strain and damage. A significant advantage of carbon fiber sensors is their seamless integration with the composite material, eliminating the need for external devices and ensuring the preservation of structural integrity while continuously providing essential data on the health of the structure (26, 35).

Table 3.2 – Comparison of common sensor types used in SHM for composites.

| Sensor Type                        | Working Principle                                                                          | Advantages                                                                                                                       | Disadvantages                                                                                                                     |
|------------------------------------|--------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------|
| <b>Strain Gauges</b>               | Change in electrical resistance due to mechanical deformation.                             | Mature technology, low cost, simple to use.                                                                                      | Susceptible to EMI; requires wiring; point sensing only; adhesive can degrade.                                                    |
| <b>Piezoelectric (PZT)</b>         | Generates voltage under mechanical stress (piezoelectric effect).                          | High sensitivity to dynamic loads (impacts, vibrations); rapid response; can act as both sensor and actuator.                    | Brittle; susceptible to degradation/fatigue over time; lead-based materials raise environmental concerns; requires poling.        |
| <b>Fiber Bragg Grating (FBG)</b>   | Shift in reflected light wavelength due to strain or temperature.                          | Immune to EMI; lightweight; suitable for harsh environments; can be multiplexed on a single fiber for distributed sensing.       | Requires expensive interrogator equipment; fragile optical fiber; sensitive to transverse strain and temperature cross-talk.      |
| <b>Carbon-based Piezoresistive</b> | Change in inherent electrical resistance of a carbon network (fibers, CNTs) due to strain. | Seamless integration (material is the sensor); excellent compatibility with carbon composites; potential for large-area sensing. | Signal can be complex (non-linear); sensitive to temperature and moisture; manufacturing process can alter electrical properties. |

### 3.3.4 Characteristics and Requirements for Effective Sensors

Sensors play a very crucial role in the successful implementation of any SHM system. Hence, for any material to be used as a sensor for SHM, it must have some essential characteristics for effective monitoring of structural damages. These include: durability, sensitivity, compatibility with the structure, resistance to environmental factors and integration into manufacturing processes (39). Sensors for effective SHM, are required to be capable of withstanding service loads over the entire life of the structure. They should be

resistant to degradation over time. The sensors are also required to be capable of sensing, detecting or measuring the smallest possible changes in the structural conditions. This allows the sensor to detect damages at their onset, such as micro-cracks, delaminations etc. Embedded sensor materials should be capable of blending with the composite structure, without causing significant distortion or disturbance to the parent structure. Because sensors just like the structure is most often than not, exposed to harsh environmental conditions such as variation in temperature, ultra-violet (UV) light, humidity, pressure etc., it should be capable of resisting the impact of these environmental factors on its sensitivity to the measured parameter. Due to the intricacy of some structural geometry, some complex manufacturing processes may be required to produce them. Embedded sensor materials should therefore, be capable of fitting these advanced manufacturing processes such as the 3D printing.

For effective implementation of SHM, it is crucial for sensors, particularly embedded sensors, to possess these characteristics. Additionally, sensors for aerospace application should, in addition to the above characteristics, have features like smaller geometry, lighter weights, lower power consumption, ageing resistance with longer service life, compact wiring or wireless construction, lower cost and good signal to noise ratio (18, 39).

## 3.4 Advanced Sensor Technologies and System Architectures

### 3.4.1 Key Embedded Sensor Modalities

The effectiveness of an embedded SHM system is fundamentally determined by the sensing modality chosen. While many sensor types exist, certain modalities have proven particularly suitable for integration within composite materials, with carbon-based piezoresistive sensors being especially prominent. A high-level comparison of the main sensor technologies is presented in Table 3.3.

Table 3.3 – Comprehensive performance comparison of primary embedded sensor technologies.

| Sensor Tech.                         | Key Metric(s)                                               | Typical Range                 | Strengths for Embedding                                                                          | Weaknesses for Embedding                                                                                                |
|--------------------------------------|-------------------------------------------------------------|-------------------------------|--------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------|
| <b>FBG</b>                           | Wavelength Shift, Strain Sensitivity                        | 1.2 pm/ $\mu\epsilon$         | EMI immunity, multiplexing capability, chemical inertness, good for harsh environments.          | High cost of interrogators, fragility of optical fiber during integration, need for temperature compensation.           |
| <b>PZT</b>                           | Piezoelectric coefficient ( $d_{33}$ ), Voltage Sensitivity | $d_{33}$ : 200-600 pC/N       | High sensitivity to dynamic/acoustic events, actuator capability (active SHM).                   | Brittleness can lead to cracking, requires electrical wiring/shielding, poling required, can degrade under cyclic load. |
| <b>Piezoresistive (Carbon-based)</b> | Gauge Factor (GF)                                           | Highly variable (2 to > 1000) | Excellent material compatibility (CFRP), potential for true self-sensing, scalable via printing. | Non-linear response, high sensitivity to temperature and moisture, process-dependent properties.                        |
| <b>MEMS</b>                          | Acceleration, Pressure, etc.                                | Application specific          | Miniaturization, multi-parameter sensing on a single chip, low power consumption.                | Can be a significant inclusion causing stress concentration, requires robust packaging, limited temperature range.      |

#### 3.4.1.1 Piezoresistive Properties of Carbon-Based Sensors

**Carbon Fibers:** Carbon fibers exhibit exceptional strength, stiffness, and thermal resistance, making them particularly suitable for reinforcing polymers, cement, and metals. These materials are recognized for their self-sensing or self-monitoring capabilities. It's well-established that the piezoresistive characteristics of carbon fibers are significantly influenced by the configuration of the conductive network within a matrix. Generally, applying epoxy to carbon fibers increases electrical resistivity, a phenomenon attributed to compressive residual stresses arising from epoxy shrinkage post-curing (40). For instance, a bare carbon fiber demonstrates a gauge factor ranging from 1.9 to 2.3. However, when incorporated into cured epoxy, this gauge factor enhances to 217, and it can further elevate to over 500 when carbon fibers are randomly oriented within a cement-matrix composite (41) in (40). Numerous investigations have elucidated the influence of matrix characteristics on the piezoresistive behavior of carbon fiber-reinforced composite materials. A previous study employed a 3D printing technique to integrate continuous carbon fiber tows into tensile test specimens, yielding gauge factors that varied between 0.545 and 6.686 (42).

The volume fraction of carbon fibers within composite materials is a critical parameter significantly affecting piezoresistive properties. For example, increasing carbon fiber content from 15% to 20% in composites containing cementitious fillers has been observed to alter the gauge factor from 1250 to 20 (43). Furthermore, longer fibers have been reported to exhibit enhanced gauge factors (40). The increased length of fibers correlates with a greater incidence of manufacturing defects (such as porosity) and, consequently, heightened sensitivity. Another factor that may influence the behavior of carbon fiber piezoresistive materials is fiber length. Recently, a study indicated a pronounced non-linear resistance-strain response for carbon fibers characterized by a broad length distribution (40),(44). Piezoresistivity in continuous carbon fibers can manifest as positive or negative under certain loading conditions, such as during flexural loading, due to the interplay of compressive and tensile regions. Moreover, applying elevated loading levels has been shown to reduce the gauge factor. This phenomenon is attributed to internal micro-damages or irreversible alterations in resistance, particularly evident under cyclic loading conditions. Detecting damage or delamination constitutes one of the primary applications of carbon fiber content in nanocomposite materials (40, 44).

**Carbon Nanotubes:** In recent decades, CNTs have shown remarkable potential for applications in piezoresistive devices and materials. Their exceptional mechanical, thermal, and electrical characteristics position them as exemplary candidates for use as filler agents in composite materials (45). Within CNT-based composites, piezoresistivity is fundamentally achieved through the sliding or displacement of the nanotubes. The resulting piezoresistivity can be positive or negative in structures incorporating CNTs, contingent upon their wrapping indices. Single-wall carbon nanotubes (SWCNTs) and multi-wall carbon nanotubes (MWCNTs) are the primary constituents used to induce piezoresistivity within composites comprising polymeric matrices.

The piezoresistive characteristics of composites synthesized with CNTs have been investigated with various polymeric matrices, including epoxy, polydimethylsiloxane (PDMS), polymethylmethacrylate (PMMA), polystyrene (PS), and polycarbonate. Empirical studies indicate that the sensitivity of these composites is significantly influenced by several factors, such as the matrix material, conductive mass fraction, loading nature, sample dimensions, and fabrication methodology. Typically, an increased mass fraction of the conductive filler results in diminished sensitivity while simultaneously impairing the mechanical integrity of the matrix polymer. Consequently, ongoing research is dedicated to advancing fabrication techniques for composite piezoresistive materials characterized by a low percolation threshold. For instance, methodologies like solvent casting and CNT alignment have been effectively utilized to establish the conductive network at a reduced filler mass fraction. Beyond sensitivity, the repeatability of CNT-based nanocomposites under cyclic loading conditions presents a significant challenge. The investigation referenced in Ref. (46) demonstrated notable repeatability in cyclic tensile and compression

loadings for MWCNT/epoxy nanocomposites, specifically within a limited strain range (0.2%) and achieving a gauge factor of up to 78. In a separate analysis, the gauge factor for an MWCNT/poly (glycerol sebacate) composite showed a strong dependence on loading conditions, with a reported gauge factor range of  $-0.5$  to  $-0.8$  under tensile loading, while a peak value of 42 was recorded during 3-point bending tests (45, 47, 48).

While these diverse sensor modalities form the building blocks of embedded SHM, their successful implementation and long-term reliability are critically dependent on the methods used to integrate them into the host composite structure. This integration process, as discussed in the following section, introduces its own set of significant challenges that can govern the performance of the entire SHM system.

### 3.4.2 Integration Processes and System-Level Challenges

The transition from externally mounted sensors to fully embedded systems introduces a host of manufacturing and material science challenges. The method of integration is critical as it directly impacts both the sensor's performance and the structural integrity of the host composite.

#### 3.4.2.1 Integration via Additive Manufacturing

Self-sensing in structures for SHM implementations relies on the systematic integration of sensors into the parent structure. For composite structures, achieving self-sensing necessitates excellent interaction between the sensor and the matrix, ideally surpassing that of fiber-to-matrix bonding. This strong interaction ensures that the external parameters being monitored are accurately transmitted to the sensing element (40).

There is growing interest in the additive manufacturing of materials with built-in self-sensing capabilities. This approach offers significant advantages over traditional methods, including reduced costs, on-demand production, and greater design flexibility. Notably, these materials can be manufactured using common 3D printing techniques such as Fused Deposition Modeling (FDM), also known as Fused Filament Fabrication (FFF), stereolithography (SLA), Digital Light Processing (DLP), Masked Stereolithography (MSLA), and direct ink writing (DIW). A comparison of how these processes can affect sensor performance is shown in Table 3.4 and their working principles are schematically illustrated in Figure 3.5. While sharing similarities with traditional processing, such as requiring extruded plastic filaments with continuous fibers or resin mixtures with evenly distributed conductive fillers, these methods differ in their fundamental principles (49, 50).

Table 3.4 – Impact of 3D Printing Processes on Embedded Sensor Performance.

| 3D Printing Method | Impact on Sensor Performance                                                                                                                                                                                               | Key Process Parameters to Control                                                                |
|--------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------|
| <b>FDM / FFF</b>   | Can create porosity between printed lines, affecting conductivity and repeatability. Layer adhesion quality directly impacts strain transfer to the sensor. High processing temperature can damage some sensing elements.  | Nozzle temperature, print speed, layer height, infill density, raster angle.                     |
| <b>SLA / DLP</b>   | Provides higher resolution and better surface finish, leading to more consistent and less noisy sensor properties. Limited to photocurable resins, which may have different mechanical properties than the host composite. | UV exposure energy, layer thickness, resin viscosity, filler dispersion (for conductive resins). |
| <b>DIW</b>         | Highly versatile for creating multi-material and functionally graded sensors. Performance is heavily dependent on ink rheology (viscosity, shear-thinning behavior), which affects print resolution and conductivity.      | Nozzle diameter, extrusion pressure/rate, print speed, ink formulation and viscosity.            |

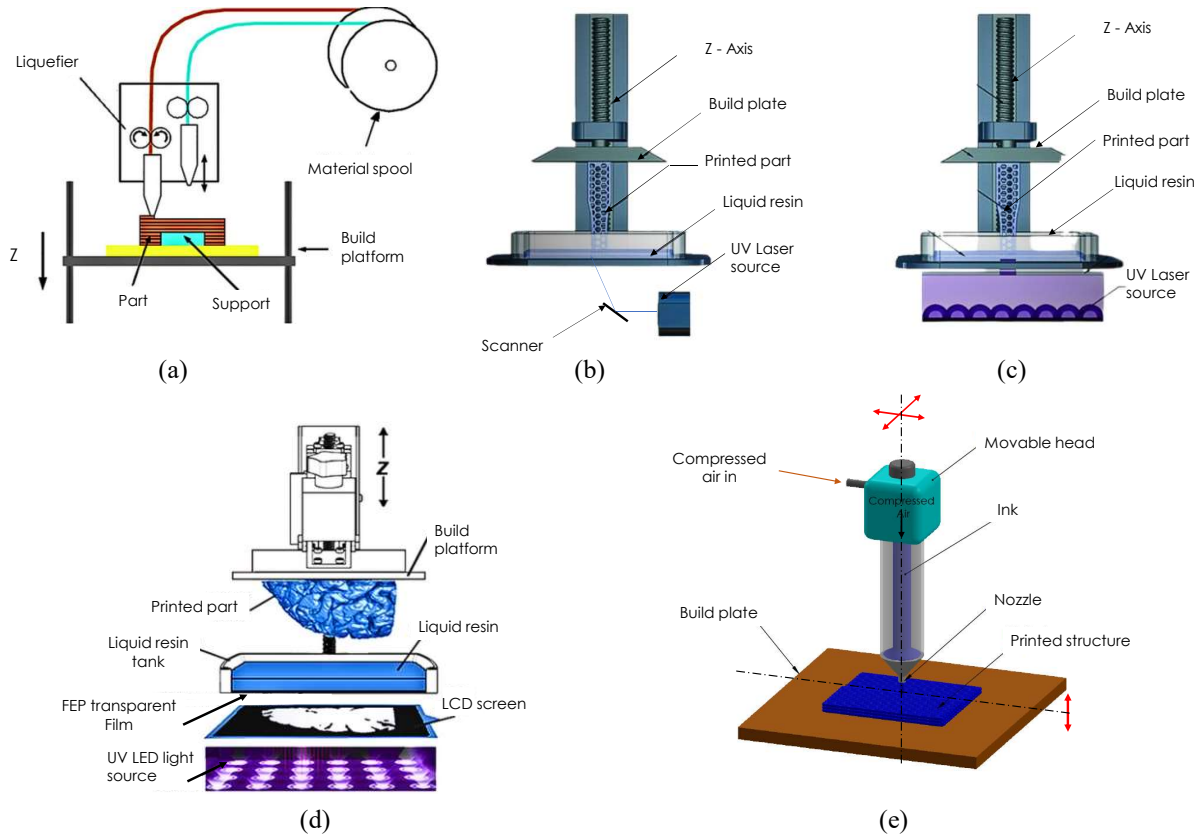


Figure 3.5 – Schematic diagrams of Various 3D Printing processes for manufacturing embedded sensors (a) Multi-material FDM process (3). (b) SLA process (4). (c) DLP process (4). (d) MSLA process (5). (e) DIW process (6)

3D printing is an innovative technology that rapidly produces complex 3D structures with high accuracy by depositing materials layer by layer (51). While SLA, DLP, and MSLA use laser curing of photosensitive resin, FFF/FDM relies on fusion-based stacking, and direct ink writing involves extruding specialized materials such as conductive inks and piezoelectric ceramics. Although 3D printing can be slower than some conventional manufacturing methods, especially for high-resolution applications, it offers unmatched material versatility. It also enables the production of fully functional sensors in a single step using conductive materials like carbon fibers, nanotubes, graphene, silver, copper, and MXenes. However, challenges remain for broader commercial adoption, including health and environmental risks from nanomaterials, recycling and life cycle issues, low production rates, and difficulties with legislation, repeatability, and software development.

#### 3.4.2.2 Challenges in Sensor-Material Integration and Durability

The integration of sensors within a composite matrix is a complex process fraught with challenges that can compromise sensor function and structural integrity. Embedded sensors are typically either material-supported (where a discrete sensor is placed within the structure) or material-embedded (where the sensing material is printed directly as part



of the structure). Both approaches face significant hurdles.

For 3D printing of material-supported sensors, the primary challenges are the printing temperature's impact on the sensors and the quality of the mechanical bonding between the sensor and the substrate or structural material. Printing temperature can induce thermal stresses in the sensor material, which transform into residual internal stresses upon cooling. These stresses can affect the sensor's ability to accurately measure an event. Conversely, poor adhesion between sensors and the structure may prevent the accurate transfer of the targeted external parameter to the sensor for proper recording.

Material-embedded sensors face challenges in maintaining the conductive element's properties identical to those of the conductive filament. This is because the filament is formed by physically mixing the substrate and conductive nanoparticles. Forcing this molten mixture through a nozzle can alter the conductivity of the printed element due to the rearrangement and reorientation of nanoparticles in the deposited material. Additionally, the size and speed of the printing nozzle can increase the porosity of the sensing element, which can consequently alter the sensor's sensitivity. A study by Stano *et al.* (52) revealed how porosity can reduce the conductivity of 3D printed conductive elements, demonstrating an increase of over 80% through a simple ironing process.

Another challenge for 3D printed sensors is the difference in modulus of elasticity and thermal expansion coefficients between the main structure and the conductive element. This discrepancy can induce internal stresses, potentially leading to internal damages such as cracks, delaminations, or premature sensor failure (53). To mitigate this problem of uneven stress distribution resulting from induced internal stresses, special advanced materials, known as mechanical metamaterials, are being explored. These materials offer unique properties like Negative Poisson Ratio (NPR), Zero Poisson Ratio (ZPR), Negative Thermal Expansion (NTE), and Zero Thermal Expansion (ZTE). These counter-intuitive properties arise from the microstructural arrays and shapes of the unit cells that form the lattice structure (50). Furthermore, studies have shown that composite materials exposed to thermal environments face challenges such as dimensional instability, which impacts sensor calibration and performance. These thermal fluctuations can also influence sensor-matrix debonding (54, 55).

Signal integrity can be compromised in embedded sensors, especially when placed in conductive or dielectric substrates. Traditionally, metallic conductive sensor materials can interact with surrounding materials, leading to signal disturbance caused by electromagnetic interference (EMI) or sometimes capacitive coupling effects, depending on the sensor type and host structure materials (55). These issues affect the accuracy of acquired data and are common in Wireless Sensor Networks (WSNs) (53). Various approaches can mitigate signal interference, including building insulative layers around embedded sensors, using shielding materials, optimizing sensor placements, and employing inkjet printing to create controlled electrical pathways with less disruption to the composite material (53).



Embedding sensors in composite structures can alter the stress distribution within the structure. This may create non-uniformity in the structure's resistance to externally applied loads, introducing unnecessary stress concentrations in areas that were not originally vulnerable. This makes the structure susceptible to unexpected failures, thereby compromising its holistic integrity (53).

Finally, a significant and often prohibitive drawback of embedding sensors is their inaccessibility. Once integrated, maintenance or replacement is typically impossible. Should a sensor fail, the entire component may need to be decommissioned, a costly proposition that forces asset managers to weigh the value of the monitoring program against the integrity of the structure itself (50). To mitigate this challenge posed by embedding sensors within composite structures, several strategies have been proposed. The systematic incorporation of redundancy in sensor network design ensures that the failure of individual nodes does not compromise overall functionality, thereby enhancing system robustness. Advances in self-healing composites and conductive materials offer another promising pathway, where minor damage can be autonomously repaired, restoring sensor performance without external intervention. Additionally, the integration of predictive health monitoring through AI and machine learning algorithms enables estimation of the sensors' remaining useful life, facilitating proactive maintenance or replacement of entire components before failures occur. Finally, modular design approaches provide a practical solution for certain applications by incorporating replaceable structural sections that house embedded sensors, thereby simplifying maintenance while preserving the integrity of the overall system. Collectively, these strategies represent a growing body of efforts aimed at addressing the maintenance challenges associated with sensor inaccessibility in multifunctional composites.

#### 3.4.2.3 Mechanisms of Sensor-Host Interaction

The fidelity and reliability of data from an embedded sensor are critically dependent on the mechanical and chemical integrity of the sensor-host interface. Effective transfer of physical quantities, such as strain, from the composite matrix to the sensor is paramount. This interaction is governed by several underlying mechanisms.

The primary mechanism for strain transfer is the physical adhesion between the sensor (or its protective coating) and the surrounding matrix material. This adhesion relies on a combination of van der Waals forces, mechanical interlocking at the micro-scale, and potentially chemical bonding if compatible resins and coatings are used (56, 57, 58). The effectiveness of this load transfer can be modeled using shear lag theory, which describes how strain is transmitted through shear stress along the interface (59, 60). Any degradation, such as interfacial debonding or a weak boundary layer, will disrupt this transmission, leading to inaccurate sensor readings that underestimate the true structural

strain (61, 60).

The sensor-host interface is a potential point of weakness over the structure's lifetime. Long-term stability can be compromised by several factors, including chemical incompatibility between the sensor coating and the polymer matrix, which can lead to material degradation. Furthermore, differential thermal expansion between the sensor and the host composite can induce cyclic stresses at the interface, potentially leading to fatigue and debonding (62, 63). Moisture ingress along the interface is another critical concern, as it can swell the matrix locally and weaken the adhesive bond, directly impacting sensor reliability (64, 65).

#### 3.4.2.4 System-Level Hardware Integration

Beyond the material science of integration, there are significant challenges at the system level. An embedded sensor is only useful if its data can be reliably acquired, powered, and transmitted. Integrating the necessary hardware within a composite structure without compromising its integrity is a major hurdle. This includes embedding wiring for data and power, which can act as a stress concentrator or a pathway for moisture ingress. Furthermore, powering embedded sensors is a critical issue; while some may be passive, many require continuous power, necessitating either embedded batteries with finite lifespans or innovative energy harvesting solutions. Lastly, the data acquisition (DAQ) hardware must be embedded in itself or placed near it, with robust connections that can survive the operational life of the structure. These system-level considerations are crucial for the practical implementation of any embedded SHM technology.

### 3.4.3 Advanced SHM System Architectures

Beyond individual sensors, the architecture of the entire SHM system dictates its overall capability and effectiveness. Modern systems leverage smart sensors, wireless networks, and hybrid approaches to create comprehensive monitoring solutions.

#### 3.4.3.1 Smart and Wireless Sensor Networks

The adoption of advanced sensor technologies has revolutionized SHM by integrating functionalities like self-diagnosis, wireless communication, and real-time data processing. These "smart" sensors play a crucial role in collecting accurate, high-quality data while reducing the operational complexities associated with traditional wired systems. These sensors, which come with capabilities like event-triggered sensing and multi-modal data collection, are designed to monitor parameters such as strain, temperature, vibration, and displacement. As a result, they play a critical role in advanced SHM tasks (66, 67).

Wireless smart sensors (WSS), such as Martlet nodes and Xnodes, have been integrated into structures like bridges, wind turbines, and railway infrastructure to gather data

on environmental and operational conditions (68). By enabling remote monitoring, these systems help reduce maintenance costs and facilitate the implementation of predictive maintenance techniques. The use of vibration energy harvesting and solar-powered nodes further enhances their utility in long-term deployments, ensuring continuous operation without frequent manual intervention (69, 70). WSS exhibit some degree of autonomy in their complete operation, ranging from data acquisition, transmission, processing, analysis and decision making. Because the process starts with data acquisition, WSSN are usually incorporated with wireless data acquisition capabilities. This allows for prompt detection and transmission of events. However, for most systems, events are not continuously happening. The sensors will therefore be idling at the same time consuming energy. To address this issue especially for systems that will need long term monitoring, systematic wireless data acquisition mechanisms are developed, encompassing optimized sensor dormancy periods and focusing on duty cycling utilization. These mechanisms are either schedule-based or event-triggered (17). The comparison between these two data acquisition mechanisms are summarized in Table 3.5.

Table 3.5 – Comparison between the two main wireless data acquisition mechanisms (17)

|              | Schedule-Based                                                              | Event-Triggered                                                                                       |
|--------------|-----------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------|
| Activation   | Wakes at pre-set times to record data.                                      | A low-power sentinel node detects an event and wakes a high-fidelity node to record.                  |
| Advantages   | Predictable battery life.                                                   | Extends battery life when events are infrequent.                                                      |
| Limitations  | May miss events between scheduled recordings; unsuitable for dynamic loads. | Unpredictable battery life; may miss events outside the sentinel's detection scope (e.g., vandalism). |
| Applications | Statically loaded structures (e.g., dams, buildings).                       | Dynamically loaded structures (e.g., bridges, aircraft, wind turbines).                               |

Recent advancements in sensor technology, such as miniaturized micro electromechanical systems (MEMS) and devices with enabled Internet of Things (IoT), have significantly enhanced the capabilities of SHM systems. MEMS accelerometers, for example, have demonstrated their potential in low-cost and high-precision applications by providing reliable data to assess the dynamic characteristics of bridges and other civil structures (71). These compact sensors facilitate easy installation and reduce the need for extensive wiring, making them highly adaptable to various structural configurations.

IoT-enabled sensors integrated into WSSNs further amplify the benefits of SHM by enabling seamless data transmission and real-time analysis. The deployment of IoT systems in large-scale infrastructures, such as the Hangzhou East Railway Station, highlights their ability to monitor multiple parameters simultaneously, leveraging tree-type network topologies for efficient communication across 323 sensors (72). This ensures comprehensive lifecycle monitoring and improved understanding of internal force redistributions in

complex structures. Today, sensor manufacturers are building universal and multipurpose sensors that can be used in different structures and for different applications. These sensors are made with the flexibility of surface mounting or embedded in the structure. Most of these sensors are equipped with enhanced smart sensing capabilities to align with the modern world SHM realities, such as wireless data transmission, AI-driven data analysis techniques, among others. Examples of these sensors are presented in Figure 3.6.



Figure 3.6 – Commercially manufactured multipurpose sensor (a) Custom designs (b) Standard layers (c) Single sensors (7).

A number of experimental studies have addressed the issue of power source associated with WSSNs. For example Popovic *et al.* (73) designed an event-driven monitoring system based on WSSN with a sentinel node to trigger a high fidelity monitoring node. The system demonstrated reliable sensing and extended battery life, however, because of how the sentinel node was programmed, data for other events outside the scope of its operations could be lost. Similar systems have been designed with programmable event detection to reduce lost data (74). Lin *et al.* (8) built a monitoring system using MEMS accelerometers for the rapid after-earthquake assessment of buildings with the ability to rapidly reconstruct missing data as used in Changping Guangdian mansion in Beijing city illustrated in Figure 3.7. These case studies are summarized in Table 3.6.

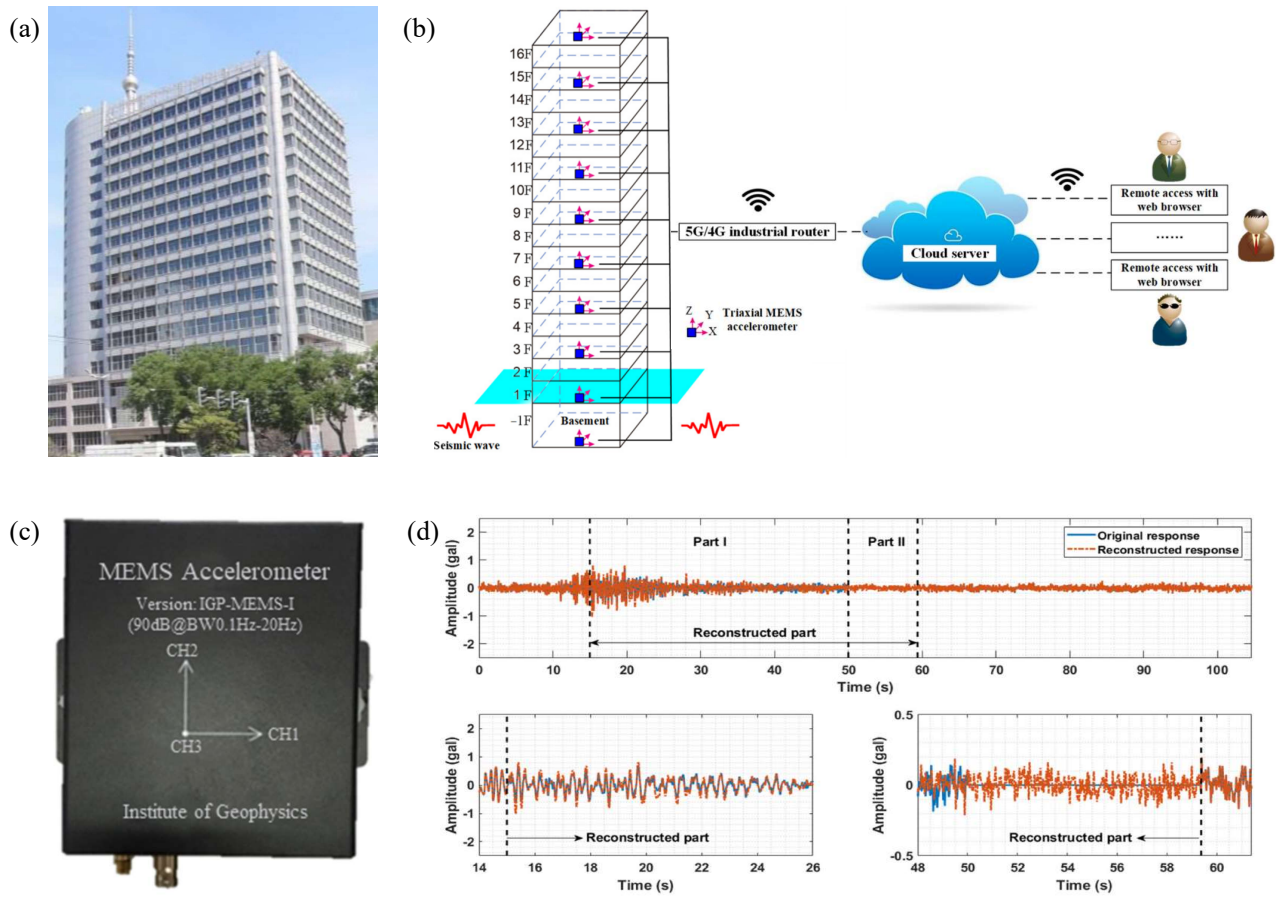


Figure 3.7 – Overview of the developed WSSN for a building safety assessment (a) The Changping Guandian mansion in Beijing city used as case study. (b) Schematic diagram of the building safety monitoring system. (c) The triaxial cost-effective MEMS accelerometer used for the program (d) a Comparison between original and reconstructed Z-axial acceleration response of the third floor (adapted from (8)).

Table 3.6 – Summary of research works conducted on Event Triggered WSSN

| Author | Data acquisition mechanism | Features of the WSSN                                      | Advantages                                          | Drawbacks                            |
|--------|----------------------------|-----------------------------------------------------------|-----------------------------------------------------|--------------------------------------|
| (73)   | Event-Triggered (ET)       | SN+MN                                                     | Extended battery life                               | Missing data due to response Latency |
| (74)   | ET                         | Customizable ET+ Ultra-low-power MC                       | Battery life extended                               | Missing data                         |
| (75)   | Demand-Based (DB)          | Programmable ET switch+high fidelity Monitoring Node (MN) | Improved battery life                               | Missing data (Very few)              |
| (8)    | ET                         | Reconstruction of missing data                            | No missing data                                     | -                                    |
| (76)   | ET                         | Ultra-low-Power ET                                        | On-demand, high fidelity sensing & no missing event | -                                    |

### 3.4.3.2 Hybrid Sensor Systems

Different sensors when used as stand-alone sensors for SHM of composite structures or for damage detection, besides their main advantages which prompted for their choices, always have some drawbacks, which limited their operations to some specific applications. A systematic practice of combining these different types of sensors in a SHM system is known as the “hybrid sensor system”. In the aerospace industry, FBG sensors are often combined with piezoelectric sensors to monitor and evaluate airplane structures by detecting acoustic emission from potential damage sites (77, 78). This system allows for more efficient monitoring systems by leveraging on the individual sensor strengths and complementing each other’s weaknesses. For example, some sensors can be very strong and durable, but limited by sensitivity, resolution, and probably the range of data it can measure. Some can be very sensitive, immune to harsh environmental conditions, and have a low signal-to-noise ratio, but very fragile and difficult to integrate in some complex structures. Sometimes this same term “hybrid sensor system” is not used to only signify the combination of more than one sensor material, but a combination of a sensor material and a non-sensing material with the aim of consolidating the operations of the sensor, e.g., the combination of a unidirectional layer of S-glass/epoxy and another unidirectional layer of ultra-high modulus (UHM) carbon/epoxy for the damage detection of low energy impact (79). It can also be used to signify the use of different methods in the implementation of an SHM project, e.g. the combination of a numerical finite element modeling with a machine learning algorithm in an SHM framework. For example; Svendsen (80) developed a hybrid SHM framework for monitoring bridge damage that combines the use of a calibrated numerical finite element (FE) model to generate data



from different structural state conditions under varying environmental conditions with a machine learning algorithm in a supervised learning approach.

Hybrid sensor systems offer significant advantages in complex SHM applications, including enhanced versatility, improved redundancy, and the ability to monitor multiple parameters simultaneously. One of the most significant benefits of hybrid sensor systems is improved redundancy. The integration of multiple sensing mechanisms, such as Rayleigh, Brillouin, and Raman scattering, provides multiple layers of data verification, thereby reducing the likelihood of false alarms and errors in fault detection (81). Another key advantage of hybrid sensor systems is their versatility. These systems are capable of monitoring diverse parameters such as strain, temperature, and vibration using a single sensing fiber, thereby simplifying system design (82). Despite these numerous advantages, hybrid sensor systems present certain challenges. The integration of different sensing technologies introduces a level of complexity that necessitates advanced processing techniques and sophisticated data fusion methodologies.

#### 3.4.3.3 Data Processing and Analysis

The advances in embedded sensor technologies have led to the generation of vast quantities of complex, high-dimensional data. The raw data from sensors is often noisy and influenced by operational and environmental variability. Therefore, advanced data processing is a critical and indispensable component of any modern SHM system. This process typically involves several stages: signal conditioning and filtering to remove noise and unwanted frequencies; feature extraction, where damage-sensitive features (e.g., amplitude changes, frequency shifts, statistical moments) are identified and extracted from the cleaned signal; and finally, pattern recognition or damage classification. Increasingly, machine learning and artificial intelligence algorithms are being employed for this final stage. Supervised learning models, such as Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs), can be trained on data from known structural states (healthy and damaged) to automatically classify the condition of a structure. The integration of these intelligent data processing techniques is crucial for moving towards autonomous, reliable, and predictive SHM frameworks (67).

### 3.5 Factors Affecting Sensor Performance

#### 3.5.1 Operational Loading Conditions

The performance and durability of sensors in SHM applications are significantly influenced by the mechanical loads they experience. In high-stress environments, such as aerospace and automotive structures, sensors are subjected to varying stresses, strains, and dynamic loads that can lead to inaccuracies or failure. For example, sensors in automotive applica-

tions must adapt to rapid changes in load profiles from acceleration and braking, which can cause signal degradation (83). Similarly, piezoelectric sensors on aircraft are exposed to extreme vibrations that may lead to cracking and disbonding of the sensor or its adhesive layer (84, 85). A comprehensive understanding of these loading conditions is essential for designing robust sensors and ensuring the reliability of SHM systems.

### 3.5.2 Environmental Factors

Beyond mechanical loads, external environmental conditions including fluctuations in temperature, moisture, chemical exposure, and radiation, pose significant challenges to sensor functionality. These factors can alter sensor readings, obscure damage signatures, and accelerate material degradation, thereby compromising the accuracy and reliability of the SHM system. Developing systems capable of compensating for such environmental variations is critical for effective damage detection.

#### 3.5.2.1 Temperature Effects

Temperature fluctuations are a primary source of error and degradation for nearly all sensor types. From a mechanistic standpoint, temperature changes can induce thermal expansion in the host structure and the sensor itself ( $\Delta L/L = \alpha \Delta T$ ), which can be misinterpreted as mechanical strain. For FBG sensors, temperature also alters the fiber's refractive index (the thermo-optic effect), causing a shift in the measured Bragg wavelength that can mask strain-induced shifts (86). For piezoresistive sensors, temperature affects the intrinsic resistivity of the conductive network and can cause differential thermal expansion between the filler and matrix, altering the baseline resistance.

In structures like cable-stayed bridges, thermal responses can account for 63% to 93% of the variations in measured cable forces, potentially masking the true structural changes (87). To address this, specialized interpretation approaches such as temperature-based measurement-interpretation (TB-MI) have been developed (88). Furthermore, extreme temperature cycling, particularly in aerospace applications, can induce thermal distress in sensors like piezoelectric wafer active sensors (PWAS), degrading adhesive bonds and distorting wave propagation, which in turn affects damage detection accuracy (89, 90).

#### 3.5.2.2 Moisture and Chemical Effects

Moisture absorption is another critical factor, especially for sensors embedded in composite materials. Moisture penetrates polymer matrices via diffusion and capillary action, causing hygroscopic swelling and altering the material's mechanical, thermal, and dielectric properties (91). This process directly affects sensor performance. For FBG sensors, moisture-induced swelling can cause wavelength shifts that lead to measurement errors



(91, 92). For piezoelectric sensors, moisture alters wave propagation characteristics in the host material, impacting sensitivity and response (93).

The diffusion process in composite materials can often be described by Fick's laws. For one-dimensional diffusion through a plate of thickness  $d$ , the moisture concentration  $c$  over time  $\tau$  and position  $z$  is given by:

$$\frac{\partial c}{\partial \tau} = D \frac{\partial^2 c}{\partial z^2} \quad (3.1)$$

where  $D$  is the diffusion coefficient. The solution for the total mass change  $m(t)$  over time can be approximated by (94):

$$\frac{m(t)}{m_m} \approx 1 - \exp \left[ -7.3 \left( \frac{Dt}{d^2} \right)^{0.75} \right] \quad (3.2)$$

where  $m_m$  is the mass of moisture at saturation. This relationship allows the diffusion coefficient to be calculated from weight measurements.

Moisture also affects electrical properties. It acts as a plasticizer in epoxy adhesives, reducing the elastic modulus and glass transition temperature ( $T_g$ ) (95). In conductive composites, absorbed water acts as an electrolyte, increasing conductivity and thus decreasing the material's electrical resistance, which can interfere with piezoresistive sensing (96).

In addition to moisture, sensors may face chemical exposure and corrosion, particularly in harsh environments like offshore structures. Flexible Eddy Current Array (FECA) sensors, for example, have been designed to monitor fatigue cracks while withstanding corrosive salt fog and severe vibrations (97). Mitigating the effects of moisture and chemicals often involves using protective coatings, such as hydrophobic layers on gas sensors (98), or developing sensors from intrinsically resistant materials.

### 3.5.3 Durability and Long-Term Reliability

For the practical adoption of SHM, the long-term durability and reliability of embedded sensors are paramount. Unlike conventional sensors that can be serviced or replaced, embedded sensors must function for the entire service life of the component. Long-term challenges include sensor drift, where the baseline signal changes over time due to material aging or the relaxation of manufacturing-induced residual stresses. Furthermore, sensors embedded in structures subjected to cyclic loading can experience their own fatigue, leading to signal degradation or outright failure.

The reliability of the entire SHM system also depends on its architecture. Key design parameters such as network topology (e.g., star, mesh), sensor density, and the level of redundancy must be optimized. A well-designed, redundant network can maintain functionality even with the partial failure of individual sensors, thereby enhancing the overall system's long-term reliability and robustness (99).

A critical aspect of long-term reliability, directly linked to the integration process discussed in Section 3.4.2, is the impact of embedded wiring and connectors. These components, while necessary for power and data transmission, can act as foreign bodies within the composite laminate. They can create resin-rich zones, introduce stress concentrations, and serve as potential pathways for moisture ingress, thereby locally compromising the structural integrity of the host material (100, 101). The long-term failure of the SHM system is often not due to the sensor itself, but to the degradation of these fragile electrical interconnections within an operational, load-bearing structure.

System resilience against such failures can be enhanced through strategic network design. The choice of sensor network topology plays a pivotal role in ensuring robust, long-term monitoring. For instance, a simple star topology is vulnerable, as a single failure at the central data aggregator can lead to the loss of the entire network. In contrast, a mesh topology offers significantly greater resilience by providing redundant data pathways, allowing the system to continue functioning even after the failure of individual sensors or communication links (102). This redundancy is crucial for designing durable and fault-tolerant SHM systems for safety-critical applications.

## 3.6 Case Studies and Experimental Findings

This section discusses the case studies and experimental findings of previous related research works. To ensure that the most relevant works are included in the review, a systematic search strategy was adopted. The search was carried out using the Web of Science and Scopus databases, and the keywords/search terms used: (“3D Printing” AND “Sensors” AND “Composites”). Initially, the search results returned by the databases were 550 and 791 respectively. Upon application of some filter terms that are mentioned under the inclusion and exclusion criteria, and using Mendeley reference manager to merge duplicates, a total of 190 articles were left. During the Abstract screening, 77 were further excluded, and after full text reading, 20 articles were further excluded based on relevance ground, leaving behind 93 articles for the review.

The selection of articles for review was guided by specific inclusion and exclusion criteria, such as; only research articles with experimental findings containing the search keywords were considered. To ensure relevance and recent advancements, only works published in English within the last five years (2020–2025) were included. The scope of the review was further restricted to the field of engineering, with a focus on studies involving embedded sensors either as embedded materials or as material-supportive components for structural health monitoring of composite structures. Conversely, conceptual or purely theoretical studies, including academic reviews, were excluded, as the objective was to examine relevant case studies and experimental findings. Additionally, studies published before 2020 were not considered. Research on sensors unrelated to SHM applications was

also excluded from the review.

For each of the case studies reviewed, key information was extracted. This information includes; the form in which the sensor or sensing material is manufactured in relation to the structure (sensor form). This could be as “embedded material”, where the sensor forms an integral part of the structure, or as “material supportive” where the sensor is fabricated separately and then attached to the structure using some adhesives. Other information extracted is the type of sensor used in each study, be it fiber optic, piezoelectric, piezoresistive, capacitive, magnetostrictive, etc. The active sensing material for each of the types of sensors used in the various case studies also forms the list of information extracted. Additionally, the fabrication process used for the manufacture and integration of sensor materials into the structure was also extracted for each case study. Finally, the experimental methods used in each case study, their findings, and possible application areas were also extracted. This extracted information forms the basis for all the comparisons that are presented and discussed in this section.

From the total number of case studies that were reviewed, the distribution of the different types of sensors used is illustrated in Figure 3.8. The figure shows that the piezoresistive sensor dominated the distribution with 63%, with the majority of case studies using them. This is an indication that they are the most preferred sensors for many SHM programs in composite structures. This wide acceptance, popularity, and predominance of piezoresistive sensors could be attributed to some of their unique characteristics, which include; relatively high sensitivity making them suitable for detecting strains and structural damages, ease and flexibility of integration into structures irrespective of the structural complexity, and, compared to other sensors, they have relatively simple signal processing.

Carbon based nano-fillers (CNTs, GNPs, CB, CF) which form more than 70% of the active piezoresistive sensing materials used for SHM programs, as illustrated in Section 3.6.3, are used in different substrates; thermoplastics, thermosettings, and photo polymers, to print conductive elements either directly using SLA, DLP, DIW, MEX, or to produce conductive filaments for multimaterial printing of embedded conductive elements in structural components using FDM processes.

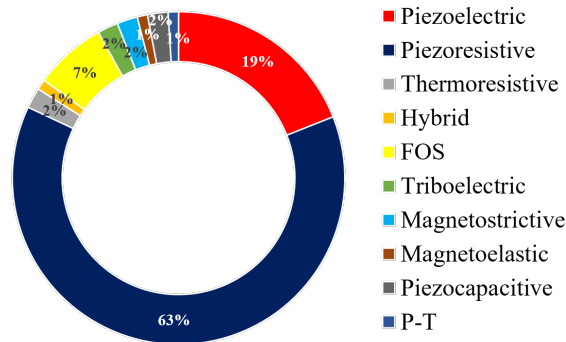


Figure 3.8 – Comparative analysis the various types of Sensors used in the case studies reviewed

Next in dominance, as illustrated in Figure 3.8, are piezoelectric sensors, which form 19% of the total of sensors used in the case studies. Due to their ability to self-generate electricity when strained, they are widely used in SHM systems for impact detection and monitoring of dynamic structural loads such as vibrations. Case studies revealed, in the use of piezoelectric sensors for low-velocity impact damage detection in aerospace structures, that the sensors were capable of monitoring real-time structural integrity and were also capable of identifying locations and severity of damage. Different materials are used for piezoelectric sensors, but the most commonly used, as illustrated in Section 3.6.2, are lead zirconate titanate (PZT) and polyvinylidene fluoride (PVDF). The lower flexibility in the integration process coupled with the susceptibility to signal degradation over time is part of the reason for their lower popularity.

Other sensors represent less than 20% of the distribution, with FOS having the highest percentage (7%), making it the third most widely used sensor in the reviewed case studies. The FOS are known for some unique properties such as high sensitivity, immunity to harsh environment and electromagnetic interference, less maintenance needs, long distance signal transmission capabilities, etc. making them the best choice for many SHM programs. However, they are less popular because they are too expensive, making them less cost-effective for many SHM programs. A very complex optical data processing system is also required. FBG sensors are the most popular FOS sensors in use, as illustrated in Section 3.6.1.

In conclusion, it is worth noting that while piezoresistive and piezoelectric sensors dominate the field as revealed the Figure 3.8, most likely due to their effectiveness in detecting strain, damage, structural changes and easy integration into structural components, FOS have a noticeable share, reflecting their growing adoption for high-precision SHM applications. Other sensor types exist but are less frequently utilized, suggesting

that they may be used for specialized or emerging research applications.

### 3.6.1 FOS based case studies and experimental findings

Fiber-Optic Sensors have been proven to be the best choice for SHM implementation programs due to their high sensitivity, immunity to electromagnetic interference, and ability to monitor distributed parameters over long distances. However, some limiting factors, as highlighted earlier in the section, made them less popular for many applications. This review examines case studies of integrated fiber optic sensors for SHM, focusing on sensor fabrication methods, active sensing materials, and experimental methods used.

A comparative analysis of the various 3D printing processes used in the integration of FOS into structures from the case studies presented in Figure 3.9(a), indicates that FDM and casting (molding) methods are widely used methods, representing the same percentage (33%) utilization. While material casting is used mostly for embedding FOS sensors in civil structures (concrete beams, columns, and slabs), FDM is used for polymeric composite structures. Other methods that are less utilized as reported in the case studies are DLP for photocurable resin substrates and selective laser sintering (SLS) for metallic structures, each representing 17% popularity. The prevalence of FDM and Casting highlights their adaptability and cost-effectiveness in FOS integration. Among the active sensor materials used in FOS case studies, as presented in Figure 3.9(b), FBG are the most commonly used fiber optic sensors, representing 50% of the materials used. For instance; Nascimento *et al.* (103) embedded FBG sensors in Nickel–Titanium (NiTi) reinforced PLA matrix using material extrusion (MEX) with the aim of monitoring the effects of thermal and mechanical strains on the structure during usage. The test results revealed that both thermal and mechanical perturbations were successfully registered by the system as a consequence of thermal and mechanical stimuli. A maximum contraction value of  $100\mu\text{m}$  was detected during heating/cooling cycles. Capova *et al.* (104) presented a novel application of embedded FBG technology for monitoring glulam and concrete beams. Material molding (casting) was used to embed the FBG sensor in the concrete beam. The results obtained proved good agreement between the measured data, the analytical data, and the reference methods. Similarly, Tomei *et al.* (105) embedded FBG sensors in PLA structural samples using FDM and analyzed the effect of the printing process/path and the aging test. The results revealed that aging increased stiffness and strength but reduced displacement, and that the tensile behavior of the printed samples are greatly affected by the printing path. Then comes the mechanoluminescent materials (ML), which have a percentage utilization of 17%. These emit light in response to mechanical stress, the intensity of which is usually proportional to the magnitude of the applied stress. Other materials that can be considered emerging materials, together made up the remaining 33% of the FOS material distribution. The dominance of FBG sensors in FOS materials demonstrates their reliability in detecting strain variations and temper-

ature changes. For the integrated sensor forms, a balanced distribution was observed as illustrated in Figure 3.9(c), where 50% of the FOS were integrated as embedded materials, while the remaining 50% were fabricated as material supportive.

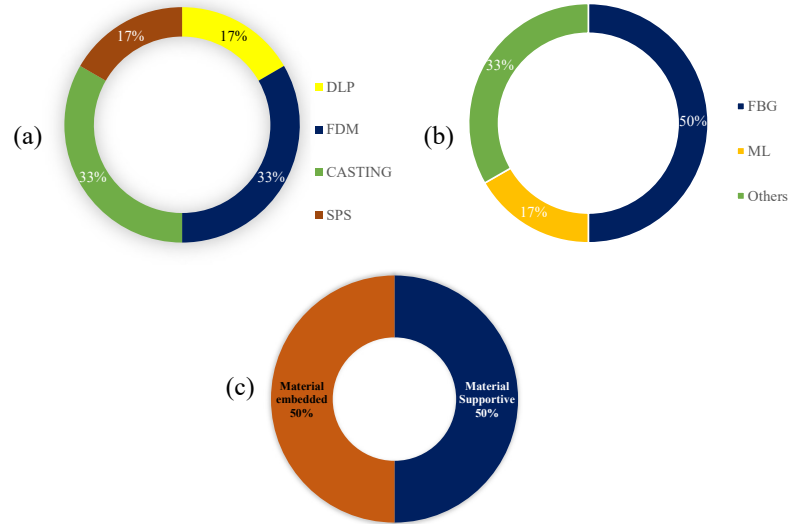


Figure 3.9 – Comparative analysis of Fiber Optic Sensors (FOS) case studies (a) Based on the Various 3D Printing processes used. (b) Based on the active sensor materials used. (c) Based on fabricated sensor form.

The summary of the case studies on fiber optic sensors is presented in Table 3.7, showing, for various works, the active sensing material, methods and experimental findings.

Table 3.7 – Summary of case studies on Fiber Optic based SHM sensors

| Author | Material                                                | Methods Used                                                                                                               | Results                                                                                                                                          |
|--------|---------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------|
| (106)  | Strontium aluminate /Eu <sup>2+</sup> /Dy <sup>3+</sup> | 3D printing via Vat photopolymerization (VP). Bayesian optimization used for process tuning. Fabricated ML strain sensors. | Achieved high ML intensity and geometric accuracy. Validated ML sensors and mechanical components.                                               |
| (103)  | FBG-Ni-Ti /PLA composite                                | Optical fiber sensors embedded during 3D printing for Non-Destructive Testing (NDT). Internal calibration required.        | Detected structural transformations. Measured thermal and mechanical changes, including 100 $\mu$ m contraction and 9.5°C temperature variation. |

Table 3.7 – continued from previous page

| Author | Material             | Methods Used                                                                                                             | Results                                                                                                                                         |
|--------|----------------------|--------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------|
| (104)  | FBG-ABS-M30          | FBG sensors embedded in concrete and timber for structural monitoring. Compared with reference sensors.                  | Maximum error of 14%. Installation issues noted but results matched analytical data.                                                            |
| (105)  | FBG                  | 3D-printed PLA samples tested with and without embedded fiber optic sensors. Finite element analysis performed.          | Aging increased stiffness and strength but reduced displacement. Normal stress-strain curves obtained.                                          |
| (107)  | Sapphire fiber optic | Sensor embedded via Spark Plasma Sintering (SPS) and Ultrasonic Additive Manufacturing (UAM). Various conditions tested. | Achieved high density (>98%) and superior mechanical properties. Optical attenuation between 0.3-1.86 dB. Limited strength reduction (~70 MPa). |
| (108)  | $\phi$ -OTDR         | Distributed fiber-optic sensing using Rayleigh scattering. Applied digital quadrature demodulation.                      | Measured over 30 km. Positioning accuracy $\pm 1.8$ m at 1 km. Response time <400 ms.                                                           |

### 3.6.2 Piezoelectric sensors' case studies and experimental findings

The chart analysis as presented in Figure 3.10(a), offers a comprehensive examination of the distribution of 3D printing and fabrication methodologies employed in the case studies, highlighting significant trends in the development of sensors. The pie chart delineates various fabrication techniques, illustrating that Direct Ink Writing and Material Extrusion emerge as the most popular methods, with each constituting 27% of the analyzed cases. This observation implies that these techniques are extensively embraced due to their efficacy and accessibility. Other prominent methodologies, including Friction Stir Processing (FSP), FDM in conjunction with Laser Sintering (FDM+LS), Tape Casting, and DLP combined with DIW, each contribute 7%, indicating a moderate level of adoption. Techniques that are employed less frequently, such as SLA, Casting/molding, and DLP, each account for 6% of the total cases analyzed.

The subsequent section of the chart analysis concentrates on the active piezoelectric materials utilized in these studies. As illustrated in Figure 3.10(b), PZT-based and PVDF-based materials predominate within the domain, each representing 32% of the ap-



plications surveyed. Their substantial adoption underscores their established effectiveness in SHM contexts. Chang *et al.* (109) developed a piezoelectric polymer composite using functionalized micro Pb[(MgNb)ZrTi] (PMN-PZT). The optimum mix for the composite constituents as well as the printing parameters was first determined and then using DLP-based 3D printing, auxetic structured composite was printed. The test results showed improved flexibility, a high piezoelectric coefficient, and a 300% increase in output voltage (open circuit). Tao *et al.* (110) used multimaterial extrusion-based 3D printing to manufacture a piezoelectric sensor. PDMS-PZT was used as the piezoelectric composite, and conductive electrodes from PDMS-Ag composites. The sensor was tested under both tension and compression. The performance was found to be consistent in response to the applied stress in all the tests, showing a peak-peak voltage of 86.39mV for more than 800 stress cycles at 8 Hz. Another study was conducted by Wang *et al.* (111) in which a piezoelectric pressure sensor was fabricated using SLA-based 3D printing process from PZT-oleic acid photopolymer. The test results revealed that 72 wt% paste prepared with oleic acid-grafted and modified piezoelectric ceramic particles has good stability, and the piezoelectric voltage constant of the piezoelectric composites fabricated with paste was  $220.2 \times 10^{-3} \text{VmN}^{-1}$ , and the piezoelectric sensitivity of the piezoelectric composite after topology optimization could reach  $30 \text{ mV} \cdot \text{kPa}^{-1}$ . Rolof *et al.* (112) developed a piezoelectric composite of PZT-photopolymer for SHM sensing using guided ultrasonic wave (GUW). Tape casting was used for the fabrication of the composite, which was eventually covered with electrodes polarized in an electric field and afterwards attached to an aluminum waveguide. The test results for the sensor and occurring reflections as measure for wave interactions are compared to commercial piezoelectric discs to evaluate their performance. The sensitivity was found to vary with sensor size and orientation. Meanwhile, the sensitivity was very much less than that of commercial PZT disc. Liu *et al.* (113) proposed a self-polarized DIW 3D printing strategy for one-step manufacture of high performance PVDF-CNF (cellulose nanofiber) piezoelectric composites with low energy consumption. Composites with different formulations were printed and the test results revealed a best performance for 5wt% CNF achieving a sensitivity 2.2 times higher than conventional cast films. Pei *et al.* (114) proposed a novel 3D printing strategy that is microwave assisted for manufacturing multiple piezoelectric generators (PEGs) consisting of periodically intercalated piezoelectric and conductive layers. 3D graphene nanoplatelets (GNPs) network was used for the electrode. The test results show significant increase in output current of the PEG and an improved electromechanical coupling performance. Spanou *et al.* (115) manufactured a piezoelectric sensor using DIW-based 3D printing process. Two composite inks of polyvinylidene fluoride-trifluoroethylene (PVDF-TrFE) and that with reduced graphene oxide (PVDF-TrFE-rGO) were prepared and printed on different substrates, with the latter being used as conductive electrode. It was observed that at 1.5wt% rGO was found to be the minimum that achieved percolation with a conductivity of  $2.8 \text{ S/cm}$ .



It was also demonstrated that the inks can be used to create a full 3D-printed piezoelectric device with the predicted response.

Other materials, including ZnO-based (11%), BaTiO<sub>3</sub>-based (10%), and laser scribing graphene (LSG)-based (5%) alternatives, indicate a lower yet still pertinent level of utilization. Concurrently, alkali activated cement (AAC) and Paper & Kapton film sensors (a form of triboelectric nanogenerators) emerge as the least frequently selected options, with each comprising merely 5% of the overall distribution, suggesting specialized but limited application scenarios.

In relation to the form of the manufactured sensors, the analysis as illustrated in Figure 3.10, reveals that 70% of the fabricated sensors used in the case studies are predominantly material supportive, implying how relatively difficult it could be to manufacture structures with some piezoelectric sensors forming an integral part of them. Many piezoelectric materials, such as PZT and PVDF, require specific processing conditions (e.g., high-temperature sintering, poling, or specialized deposition techniques) that might not be compatible with the structural material itself. By independently fabricating the sensor, researchers can optimize its properties before integrating it with the structure (116),(117),(118). The remaining 30% relate to the direct incorporation of piezoelectric materials into structures, highlighting instances where integrated sensing capabilities are prioritized and made possible.

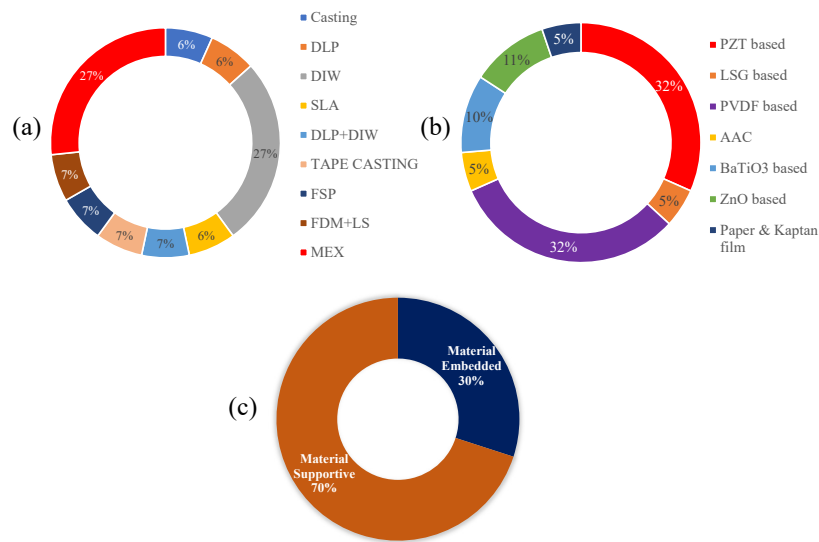


Figure 3.10 – Comparative analysis of Piezoelectric Sensors case studies (a) Based on the Various 3D Printing processes used. (b) Based on the active sensor materials used. (c) Based on fabricated sensor form.

Table 3.8 provide a comprehensive exploration of case studies on piezoelectric-based SHM sensors, elucidating the materials used, fabrication methods, and performance metrics. A variety of piezoelectric materials were utilized, including PMT-PZT, PVDF, ZnO nanowires (NWs), AAC, GNPs/PVDF, and origami structure triboelectric nanogenera-

tors (EO-TENG). These materials span from traditional piezoelectric ceramics, such as PZT, to nascent materials, such as triboelectric nanogenerators, thereby showcasing the dynamic evolution of sensor technology.

Concerning fabrication methodologies, 3D printing techniques such as DLP, DIW, FDM, and SLA were widely adopted, corroborating the trends identified in the analysis of Figure 3.10. Additional techniques, including photocurable 3D printing, laser scribing, friction stir processing, and electromechanical testing, were also employed in selected instances. Furthermore, sophisticated integration methods such as Electromechanical Impedance (EMI) modeling, capacitance testing, and machine learning-based analyses contributed to enhancing sensor functionality.

The results and performance metrics derived from these case studies underscore significant progress in SHM sensor technology. Numerous studies reported elevated voltage output, increased sensitivity, and commendable mechanical flexibility, rendering these sensors well suited for SHM applications. Some investigations also highlighted potential areas for enhancement, such as inconsistencies in sensitivities within isotropic coatings, which could pave the way for further refinements. ZnO NW-based sensors demonstrated notably high sensitivity, achieving levels of up to 32.79 mV/kPa, demonstrating substantial potential for pressure sensing applications. Additionally, PZT-coated MEMS and GNPs/PVDF composites exhibited excellent dielectric characteristics and mechanical reliability, thereby further endorsing their application in SHM contexts.

Table 3.8 – Summary of case studies on Piezoelectric based SHM sensors

| Author | Material                       | Methods Used                                                                                  | Results                                                                                            |
|--------|--------------------------------|-----------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------|
| (109)  | PMT-PZT in Photo polymer       | 3D printing, Corona poling, Tensile testing, Piezoelectric response evaluation, FTIR analysis | Increased voltage from 2V to 6V, 50% stretchability, Good flexibility, High piezoelectric response |
| (110)  | PDMS/PZT ink, PDMS/Ag ink      | Multi-material 3D printing, Rheometry, Capillary flow, Compression tests, Microscopy          | V <sub>pp</sub> : 41.14 mV (planar), 152.43 mV (hemisphere), 86.39 mV (spiral-hexagon)             |
| (119)  | PZT+Oleic-acid (Photo-polymer) | Photocurable 3D printing, Topology optimization, Composite material mixing                    | Piezoelectric voltage constant: $220.2 \times 10^{-3}$ Vm/N, Sensitivity: 30 mV/kPa                |
| (112)  | PZT+photo polymer              | Tape casting, Adhesive bonding, Waveguide reflections                                         | Detects GUW in isotropic media, Varying sensitivities based on sensor shape                        |

Table 3.8 – continued from previous page

| Author | Material                          | Methods Used                                                                | Results                                                                                                            |
|--------|-----------------------------------|-----------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------|
| (120)  | PZT coated with epoxy             | EMI method, Embedded sensors, VBA Macro, Impedance analysis                 | Detects fractures in 3DCP concrete, Reinforces under load, Sensitivity improvement needed                          |
| (121)  | PZT-5H soft grade                 | EMI-based damage monitoring, Machine learning, CNN-LSTM hybrid model        | EPS detects early damage, RF classifier accuracy: 0.91, Conductance signature variations                           |
| (113)  | PVDF/CNF                          | DIW 3D printing, Annealing, Mechanical stretching, Capacitor charging       | Voltage: 3.4V at 30N, Sensitivity: 103.7 mV/N, Response time: 12ms, Stable over 7200 cycles                        |
| (114)  | GNPs/PVDF                         | Microwave-assisted 3D printing, DMA, TEM, FESEM, Dielectric analysis        | Short-circuit current: 1.5 $\mu$ A (MP-PEG), 0.4 $\mu$ A (MS-PEG), Power density: 8.6–10.7 $\mu$ W/cm <sup>2</sup> |
| (115)  | PVDF-TrFE                         | DIW 3D printing, Reduced graphene oxide ink, Metal nozzle deposition        | Capacitance: 37 pF (expected), 35 pF (measured), Phase angle: 88.9°                                                |
| (122)  | PVDF+PLA +CPLA                    | Multi-method 3D printing, Electrode poling, Extrusion filling               | SNR: 27 dB (shielded sensor), 3.5 dB (partially shielded)                                                          |
| (123)  | PVDF-TrFE                         | Three poling techniques, Silicone oil bath poling, Extrusion printing       | Sensitivity: 1.18 V/N, Piezoelectric coefficient: 25 pC/N                                                          |
| (124)  | PVDF (FFIGWT)                     | Finite element simulation, Numerical analysis, Experimental validation      | Improved wave excitation and reception, Detects composite material defects                                         |
| (125)  | EO-TENG (Paper+ Kapton film)      | Origami triboelectric nanogenerator, Contact-separation mechanism           | Open-circuit voltage: 105V, Short-circuit current: 58 $\mu$ A, Charge transfer: 66 nC                              |
| (126)  | OS-TENG (Polyethylene+ Si-rubber) | Buckling-Restrained Brace design, Mechanical testing, Origami reinforcement | Peak voltage: 48.05 mV, Higher performance in multi-pair devices                                                   |

Table 3.8 – continued from previous page

| Author | Material                            | Methods Used                                                               | Results                                                                                                             |
|--------|-------------------------------------|----------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------|
| (127)  | BaTiO <sub>3</sub> NPs + Elastomers | DLP 3D printing, Direct-write electrodes, Mechanical testing               | Output voltage: 0.29V, Current density: $0.20 \mu\text{A}/\text{cm}^2$ , Power density: $57 \text{ nW}/\text{cm}^2$ |
| (128)  | Barium Titanate in AA5083-H111      | Friction Stir Processing, Solid-state reinforcement                        | Electrical sensitivity: $12.0 \times 10^{-4} \mu\text{V}/\text{MPa}$ , Improved strength and hardness               |
| (129)  | LSG/PEEK                            | Laser scribing, 3D printing, Metamaterial design                           | Stretchability: 118%, Power: $2.3 \text{ mW}/\text{m}^2$ , Material differentiation capability                      |
| (130)  | AAC Materials                       | Cement compatibility assessment, Mechanical testing, Impedance analysis    | Extrudability and buildability validated, Fatigue test: 1500 cycles                                                 |
| (131)  | ZnO NWs                             | Hydrothermal synthesis, Capacitive sensing, Load monitoring algorithm      | Strength increase: 4.9% (flexural), 8.8% (shear), Load localization error: 3 mm                                     |
| (132)  | ZnO NWs - CFRC                      | Acoustic emission, Thermal imaging, Ultrasonic testing, Mechanical testing | Piezoelectric voltage: 150–830 mV, Sensitivity: $32.79 \text{ mV}/\text{kPa}$                                       |

In conclusion, the analysis underscores that DIW and MEX remain the preeminent fabrication methodologies, highlighting the escalating importance of additive manufacturing within Structural Health Monitoring (SHM) technology. Polyvinylidene fluoride (PVDF) and lead zirconate titanate (PZT)-based materials continue to predominate in this domain; however, novel materials such as zinc oxide nanowires (ZnO NWs) and barium titanate (BaTiO<sub>3</sub>) composites are emerging as viable alternatives. Furthermore, a substantial proportion of piezoelectric sensor materials (70%) face challenges with respect to integration within structural frameworks. Lastly, performance indicators such as voltage output, flexibility, and mechanical durability remain critical assessment criteria in evaluating the efficacy of these sensors.

### 3.6.3 Piezoresistive Sensors' case studies and experimental findings

Figure 3.11 presents a comparative analysis of piezoresistive sensors, highlighting key aspects such as the 3D printing processes used, the active sensor materials used, and the forms in which the sensors are fabricated. The data presented in Figure 3.11(a) reveal that

a variety of additive manufacturing techniques have been explored for the fabrication of sensors. Among these, FDM, DIW, and DLP are the most commonly utilized methods. Additionally, techniques such as Selective Laser Melting (SLM), SLA, and Screen Printing contribute to a lesser extent, reflecting their niche applications in sensor development. In terms of active sensor materials, Figure 3.11(b) shows that carbon-based nanomaterials, particularly CNTs, dominate the field, accounting for approximately 43% of the materials used. Iervolino *et al.* (133) manufactured a piezoresistive sensor by loading two photopolymers (a free-radical resin and a hybrid cationic/free-radical photopolymer) separately with MWCNTs. Rheology and photo-calorimetric analyses were performed with different wt% MWCNTs, and SLA-based 3D printing was used to print test samples. The result revealed an optimum mix for the electro-active system, for the free radical resin as 0.25% with conductivity value of  $0.0006 \text{ Scm}^{-1}$ . Song *et al.* (134) developed a 3D printable flexible piezoresistive composite containing various amounts of hybrid fillers (micro-scale Cu particles and MWCNTs similar to cilia). The test results revealed that with an optimal hybrid filler content of 17.5 vol.%, a piezoelectric composite exhibiting a guage factor of 6.04 was successfully printed. Peng *et al.* (135) fabricated a conductive poros sensor with complex triply periodic minimal surface (TPMS) structures using a 3D printed sacrificial mold and enhancement of MWCNTs. Different pore sizes and unit cell types were used for the study. The test results show the highest responsive strain value of 61% with the D-based structure cured by self-resistance electric heating, with a corresponding resistance response value of 0.97. Li *et al.* (136) reported a study on a novel method for the integrated manufacturing of silicone-based multifunctional soft robotic components based on multi-material embedded 3D printing. This objective was achieved by directly printing a diluted platinum catalyst ink within a removable silicone oil matrix. The results of the study showed that the integrated sensors exhibit excellent linearity (0.99), repeatability, and stability, further demonstrating the feasibility and superiority of the proposed method for manufacturing soft robotics. Dan *et al.* (137) fabricated a biocompatible and biodegradable piezoresistive functional composite containing MWCNTs in polyhydroxybutyrate (PHB) matrix by melt-mixing. The nanomaterial dispersion, morphology, electrical, thermal and mechanical properties, and the crystallization behavior of both types of composites were investigated. From the test results, electrical percolation thresholds were found to be within the ranges of 0.25 to 0.5 wt % and 0.5 to 0.75 wt % for composites made with the two different types of PHB, and the results suggested potential applications for biomedical electronic devices. Stan *et al.* (138) investigated the piezoresistive behavior for FFF of recycled polymer-CNT nanocomposites (CNT-TPU). The changes induced by mechanical recycling were closely monitored by melt flow index, thermal, mechanical, electrical, and piezoresistive properties. The results show that the recycled CNT-TPU nanocomposites exhibit very good printability with mechanical and electrical properties that are generally comparable with those for the virgin nanocomposites. However, a sig-

nificant decrease in the elongation at break was reported as a major challenge. Other significant materials include graphene nanopellets, carbon black (CB), carbon fiber (CF) and metallic nanowires (AgNWs), all of which exhibit favorable electrical and mechanical properties for structural health monitoring. For example, Yao *et al.* (139) manufactured a self sensing pipe joints using short carbon fiber conductive composites (SCFCCs) to monitor pipeline internal pressure and joint damages, leveraging on the piezoresistive properties of the composites. cyclic internal pressure tests was used to evaluate the sensor responsiveness. The results demonstrated significant improvement in sensitivity up to 90 times higher than that of conventional strain gauges. Overall, the self-sensing method proves to be capable of capturing damages inside pipe joints, presenting a promising approach for in-situ structural health monitoring of composite pipes. Jeon *et al.* (140) developed thermo-resistive temperature sensor from an electrically conductive PLA-CB composite using an FDM-based 3D printing process. The temperature-resistivity behavior of PLA-CB was evaluated for different stacking sequences of PLA-CB layers printed with  $[0^\circ/0^\circ]$ ,  $[-45^\circ/45^\circ]$ , and  $[0^\circ/90^\circ]$  plies. The sensor yielded a temperature coefficient of resistance of  $6.62\%/^\circ\text{C}$  with high stability over repeated cycles. Xiao *et al.* (141) proposed the use of graphene nanoplatelets/polydimethylsiloxane (GNPs/PDMS) composite for manufacturing a flexible piezoresistive sensor. DIW-based 3D printing process was used to mold the piezoresistive unit onto the PDMS substrate. The performance metrics for the developed sensor tested include the micro-morphological observation and rheological properties, and the effects of the sensitive unit structural parameters on the piezoresistive performance. The test results display a sensitivity of  $0.0602\text{ kPa}^{-1}$  over a wide detection range from 0 to 350 kPa and good repeatability (almost 5000 times), proving the ability of the sensor to accurately recognize pressure signals generated by movements of different body parts, demonstrating the excellent potential of the sensor for signal monitoring of human health and movement. Wang *et al.* (142) developed a flexible, highly sensitive strain sensor using polyamide (PA) and silver nanowires, with an asymmetric concave honeycomb structure, achieving a strain gauge factor of 102735.17 and stable performance over 2500 cycles. The sensor was integrated with deep learning algorithms to create a wearable voice interface platform, demonstrating 83.25% accuracy in recognizing vocalized words and detecting human movements and physiological signals. Moreover, emerging hybrid materials, such as MXene with Carbon Fiber composites, are being increasingly explored due to their unique conductivity and mechanical resilience, offering potential improvements in sensor performance.

Regarding the fabricated sensor forms, the distribution between Material Embedded and Material Supportive sensors is nearly equal, with embedded sensors constituting 49% and supportive sensors accounting for 51%.

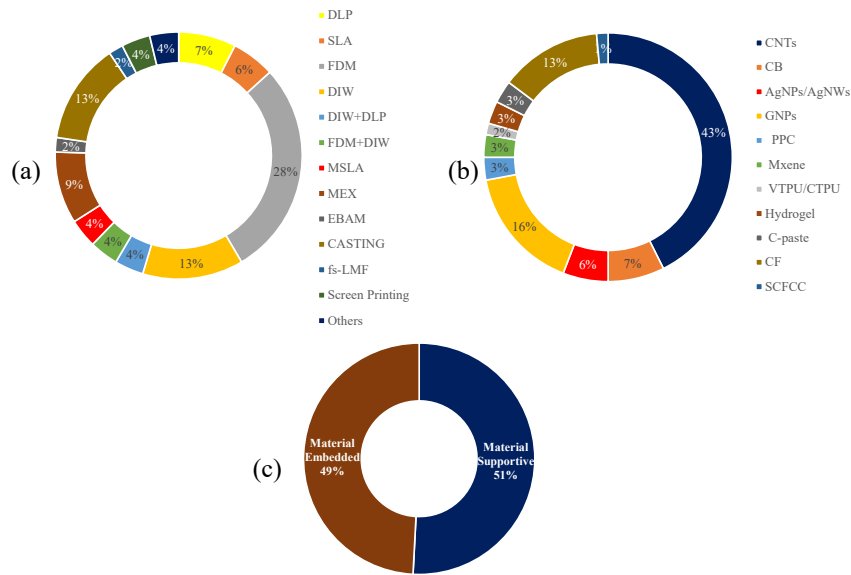


Figure 3.11 – Comparative analysis of Piezoresistive Sensors case studies (a) Based on the Various 3D Printing processes used. (b) Based on the active sensor materials used. (c) Based on fabricated sensor form.

Table 3.9 provide a comprehensive overview of various case studies on piezoresistive SHM sensors, categorizing them according to material composition, fabrication methods, mechanical and electrical characterization, thermal properties, and key performance metrics such as gauge factor, sensitivity, and conductivity.

A key observation from the case studies is the dominance of carbon-based composites in SHM applications. Materials such as CNTs, Graphene, Carbon Black, Carbon Fiber, and GNPs are widely utilized due to their exceptional electrical conductivity, mechanical strength, and compatibility with a broad range of substrate materials. Additionally, hybrid composites incorporating polymers such as PDMS, TPU, and Polypyrrole (PPy), as well as metallic particles such as Ag and Cu, are being increasingly investigated for their enhanced multifunctionality.

Furthermore, additive manufacturing techniques, particularly 3D printing methods such as DIW, SLA, FDM, and DLP, play a crucial role in sensor fabrication. Advances in multi-material printing and hybrid manufacturing approaches have shown promising results, enabling the production of highly customized and structurally integrated sensors.

Another critical aspect of the piezoresistive sensors, as observed from the case studies, is their sensitivity and gauge factor. Many studies report high gauge factors exceeding 100, demonstrating excellent sensitivity to strain variations. Specific materials, including MXene, AgNWs, and TPU composites, exhibit remarkable responsiveness, making them particularly suitable for dynamic strain sensing applications.

Finally, the case studies highlight the multifunctionality of certain sensor materials, which offer self-sensing and self-healing properties. These features contribute to the long-term reliability of SHM systems by enhancing durability and resilience. Additionally,



considerations such as electrochemical and thermal stability are essential for ensuring sustained sensor performance under varying environmental conditions.

Table 3.9 – Summary of case studies on Piezoresistive based SHM sensors

| Author | Material               | Methods Used                                                     | Results                                                                                                                 |
|--------|------------------------|------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------|
| (133)  | MWCNTs + Photopolymers | Stereolithography, electrical measurements, SEM, TEM, UV curing. | Electrical conductivity increased by seven orders of magnitude with 0.25 wt% filler; solid-like behavior at low strain. |
| (134)  | Cu-MWCNTs-TPU          | Mechanical milling, 3D printing, tensile testing.                | Gauge factor up to 6.04; strain range exceeded 20%; electrical resistivity decreased with filler volume.                |
| (135)  | PDMS/CNTs              | 3D printing, self-resistance electric heating, TPMS structures.  | Maximum strain response of 61%; resistance response value of 0.97.                                                      |
| (136)  | Si-MWCNTs              | EMB3D printing, multi-material integration, silicone matrix.     | Gauge factor of 3.59 (0-27% strain) and 7.18 (27-80% strain).                                                           |
| (143)  | MWCNTs + Photopolymer  | DLP printing, UV-polymerization, tensile testing.                | Gauge factor of 2.0 for strain range 0-100%.                                                                            |
| (144)  | ABS/CNT                | FDM, filament extrusion, electrical conductivity tests.          | Resistivity decreased with CNT content (0.15 $\Omega\text{m}$ at 9.09 wt%).                                             |
| (145)  | Si-CNTs                | Embedded 3D printing, DIW, curing tests.                         | Gauge factor of 3.4; max tensile strain 535%.                                                                           |
| (146)  | MWCNTs /PPy/FPU        | Machine learning regression, SEM, tensile testing.               | $R^2$ and RMSE evaluated for ML models.                                                                                 |
| (147)  | CNTs/SCFs /Epoxy       | Hybrid additive manufacturing, FDM, stereolithography.           | Tensile strength of 36 MPa; resistance increased by 105% at 150% strain.                                                |
| (148)  | TPU/CNTs /Ag-NPs       | FDM, electromechanical tests, tunneling model analysis.          | Gauge factor of 43260 at 250% strain; response time 57 ms.                                                              |
| (149)  | CNTs/TPU               | FDM, ultrasonic cavitation treatment.                            | Sensitivity, deformation recovery, cyclic response evaluated.                                                           |



Table 3.9 – continued from previous page

| Author | Material                         | Methods Used                                                    | Results                                                       |
|--------|----------------------------------|-----------------------------------------------------------------|---------------------------------------------------------------|
| (111)  | CF+ACP;<br>Magnetite<br>+CF+CNTs | 3D printed sensors, structural health monitoring.               | Resistivity changes reflected damage detection.               |
| (150)  | MWCNTs+<br>Polyimine             | DIW 3D printing, four-point probe resistance measurement.       | Conductivity stable over cycles; elastic modulus 490-520 MPa. |
| (137)  | PHB+ MWCNTs                      | Extrusion, melt mixing, biocompatibility tests.                 | Young's modulus, strain at break tested.                      |
| (138)  | TPU+CNTs                         | Mechanical recycling, filament extrusion, CNT content analysis. | Gauge factor up to 115 for 3 wt% CNTs.                        |
| (151)  | AESO+<br>MWCNT                   | Additive manufacturing, FTIR, profilometry.                     | Electrical conductivity varied with print orientation.        |
| (152)  | MWCNT+<br>PDMS                   | DIW, SLA, DLP.                                                  | Sensitivity of 6.3 $\Omega$ /kPa over 1132 kPa.               |
| (153)  | FPU+CNT+<br>PPy                  | DLP, UV photopolymerization.                                    | Gauge factor of 91.9 at 20% strain.                           |
| (154)  | MWCNTs+ flexi-<br>ble resin      | FDM, SLS, DLP.                                                  | Gauge factor of 8.98 (0-40% strain).                          |
| (155)  | PDM-CNTs-PI                      | Extrusion printing, inkjet, laser writing.                      | TCR of -0.52%/°C, response time 8s.                           |
| (156)  | PC + CNTs                        | Solvent casting, FDM, thin film processing.                     | Gauge factor from 0.1 to 1.7.                                 |
| (157)  | TPU+Mxene<br>+MWCNTs             | FDM, electrostatic compounding, FEA.                            | Sensitivity of 132 kPa <sup>-1</sup> (0-5.7 MPa).             |
| (158)  | TPU+CNTs<br>+AgNWs               | Immersion, ultrasound patterning, SEM.                          | Gauge factor: 691 (region I), $1.1 \times 10^4$ (region III). |
| (159)  | CNTs-BP strips                   | Bending tests, voltage response recording.                      | Gauge factor from Wheatstone Quarter-Bridge analysis.         |
| (160)  | CNTs+SCF<br>+TPU                 | Tensile tests, resistance evolution, FDM.                       | Gauge factor: 0.59 (W-shape), 0.717 (U-shape).                |
| (161)  | CB+CNTs                          | AC impedance spectroscopy, cyclic loading.                      | Frequency change ratio (FCR), stress sensitivity.             |

Table 3.9 – continued from previous page

| Author | Material                    | Methods Used                                                                                                                                  | Results                                                                                                                     |
|--------|-----------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------|
| (162)  | CNTs+CFs<br>+TPU            | 3D printing, thermal analysis,<br>mechanical tests                                                                                            | Heating rate: 0.1-0.25 °C/s<br>(10-20V DC)                                                                                  |
| (163)  | GCNTs and PA                | 3D-FBPS design, weaving,<br>vacuum filtration                                                                                                 | Sensitivity: 76.48 kPa <sup>-1</sup> (0-5<br>kPa), response time: 13 ms                                                     |
| (164)  | MWCNTs+<br>CB+GNSs+<br>PDMS | Solution blending, composite<br>preparation                                                                                                   | Sensitivity, stretchability, and<br>hysteresis analyzed                                                                     |
| (165)  | UHPC+MCF<br>+CCMF+G         | 3D printing, cyclic load tests,<br>frequency analysis                                                                                         | Strain gauge factor: 540, SNR:<br>21.98 dB, MAE: 74 $\mu\epsilon$                                                           |
| (166)  | CF+ACP                      | Digital image correlation, flex-<br>ural tests                                                                                                | Mechanical properties, electri-<br>cal resistivity analyzed                                                                 |
| (167)  | CF+CP                       | 3D printing, manual pouring,<br>compression tests                                                                                             | Max stress: 15.27 MPa, resis-<br>tance: 274.2 $\Omega$ .cm                                                                  |
| (139)  | SCFCCs                      | Self-sensing via resistance<br>monitoring                                                                                                     | Sensitivity up to 90x improve-<br>ment over strain gauges                                                                   |
| (168)  | CF                          | Rheology, porosity analysis,<br>piezoresistivity tests                                                                                        | Optimal CF dosage: 0.4 vol.%,<br>self-sensing capability tested                                                             |
| (140)  | PLA/CB                      | Dual nozzle extrusion, resis-<br>tance temperature detector                                                                                   | Response/recovery times: 4<br>min / 3.5 min (30-45°C)                                                                       |
| (169)  | PLA/CB                      | 3D printing, mechanical and<br>electrical tests                                                                                               | Piezoresistive sensing for in-<br>situ damage detection                                                                     |
| (159)  | CNTs-BP strips              | Three-point bending, dynamic<br>mechanical analysis, and man-<br>ual impact tests. Scalable<br>and cost-effective manufactur-<br>ing methods. | Sensitivity measured via gauge<br>factor using a Wheatstone<br>bridge circuit, showing signif-<br>icant response to strain. |
| (160)  | CNTs+SCF<br>+TPU            | Tensile tests, resistance mon-<br>itoring, and FDM-based em-<br>bedding of carbon fibers.                                                     | Gauge factor (GF) in the elas-<br>tic zone: 0.59 (W-shape), 0.717<br>(U-shape). Initial resistivity:<br>46.46 $\Omega$ .    |

Table 3.9 – continued from previous page

| Author | Material            | Methods Used                                                                        | Results                                                                                                    |
|--------|---------------------|-------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------|
| (161)  | CB+CNTs             | AC impedance spectroscopy, quasi-static cyclic loading, and dynamic cyclic loading. | Performance measured by frequency change ratio (FCR), stress sensitivity (SS), and gauge factor (GF).      |
| (162)  | CNTs+CFs+TPU        | 3D printing, TGA, wheel tracking, and mechanical tests.                             | Heating rates: 0.1-0.25 °C/s for varying voltages.                                                         |
| (163)  | GCNTs and PA        | 3D weaving, vacuum-filtered graphene oxide on silk fabric.                          | Sensitivity: 76.48 kPa <sup>-1</sup> (0-5 kPa), 63.78 kPa <sup>-1</sup> (10-50 kPa), response time: 13 ms. |
| (164)  | MWCNTs+CB+GNSs+PDMS | Solution blending for flexible conductive polymer composites.                       | Sensitivity, stretchability, linearity, hysteresis, and repeatability evaluated.                           |
| (165)  | UHPC+MCF+CCMF+G     | 3D printing, cyclic load tests, frequency response analysis.                        | Strain gauge factor: 540, resolution: 68 $\mu\epsilon$ , SNR: 21.98 dB.                                    |
| (166)  | CF+ACP              | Digital image correlation, flexural tests, and resistivity measurements.            | Evaluated mechanical properties, electrical resistivity, and piezoresistivity of specimens.                |
| (167)  | CF+CP               | 3D printing and manual pouring, tested under static and cyclic compression.         | Compressive strength: 15.27 MPa (3D printed). Lower electrical resistance: 274.2 $\Omega$ .cm.             |
| (139)  | SCFCCs              | Self-sensing method with cyclic internal pressure tests.                            | Sensitivity improvement of up to 90 $\times$ compared to strain gauges.                                    |
| (168)  | CF                  | Rheology, computed tomography, piezoresistivity, and compressive strength tests.    | Optimal carbon fiber dosage: 0.4 vol.% for best performance.                                               |
| (140)  | PLA/CB              | Dual-nozzle extrusion for resistance temperature detector (P-RTD).                  | Response time: 4 min, recovery time: 3.5 min (30-45 °C).                                                   |
| (169)  | PLA/CB              | 3D printing, three-point bending, and electrical resistance monitoring.             | High gauge factor and piezoresistive response for in-situ strain monitoring.                               |

Table 3.9 – continued from previous page

| Author | Material                          | Methods Used                                                                    | Results                                                                                       |
|--------|-----------------------------------|---------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------|
| (21)   | PLA+CB                            | 3D printing, tensile tests, non-linear regression for modeling.                 | Self-sensing capabilities depend on printing layer orientation.                               |
| (170)  | C-Paste in PLA                    | Hybrid 3D printing, inverse FEM, modal superposition method.                    | Phase delay: 0.27 rad at 30 Hz, bandwidth $\leq$ 60 Hz.                                       |
| (171)  | Carbon paste                      | Screen printing, BP neural network for deformation monitoring.                  | Accuracy: 99.52% (2.5° deflection), 89.70% (1.5° deflection).                                 |
| (172)  | P-PDMS+ Carbon                    | Direct ink writing, laser direct writing, ball milling.                         | High gauge factor (GF: 45.48) at 50% strain.                                                  |
| (141)  | GNPs/PDMS                         | Direct ink writing, screen printing, coating methods.                           | Sensitivity: 0.0602 kPa <sup>-1</sup> (0-350 kPa), linearity: R <sup>2</sup> =0.9965.         |
| (173)  | Si-R+GNPs                         | Dip-coating, FDM, frequency analysis, MOAFA optimization.                       | Gauge factor: 10.2, five times greater than metallic strain gauges.                           |
| (174)  | Graphene+ Graphite/Si PMC         | Direct ink writing, fused deposition modeling, hybrid 3D printing.              | Resistance variation (R: $\sim$ 55 k $\Omega$ to $\sim$ 150 k $\Omega$ ) with bending angle.  |
| (175)  | AMPS+HBA +Graphene (HAG) hydrogel | 3D printing with LCD light-curing; mechanical and conductivity tests performed. | Conductivity: 0.0487 S/cm; Sensitivity GF = 1.86 (100% strain); Stretchability: 1200% strain. |
| (176)  | G+MCMF +CCMF                      | Quality control, thermal imaging, electrical resistance characterization.       | Performance assessed via linearity (R <sup>2</sup> ), sensitivity (GF), and accuracy (SD).    |
| (177)  | GPLA+SMP                          | Extrusion-based additive manufacturing (EBAM); electrical and thermal testing.  | Recovery force max: 1.83 $\pm$ 0.73 N; Time to peak force: 75 $\pm$ 41 s.                     |
| (178)  | GNPs                              | Electrical impedance measurement for SHM, signal processing techniques.         | Resistance changes (R/R) and force ratio (F/F max) during shear displacement.                 |

Table 3.9 – continued from previous page

| Author | Material                    | Methods Used                                                               | Results                                                                  |
|--------|-----------------------------|----------------------------------------------------------------------------|--------------------------------------------------------------------------|
| (179)  | Nano-graphite + copper slag | Alkali excitation, ultrasonic vibration, nano-graphite coating.            | Flexural strength (MPa) and UCS (MPa) measured.                          |
| (180)  | GP+GGBS +sS                 | UCS, flexural and resistance tests, microstructural investigation.         | UCS: 36 MPa, Flexural: 3.4 MPa, Resistance: 7,779 cm.                    |
| (181)  | GO                          | DFT calculations, XRD, electron microscopy, XPS analysis.                  | Sensitivity optimized at C/O ratio of 3.15; Response: 2000 kPa.          |
| (182)  | LCEs/Ag ink                 | DLP, DIW hybrid 3D printing for functional materials.                      | Strain sensor resistance monitoring; Sheet resistance: 25.7 m/sq.        |
| (142)  | PA+AgNWs (ACHCN)            | Screen printing, FEA optimization, deep learning integration.              | GF = 102,735.17.                                                         |
| (183)  | PANI+PVA+ CNC (PPC) gel     | DIW 3D printing, CNC-regulated PANI ink, freezing for crosslinking.        | Linearity: 0.986 (0-300% strain); GF: 1.6; Response time: 105 ms.        |
| (184)  | PAR+Mxene                   | 3D printing (DLP); MXene hydrogel coating.                                 | R/R max: 0.74 at 60% strain.                                             |
| (185)  | Ti3C2Tx (Mxene)             | Mechanical tests (pressure, tensile, vibration); deep learning analysis.   | Sensitivity: $S1 = 1.3 \text{ MPa}^{-1}$ , $S2 = 0.7 \text{ MPa}^{-1}$ . |
| (186)  | VTPU+ CTPU                  | Multi-material FDM 3D printing; FEM predictions; dynamic testing.          | Resistance changes during tensile testing; cyclic performance analysis.  |
| (187)  | VP-SPB-EG hydrogel          | 3D printing, weight and resistance characterization, ultrasonic treatment. | GF varied by strain: 0.03+0.28 (0-100%), 0.016+0.98 (100-500%).          |
| (188)  | CNF+WPU +LM (Ga/In-3:1)     | DIW 3D printing; molecular dynamics; XPS analysis.                         | Tensile stress: 15 MPa; Strain: 32.5%.                                   |

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|       |                         |                                                                            |                                               |
|-------|-------------------------|----------------------------------------------------------------------------|-----------------------------------------------|
| (189) | Photo-curable composite | Electrochemical screening; in situ polymerization; additive manufacturing. | Conductivity and cyclic voltammetry analyses. |
|-------|-------------------------|----------------------------------------------------------------------------|-----------------------------------------------|

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### 3.6.4 Case studies using other sensors

Figure 3.12 provides a comparative analysis of other sensors as reported in the reviewed case studies, classified by fabrication method, active sensor material, and structural form of the fabricated sensor. In Figure 3.12(a), FDM dominates at 40%, followed by DLP and FDM+DIW (20% each), with Jetlab ink printing also contributing 20%. This reflects the increasing reliance on 3D printing for sensor fabrication. This distribution is influenced by the properties of the active sensor material, the substrate, and the relative ease with which a particular method can handle the material without altering its tunable sensing capabilities. For example, those materials in thermoplastic substrate as in Metglas2826MB (Magnetoelastic) and TPU/NaCl+CCF (Piezocapacitive) are printed using FDM process. Those in a photocurable polymers like SWCNTs/ionogel are printed using DLP process.

Figure 3.12(b) highlights that carbon-based and Fe-based materials are used equally (43% each), while MEMS sensors make up 14%. This suggests that both conductive and magnetic materials play crucial roles in sensor performance. The Fe-based systems are predominantly used as Magnetoelastics and magnetostrictives, while the carbon-based are used for Piezocapacitives and P-T sensors. Examples can be seen in Vincent *et al.* (190) in which a magnetostrictive actuator was developed using FeSiB ribbons to monitor the failure of CFRP coupons. Pancake-shaped coils were used during the measurement process to monitor changes in inductance resulting from CFRP damage. The test results demonstrated reliably in the ability to measure crack formation and propagation within the structure, demonstrating for the first time the correlation between the induction signal and elastic energy in CFRP coupon. Similarly, Ahmed *et al.* (191) investigated the viability of printing soft magnetostrictive composites for use as SHM sensors in CFRP. Two composites were prepared in the form of printable inks of 20% magnetite with dimethylformamide (DMF), and 2% nickel with N-Methyl-2-pyrrolidone (NMP) nanoparticles (NPs), and were printed using Jetlab 4 drop-on-demand technique. Clogging was observed to be the major challenge of the printing process, and the test results revealed that magnetite NPs were more ideal sensors than nickel. It demonstrated much higher saturation magnetization and reduction in the coercive field of  $49\text{Am}^2/\text{kg}$  and  $5.34\text{ kA/m}$  respectively. The magnetite coil was found to have detected a change in field as the strain was applied. Li *et al.* (192) used salt microparticles to develop a porous structured one-piece flexible capacitive pressure sensor composed of CCF electrodes on a TPU dielectric substrate. The porous structured dielectric provided the sensor with a high compression amplitude, making it much more sensitive than the unstructured sensor. In addition, it exhibited much

faster response and recovery speeds (60 and 80 ms respectively), better stability (over 1000 cycles), and a spectacular pressure resolution, making it suitable for human motion detection. Wang *et al.* (9) using MEMs, developed a wireless multiparameter monitoring system (WMPMS) with ultralow power for aircraft smart skin (ASS) with the capability to monitor multiple parameters such as random impact events, vibration, temperature, humidity, and air pressure. It was equipped with an energy self-supply module based on a thermoelectric generator to continuously power the system during flight. Experimental validation revealed excellent performance in multi-parameter monitoring and operating power consumption, and it can realize the self-supply of energy. Lastly, Figure 10(c) shows that 71% of the fabricated sensor used in the case studies are material-supported, while 29% are embedded.

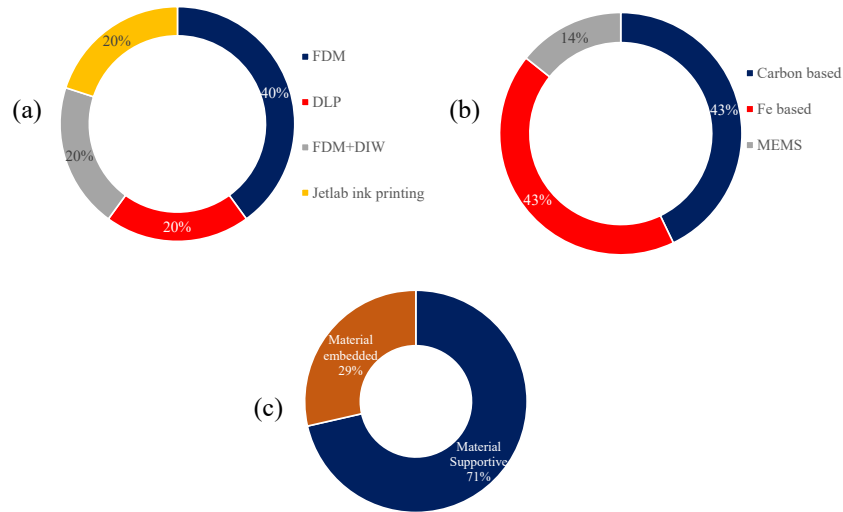


Figure 3.12 – Comparative analysis of other Sensors used in case studies (a) Based on the Various 3D Printing processes used. (b) Based on the active sensor materials used. (c) Based on fabricated sensor form.

Table 3.10 summarizes case studies on various sensors, detailing materials, fabrication and experimental methods, and performance metrics. The data show a strong presence of Fe-based (e.g., Metglas, FeSiB) used for magnetostrictives and magnetoelastics, and carbon-based materials (e.g., SWCNTs), supporting the trends observed in Figure 3.12(b). Fabrication methods include inkjet printing, 3D printing, and kirigami-based designs, demonstrating a shift towards advanced manufacturing techniques. Performance results indicate enhanced sensitivity, structural monitoring capabilities, and integration with IoT systems, reinforcing the importance of emerging materials and smart sensing technologies.

In general, both Figure 3.12 and Table 3.10 highlight the growing role of additive manufacturing in SHM sensor fabrication and the adaptability of various methods for different applications, the dominance of carbon and Fe-based materials and the preference

for supportive sensor structures in modern sensing applications. These findings underscore advances in sensor fabrication and performance, particularly in structural health monitoring and real-time sensing systems.

Table 3.10 – Summary of case studies on other sensors (Capacitive, Magnetoelastic, Manetostrictive etc.) developed for SHM program

| Author | Material                                      | Methods Used                                                                                                  | Results                                                                                                                        |
|--------|-----------------------------------------------|---------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------|
| (193)  | Metglas 2826MB (FeNiMoB) in CF/PET-G polymer  | Stochastic AutoRegressive modeling, high-pass filtering, Welch method for spectral analysis.                  | Sensors provided meaningful electrical signals despite noise; eigenfrequencies were sensitive to damage severity.              |
| (190)  | FeSiB ribbons                                 | Embedded sensors, inductance change measurement using a magnetostrictive actuator, controlled curing cycles.  | Inductance change, load vs. time, and crack length vs. time data were key performance metrics.                                 |
| (191)  | Magnetite nanoparticles (NP) with DMP solvent | Inkjet printing with optimized viscosity, sonication for nanoparticle dispersion.                             | Sensor performance assessed using gradient, intercept, and R-squared values for strain-induced magnetic field changes.         |
| (192)  | TPU+NaCl +CCF                                 | 3D-printed sensors with porous polyurethane dielectric and carbon fiber electrodes.                           | Sensitivity improved significantly with porous dielectric ( $5.15 \text{ N}^{-1}$ vs. $0.32 \text{ N}^{-1}$ for pure TPU).     |
| (194)  | PDMS+G (VK sensors)                           | Kirigami-based diaphragms, signal filtering, IoT-MQTT protocol for real-time monitoring.                      | VK sensors showed vibration sensitivity of $1.95 \text{ pF/ms}^2$ for 0.8 g and $0.80 \text{ pF/ms}^2$ for 1.0 g seismic mass. |
| (195)  | SWCNTs+ iono-gel composites                   | Electrical impedance spectroscopy (EIS), UV curing, vat photopolymerization (VPP).                            | Pressure sensitivity values reported under AC/DC conditions for different phases (S1-S4).                                      |
| (9)    | MEMS (BMA250, BMP280, SHT30)                  | Digital sensors for vibration/temperature monitoring, thermoelectric energy harvesting, aerosol jet printing. | Impact monitoring accuracy improved from 86% to 96% with the developed system.                                                 |



### 3.6.5 Advancements and Case Studies in SHM Systems

Structural Health Monitoring systems have become integral to modern engineering, providing real-time data to ensure the safety, reliability, and operational efficiency of critical structures. By embedding advanced sensors directly into materials, particularly composites, these systems facilitate proactive maintenance and the early identification of damage before it becomes critical. The applications span numerous high-stakes industries, each with unique monitoring challenges and solutions.

#### 3.6.5.1 Aerospace Applications

In the aerospace sector, SHM is crucial for maintaining the structural integrity of aircraft and spacecraft under extreme operational conditions. These systems enable continuous assessment, allowing for proactive maintenance strategies that enhance safety (124). A variety of sensor technologies are employed; fiber optic sensors, prized for their immunity to electromagnetic interference, measure temperature and strain in harsh environments, while piezoresistive sensors detect failure signals (107, 196, 179).

These sensors are highly effective at identifying different damage modes in composites. For instance, Fiber Bragg Grating sensors embedded in the midplane of laminates can detect delamination by measuring strain variations, while integrated acoustic emission sensors can identify the formation of microcracks by analyzing wave frequencies during mechanical loading (99, 197). This capability is essential for detecting issues like barely visible impact damage (BVID), which can be missed by conventional inspections.

Advanced SHM architectures are demonstrated in case studies involving Unmanned Aerial Vehicles (UAVs). One example is a wireless multi-parameter monitoring system (WMPMS) that uses a network of MEMS and PZT discs to detect and localize impacts on an aircraft's skin, as shown in Figures 3.13 and 3.14 (9). Another is a bio-inspired UAV wing embedded with a dense, multi-modal network of 148 micro-sensors (Figure 3.15) for comprehensive, real-time health monitoring (10).

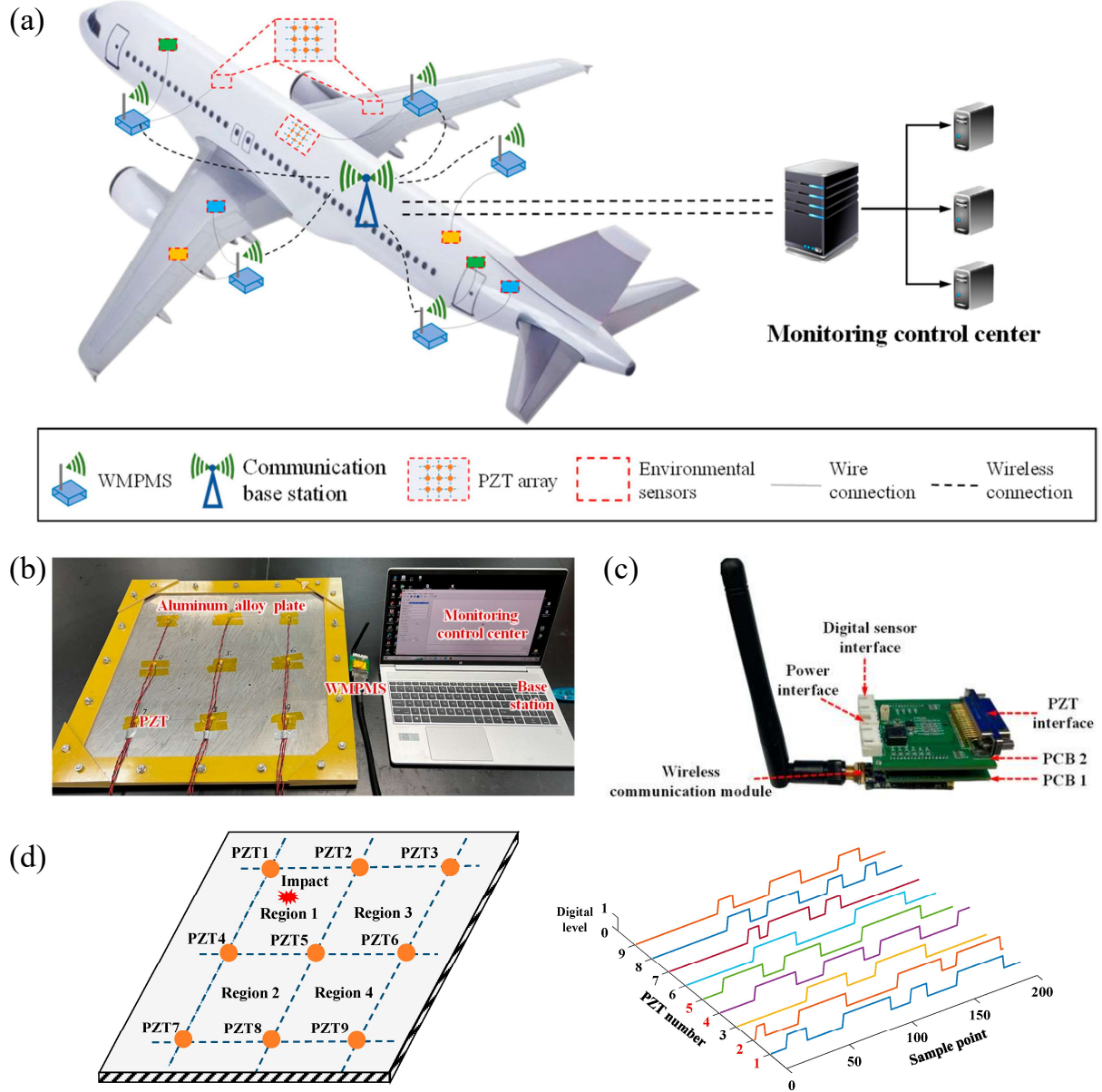


Figure 3.13 – Typical diagram for WMPMS (a) Architecture of ASS-based multi-parameter monitoring of an aircraft. (b) Experimental setup of impact monitoring. (c) The developed WMPMS. (d) Example of impact monitoring; impact occurring region and digital sequences (9).

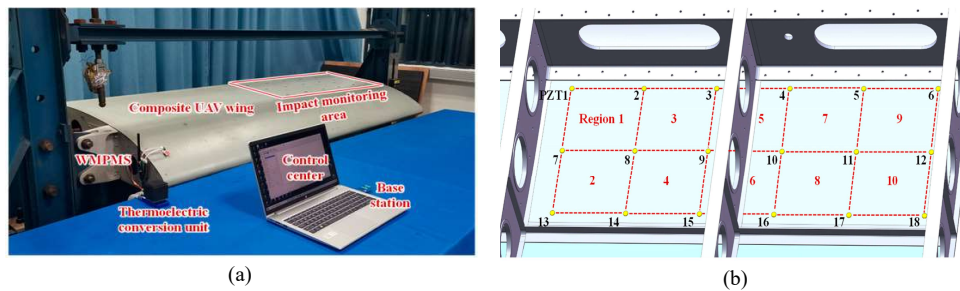


Figure 3.14 – Typical diagram for the WMPMS further validation (a) Multi-parameter monitoring of the composite UAV wing. (b) PZT placement on the impact monitoring regions. (9).

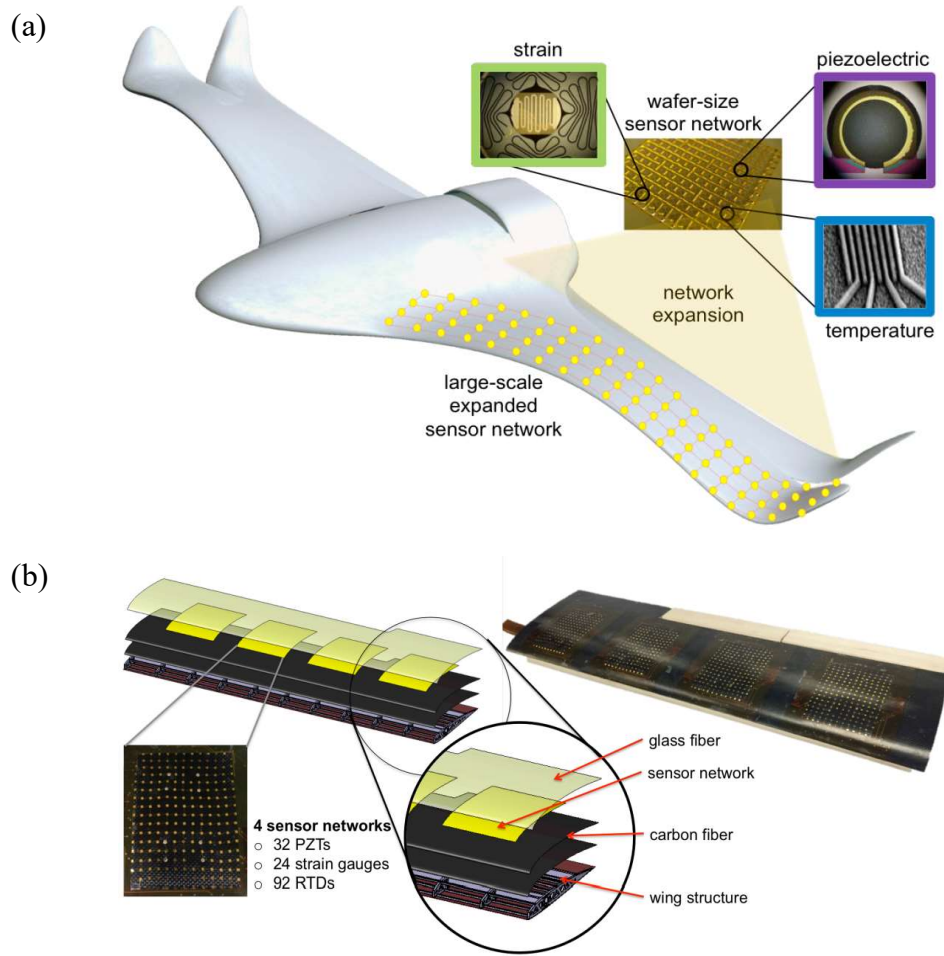


Figure 3.15 – Bio-inspired intelligent composite UAV wing with multi-modal stretchable embedded sensor network (a) Schematic representation of the intelligent UAV wing concept. (b) Exploded design view with a total of 148 micro-sensors embedded in the composite layup. (10).

### 3.6.5.2 Automotive Applications

In the automotive industry, SHM is used to enhance the safety and performance of vehicles that utilize carbon fiber composites for their lightweight and high-strength properties. Embedded sensors continuously evaluate the structural integrity of components by detecting variations in strain and stress under diverse driving scenarios. This proactive approach allows for the early detection of potential failures resulting from collisions or material fatigue (190, 198). A prominent application is the "smart tire" in high-performance racing, where embedded sensors monitor pressure, temperature, and wear in real-time. This data enables teams to make informed decisions about pit stops, ensuring optimal vehicle performance and preventing catastrophic tire failures, as illustrated in Figure 3.16 (127, 11).

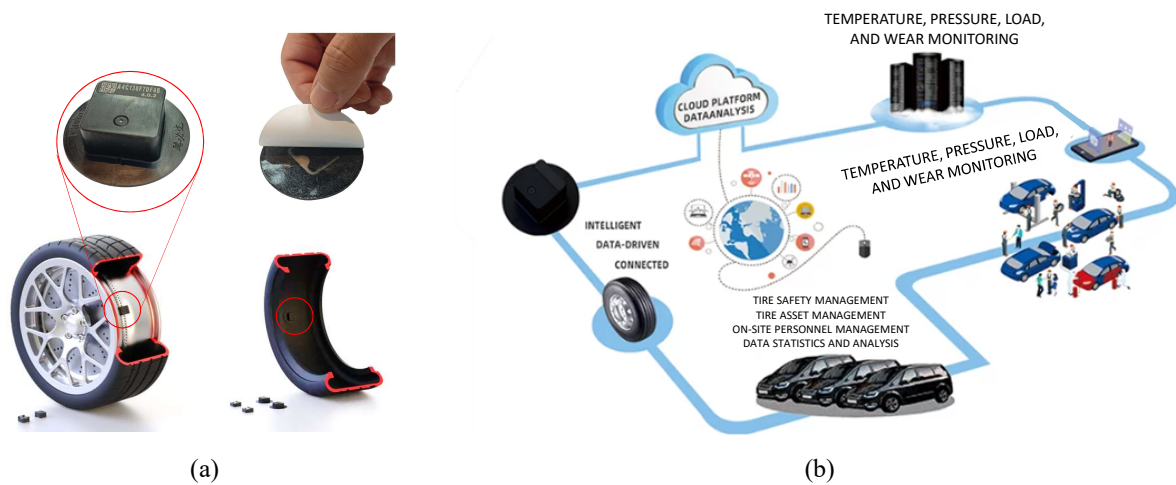


Figure 3.16 – Typical case study for smart tire monitoring for high performance automotive applications. (a) sensor installation details. (b) The intelligent tire management system network. (11).

### 3.6.5.3 Civil Infrastructure and Energy Applications

SHM is essential for maintaining the integrity and longevity of large-scale civil infrastructure. A landmark case study is the 3D-printed MX3D steel bridge in Amsterdam, which was equipped with a dense network of nearly 100 sensors (accelerometers, strain gauges, thermistors, etc.) to continuously assess its structural behavior (Figures 3.17 and 3.18). This integration of sensors with IoT connectivity provides a valuable model for monitoring complex structures (12). While the MX3D bridge is constructed from stainless steel rather than a composite material, it serves as a landmark case study in the implementation of a dense, multi-modal sensor network for a complex, additively manufactured structure, offering valuable lessons applicable to future large-scale composite projects. Beyond bridges, SHM is used in high-rise buildings to monitor responses to wind and seismic loads, in pipelines to detect leaks, and in concrete structures where embedded optical fiber sensors can identify microcracks at early stages (198, 196). Integrating this data with predictive analytics enables engineers to develop data-driven maintenance strategies, optimizing resource allocation (111). Another practical application involved embedding fiber optic sensors in the road pavement in Australia to monitor mining-induced strains (Figure 3.19) (13).

In the energy sector, SHM is used to monitor critical assets like wind turbines. A program in Colorado, USA, addressed blade and tower failures by installing a robust network of FBG sensors, accelerometers, and RTDs inside turbine blades (Figure 3.20). This system monitors large strains, temperature, and vibrations, with data accessible remotely, enabling proactive maintenance to improve the reliability of wind energy projects (??).



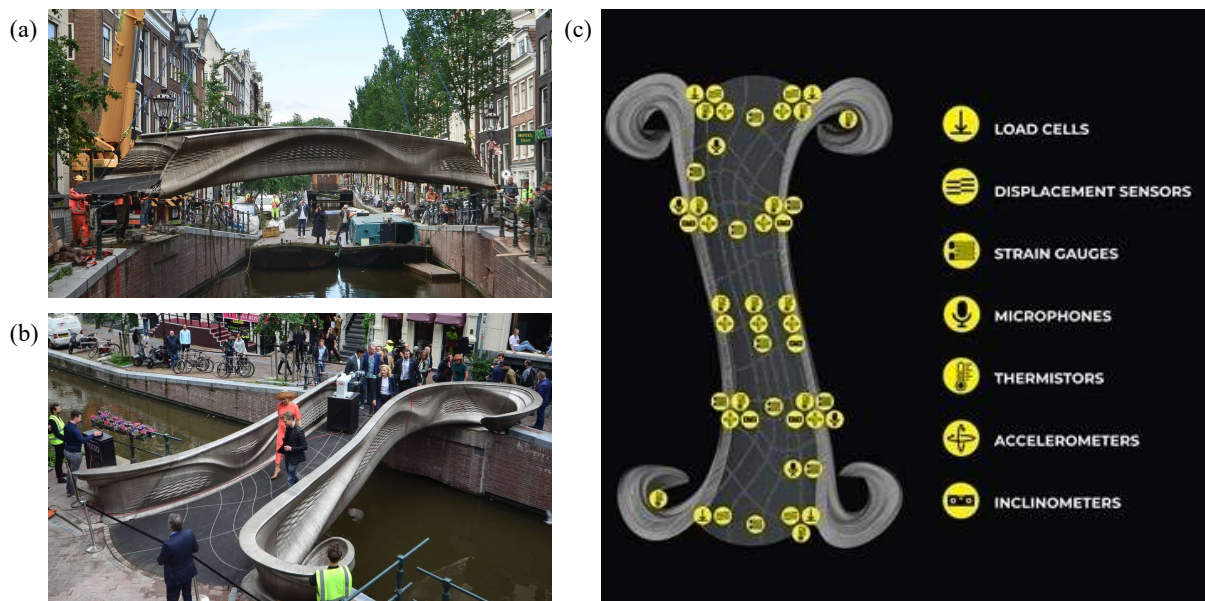


Figure 3.17 – The MX3D bridge at Amsterdam (a) The 3D printed bridge being installed (b) The bridge during commissioning (c) The sensor layout on the MX3D bridge. (12).

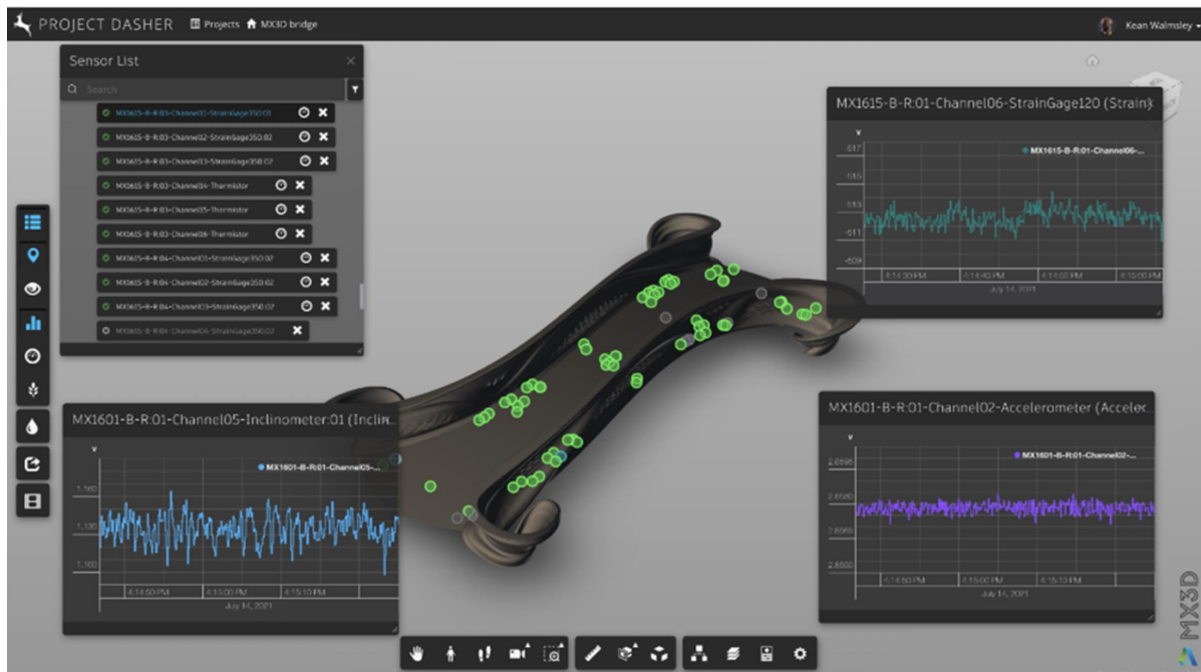


Figure 3.18 – The MX3D bridge the real-time data visualization program interface. (12).

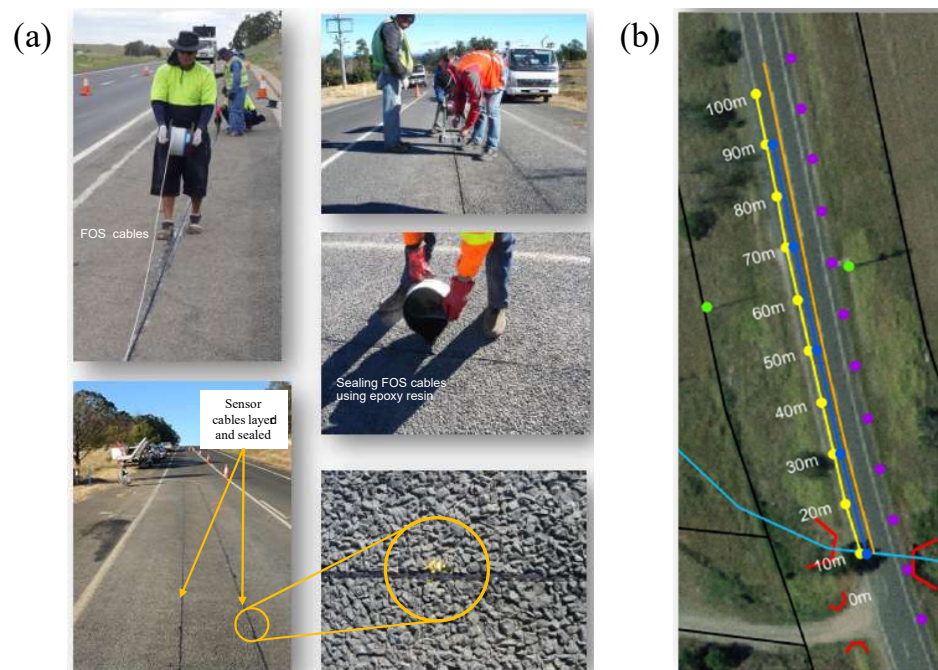


Figure 3.19 – Wilton Road, Appin, Australia monitoring case study. (a) FOS cables lay-up and sealing. (b) Location of FOS cables installation. (13).

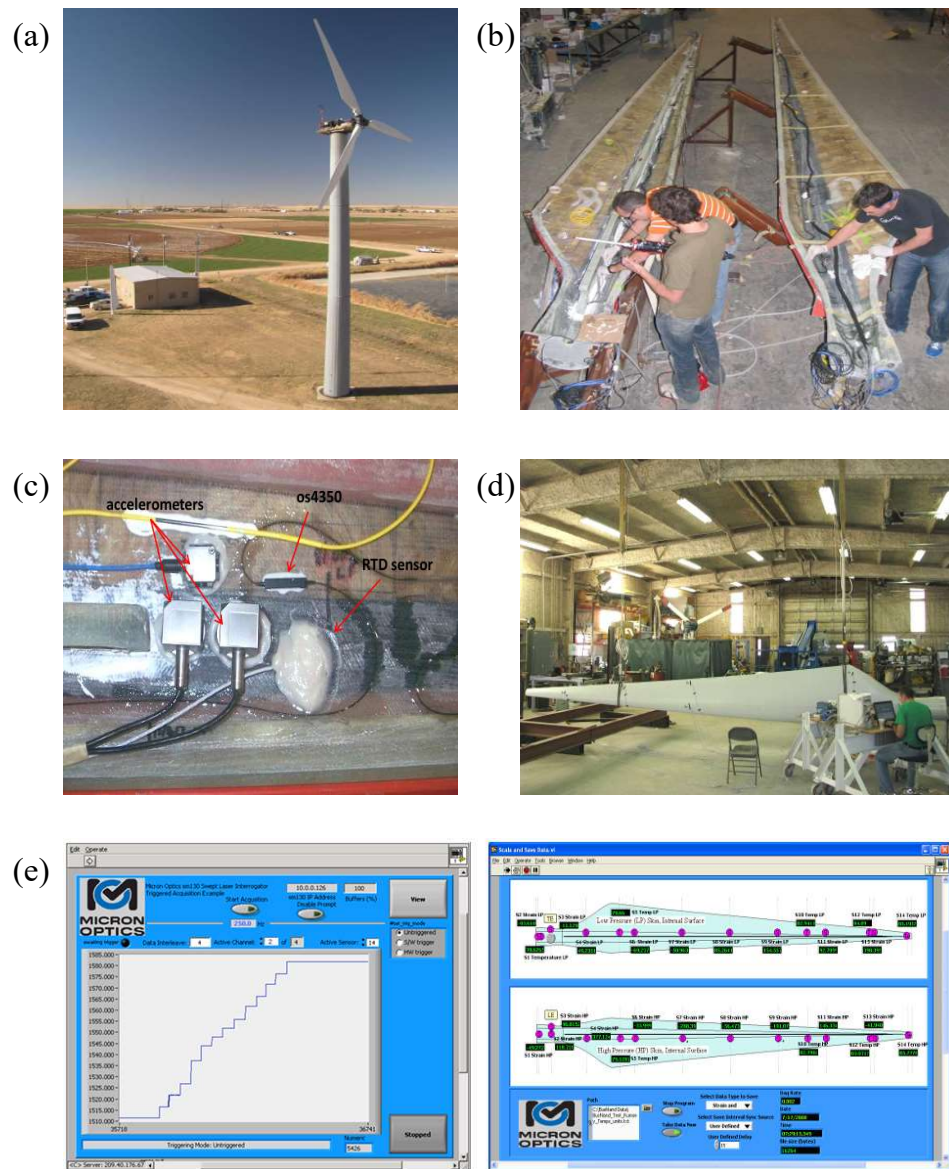


Figure 3.20 – Wind turbine monitoring program at Colorado, USA. (a) Wind turbine installed (b) Installing the sensing systems on the Sblade. (c) Sblade Calibrated sensor network. (d) Sblade in static edge deflection testing position. (e) Monitoring software User Interface. (??).

### 3.6.6 Performance of Embedded Sensors Under Varying Conditions

The reliability of embedded sensors is fundamentally tied to their durability under both mechanical and environmental stressors. Experimental research has confirmed that sensors like piezoresistive types maintain consistent performance even after prolonged exposure to cyclic loading, demonstrating their resilience in dynamic environments (199). By being embedded within a host composite, these sensors gain inherent protection against external factors, improving their lifespan and stability compared to surface-mounted counterparts (200). However, challenges remain, including long-term drift and managing inter-laminar

stress concentrations. The effectiveness of sensors is also linked to the host material's properties, with variations in surface roughness and boundary conditions contributing to non-uniform responses, highlighting the need for precise integration and calibration (197). Moisture presents a particularly pervasive challenge to sensor performance. Research has demonstrated that moisture absorption significantly impacts SHM components in multiple ways. Mechanically, it acts as a plasticizer in epoxy adhesives, reducing their modulus to as little as 25% of the dry-state value (95). Electrically, it can alter the resistance of nanocomposite films at high humidity and cause zero signal drift in strain gauge systems, introducing measurement inaccuracies (201, 202). Furthermore, moisture complicates damage assessment in composites by altering wave propagation characteristics, which can increase signal dispersion and reduce wave amplitude, potentially masking the signatures of impact damage (93). While certain sensors like FBGs have shown superior durability in high-humidity environments (203), accounting for moisture-induced variations is critical for ensuring the overall accuracy and longevity of SHM systems.

## 3.7 Discussion: Challenges and Future Directions

While the potential of embedded sensors for SHM is evident, their transition from academic research to widespread, certified industrial use is contingent upon addressing several formidable challenges. Across diverse applications, a consistent pattern emerges: the unparalleled ability of embedded sensors to detect in-situ and subsurface damage is counterbalanced by complexities in long-term reliability, data interpretation, and manufacturing integration. This section provides a critical discussion of these key challenges and outlines promising directions for future research.

### 3.7.1 Challenge 1: Assuring Long-Term Reliability and Durability

The most significant barrier remains the uncertainty surrounding the long-term reliability and durability of embedded sensors within harsh operational environments. Once integrated and cured within a composite structure, sensors are inaccessible for repair, replacement, or recalibration, a "place-and-pray" condition that demands exceptional robustness. These sensors must endure decades of exposure to temperature fluctuations, humidity variations, cyclic mechanical loading, and chemical interactions with the host matrix. Several failure modes are critical such as **Sensor Drift**: A gradual change in sensor output over time without a corresponding change in the measured parameter, which compromises long-term monitoring accuracy; **Interfacial Debonding**: Mismatches in thermal expansion or chemical incompatibility between the sensor and host material can lead to debonding at their interface, causing signal degradation or complete failure (39);



and **Material and Wire Fatigue**: Repeated mechanical loading can cause microscopic crack propagation in sensor leads, eventually resulting in electrical discontinuity. Similarly, the sensing materials themselves can age, altering their piezoresistive or other physical characteristics and degrading measurement fidelity over time. Research must focus on a holistic approach to sensor longevity. This includes developing novel encapsulation and coating materials that are both chemically compatible with host resins and robust enough to withstand decades of thermo-mechanical cycling. Accelerated aging protocols are urgently needed to validate sensor performance over a projected service life. Furthermore, a shift towards proactive reliability assessment is required, incorporating physics-of-failure models to predict the sensor's own remaining useful life and building in redundancy through networked sensor arrays (99, 100, 101, 102, 204).

### 3.7.2 Challenge 2: Data Interpretation and Management at Scale

The proliferation of embedded sensor networks creates a "data deluge" where the sheer volume of data can overwhelm traditional processing and storage systems (205). Critically, distinguishing genuine damage signals from operational and environmental noise presents a major challenge. Signals are often convoluted mixtures of mechanical responses and influences from temperature, moisture absorption, and residual curing stresses. These factors can mimic damage signatures, leading to false positives that undermine system reliability and user confidence. This laboratory-to-field gap is a primary obstacle. While performance in controlled lab settings is promising, real-world conditions introduce uncontrolled variables like extreme temperature gradients and unpredictable load spectra, which can induce signal drift, reduce the signal-to-noise ratio, and complicate data analysis. The field must move towards intelligent sensing architectures that incorporate **edge computing**, where initial data processing, noise filtering, and feature extraction are performed locally at the sensor node. This reduces the burden on data transmission, which can be prohibitively expensive for remote structures. The development of robust **machine learning and AI algorithms** is a critical frontier. These models must be specifically trained on data from embedded systems to deconvolve complex signals, compensate for environmental variability, and enable a shift from reactive damage detection to truly predictive analytics (67, 206, 207, 208, 209, 210).

### 3.7.3 Challenge 3: Sensor-Process-Structure Integration

While an embedded sensor should ideally act as a passive observer, it is in reality a foreign object that can introduce defects. An optical fiber or piezoelectric wafer can create resin-rich pockets, disrupt local fiber alignment, and act as a stress concentration point,

potentially becoming a site for damage initiation (211). This challenge is magnified during automated manufacturing processes like Automated Fiber Placement (AFP), where sensor integration must be achieved without disrupting production speed and precision. The variability between manual laboratory embedding and high-volume industrial manufacturing often leads to inconsistencies in placement, adhesion, and sensor survivability. Research must focus on the **co-design of sensors and composite manufacturing processes**. This includes developing "low-profile" or near-zero-intrusiveness sensors, such as printed sensors using conductive inks that conform to the laminate structure with minimal disruption (212, 213). Another promising avenue is the use of **advanced and metamaterial-based sensors** with tailored properties, such as a zero thermal expansion coefficient, to better manage strain transfer and decouple signals from thermal fluctuations. Finally, advanced multi-physics simulation tools are needed to model the sensor-host interaction during curing and under load, allowing for the optimization of sensor placement to minimize its structural impact before manufacturing (22, 214, 215, 216).

#### 3.7.4 Challenge 4: Standardization and Certification

For embedded SHM to be adopted in safety-critical applications like commercial aircraft, a clear framework for standardization and certification is essential. The field currently lacks industry-wide standards for embedded sensor performance, reliability, testing protocols, and data formats. Without these, it is difficult to compare results, ensure interoperability, or establish a baseline for their performance. Certification authorities, such as the Federal Aviation Administration (FAA) and European Union Aviation Safety Agency (EASA), require robust validation that the embedded SHM system does not negatively impact the structure's airworthiness and that its data is reliable enough for maintenance decisions. A concerted effort is needed from academia, industry, and regulatory bodies to develop consensus-based standards and benchmark testing protocols. A promising pathway to support certification is the development of "**digital twins**", high-fidelity virtual models continuously updated with data from the embedded sensor network. These digital twins can be used to run virtual tests, simulate damage scenarios, and provide the robust, evidence-based data required to validate system performance and support the certification process (217, 218, 219).

#### 3.7.5 Challenge 5: System Autonomy and Power Management

Providing a sustainable power source for the decades-long service life of a structure is a fundamental challenge. Traditional batteries are unfeasible due to finite lifespans and the impracticality of replacement (220). While wired power is an option, it adds weight, com-

plexity, and potential failure points, undermining the benefits of an embedded approach (221). This necessitates a move towards fully autonomous sensor nodes. The ultimate goal is to create "fit-and-forget" SHM systems. This requires a two-pronged approach. The first is **energy harvesting**, developing materials and devices (e.g., piezoelectric, thermoelectric) capable of converting ambient energy like vibrations and thermal gradients into electrical power (222). The second is the advancement of **ultra-low-power electronics and wireless communication protocols**, designing systems that spend most of their life in a near-zero-power "sleep state" and only wake to measure and transmit data when triggered. The synergy of these two areas is the most promising path toward true autonomy (223, 224).

### 3.7.6 Challenge 6: Economic Viability and Cost-Benefit Analysis

Ultimately, widespread adoption is governed by economic considerations. The total cost includes not just the sensor hardware but also data acquisition systems, software, and modifications to existing manufacturing processes. The return on investment realized through extended service life, reduced maintenance, and improved safety, is difficult to quantify and is spread over decades (225). Comprehensive techno-economic analyses are needed to account for the full lifecycle costs and benefits of embedded SHM. The development of modular, **"plug-and-play" sensor architectures** could reduce integration costs by standardizing installation procedures (226). Furthermore, new business models, such as shared data platforms and **"sensor-as-a-service"**, could distribute costs across stakeholders and provide access to advanced analytics, making the technology more accessible and economically viable (227).

## 3.8 Chapter Conclusion

This review provided a comprehensive analysis of the evolution, advancements, and critical challenges of embedded sensor technologies for the Structural Health Monitoring of composite structures. We have traced the development from traditional, offline inspection methods to the current paradigm of integrated, self-sensing systems. A key finding from the extensive analysis of recent case studies is the clear predominance of piezoresistive sensors, particularly those based on carbon nanofillers, which are favored for their seamless integration potential through additive manufacturing techniques like FDM and DIW. The review also critically assessed other key modalities, including piezoelectric and fiber optic sensors, highlighting their respective strengths and weaknesses.

While progress has been significant, this review also underscores that several persistent challenges must be addressed to unlock the full potential of embedded SHM. The

analysis consistently revealed that sensor performance is deeply affected by environmental factors, sensor-material compatibility issues, and the complexities of the integration process itself, which can introduce defects and compromise both sensor and structural integrity. The reliability and long-term durability of these integrated systems under real-world operational and environmental conditions remain a primary concern. By focusing future research on robust sensor packaging, intelligent data processing, and standardized integration protocols, the promise of creating truly "smart" and self-aware composite structures can be fully realized.

## 4 Design Optimization of 3D-Printed Piezoresistive Sensors for Integrated Structural Health Monitoring

Additively manufactured piezoresistive sensors offer a promising route for creating smart structures with integrated Structural Health Monitoring (SHM) capabilities. However, their performance is highly dependent on geometric design, which presents a complex multi-objective optimization problem. To address this, this work presents a combined experimental and computational framework for optimizing 3D-printed, conductive PLA piezoresistive strain sensors. A Design of Experiments (DOE) was conducted to investigate four geometric parameters (trace width, inter-trace distance, thickness, and end-loops) across three integration types. The resulting response surfaces-linking geometry to gauge factor ( $GF$ ), maximum strain ( $\varepsilon_{\max}$ ), and elastic modulus ( $E$ )-were modeled using Gaussian Process Regression (GPR). A Multi-Objective Particle Swarm Optimization (MOPSO) algorithm, coupled with TOPSIS, was then employed to navigate the conflicting objectives of maximizing sensitivity while minimizing structural stiffness impact. Key optimized solutions were fabricated and experimentally validated via uniaxial tensile tests monitored with Digital Image Correlation (DIC). The fully embedded configuration yielded the highest sensitivity ( $GF = 59$ ) but compromised host stiffness. However, an optimized, scaled variant of this design restored stiffness to near-native levels ( $E = 2.18$  GPa) while retaining high sensitivity. The validated “Experiment-Model-Optimize-Validate” workflow provides a generalizable methodology for designing and tailoring additively-manufactured sensors for specific applications.

## 4.1 Introduction

The integration of self-monitoring capabilities into engineering structures, commonly known as Structural Health Monitoring (SHM), represents a significant paradigm shift in asset management and safety assurance (228, 229). Unlike traditional non-destructive testing (NDT) methods, which are often periodic and labor-intensive, SHM systems provide continuous, real-time data on a structure's condition (230). This approach offers the profound advantage of detecting damage at its inception, thereby preventing catastrophic failures, reducing maintenance costs and operational downtime, and extending the service life of critical components (67, 194, 147). The evolution of SHM has been further accelerated by advancements in wireless sensor networks, energy harvesting, and the application of machine learning (ML) algorithms for intelligent data interpretation and damage prognosis (231, 52).

At the heart of any SHM system lies the sensing technology. For decades, conventional strain sensors, such as metallic foil gauges, have been the cornerstone of experimental stress analysis and structural monitoring. While effective, these sensors present notable limitations. Their application is typically restricted to the surface of structures, making them susceptible to debonding and damage from environmental factors (53, 19). Furthermore, their integration onto components with complex geometries can be challenging and time-consuming, and their material properties are often dissimilar to the host structure, particularly in the case of polymer composites, which can alter local stress fields (53, 232). These drawbacks highlight a pressing need for novel sensing solutions that are not merely attached to a structure but are an intrinsic part of it (53, 19).

Additive Manufacturing (AM), or 3D printing, has emerged as a transformative technology that directly addresses this need. AM enables the fabrication of components with highly complex geometries and the ability to embed functionalities directly within a material or structure during the manufacturing process (194, 147, 53). This capability has paved the way for the development of smart structures with self-sensing properties (156). By utilizing functional materials, such as conductive thermoplastic filaments, it is now possible to print sensors that are monolithically integrated into a structural component, eliminating the interface issues that plague traditional sensors and allowing for monitoring in previously inaccessible locations (194, 53).

Among the various functional materials available for AM, conductive polymer composites based on polylactic acid (PLA) have garnered significant interest for strain sensing applications. These materials, typically rendered conductive by incorporating carbon-based fillers like carbon black or graphene, exhibit a piezoresistive behavior (i.e. their electrical resistance changes in response to applied mechanical strain) (20, 21, 52). The low cost, biocompatibility, and ease of processing of PLA make it an attractive matrix material. However, the electromechanical properties of 3D-printed conductive PLA are highly anisotropic and exquisitely sensitive to the printing parameters, such as layer height, in-

fill density, and printing orientation (21, 20). This complex relationship necessitates a systematic approach to fabrication to ensure the resulting sensors are both reliable and sensitive (173).

Therefore, the central challenge lies in understanding and optimizing the AM process to fabricate structure-integrated piezoresistive sensors with desired performance characteristics, such as high strain sensitivity (gauge factor), linearity, and working strain range. Because the study is focused on self-integrated/embedded sensing, the study included analyses of the degree to which the structural integrity is affected as determined by change in material's stiffness (elastic modulus) (53, 20). While optimization of sensor geometry exists, amidst the pool of research works that focused on development, characterization and optimization of functional composites for sensing applications, there is limited research on systematic, multi-objective optimization frameworks that simultaneously address sensitivity and structural stiffness using the specific Experiment-Model-Optimize workflow presented here. (173, 147). This study aims to bridge that gap by presenting a comprehensive methodology for the design, multi-objective optimization, and experimental validation of a 3D-printed piezoresistive strain sensor based on conductive PLA. The objective is to develop a robust framework that leverages statistical design of experiments and response surface methodology to identify optimal geometry parameters that yield superior sensing performance, thereby advancing the development of low-cost, integratable smart structures. It should be noted that while standard tensile specimens are employed here for validation purposes, the proposed optimization methodology is host-agnostic and intended for general application to any load-bearing FDM component. Furthermore, the fully embedded configuration is intended specifically for new components manufactured via additive manufacturing (AM) where the sensor is printed in situ, whereas the surface-integrated configuration (similar to a smart patch) would be the appropriate application method for existing structures.

The novelty of this work lies in systematically analyzing the impact of geometry and some manufacturing parameters on the performance of additively manufactured piezoresistive strain sensors made from commercial conductive PLA. This study aims to optimize the sensor's geometric configuration to enhance its piezoresistive response. The optimized design is then rigorously tested under quasi-static loading conditions to validate the performance predictions, with the optimization process guided by the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) decision-making method. This comprehensive approach ensures that the optimized geometry delivers superior strain sensing performance while maintaining the structural integrity of the sensor. Before initiating the full factorial Design of Experiments (DoE) and optimization stages, a preliminary experimental study was conducted to assess the effect of sensor embedding depth on strain-transfer efficiency and piezoresistive response. This baseline investigation revealed a strong depth-dependent increase in sensitivity, with fully embedded sensors exhibiting

a significantly higher Gauge Factor compared to surface-mounted and sub-surface configurations. These findings motivated the decision to fix the embedding position for the subsequent DoE and to focus the optimization on geometric design variables. Lastly, it is worth noting that, this study focuses on the optimization of the transducer (sensor) element itself; complete system integration (DAQ, power, wireless transmission) is a separate challenge often addressed by embedding separate modules or printing conductive wiring channels.

## 4.2 Smart structures

### 4.2.1 Piezoresistivity in Conductive Polymer Composites

The fundamental principle enabling self-sensing (strain) in smart structures, made of electrically conductive materials, is the piezoresistive effect, where a material's electrical resistance changes in response to mechanical deformation (233). In conductive polymer composites (CPCs), this effect is primarily attributed to the alteration of the internal conductive network formed by filler particles, such as carbon black (CB), carbon nanotubes (CNTs), or graphene, dispersed within a dielectric polymer matrix (20, 234). When subjected to strain, the distances between adjacent conductive particles change, which significantly impacts the dominant electron transport mechanism (quantum tunneling) (235). As the material is stretched, the inter-particle distance increases, raising the tunneling resistance and, consequently, the bulk resistance of the composite. Conversely, under compression, the particles move closer, reducing the resistance. The sensitivity of this response is highly dependent on the filler concentration, morphology, and dispersion within the matrix. A filler concentration near the percolation threshold: the critical concentration at which a continuous conductive path is formed, typically yields the highest sensitivity, as minor deformations can cause substantial changes in the connectivity of the network (236).

### 4.2.2 Additive Manufacturing for Integrated Sensing

Fused Deposition Modeling (FDM), a prominent Additive Manufacturing technique, has opened new frontiers for fabricating sensors with complex geometries that can be monolithically integrated or embedded within structural components (237, 238). Unlike traditional surface-mounted sensors, 3D-printed sensors eliminate the adhesive interface, which is often a point of failure, and allow for strain monitoring in previously inaccessible internal locations (239). This integration has enabled the creation of fully functional smart structures, such as a 3D-printed load cell with embedded strain gauges configured in a full Wheatstone bridge, all fabricated in a single manufacturing step (240). Researchers have successfully demonstrated the viability of FDM for producing piezoresistive sensors using



various CPC filaments, from rigid PLA to flexible TPU (241, 157, 160), confirming that these sensors can effectively monitor both static and dynamic loads and can be tailored for specific applications like monitoring torque in bolted joints (234).

### 4.2.3 Influence of FDM Process Parameters on Sensor Performance

While FDM offers significant advantages, the electromechanical properties of the resulting sensors are exquisitely sensitive to the chosen process parameters. The anisotropic nature of the FDM process, where material is deposited layer-by-layer, creates a complex microstructure that dictates both the mechanical integrity and the electrical conductivity of the printed part (235). Numerous studies have investigated the link between printing parameters and sensor performance (242, 243). It is widely reported that raster angle is a dominant factor, with a  $0^\circ$  orientation parallel to the load yielding the highest sensitivity (235, 244). Other key parameters include layer thickness, nozzle temperature, and infill density, which collectively influence the interlayer bonding and the continuity of the conductive network (20, 245). The complexity and interplay of these parameters have led researchers to employ advanced optimization methods. For instance, Razbin et al. (246) utilized soft computing techniques, including fuzzy logic and genetic algorithms, to effectively model and optimize the FDM process for piezoresistive sensors, demonstrating the potential of computational tools to navigate the vast design space.

### 4.2.4 Effect of Sensor Geometry and Design

Beyond the material properties and printing parameters, the geometric design of the sensor itself is a critical determinant of its performance. The gauge factor, a key measure of sensitivity, is not only a function of the material's intrinsic piezoresistivity but also of the sensor's structural layout. Drawing parallels with traditional metallic foil gauges, the pattern of the conductive trace significantly influences its response to strain. Multiscale modeling and experimental work by Arana et al. (247) on CNT-based strain gauges revealed that the gauge factor could be tuned by altering geometric parameters. They found that sensitivity increases with a greater number of end loops in a serpentine pattern, a decreased grid width, and a reduced end loop height. This is because the geometry dictates how the strain is concentrated and distributed throughout the conductive path, thereby amplifying the change in resistance. This highlights that a holistic optimization approach must consider not only the material and process parameters but also the macroscopic design of the sensing element.

The geometry parameters have been varied also across different works by different authors, from where insights were obtained as to how design variable bounds are set. Example, for the trace width ( $w_1$ ), the range of 0.8–2.0 mm was chosen in line with Gooding et al. (237), who employed widths of 1, 1.5, and 2 mm for strain gauge fabrication;

Shahriar (238), who used 0.6 mm to balance structural integrity and sensitivity; and Yang et al. (236), who reported a width of 1.5 mm for CB/TPU-based strain sensors. The height of the trace ( $t$ ) was set between 0.2–1.2 mm, consistent with prior studies showing that lower thicknesses enhance sensitivity. Specifically, Gooding et al. (237) explored values of 0.2, 0.4, and 0.6 mm, Babich et al. (244) demonstrated increased sensitivity at  $t = 0.3$ –0.9 mm, Shahriar (238) highlighted the sensitivity improvement at  $t = 0.6$  mm, and Sanatgar et al. (235) successfully printed sensors with  $t = 1$  mm using MWCNT/PLA. For the gage width ( $W$ ), Hwang et al. (233) developed a MWCNT/epoxy strain sensor with a 9.5 mm grid width, which served as a practical reference. In this study, however,  $W$  was treated as a variable since it depends on the number of end loops incorporated in the sensor design. Finally, the gage length ( $L$ ) was set to 25 mm, supported by evidence from Hwang et al. (233), who used 10 mm as a baseline, and Kim et al. (248), who demonstrated that longer lengths (10, 20, and 30 mm) improve both sensitivity and linearity.

The existing literature provides a strong foundation, confirming the viability of FDM-fabricated sensors and identifying the key parameters influencing their performance. However, two primary gaps remain. First, while the qualitative effects of individual printing parameters are known, a systematic, multi-objective optimization using statistical methods to balance the inherent trade-offs between sensitivity, linearity, working strain, and modulus of elasticity is not yet fully established for conductive PLA. Recent work has shown the power of computational approaches like fuzzy logic and genetic algorithms (246), yet a robust framework based on Design of Experiments (DoE) and Response Surface Methodology (RSM), methods widely used for industrial process optimization, is still needed to create predictive models for sensor fabrication. Second, studies often focus on either process parameters or sensor geometry in isolation. A comprehensive approach that integrates the optimization of both process parameters and sensor geometry is necessary for developing reliable, high-performance sensors. While process parameters are a critical factor, this study aims to bridge the latter gap by developing a robust DoE and RSM framework to perform a multi-objective optimization of the sensor's geometric design for a fixed, reliable FDM process. This creates a clear and practical methodology for fabricating tailored sensors for SHM applications.

### 4.3 Methodology

Tensile test specimens were additively manufactured with integrated piezoresistive sensors shaped in the form of a strain gauge. To investigate the influence of manufacturing and geometric parameters on sensor performance, a Design of Experiments (DoE) approach was employed.

Three categorical factors were introduced into the experimental design. Two factors corresponded to the infill pattern of the substrate structure, namely rectilinear and

aligned, while the third corresponded to the sensor position (fully embedded). These categorical variables formed the basis for subdividing the overall experiment into three groups (DoE 1, 2, & 3). For the rectilinear and aligned configurations, the sensor was surface-integrated, i.e., printed directly on the surface of the tensile test specimen. In contrast, in the fully embedded configuration, the sensor was fabricated entirely within the mid-plane of the substrate structure.

Each subgroup shared in common four continuous design variables: sensor trace width ( $w_1$ ), inter trace distance ( $w_2$ ), trace thickness ( $t$ ), and number of end loops ( $N$ ). The recorded responses comprised the gauge factor (GF), linearity coefficient ( $R^2$ ), maximum measurable strain ( $\varepsilon_{\max}$ ), and elastic modulus ( $E$ ).

The influence of the design variables was initially explored using the response surface methodology (RSM) within each subgroup. Subsequently, multi-objective optimization was carried out using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), considering two weighting schemes: (i) equal weights assigned to all responses and (ii) higher weight assigned to the gauge factor (GF). The weighting schemes chosen are demonstrative; the framework allows engineers to adjust these weights to suit specific demands, such as those found in aerospace or civil applications, as needed. The optimum sensor geometries obtained from both weighting schemes were validated against the predicted responses from the optimization models.

### 4.3.1 Materials

The sensing element is additively manufactured using a brand of CrownMulti conductive PLA, a commercially available 3D printing filament on a GTMax3D brand of polylactic acid substrate thanks to the multi-material fused filament fabrication technology. Detailed information on the conductive PLA filament as provided in the manufacturer's information datasheet is presented in Table 4.1.

Table 4.1 – Technical specifications of conductive PLA filament.

| Parameter                 | Value          |
|---------------------------|----------------|
| Product Material          | Conductive PLA |
| Consumables Color         | Black          |
| Consumable Wire Diameter  | 1.75 mm        |
| Net Weight of Consumables | 0.5 kg / 1 kg  |
| Printing Temperature      | 190–225°C      |
| Bottom Plate Temperature  | None or 60°C   |
| Printing Speed            | 30–90 mm/s     |
| Conductivity              | $10^{-4}$ S/m  |

### 4.3.2 Design of Experiments

For the design of experiments, both categorical and continuous control parameters were considered. The categorical factors comprised:

- **Infill pattern:** rectilinear and aligned,
- **Sensor position:** fully embedded (mid-plane of the substrate) versus surface-integrated.

These categorical factors formed the basis for subdividing the experimental campaign into three groups (DoE 1–3). For the rectilinear and aligned cases, the sensor was surface-integrated (printed directly on the specimen surface), whereas for the fully embedded case, the sensor was entirely printed inside the substrate structure.

Each subgroup shared four continuous design variables: trace width ( $w_1$ ), inter-trace distance ( $w_2$ ), trace thickness ( $t$ ), and number of end loops ( $N$ ). These continuous control parameters are illustrated in Figure 4.1, and their bounds are summarized in Table 4.2. The geometric bounds selected for the DoE were determined based on FDM resolution limits, flow-stability considerations, and literature-reported bounds for conductive polymer sensing elements. Readers are referred to Section 2.4 for the explicit justifications and literature sources derived for these values. Other geometric attributes, such as the sensor gauge length (25 mm) and the outer inter-trace distance (2 mm), were kept constant throughout.

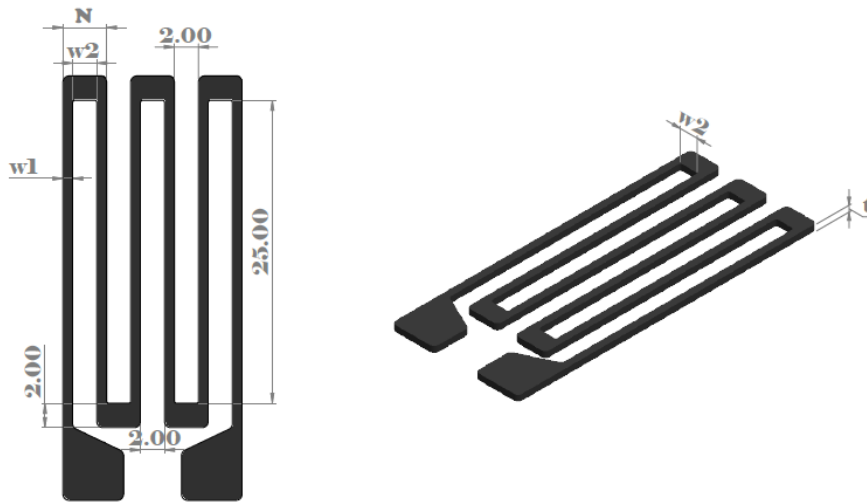


Figure 4.1 – Typical sensor geometry showing continuous DoE control parameters.

The response variables observed included the gauge factor (GF), the maximum measurable strain ( $\epsilon_{\max}$ ), the linearity of the resistance-strain response (represented by the coefficient of determination  $R^2$ ), and the elastic modulus ( $E$ ) of the sensor surface-integrated and fully embedded samples.

Table 4.2 – Design of Experiment (DoE) Continuous Variables

| Design Variables          | Symbol | Lower Bound | Upper Bound |
|---------------------------|--------|-------------|-------------|
| Trace width [mm]          | $w_1$  | 0.8         | 2.0         |
| Inter-trace distance [mm] | $w_2$  | 0.0         | 2.0         |
| Trace thickness [mm]      | $t$    | 0.2         | 1.2         |
| Number of end loops       | $N$    | 2           | 4           |

Initial data analysis was conducted using a two-level factorial design in *Minitab* statistical software, employing only the lower and upper bounds of each design variables as presented in the DoE control parameter table which yielded a total of 16 different geometry configurations, constituting the test samples for the experiment as presented in table 4.3. In defining the bounds for the DoE to optimize the sensor geometry, the selected intervals were not arbitrary, but guided by prior literature (see Section 4.2.4).

However, the preliminary results indicated that the two-level factorial design were insufficient to draw a final conclusion about the influence of the design variables on the responses. As a result, additional central points were introduced, which prompted for the adoption of Central Composite Design (CCD) Response Surface Methodology (RSM) approach for the final optimization process.

Table 4.3 – DoE Sample Configuration

| Sample ID | $w_1$ [mm] | $w_2$ [mm] | $t$ [mm] | $N$ |
|-----------|------------|------------|----------|-----|
| Sample 1  | 0.8        | 2.0        | 0.2      | 4   |
| Sample 2  | 0.8        | 2.0        | 1.2      | 4   |
| Sample 3  | 2.0        | 2.0        | 0.2      | 4   |
| Sample 4  | 2.0        | 2.0        | 1.2      | 4   |
| Sample 5  | 0.8        | 0.0        | 0.2      | 4   |
| Sample 6  | 0.8        | 0.0        | 1.2      | 4   |
| Sample 7  | 2.0        | 0.0        | 0.2      | 4   |
| Sample 8  | 2.0        | 0.0        | 1.2      | 4   |
| Sample 9  | 0.8        | 2.0        | 0.2      | 2   |
| Sample 10 | 0.8        | 2.0        | 1.2      | 2   |
| Sample 11 | 2.0        | 2.0        | 0.2      | 2   |
| Sample 12 | 2.0        | 2.0        | 1.2      | 2   |
| Sample 13 | 0.8        | 0.0        | 0.2      | 2   |
| Sample 14 | 0.8        | 0.0        | 1.2      | 2   |
| Sample 15 | 2.0        | 0.0        | 0.2      | 2   |
| Sample 16 | 2.0        | 0.0        | 1.2      | 2   |

### 4.3.3 Samples Fabrication

All samples were fabricated using a Bambu Lab X1E Carbon Combo 3D printer, equipped with a 0.4 mm nozzle and an Automatic Material System (AMS) for multi-material management. This printer was specifically selected due to its enclosed build chamber and heated bed, which together provide complete environmental control over the printing ambience. Such control is crucial for producing consistent and dimensionally stable samples, especially when printing with functional or conductive filaments that are sensitive to thermal gradients and moisture.

In addition to environmental control, the Bambu Lab X1E offers high dimensional accuracy and repeatability, making it ideal for research-focused fabrication. It supports the use of industry-standard 1.75 mm filament diameters and allows for seamless multi-material handling through its AMS, which enables automatic filament switching without manual intervention. This combination of features made it suitable for fabricating samples with embedded sensor geometries that require precise alignment and inter-material coordination.

To ensure uniformity, all printing parameters were held constant for every sample, except for the infill pattern, which was one of the controlled variables in the Design of Experiments (DoE). The specific printer settings employed in the fabrication are summarized in Table 4.4. It is worth noting that sample fabrication was consistent and repeatable using the specified commercial printer and settings. The printing yield for the samples was effectively 100% once the parameters were dialed in.

Table 4.4 – Printing settings of the Bambu Lab X1E Carbon Combo 3D printer

| Parameter                     | Value               |
|-------------------------------|---------------------|
| Printing temperature [°C]     | 220                 |
| Layer height [mm]             | 0.08                |
| Initial layer height [mm]     | 0.20                |
| Printing speed [mm/s]         |                     |
| Solid infill (substrate)      | 150                 |
| Walls, top & bottom layers    | 60                  |
| Infill density [%]            | 100                 |
| Top surface pattern           | Monotonic line @45° |
| Sparse infill pattern         | 45° Rectilinear     |
| Internal solid infill pattern | 45° Rectilinear     |
| Bottom surface pattern        | Monotonic line @45° |
| Nozzle diameter [mm]          | 0.4                 |

The test samples were designed based on the ASTM D638 Type III dog-bone geometry, with a fixed thickness of 4 mm. However, due to constraints imposed by the geometric upper bounds of certain control parameters, specifically, a maximum trace width ( $w_1$ ) of

2 mm and a maximum of four end loops ( $N = 4$ ), combined with a constant outer inter-trace distance of 2 mm, the standard gauge section width of the ASTM D638 design was insufficient. As a result, the central width of the dog-bone sample was increased to 33 mm to accommodate the embedded sensor traces while preserving mechanical integrity and enabling consistent geometry across all samples.

Although this geometry does not strictly conform to the ASTM D638 specification, such adherence was not required for the purposes of this study, as no mechanical characterization of the base or conductive material was intended. Rather, the dog-bone shape was adopted solely as a structural platform to integrate the sensing elements. Importantly, because the samples are subjected to uniaxial tensile loading, the narrowed central section of the dog-bone geometry facilitates stress concentration in the region of interest, precisely where the strain sensors are embedded. This enables more reliable strain localization and ensures that the sensor outputs correspond to the highest-stress regions under loading. A CAD model showing the modified geometry and one of the sensor configurations is provided in Figure 4.2.

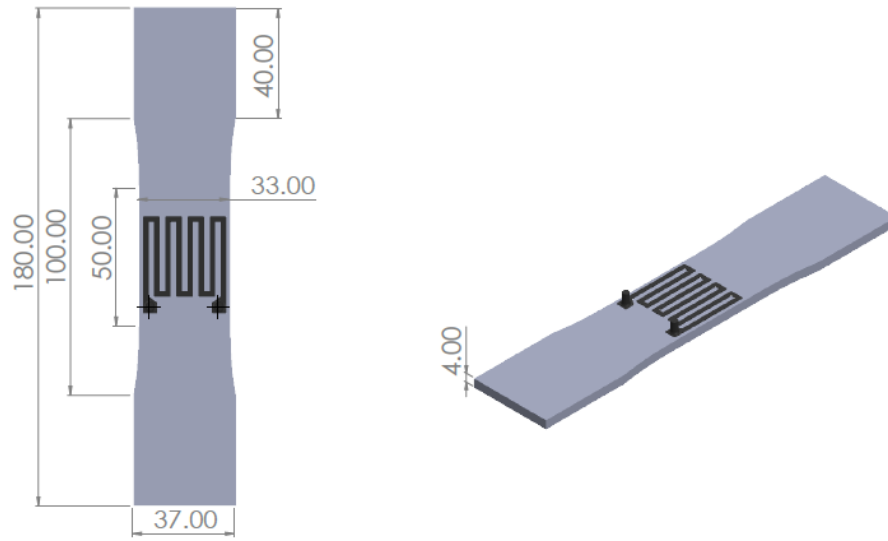


Figure 4.2 – CAD model of the DoE sample, illustrating dimensions and a representative sensor geometry configuration.

The multi-material extrusion capability of the printer enabled the integration of both structural and sensing elements in a single manufacturing step. During fabrication, the printer automatically switched between standard and conductive filaments to construct different features of the samples with high spatial accuracy. However, one significant challenge encountered was the potential for cross-contamination between materials during the switching process, given that the printer operates with a single extrusion nozzle. Such contamination could compromise the electrical conductivity of the printed sensor traces. To eliminate this risk, the printer’s flushing volume setting was empirically optimized. Multiple test prints were conducted in which the extruded traces were visually examined



for residual material from the previously used filament. It was observed that a flushing volume of  $675 \text{ mm}^3$  provided near-complete purging of the nozzle. To ensure absolute elimination of cross-contamination, an additional margin was introduced, bringing the final flushing volume setting to  $800 \text{ mm}^3$ . This conservative approach guaranteed the purity of the conductive paths throughout the DoE sample set.

The test samples were first modeled using SolidWorks<sup>®</sup> computer-aided design (CAD) software. These tensile test specimens were specifically designed to accommodate surface-integrated, strain-gauge-shaped piezoresistive sensors.

The CAD models were exported as STL files and imported into the Bambu Lab slicer software, which generated the corresponding G-code used by the 3D printer. The samples were subsequently fabricated using a Bambu Lab X1E 3D printer in Smart Structures laboratory at Federal University of Itajubá. Each specimen was printed with out-of-plane terminal features on the sensors to facilitate electrical connections during data acquisition. Figure 4.3 shows the Bambu Lab X1E printer with its enclosed printing chamber, along with the samples being printed.

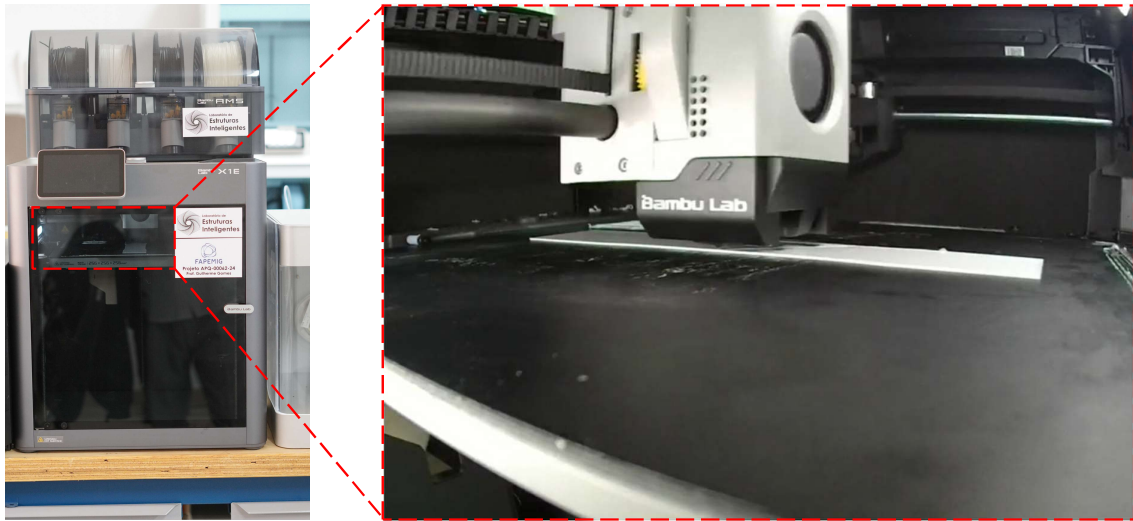


Figure 4.3 – Bambu Lab X1E Carbon Combo 3D printer with enclosed printing chamber and samples being printed.

All samples were printed in accordance with the DoE matrix, capturing the combinations of trace width, inter-trace distance, number of end loops, and infill patterns. Representative images of the printed samples are shown in Figure 4.4.



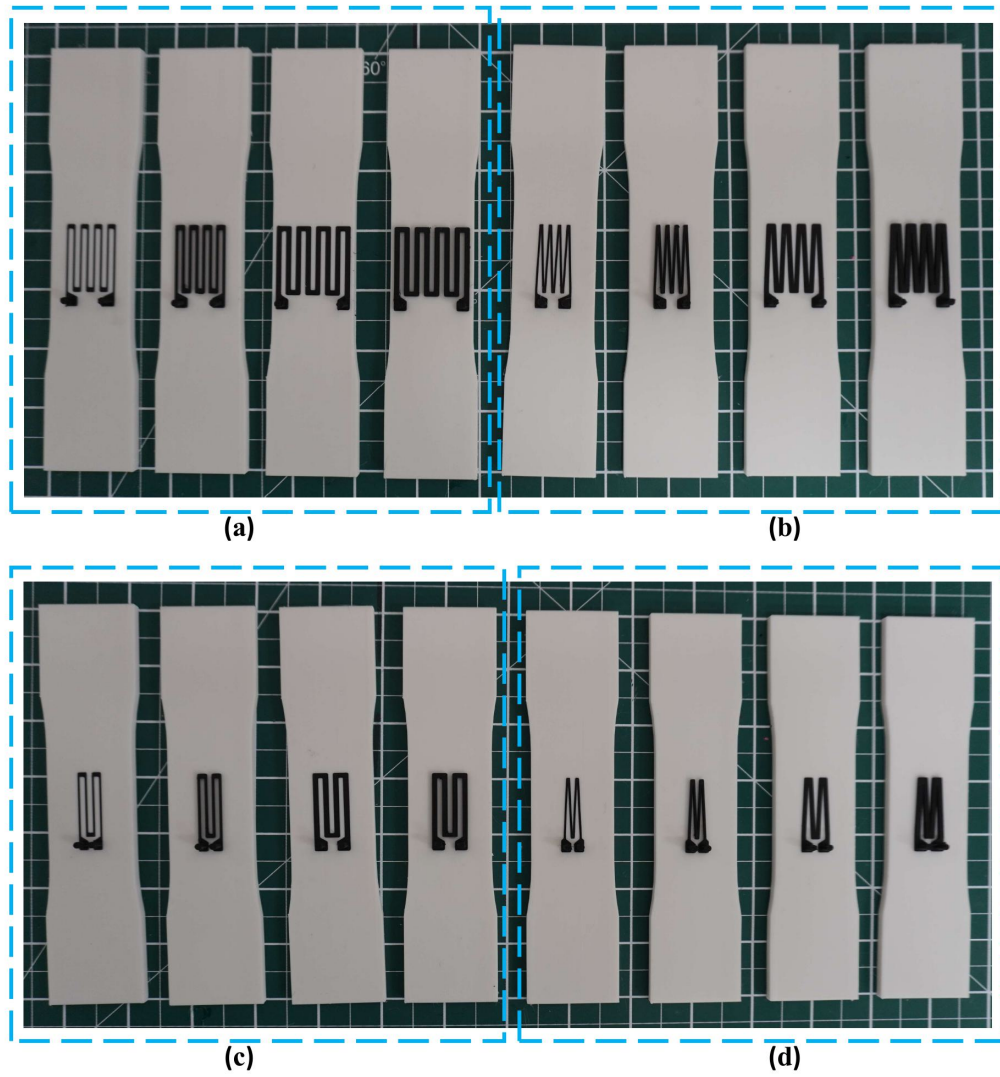


Figure 4.4 – 3D printed DoE test samples: (a) Four end loops and 2 mm inner inter-trace distance; (b) Four end loops and 0 mm inner inter-trace distance; (c) Two end loops and 2 mm inner inter-trace distance; (d) Two end loops and 0 mm inner inter-trace distance.

#### 4.3.4 Experimental Setup

Following fabrication, the test samples were subjected to simultaneous mechanical and electrical testing to evaluate the piezoresistive response under tensile loading. The mechanical tests were carried out using an Instron 34TM-10 universal testing machine (UTM), equipped with a 10 kN load cell and controlled via Instron’s proprietary Bluehill software. The machine was configured to apply a quasi-static monotonic tensile load at a constant crosshead speed of 5 mm/min until the failure of the specimen. The UTM automatically recorded mechanical parameters including time, displacement, strain, load, and stress, and exported them in comma-separated values (CSV) format for post-processing.

In parallel, electrical data acquisition was performed using a RIGOL DM858E digital multimeter. The multimeter was selected for its capability to directly and accurately

measure electrical resistance without the need for auxiliary signal conditioning circuits, thereby reducing complexity and potential sources of error in the measurement chain. The electrical terminals of the embedded piezoresistive sensors were connected to the multimeter via the integrated out-of-plane contact features fabricated during the printing process. The experimental setup showing the universal testing machine with the mounted sample connected to the electrical data acquisition system is presented in Figure 5.11.

The multimeter was interfaced with a computer, and a custom Python script was developed to automate the acquisition and processing pipeline. The script was designed to isolate the required resistance signal, compute the relative change in resistance ( $\Delta R/R$ ), display real-time plots of both resistance and  $\Delta R/R$  versus time, and save all relevant data in CSV format for further analysis.

To establish the relationship between mechanical deformation and electrical response, the time stamps recorded by both the UTM and the electrical DAQ system were synchronized. This alignment allowed for point-by-point matching of mechanical strain values with corresponding  $\Delta R/R$  readings. From this synchronized dataset, the plot of  $\Delta R/R$  as a function of strain was generated for each sample.

The gauge factor (GF) of the piezoresistive sensor, which quantifies its sensitivity to mechanical strain, was evaluated using the standard expression:

$$\text{GF} = \frac{\Delta R/R}{\varepsilon} \quad (4.1)$$

where  $\Delta R/R$  is the relative change in resistance and  $\varepsilon$  is the corresponding mechanical strain, obtained from the UTM. The GF was computed from the slope of the linear portion of the  $\Delta R/R$  versus strain curve. In this study, GF evaluation was used to characterize the strain sensitivity of each sensor configuration as part of the performance assessment.

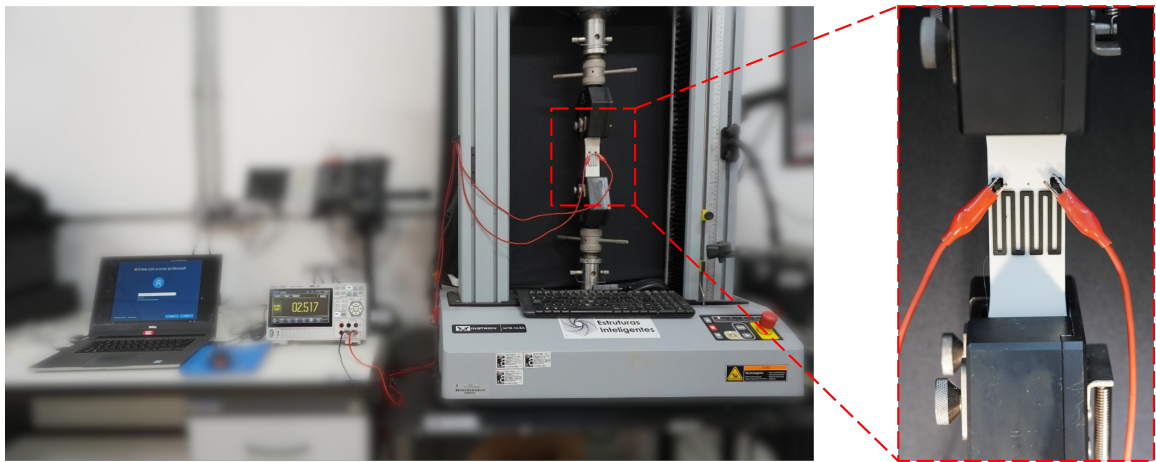


Figure 4.5 – Experimental setup showing the universal testing machine with the mounted sample connected to the electrical data acquisition system.

### 4.3.5 Baseline Experimental Phase: Influence of Sensor Embedding Depth

To establish the foundational behavior of the additively manufactured CPLA piezoresistive strain sensor prior to the main DoE study, a baseline investigation was performed to quantify the influence of embedding depth on piezoresistive performance. Using the same trace geometry, materials, and printing system described in the previous subsections, three integration configurations were fabricated:

1. **Surface-integrated:** sensor trace printed on the top surface.
2. **Partially embedded (sub-surface):** sensor trace printed flush with the upper interface.
3. **Fully embedded:** sensor trace printed at mid-thickness within the PLA host.

All samples were printed on the Bambu Lab X1E Carbon Combo using identical processing parameters. The mechanical and electrical characterization followed the same procedure as detailed previously, using synchronized UTM and multimeter acquisition for strain and resistance measurements.

Figure 4.6 illustrates the three integration strategies with the CAD models shown in Figure 4.6a and printed samples shown in Figure 4.6b, while the corresponding responses are reported in Section 4.4.1. The variables extracted from these tests include Gauge Factor, linearity, and maximum working strain.

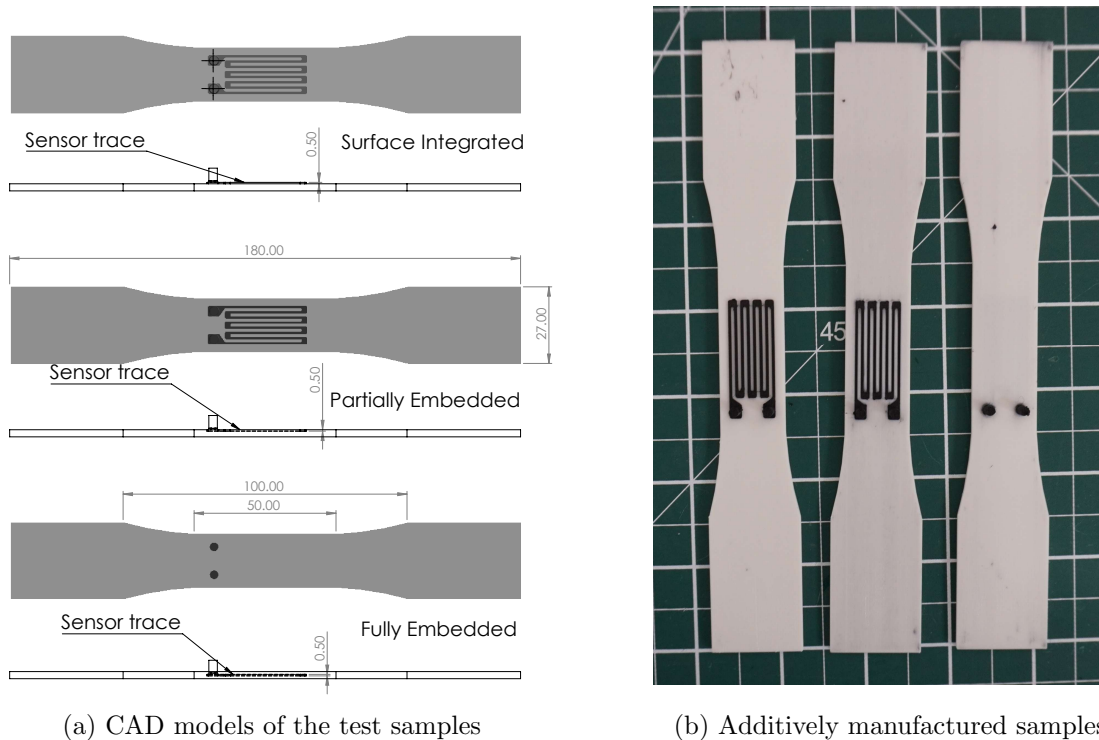


Figure 4.6 – Images of test samples showing the three integration strategies

This preliminary phase served two purposes: (i) to evaluate how strain-transfer mechanisms are affected by embedding depth, and (ii) to identify the most favorable integration strategy for subsequent geometric optimization using DoE.

#### 4.3.6 Optimization Problem Formulation

The optimization problem involves both continuous and discrete design variables. The continuous variables are defined as  $x_1 = w_1$ ,  $x_2 = w_2$ , and  $x_3 = t$ , representing the width, thickness, and material thickness of the sensor, respectively. The discrete integer variable is  $x_4 = N$ , which represents the number of sensor layers. Additionally, the categorical variable corresponding to the sensor integration type is represented using three binary variables:  $x_5 = \text{surface-rectilinear}$ ,  $x_6 = \text{surface-aligned}$ , and  $x_7 = \text{embedded}$ . These categorical variables are constrained such that exactly one of them takes the value 1 in any feasible design configuration, ensuring only one sensor integration type is chosen.

Thus, the full design vector is expressed as:

$$\mathbf{X} = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7\}.$$

The multi-objective optimization problem aims to simultaneously maximize three key performance metrics, which are defined as follows:

$$\begin{aligned} \text{Maximize:} \quad & \mathcal{F}(\mathbf{X}) = \{\mathcal{F}_1(\mathbf{X}), \mathcal{F}_2(\mathbf{X}), \mathcal{F}_3(\mathbf{X})\} \\ \text{where:} \quad & \mathcal{F}_1(\mathbf{X}) = \text{Gauge Factor (GF)}, \\ & \mathcal{F}_2(\mathbf{X}) = \text{Maximum Strain } (\varepsilon_{\max}), \\ & \mathcal{F}_3(\mathbf{X}) = \text{Elastic Modulus } (E). \end{aligned} \tag{4.2}$$

The optimization problem is subject to the following constraints on the design variables:

$$h_1(\mathbf{X}) : x_5 + x_6 + x_7 = 1, \quad x_5, x_6, x_7 \in \{0, 1\}, \tag{4.3}$$

$$0.8 \leq x_1 \leq 2.0, \tag{4.4}$$

$$0.0 \leq x_2 \leq 2.0, \tag{4.5}$$

$$0.2 \leq x_3 \leq 1.2, \tag{4.6}$$

$$2 \leq x_4 \leq 4, \quad x_4 \in \mathbb{Z}. \tag{4.7}$$

This formulation defines a mixed-integer, multi-objective optimization problem (MI-MOOP) over a constrained, mixed-variable design space. The objective functions  $\mathcal{F}_i(\mathbf{X})$  are evaluated based on experimental data and are subject to the defined design constraints.

A two-stage methodology was adopted to solve the MI-MOOP defined previously. First, surrogate models were developed from experimental data to create computationally

efficient approximations of the objective functions. Second, these models were used within a multi-objective optimization algorithm to identify the set of optimal solutions.

To map the design vector  $\mathbf{X}$  to the performance metrics  $\mathcal{F}(\mathbf{X})$ , a set of eight different regression methods was evaluated for their predictive accuracy. The algorithms considered are listed in Table 4.5.

Each model was trained using the experimental dataset, where the categorical integration type was encoded via one-hot encoding as detailed in Eq. (4.3). To evaluate the performance of each model, the coefficient of determination ( $R^2$ ) was calculated, and the model yielding the highest validation  $R^2$  was selected as the objective function evaluator in the optimization stage. The algorithms were implemented in MATLAB and optimized using the hiperparameters defined in Table 4.5.

Table 4.5 – Summary of Algorithms and Hyperparameters Used in Surrogate Model Development

| Algorithm | Key Hyperparameters                                                                                                      |
|-----------|--------------------------------------------------------------------------------------------------------------------------|
| GPR       | Kernel Function: Squared Exponential<br>Hyperparameter Optimization: Auto<br>Acquisition Function: Expected Improvement  |
| SVM       | Kernel Function: Default<br>Hyperparameter Optimization: Auto                                                            |
| DT        | Criterion: MSE (Mean Squared Error)<br>Hyperparameter Optimization: Auto                                                 |
| LR        | Optimization Method: Auto<br>Hyperparameter Optimization: Auto                                                           |
| NLR       | Model: Nonlinear Polynomial Fit<br>Hyperparameter Optimization: None                                                     |
| ENS       | Number of Trees: Auto<br>Hyperparameter Optimization: Auto                                                               |
| ANN       | Hidden Layers: 30 Neurons<br>Training Data Split: 70% Training, 15% Validation, 15% Test<br>Activation Function: Sigmoid |
| RSM       | Model Type: Quadratic Polynomial<br>Hyperparameter Optimization: None                                                    |

The models were trained using the full dataset, which was shuffled for reproducibility. The predictive performance of each model was assessed based on the coefficient of determination ( $R^2$ ), and the model with the highest  $R^2$  on the validation set was selected for the optimization process. This surrogate model evaluation allows for an efficient exploration of the design space in the subsequent optimization phase.

The selected surrogate model was then used in the multi-objective optimization problem formulation to maximize the key performance metrics (Gauge Factor, Maximum Strain, and Elastic Modulus) and identify the optimal sensor design configuration.

The optimization was performed using the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm, implemented in MATLAB. The best-performing surrogate model from the previous stage was used to evaluate the fitness of each particle in the swarm. The key MOPSO hyperparameters were configured as shown in Table 4.6.

Table 4.6 – Key Hyperparameters of the MOPSO Algorithm

| Hyperparameter        | Value                         |
|-----------------------|-------------------------------|
| Population Size       | 700 (100 per design variable) |
| Maximum Generations   | 100                           |
| Inertia Weight        | 0.4                           |
| Cognitive Coefficient | 2.0                           |
| Social Coefficient    | 2.0                           |

The algorithm was configured to handle the mixed-variable constraints defined in Eqs. (4.3)-(4.7).

The MOPSO algorithm yields a set of non-dominated solutions known as the Pareto front, which illustrates the optimal trade-offs among the three conflicting objectives. To select a single, balanced solution from this front, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) was employed. TOPSIS identifies the solution that is geometrically closest to the ideal objective vector and farthest from the nadir vector. The design vector  $X_{\text{opt}}$  corresponding to this solution was identified as the final optimal design configuration. These optimum solutions were eventually experimentally validated.

## 4.4 Results and Discussion

This section presents the results of the experimental characterization, surrogate modeling, and multi-objective optimization, based on the full DoE dataset presented in Table A.1. A primary analysis of the data immediately reveals that the sensor’s performance operates in two distinct piezoresistive regimes. A clear categorical distinction is observed: the configurations in DoE 3 consistently yield a Gauge Factor (GF) an order of magnitude higher (ranging from 26.6 to 81.16) than those in DoE 1 and DoE 2 (ranging from 0.43 to 5.54). This categorical factor, likely representing a fundamental change in sensor design (e.g., surface-integrated vs. embedded), is thus the single most dominant variable influencing sensitivity.

Further analysis within these regimes highlights complex and, in some cases, inverted trends related to the geometric design variables. For instance, the effect of trace thickness

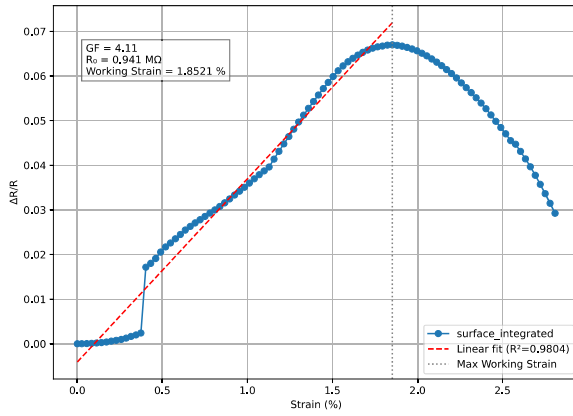
( $t$ ) is inverted between the two regimes. For the low-GF configurations (DoE 1 & 2), there is a strong inverse correlation where increasing trace thickness (e.g., from 0.2 mm to 1.2 mm) causes the GF to collapse. This trend, which supports the validation findings in Section 4.4.7, is completely absent and even reverses in the high-GF regime (DoE 3). Similarly, the effect of the number of end loops ( $N$ ) is non-intuitive; the highest performing sensor in the entire dataset ( $\text{GF} = 81.16$ ) was achieved with the *lowest* number of end loops ( $N = 2$ ), suggesting that simply increasing this geometric parameter can be detrimental to its piezoresistive sensitivity.

Building on this analysis of the fundamental piezoresistive behaviors and trade-offs, this section then details the development of the surrogate models and the multi-objective optimization process used to navigate this complex design space and identify the optimal sensor geometries.

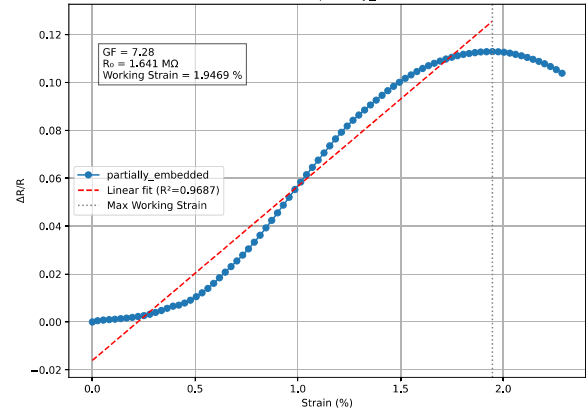
#### 4.4.1 Results: Phase I - Effect of Embedding Depth

Figure 4.7 shows the characteristic  $\Delta R/R$  vs strain curves for the different integration strategies. Figures 4.7a, 4.7b and 4.7c present the piezoresistive responses for surface-integrated, partially embedded, and fully embedded samples respectively. All configurations exhibit a linear piezoresistive response, but with clear differences in sensitivity.

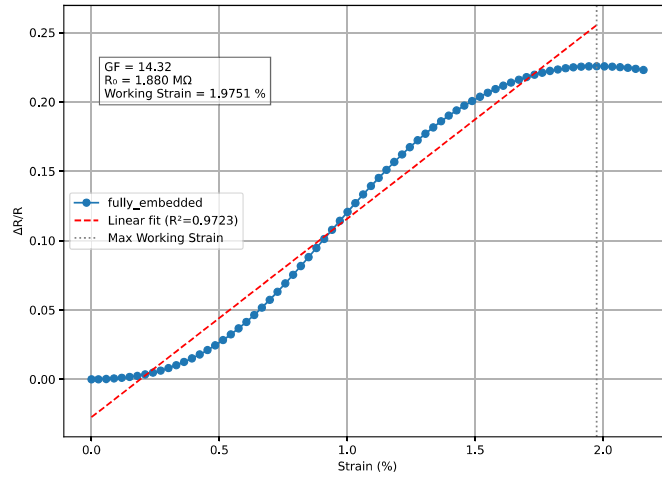




(a) Surface-integrated sensor.



(b) Partially embedded sensors.



(c) Fully embedded sensor.

Figure 4.7 – The characteristic  $\Delta R/R$  vs strain curves for the three integration strategies

Table 4.7 – Sensor geometry and performance summary for the three integration strategies.

| Parameter                   | Surface-integrated | Partially embedded | Fully embedded |
|-----------------------------|--------------------|--------------------|----------------|
| $w_1$ (mm)                  | 0.80               | 0.80               | 0.80           |
| $w_2$ (mm)                  | 1.00               | 1.00               | 1.00           |
| $t$ (mm)                    | 0.50               | 0.50               | 0.50           |
| $N$                         | 4                  | 4                  | 4              |
| L.P. (mm)                   | 6.40               | 14.40              | 20.80          |
| $A_{tr}$ (mm <sup>2</sup> ) | 160                | 360                | 520            |
| $A_t$ (mm <sup>2</sup> )    | 236.35             | 465.97             | 693.54         |
| GF                          | 4.11               | 7.28               | 14.32          |
| $R^2$                       | 0.9804             | 0.9687             | 0.9723         |
| $\varepsilon_{\max}$ (%)    | 1.85               | 1.95               | 1.98           |



**Notes:** L.P.: Effective loaded perimeter of the sensor trace.  $A_{tr}$ : Active area of the sensor trace.  $A_t$ : Total active sensor area.

Table 4.7 summarizes the extracted performance metrics. The Gauge Factor increases monotonically with embedding depth: from 4.11 (surface) to 7.28 (sub-surface) and 14.32 (fully embedded). Linearity remained high across all cases ( $R^2 > 0.96$ ), and the maximum working strain was similar ( $\varepsilon_{\max} \approx 1.9\%$ ).

Figures 4.8 and 4.9 further reveal that total active area ( $A_t$ ) and loaded perimeter (L.P.) increase substantially with deeper embedding. This trend correlates strongly with the observed GF enhancement, indicating that the larger sensor-matrix contact interface improves strain-transfer efficiency.

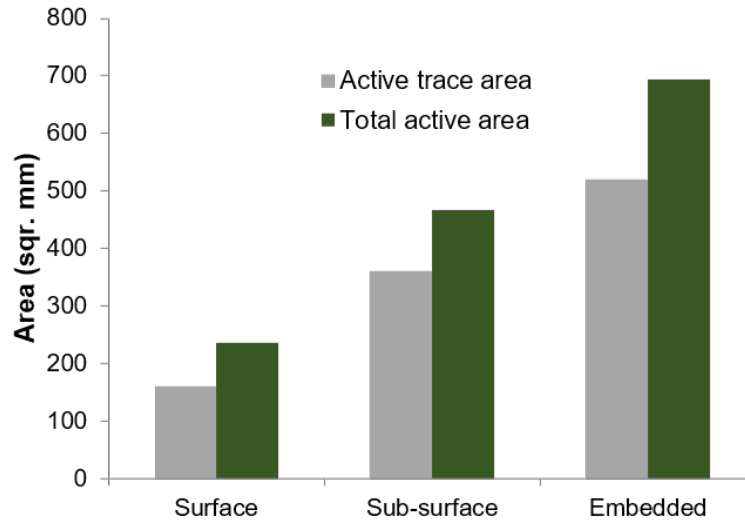


Figure 4.8 – Active trace area ( $A_{tr}$ ) and total active area ( $A_t$ ) for surface, sub-surface, and embedded sensors.

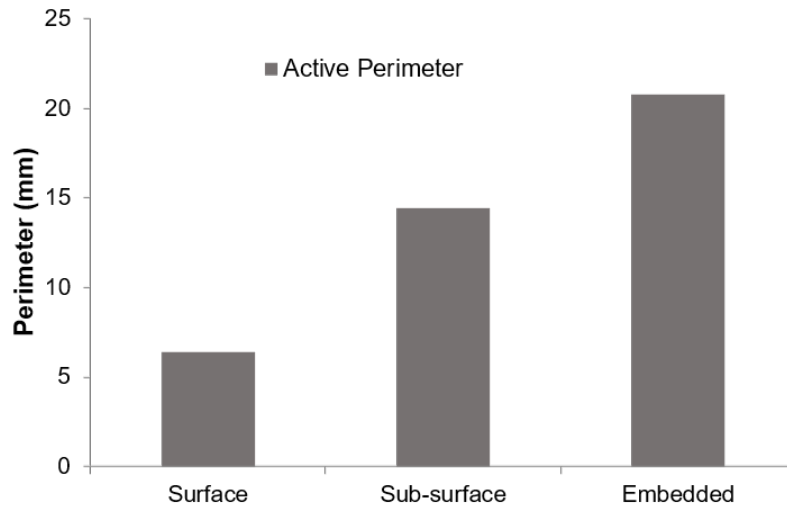


Figure 4.9 – Loaded perimeter ( $L.P.$ ) as a function of sensor embedding depth.

These results established the embedded configuration as the most effective for high-sensitivity sensing. Therefore, the DoE and subsequent optimization presented in the remaining parts of this section were performed using fully embedded sensors (for embedded configurations), enabling the geometry-dependent behavior to be isolated without confounding effects from depth variation.

#### 4.4.2 Results: Phase II - Piezoresistive Characterization of Sensor Types

The three categorical factors; rectilinear infill, aligned infill, and fully embedded, formed distinct experimental subgroups (DoE 1, 2, and 3). Representative piezoresistive response curves for a sample from each subgroup are shown in Figure 4.10, highlighting the profound impact of the sensor's integration type on its performance.

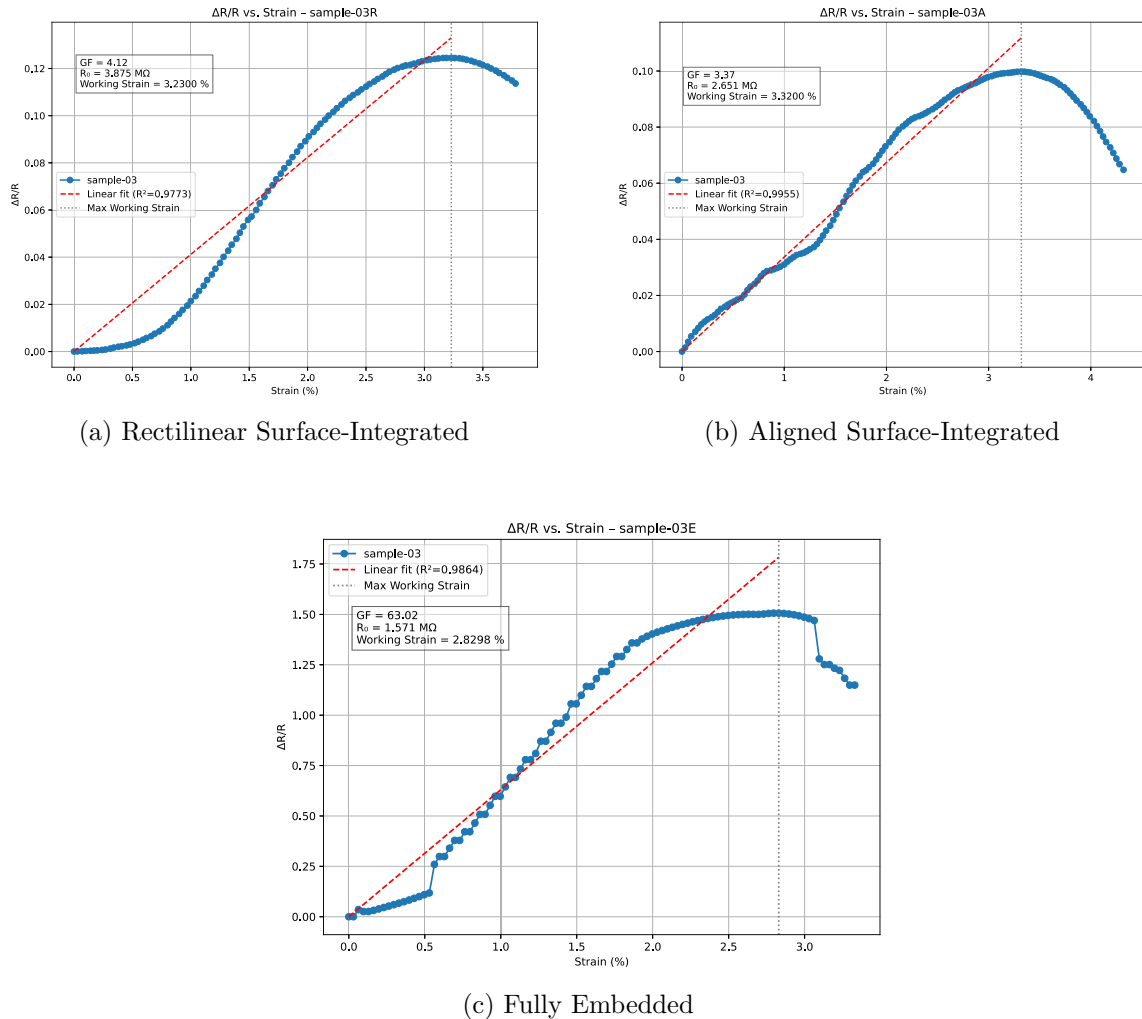


Figure 4.10 – Representative piezoresistive response ( $\Delta R/R$  vs. Strain) for samples of the same configuration from the three experimental subgroups, illustrating their distinct behaviors.

The characteristic shapes of these curves are dictated by the distinct load transfer

mechanisms inherent to each integration method. For the surface-printed configurations, the load is transferred to the sensor predominantly through shear at a single interface. This makes the sensor vulnerable to damage, such as delamination or micro-cracking, at the closest layer to the load transfer interface under continued strain. This behavior can lead to the downward trend in resistance observed after the initial peak. Conversely, the fully embedded sensor exhibits a robust, monotonic increase in resistance with strain. This superior performance is attributed to a significantly larger load transmission interface, as the entire sensor body is in intimate contact with the surrounding host structure. This configuration distributes shear stresses more effectively, constrains the sensor to prevent localized failure, and allows the piezoresistive network to respond consistently up to the point of material failure.

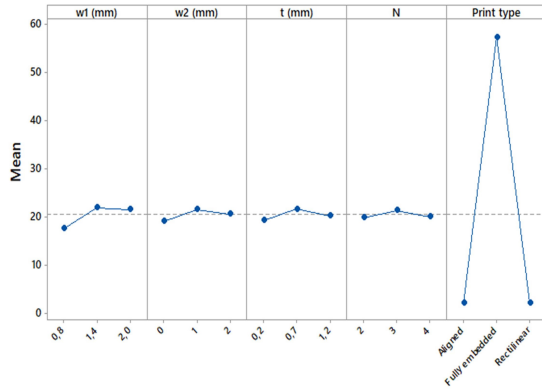
A striking difference is observed in the sensitivity. The two surface-integrated sensors, rectilinear and aligned (Figures 4.10a and 4.10b), exhibit relatively low gauge factors (GF) of 2.52 and 3.31, respectively. Their response is initially characterized by high linearity ( $R^2 > 0.98$ ). In contrast, the fully embedded sensor (Figure 4.10c) demonstrates a dramatically higher GF of 45.84, an order of magnitude greater than its surface-integrated counterparts. This finding is consistent across the DoE, as highlighted in the main effects analysis (see Section 4.4.3), and heavily influences the subsequent optimization.

#### 4.4.3 Sensitivity Analysis

A comprehensive sensitivity analysis was conducted to quantify the influence of both geometric variables and the categorical integration strategy on the sensor performance. The analysis employed ANOVA models generated in *Minitab* and was carried out independently for each response variable. Main effects plots, standardized Pareto charts, and residual diagnostics were used to interpret the statistical behavior and to validate the underlying assumptions.

Across all four responses, the categorical factor *Print type* (surface-integrated, aligned surface-integrated, fully embedded) consistently emerged as the dominant source of variation. This effect is particularly striking for GF, where embedded sensors produced a substantial and statistically significant increase in sensitivity compared to both surface-integrated configurations. As shown in Figure 4.11a, the transition from surface-mounted to embedded printing yields a steep rise in GF, corroborating the trends identified previously in Section 4.4. The Pareto chart in Figure 4.12a reinforces this observation, as *Print type* overwhelmingly exceeds the significance threshold. This behavior reflects the improved interfacial load transfer enabled by embedding, whereby the conductive network undergoes more uniform mechanical deformation.

Although *Print type* exerted the largest influence, several geometric parameters demonstrated meaningful, though secondary, contributions to specific responses. For GF, the trace width  $w_1$  was identified as a statistically significant main effect ( $p = 0.000$ ),



(a) Main effects for Gauge Factor (GF)

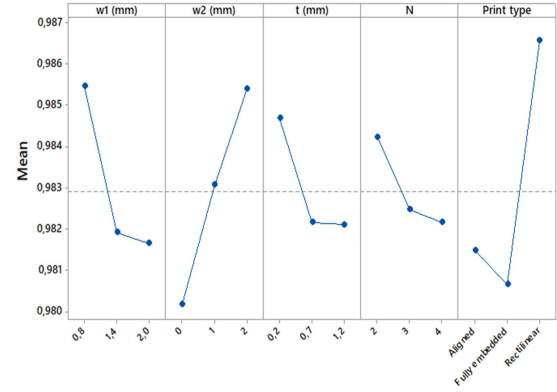
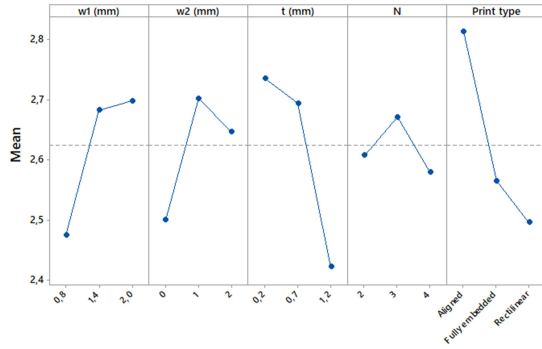
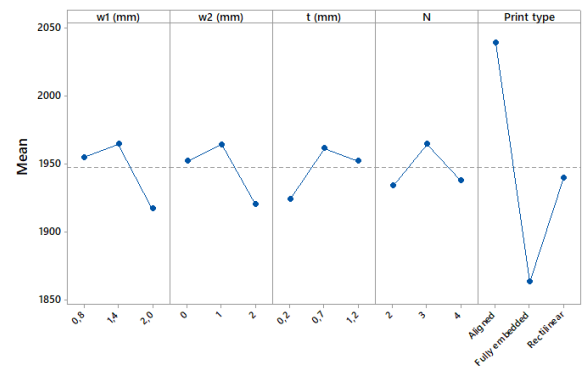
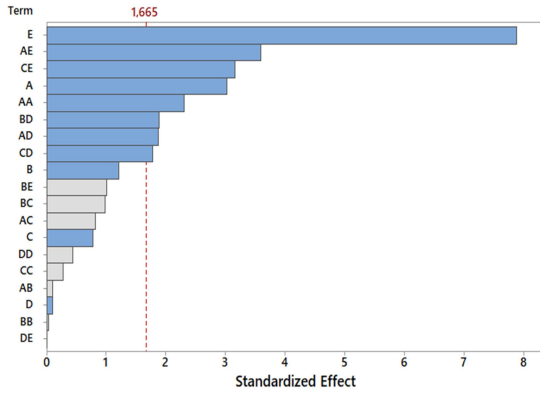
(b) Main effects for Linearity ( $R^2$ )(c) Main effects for Max. Strain ( $\epsilon_{max}$ )(d) Main effects for Elastic Modulus ( $E$ )

Figure 4.11 – Main effects plots for each of the four response variables, illustrating the mean effect of each design variable on the output.

indicating that variations in conductive path width modulate how deformation propagates through the sensing element. The remaining geometric parameters ( $w_2$ ,  $t$ , and  $N$ ) did not show significant individual effects on GF; however, several important two-way interactions, particularly involving  $w_1$  and  $t$  with  $Print\ type$  were significant. These interactions indicate that the influence of geometric parameters is strongly dependent on whether the sensor is printed on the surface or embedded, highlighting the coupled nature of geometry and embedding depth.

Linearity ( $R^2$ ) was generally insensitive to the design variables, with all tested configurations producing highly linear piezoresistive responses ( $R^2 > 0.93$ ). ANOVA identified  $Print\ type$  as the only significant categorical factor, while  $w_1$  did not exhibit a significant main effect. A mild nonlinear contribution was detected through a significant  $w_1^2$  term, although its practical impact remained small. These observations are consistent with the minimal variation seen in Figure 4.11b and justify the exclusion of  $R^2$  from subsequent optimization activities.



(a) Pareto chart for Gauge Factor (GF)

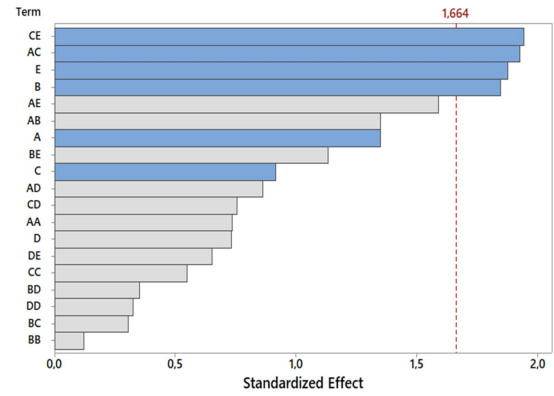
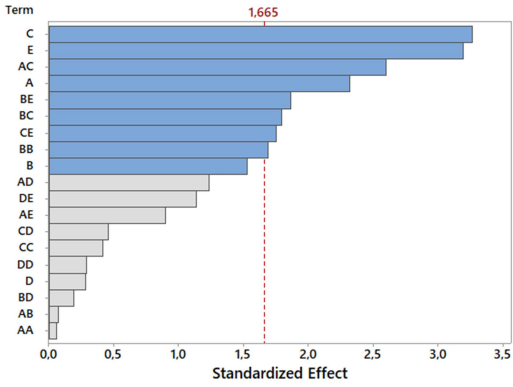
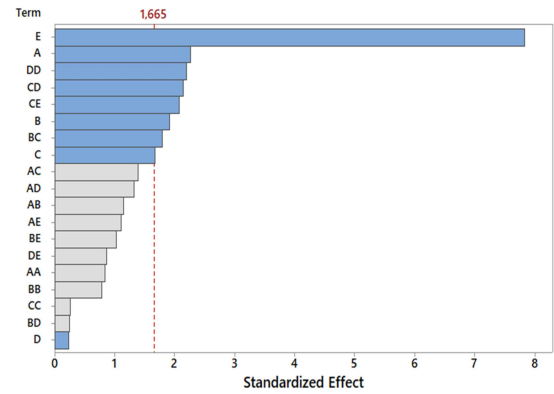
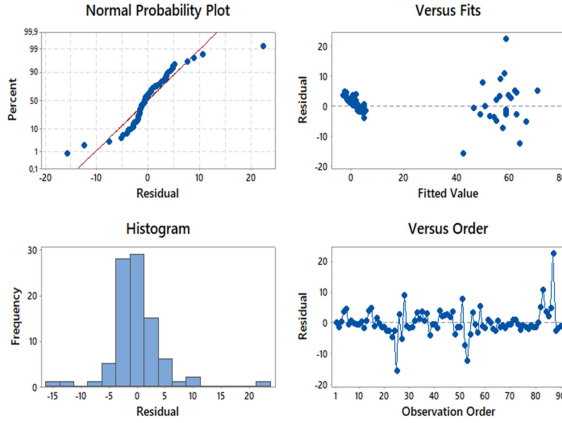
(b) Pareto chart for Linearity ( $R^2$ )(c) Pareto chart for Max. Strain ( $\varepsilon_{\max}$ )(d) Pareto chart for Elastic Modulus ( $E$ )

Figure 4.12 – Pareto charts showing standardized effects for each response. Effects exceeding the red reference line are statistically significant,  $p < 0.05$  (legend:  $A = w_1$ ,  $B = w_2$ ,  $C = t$ ,  $D = N$  and  $E = \text{print type}$ ). A gray bar represents a term not in the model.

In contrast,  $\varepsilon_{\max}$  exhibited a stronger dependency on geometric characteristics, with the trace thickness  $t$  emerging as a highly significant factor ( $p = 0.000$ ). Increasing  $t$  reduced the maximum allowable strain, which can be attributed to the increased stiffness introduced by the thicker conductive region. *Print type* also significantly influenced  $\varepsilon_{\max}$ , and several interactions such as  $w_1 \times t$ ,  $w_2 \times t$ , and  $t \times \text{Print type}$  were statistically significant, demonstrating that the strain limit is governed jointly by geometric design and embedding strategy. It is believed that the observed statistical interactions between trace width ( $w_1$ ) and thickness ( $t$ ) are driven by interfacial fidelity. The fully embedded sensors have a different bonding interface compared to surface sensors, which alters how the geometry transfers strain through the conductive network. The number of loops  $N$  was not statistically significant as a main effect, although small trends were visually evident.

The elastic modulus  $E$  was similarly dominated by *Print type*, with embedded sen-

sors reducing global stiffness due to local compliance and the presence of multi-material interfaces. The trace thickness  $t$  and its quadratic term were also significant contributors, confirming that the geometry of the conductive path alters local stiffness distributions. Other geometric variables ( $w_1$ ,  $w_2$ , and  $N$ ) exhibited no significant main effects, though interactions involving  $t$  and *Print type* were relevant. The trends observed in Figure 4.11d align with these findings.



(a) Residual plots for Gauge Factor (GF)

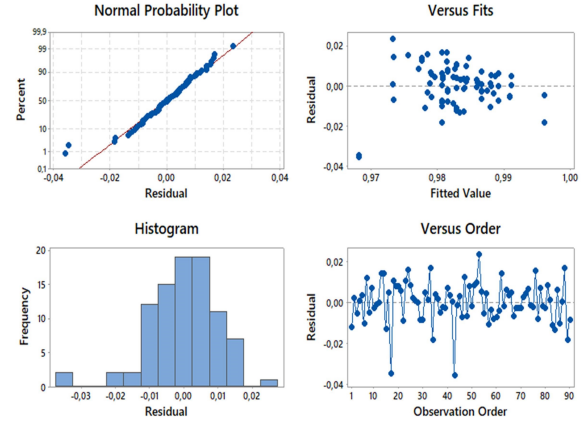
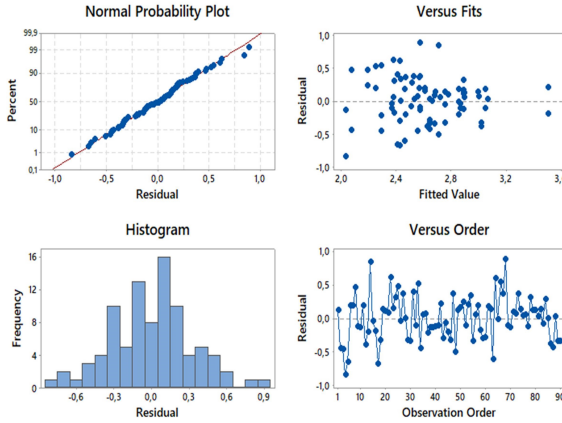
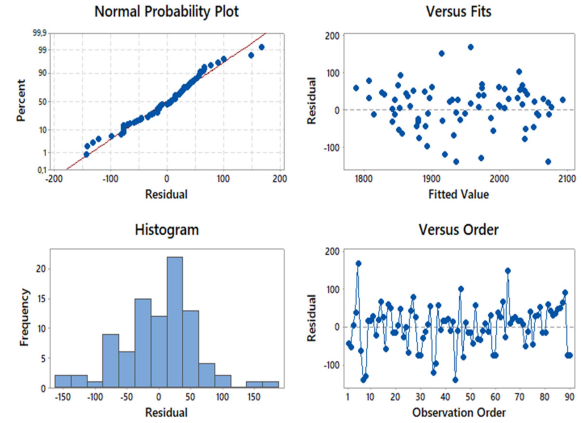
(b) Residual plots for Linearity ( $R^2$ )(c) Residual plots for Max. Strain ( $\varepsilon_{\max}$ )(d) Residual plots for Elastic Modulus ( $E$ )

Figure 4.13 – Residual plots validating ANOVA model assumptions for all four responses.

Residual analyses, as presented in Figure 4.13a - 4.13d, confirmed the adequacy of all models: no heteroscedasticity, abnormality, or influential outliers were detected, reinforcing the robustness of the ANOVA results. Overall, the sensitivity analysis reveals a clear hierarchy of influence: *Print type* is the dominant factor across all responses;  $w_1$  significantly influences GF;  $t$  strongly affects  $\varepsilon_{\max}$  and  $E$ ; several interactions involving  $t$  and *Print type* govern the detailed response behavior; and  $w_2$  remains negligible within the investigated design space. These insights guided the selection of design variables and constraints for the surrogate-based optimization presented in the next section.

#### 4.4.4 Performance of Surrogate Models

To accurately model these complex behaviors for optimization, eight different regression methods were evaluated as surrogate models. The predictive accuracy of each model, quantified by the coefficient of determination ( $R^2$ ), is summarized in Figure 4.14 and detailed in Table 4.8.

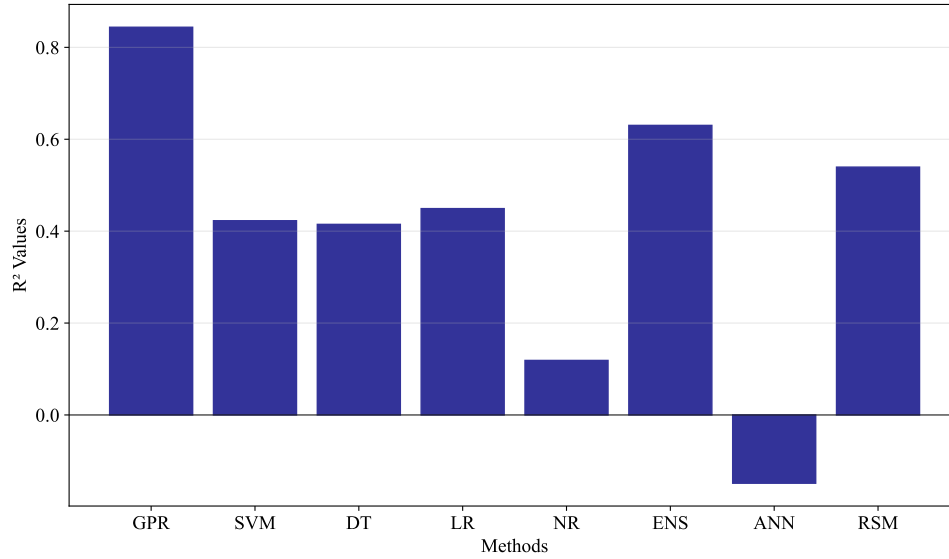


Figure 4.14 – Average  $R^2$  scores for the eight regression models evaluated.

Table 4.8 – Summary of regression analysis results ( $R^2$  scores) for different methods

| Method    | $\mathcal{F}_1 = \text{GF}$ | $\mathcal{F}_2 = \mathbf{R}^2$ | $\mathcal{F}_3 = \varepsilon_{\max}$ | $\mathcal{F}_4 = E$ |
|-----------|-----------------------------|--------------------------------|--------------------------------------|---------------------|
| GPR       | 0.9611                      | 0.9182                         | 0.4959                               | 1.0000              |
| SVM       | 0.9537                      | 0.0000                         | 0.2032                               | 0.5337              |
| DT        | 0.9685                      | 0.0556                         | 0.1015                               | 0.5336              |
| LR        | 0.9563                      | 0.0534                         | 0.2077                               | 0.5791              |
| NR        | 0.0064                      | 0.1304                         | 0.2376                               | 0.1005              |
| ENS       | 0.9703                      | 0.4181                         | 0.3918                               | 0.7407              |
| ANN       | 0.0001                      | 0.0000                         | -0.3594                              | -0.2350             |
| RSM (DoE) | 0.9874                      | 0.1020                         | 0.3728                               | 0.6955              |

Gaussian Process Regression (GPR) demonstrated the most robust performance, achieving the highest average  $R^2$  score. GPR was particularly effective at modeling the elastic modulus ( $E$ ) and the gauge factor (GF), which, as shown in Figure 4.10, varies significantly between sensor types. In contrast, the Artificial Neural Network (ANN) model performed very poorly, likely due to the limited dataset size. Based on its superior predictive accuracy, the GPR model was selected as the surrogate for the multi-objective optimization phase. A qualitative comparison of the Pareto fronts generated by all eight

models further justifies this choice, as the GPR front is among the most well-defined and least scattered (see Figure B.1 for all Pareto fronts).

#### 4.4.5 Multi-Objective Optimization

The selected GPR surrogate model was integrated with the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm to find the Pareto optimal set of solutions. The  $R^2$  scores for all the DoE configurations were found to be high (all above 0.93, with the majority at 0.98). Given this high linearity,  $R^2$  was removed as an objective, reducing the problem to three responses (GF,  $\varepsilon_{\max}$ , and  $E$ ). The resulting Pareto fronts for the two investigated weighting schemes; (a) higher weight on GF and (b) equal weights, are depicted in Figure 4.15. The red star indicates the final optimal solution selected by TOPSIS.

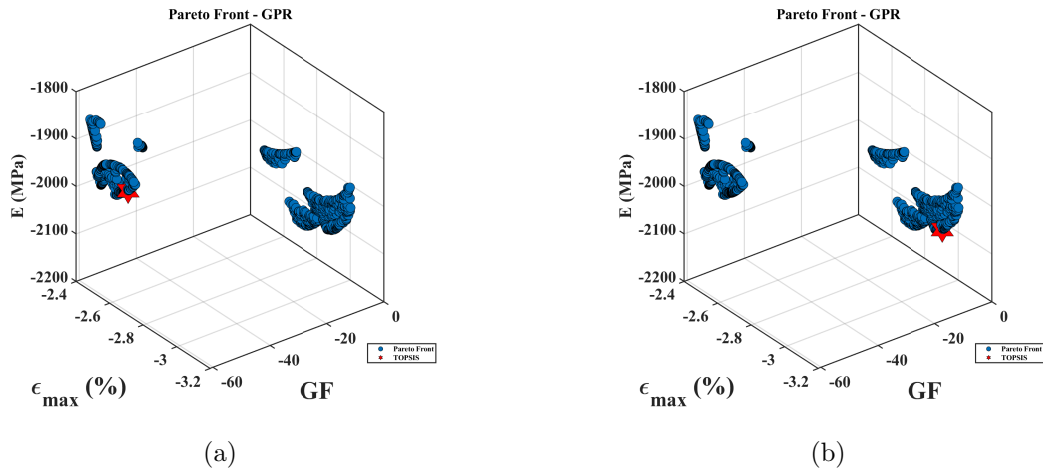


Figure 4.15 – Pareto fronts obtained from the GPR-based MOPSO for the two weighting schemes (a) 0.7 of the weight given to GF, and 0.3 shared equally between  $\varepsilon_{\max}$  and  $E$  (b) equal weight given to all the objectives.

The plots illustrate the inherent trade-offs between the objectives. The red star on each plot marks the single balanced solution selected from the front using the TOPSIS method, representing the best compromise among the conflicting objectives for that weighting scheme.

#### 4.4.6 Optimal Sensor Geometries and Validation

The final optimal design parameters corresponding to the TOPSIS solutions are presented in Table 4.9. These results highlight how the optimization objectives steer the design toward different configurations based on the behaviors observed during characterization.

When a high weight (0.70) was assigned to the gauge factor, the optimal solution converged to a Fully Embedded sensor type. This directly reflects the experimental find-



Table 4.9 – Optimal solutions obtained using TOPSIS with different weight distributions.

| Optimal Solution<br>Parameters | TOPSIS                   |                          |
|--------------------------------|--------------------------|--------------------------|
|                                | $k = [0.70, 0.15, 0.15]$ | $k = [0.33, 0.33, 0.33]$ |
| Regressor                      | GPR                      | GPR                      |
| $w_1$ (mm)                     | 2.000                    | 2.000                    |
| $w_2$ (mm)                     | 1.458                    | 1.915                    |
| $t$ (mm)                       | 0.200                    | 1.055                    |
| $N$ [-]                        | 3.000                    | 2.000                    |
| Type                           | Fully Embedded           | Aligned                  |
| GF                             | 59.097                   | 4.169                    |
| Max. strain (%)                | 2.677                    | 2.976                    |
| $E$ (MPa)                      | 1950.331                 | 2089.975                 |

ings in Section 4.1, where the embedded configuration yielded the highest sensitivity by a large margin (Figure 4.10c). The predicted GF of 59.10 represents the peak performance achievable for this design space.

Conversely, when equal weights were applied, the optimization prioritized a more balanced performance, selecting an Aligned surface-integrated sensor. This configuration sacrifices the extreme sensitivity of the embedded design for a higher predicted elastic modulus and maximum strain. This yields a more robust sensor for applications where mechanical properties are as critical as piezoresistive sensitivity. The final step involves fabricating and testing these two optimal geometries to validate their performance against the model predictions.

#### 4.4.7 Validation of Optimized Sensor Configurations

The two optimal sensor configurations predicted by the optimization model; TOPSIS 0.33 and TOPSIS 0.70, were experimentally fabricated and evaluated under quasi-static tensile loading. In addition, a third configuration, designated as *TOPSIS 0.70-scaled*, was introduced as a post-optimization variant to address the observed stiffness reduction associated with fully embedded sensors. This variant was geometrically scaled down by 50% in the sensor trace dimensions to investigate whether the stiffness penalty could be mitigated without compromising the gauge factor.

The validation campaign combined stress-strain data from the universal testing machine with full-field strain measurements obtained via Digital Image Correlation (DIC). The representative strain fields for each configuration are shown in Figures 4.16 - 4.18, revealing consistent localization within the gauge section, confirming that the strain fields were properly captured.

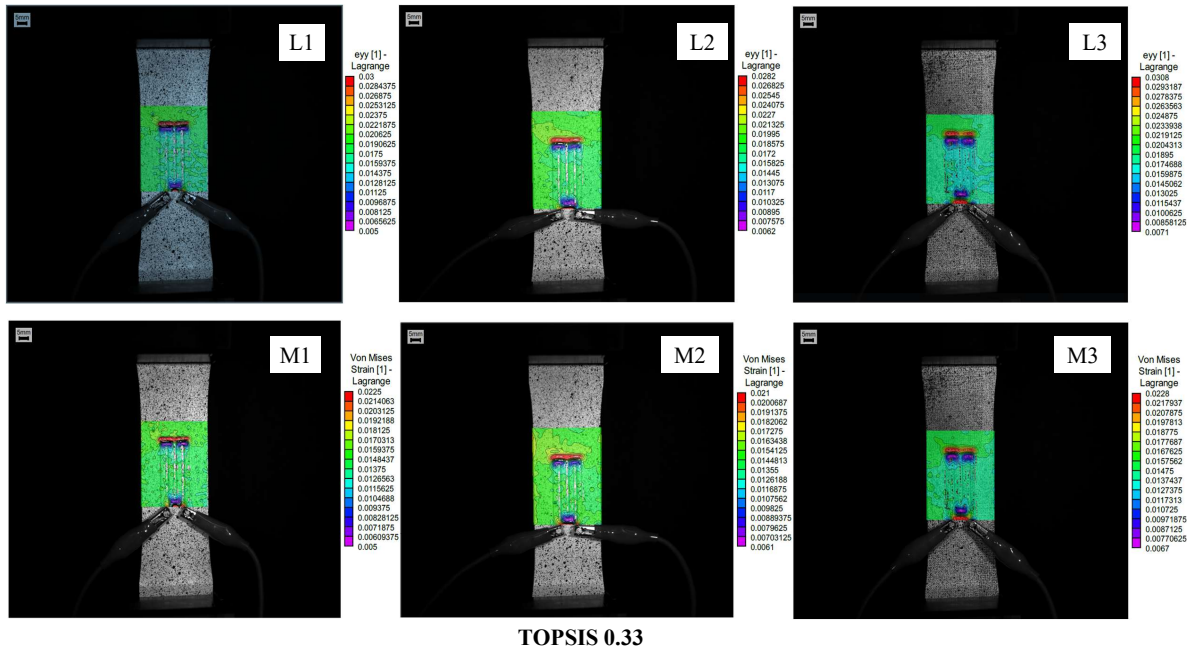


Figure 4.16 – DIC strain fields for the validated configurations for TOPSIS 0.33 ( $k = [0.33, 0.33, 0.33]$ ).

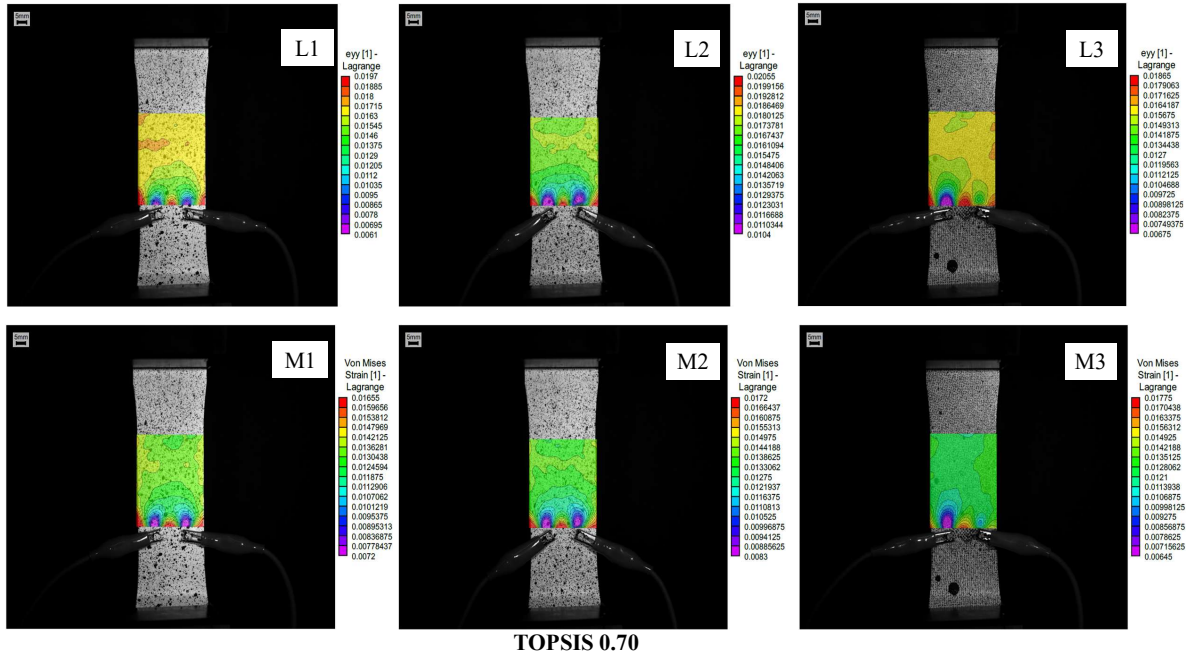


Figure 4.17 – DIC strain fields for the validated configurations for TOPSIS 0.70 ( $k = [0.70, 0.15, 0.15]$ ).

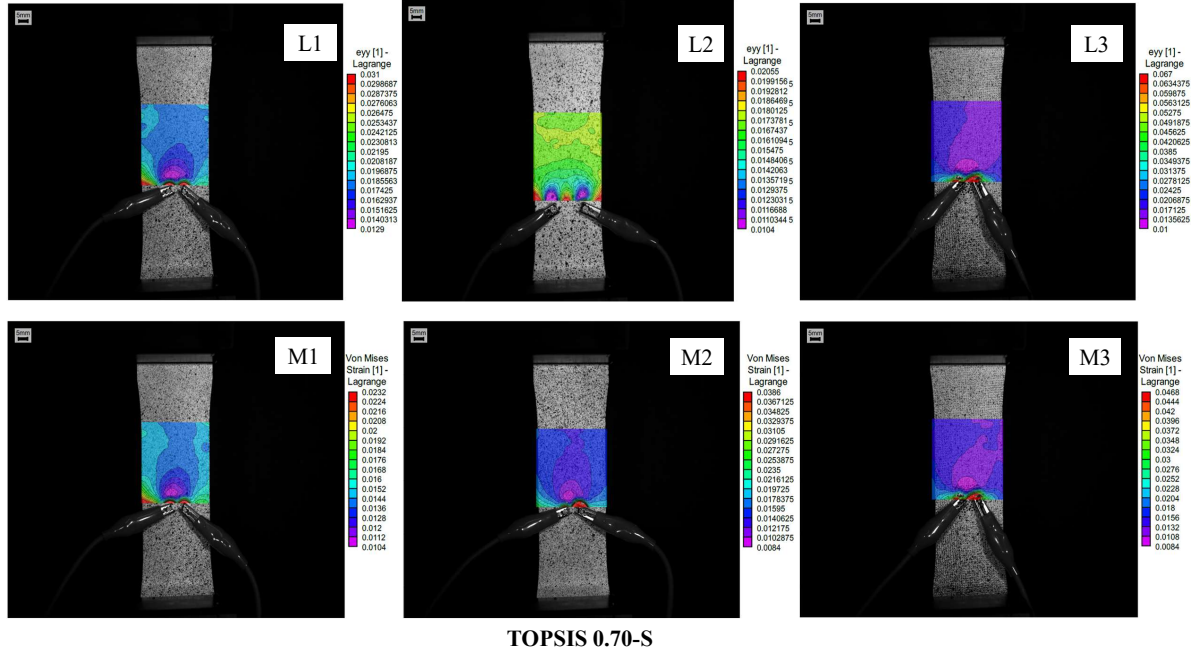


Figure 4.18 – DIC strain fields for the validated configurations for TOPSIS 0.70-scaled.

Table 4.10 summarizes the DIC-based maximum principal strain components, including the longitudinal ( $\varepsilon$ ), transverse ( $\varepsilon_{yy}$ ), and von Mises equivalent strains. For all configurations, the ratio  $\varepsilon_{yy}/\varepsilon$  ranged between 0.51 and 0.65, indicating a predominantly uniaxial stress state within the gauge section which is an essential condition for valid gauge factor evaluation.

Table 4.10 – Summary of DIC-based data and load cell data for the optimum configurations.

| Configuration      | $\varepsilon_{\max}$ (load cell) (%) | $\varepsilon_{yy,\max}$ (DIC) (%) | $\varepsilon_{v-m,\max}$ (DIC) (%) | $\varepsilon_{yy}/\varepsilon$ |
|--------------------|--------------------------------------|-----------------------------------|------------------------------------|--------------------------------|
| TOPSIS 0.33        | 3.40                                 | 2.07                              | 1.51                               | 0.61                           |
| TOPSIS 0.70        | 3.30                                 | 1.69                              | 1.39                               | 0.51                           |
| TOPSIS 0.70-scaled | 3.20                                 | 1.91                              | 1.51                               | 0.59                           |

Table 4.11 compares the experimental and predicted responses for each configuration in terms of gauge factor (GF), maximum strain, and elastic modulus ( $E$ ). The percentage difference quantifies the deviation between prediction and experiment.

A critical observation is that the deviation trend varies by configuration. For the *Aligned surface-integrated* (TOPSIS 0.33) case, the model substantially overestimated the gauge factor, suggesting that its predictive accuracy is more reliable for embedded-type sensors, consistent with the surrogate model training bias. The supposed overestimation could be verified from the DoE full data (Table A.1) where all configurations with trace thicknesses  $t$  above 1 mm performed worse in terms of GF. The *Fully embedded* (TOPSIS 0.70) sensor demonstrated good agreement in the maximum strain and modulus, meanwhile a noticeable GF deviation of about 13.3% above the predicted value

Table 4.11 – Comparison between experimental and predicted results for the optimum solutions.

| Parameter                | TOPSIS 0.33 |        |        | TOPSIS 0.70 |        |        | TOPSIS 0.70-scaled |        |        |
|--------------------------|-------------|--------|--------|-------------|--------|--------|--------------------|--------|--------|
|                          | Exp.        | Pred.  | % Err. | Exp.        | Pred.  | % Err. | Exp.               | Pred.  | % Err. |
| GF                       | 1.33        | 4.17   | 68.1↓  | 66.95       | 59.10  | 13.3↑  | 62.12              | 59.10  | 5.1↑   |
| $\varepsilon_{\max}$ (%) | 3.280       | 2.976  | 10.2↑  | 2.580       | 2.677  | 3.6↓   | 2.680              | 2.677  | 0.1↑   |
| $E$ (MPa)                | 2084.3      | 2089.9 | 0.3↓   | 2067.3      | 1950.3 | 6.0↑   | 2179.9             | 1950.3 | 11.8↑  |

was recorded. This discrepancy is considered to be condition-dependent, likely arising from subtle imperfections intrinsic to the conductive filament (composition and dispersion quality) from which the sensor is printed. Although the reported value represents the average of three replicates, such imperfections may have introduced consistent bias across measurements. The analyses of these factors are outside the scope of this study and hence were not explicitly accounted for in the optimization model. The performance of its down-scaled counterpart (TOPSIS 0.70-scaled) supports this conclusion.

The down-scaled configuration (TOPSIS 0.70-scaled) showed the best overall agreement between experiment and prediction, with less than 12% deviation in all measured responses. More importantly, the 50% geometric scaling successfully mitigated the stiffness reduction observed in the embedded sensors while maintaining a comparable gauge factor. This outcome validates the design rationale for post-optimization scaling and demonstrates that structural-functional trade-offs in embedded sensor designs can be effectively managed through dimensional adjustment.

From a broader perspective, these results confirm that the proposed optimization framework can predict response trends with strong physical consistency, even though absolute magnitudes may vary depending on local printing quality and interface integrity. In particular, variations in *interfacial fidelity*—that is, the geometric accuracy and bonding quality at the sensor-host interface, can influence strain transfer efficiency and stiffness. Likewise, differences in *interfacial conductivity*, which reflects the continuity of the conductive network and the contact resistance between printed layers, can alter the effective gauge factor. Future models could incorporate these interfacial characteristics, together with residual stress and thermal effects, to further improve prediction accuracy and reproducibility (249).

#### 4.4.8 Discussion

The baseline depth-study demonstrated that embedding depth has a primary influence on sensor sensitivity, even when the trace geometry is held constant. The increase in both active area and loaded perimeter with deeper embedding directly enhanced mechanical coupling between the PLA matrix and the CPLA trace. This resulted in a larger resistance

change per unit strain, explaining the strong increase in GF observed in the fully embedded samples. These findings reinforce the interpretation of the DoE results discussed later in this section: geometric parameters modulate sensitivity, but the integration position fundamentally governs the strain-transfer regime. By fixing the embedding depth for the DoE, it was possible to isolate the contribution of micro-geometry and evaluate its influence without interference from depth-related effects.

The experimental validation underscores the feasibility of optimizing FDM-based piezoresistive sensors through statistical and surrogate-assisted methods. The strong correlation between the predicted and experimental elastic modulus ( $E$ ) confirms that the surrogate model correctly captured mechanical stiffness trends across configurations. The discrepancies in gauge factor predictions, particularly for the surface-integrated sensors, likely stem from the microstructural variability inherent in conductive PLA, such as inconsistent filler percolation paths and interlayer bonding defects (250).

The substantial 68.1% over-prediction of the gauge factor (GF) for the *Aligned surface-integrated* (TOPSIS 0.33) configuration is a critical finding that points to a classic challenge in data-driven optimization: a failure of surrogate model generalization. The discrepancy suggests the model has overfitted to its training data and is now failing to extrapolate accurately to a different, less-represented design region (i.e., surface-integrated vs. embedded). This issue can be attributed to two interconnected factors drawn from modeling and materials literature. Hence, this error is attributed to overfitting due to the sparse training data, as explained earlier, for that specific regime. Expanding the dataset or using physical constraints would be the correct mitigation strategy for future work.

First, the optimization process itself can induce overfitting. While surrogate models (e.g., Gaussian Processes or Neural Networks) are powerful, their hyperparameters are often tuned to maximize performance on a given dataset. This optimization of a large space of parameters could result in overfitting of models (251). Consequently, the TOPSIS algorithm likely identified a sweet spot that was a statistical artifact of this overfitting rather than a representation of true physical performance. Such data-driven optimization problems are also typically non-convex (252), meaning the solution landscape is populated with false peaks (local optima). The optimizer, guided by the overfitted model, has likely converged on one of these false peaks, leading to a drastically over-optimistic prediction.

Second, the underlying physics of the FDM-printed sensor material is inherently noisy and complex, providing a fertile ground for such overfitting. The piezoresistive properties are dominated by the multiscale complexity of the conductive filler network (253). This complexity is exacerbated by the FDM process, which introduces significant anisotropy; factors like infill pattern and printing orientation are known to be critical (250). This anisotropy, combined with material inconsistencies like non-uniform filler distribution, means the data is likely non-Gaussian and the features complex (254).

A purely data-driven model demand(s) prohibitively large datasets to capture such

complex, anisotropic behavior (253, 255). Given that the model training was biased toward embedded sensors, it was forced to extrapolate for the surface-integrated case. In doing so, it applied simplified (e.g., stationary) assumptions to a complex, non-stationary domain, leading to the suboptimal estimates (254) and the 68.1% error observed.

Although the primary objective of any SHM program is damage detection at its early stage such that proactive measures could be taken against total structural failures, currently owing to the scope of this study, the sensor was used to provide a global strain reading which could correlate to stiffness loss (indicating the presence of damage). While differentiating specific damage modes (like delamination vs. cracking) implies distinct strain-field signatures, fully classifying these modes would likely require advanced signal processing or sensor networks, which is a promising direction for future work.

The DIC strain maps provided additional insight into the local strain field around the embedded sensors. The homogeneity of the von Mises strain contours for TOPSIS 0.70 and TOPSIS 0.70-scaled indicates efficient load transfer between the sensor and the host structure, aligning with reports that fully embedded CPC-based sensors exhibit superior stress coupling (249). Conversely, the higher strain gradient observed in the surface-aligned (TOPSIS 0.33) configuration confirms weaker mechanical coupling, explaining its lower gauge factor.

Overall, the experimental trends validate the model's primary inference: embedding the sensor enhances sensitivity (GF) but compromises stiffness ( $E$ ). The successful mitigation through geometric scaling demonstrates a practical pathway for balancing these competing effects in additively manufactured smart structures.

## 4.5 Limitations

It is worth noting that this study is limited to the optimization of geometric parameters (as defined in Section 4.3.6) of strain-gauge-shaped piezoresistive sensors. The performance metrics considered for the study were limited to sensitivity (GF), maximum working strain ( $\varepsilon_{\max}$ ), linearity ( $R^2$ ), and stiffness ( $E$ ), the latter representing the structural impact of sensor integration on the host. This is because these four are the responses hypothesized to be most directly influenced by the geometric variables considered for the study.

Other important sensor performance metrics exist, such as hysteresis (a measure of how the sensor's resistance-strain curve differs between loading and unloading cycles), repeatability/cyclic stability (a measure of how the sensor's baseline resistance and sensitivity remain stable over many cycles), drift/creep (whether the resistance value drifts over time when held at a constant strain), and temperature dependency. However, these metrics are, to a large extent, highly material-specific and more influenced by material composition. They do not have as strong a correlation with the sensor's geometry, in which the material is molded. Since this study focuses on sensor geometry - not material



composition, formulation, or development, the latter four were considered out of scope.

Additionally, since the study was conducted using a PLA-based material system, the conclusions drawn may not be generalized to all sensor material systems. The results are likely valid for PLA materials (specifically the CrownMulti CPLA) and possibly for other materials with similar properties. Therefore, future work should explore the response of other material systems to their geometric design variables and compare the resulting optimal solutions.

## 4.6 Conclusion

This work presented a comprehensive framework for the multi-objective optimization of 3D-printed, strain-gauge-shaped piezoresistive sensors. By systematically coupling a Design of Experiments (DOE) with Gaussian Process Regression (GPR) and a Multi-Objective Particle Swarm Optimization (MOPSO) algorithm, we successfully modeled and navigated the inherent conflict between maximizing sensor sensitivity (Gauge Factor) and maintaining the mechanical integrity (Stiffness) of the host structure.

The primary findings demonstrate that a fully embedded sensor configuration achieves superior sensitivity ( $GF \approx 59$ ) compared to surface-mounted designs. More importantly, we identified and experimentally validated an optimal, scaled variant of this embedded design that restores the host stiffness to near-native levels ( $E \approx 2.18$  GPa) without a significant compromise in piezoresistive performance.

Furthermore, the preliminary embedding-depth study established full embedding as the most effective integration strategy, forming the basis upon which the DoE-driven geometric optimization was built.

While these quantitative results are specific to the CPLA material system used, the core contribution of this manuscript is the robust and validated (Experiment-Model-Optimize-Validate) workflow. This methodology serves as a powerful and generalizable template for researchers to optimize other additively-manufactured sensor systems, even when using different conductive filaments, printing technologies, or host materials.

As detailed in the limitations, this study deliberately focused on geometric optimization, as the chosen performance metrics ( $GF$ ,  $\varepsilon_{\max}$ ,  $R^2$ , and  $E$ ) are strongly correlated with sensor geometry. Key material-dependent characteristics, such as hysteresis, cyclic stability, and thermal drift, were considered out of scope. Therefore, future work should proceed in two clear directions: *i*) Application of this optimization framework to other promising sensor material systems (e.g., flexible TPU-based composites) to compare optimal geometric solutions; and *ii*) A complete reliability and characterization study of the geometrically-optimized designs identified in this work to fully assess their long-term stability and field-readiness for real-world applications. Future work will also investigate the Fatigue Life of the scaled variant of the embedded designs as a critical parameter for

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long-term reliability.



## 5 System-Level Integration of Embedded 3D-Printed Piezoresistive Sensors for Real-Time Strain Monitoring of a Load-Bearing Pylon Structure

Structural Health Monitoring (SHM) is essential for ensuring the longevity and safety of critical infrastructure. While additive manufacturing (AM) has enabled the development of low-cost, embedded piezoresistive sensors, most existing research remains confined to laboratory-scale coupons, leaving a significant gap in system-level implementation and validation. This study bridges this gap by integrating optimized 3D-printed piezoresistive strain sensors into a complex, load-bearing pylon-type structure. Utilizing a multi-material Fused Deposition Modeling (FDM) process, conductive PLA sensors were embedded within a structural pylon framework. To address the inherent inaccessibility of embedded sensors, a redundant sensing architecture was developed, guided by Finite Element Analysis (FEA) to identify critical strain hotspots. The electromechanical performance was validated through experimental testing, using Digital Image Correlation (DIC) to provide full-field strain comparisons. Results demonstrate high agreement between numerical predictions, DIC measurements, and the real-time electrical response of the embedded sensors. Quantitative evaluation revealed that the embedded sensing network maintained strong signal linearity ( $R^2 = 0.89$  to  $0.97$ ) up to a peak localized strain of 2.1%. Furthermore, the redundant sensors exhibited Gauge Factors (GF) ranging from 1.64 to 5.68, effectively detecting an asymmetric structural deformation caused by an off-axis loading anomaly. The sensor network successfully maintained continuous monitoring capability with negligible viscoelastic lag, demonstrating enhanced dynamic tracking fidelity and fault tolerance. This work provides a scalable framework for transitioning from isolated sensor optimization to integrated, self-sensing structural systems, offering a robust solution for real-time SHM in aerospace and civil engineering applications.

### 5.1 Introduction

Structural health monitoring (SHM) has emerged as an important engineering strategy for ensuring the safety, reliability, and longevity of critical structures through continuous or periodic assessment using integrated sensing systems. The demand for safer engineering systems has accelerated SHM adoption across civil infrastructure, aerospace, and energy

sectors. Within these systems, strain monitoring is vital as a direct mechanical indicator of stress redistribution, deformation, and damage initiation.

Recent advances in additive manufacturing (AM) and smart materials have enabled lightweight, low-cost sensing solutions integrated directly into components. Among these, embedded piezoresistive sensors fabricated via conductive AM materials have gained attention due to their geometric flexibility and compatibility with complex shapes. Unlike externally attached gauges, embedded sensors offer improved strain transfer, reduced aerodynamic interference, and enhanced protection within load-bearing components, making them ideal for next-generation aerospace SHM (256, 257, 258, 259).

However, moving these technologies from the lab to the field remains challenging. Recent studies highlight persistent limitations such as calibration drift, environmental variability, and a lack of standardized data frameworks (257). Furthermore, as noted by Musa et al. (249), much of the current research remains confined to laboratory-scale coupons, focusing on material characterization and signal compensation rather than system-level deployment (260, 246). This lack of scalability underscores the need to transition optimized sensing solutions to structurally complex, application-relevant components.

In addition to scalability, long-term reliability is a concern. Since embedded sensors are inaccessible for repair, Musa et al. (249) and Carani et al. (99) emphasize the role of sensor density and redundancy. Strategically designed redundant networks can preserve monitoring capability even if individual sensors fail.

Conventional technologies, such as metallic foil strain gauges and fiber Bragg grating (FBG) sensors, face limitations in complex, long-term embedded applications. Foil gauges are susceptible to debonding and environmental degradation, and their integration into curved or confined load paths is often difficult (249, 261, 262). Furthermore, external mounting can alter local aerodynamics (263). While optical FBG sensors offer high sensitivity, they introduce high costs, system complexity, and fragility that complicate deployment in low-cost, 3D-printed polymeric structures (264, 265). These limitations drive the interest in integrated Fused Deposition Modeling (FDM) sensors.

The catastrophic potential of undetected structural degradation in these components is starkly underscored by the recent crash of United Parcel Service (UPS) flight 2976 on November 4, 2025. Shortly after takeoff, the MD-11F aircraft suffered a catastrophic structural failure when its left engine and pylon completely separated from the wing (266). As captured by airport surveillance (Figure 5.1), the separation led to an uncontrollable flight state and subsequent ground impact.

Ongoing investigations by the National Transportation Safety Board (NTSB) have revealed extensive fatigue cracking within the spherical bearing race of the pylon's aft mount bulkhead, a critical load-transfer node to the wing clevis (266).

The enormous financial burden, severe operational disruptions, and tragic loss of life stemming from this localized structural failure highlight the severe limitations of con-



Figure 5.1 – Surveillance footage sequence illustrating the catastrophic separation of the left engine and pylon from the wing of the UPS Flight 2976 MD-11F aircraft shortly after takeoff (adapted from (14)).

ventional, interval-based scheduled maintenance paradigms. Consequently, this incident strongly reinforces the critical imperative for implementing continuous, real-time internal diagnostic capabilities within complex aerospace sub-assemblies. Furthermore, it directly justifies the selection of the wing pylon architecture in the present study as a high-fidelity candidate for validating embedded, self-sensing SHM technologies.

Despite the clear necessity for such technologies, a critical **research gap** persists in the practical deployment of 3D-printed piezoresistive sensors. The current state-of-the-art predominantly restricts its scope to the electromechanical characterization of standardized, isolated laboratory coupons. Comprehensive, field-relevant validations of these sensing elements integrated into geometrically complex, load-bearing structures, under representative operational constraints, are severely lacking. Transitioning these optimized sensors from controlled laboratory novelties into reliable, system-level diagnostic tools remains a pressing scientific challenge.

To address this gap, this study is one of the first to demonstrate an optimized 3D-printed piezoresistive sensor embedded within a pylon-type structure for real-time SHM. By moving beyond coupons, this work combines system-level deployment, redundant architecture, and Digital Image Correlation (DIC) validation. The main contributions are:

- **System-Level Implementation:** Transitioning 3D-printed sensors from coupons to a structurally relevant pylon-type load-bearing component.
- **FEA-Driven Placement:** A CAD/FEA framework to identify strain-critical regions for precise sensor embedding.
- **Redundant Architecture:** Utilizing multiple sensors in equivalent load paths to ensure fault tolerance and monitoring continuity.
- **Multi-Material Fabrication:** Simultaneous printing of structural and sensing elements in a single, unified process.
- **Experimental Validation:** Using DIC to verify the agreement between numerical predictions and real-time sensor outputs.

## 5.2 Additive Manufacturing and Piezoresistive Sensors

Fused Deposition Modeling has increasingly transitioned from a rapid prototyping tool to a robust manufacturing method for functionally integrated smart structures. A significant advancement in this domain is the advent of conductive thermoplastic composites (e.g., carbon-black doped TPU and PLA-CNT), which exhibit pronounced piezoresistive responses under mechanical deformation. The fundamental electro-mechanical behavior, optimal extrusion parameters, and microstructural characteristics of these FDM-printed piezoresistive sensors have been extensively investigated at the laboratory scale, enabling high sensitivity and tailored structural stiffness.

### 5.2.1 Piezoresistive Behavior and Process Optimization

Recent experimental characterizations have established clear correlations between the electromechanical response of FDM-printed sensors and their material composition, printing history, and geometry. Literature demonstrates that conductive composites can exhibit varying piezoresistive sensitivities depending on filler dispersion and matrix mechanics (260, 267, 268). Furthermore, the thermal printing history, including extrusion temperatures and post-fabrication thermal annealing, has been shown to significantly influence the conductive percolation networks, dictating sensor linearity, hysteresis, and baseline resistance (269).

Beyond material properties, sensor geometry and topology play a critical role in performance. Parameters such as trace width, inter-trace spacing, end-loops, and complex lattice topologies dictate local strain concentrations, allowing designers to maximize the usable strain range and achieve exceptionally high Gauge Factors (GF) (267, 270). The piezoresistive sensitivity of these embedded sensors is mathematically quantified by the

GF, which expresses the ratio of the fractional change in electrical resistance to the applied mechanical strain:

$$GF = \frac{\Delta R/R_0}{\varepsilon} \quad (5.1)$$

where  $\Delta R$  is the change in resistance,  $R_0$  is the baseline initial resistance, and  $\varepsilon$  is the applied mechanical strain.

The total resistance  $R$  of the printed conductive trace is heavily dependent on its geometric topology and the intrinsic volume resistivity ( $\rho$ ) of the FDM filament, governed by:

$$R = \rho \frac{L}{wt} \quad (5.2)$$

where  $L$  represents the effective conductive path length,  $w$  is the trace width, and  $t$  is the layer thickness.

Consequently, optimizing these specific geometric parameters directly manipulates the localized strain concentrations, thereby maximizing the sensor's piezoresistive response. To balance these competing mechanical and electrical requirements, researchers have increasingly relied on advanced optimization frameworks. Both physics-informed Design of Experiments (DOE) and data-driven methods such as Artificial Neural Networks coupled with Genetic Algorithms (ANN+GA), have been successfully deployed to identify optimal process parameters like layer height, print speed, and infill angle (268, 246). Notably, prior work by the authors utilized a multi-objective optimization workflow (MOPSO) to develop embedded conductive PLA geometries that yielded Gauge Factors up to 59 while simultaneously restoring the mechanical stiffness of the structural host (271).

Complementing these design advancements, recent studies have addressed short-term electromechanical stability and reproducibility. Lab-scale cyclic tests evaluating various commercial filaments and electrode integration strategies have successfully minimized baseline drift and demonstrated reproducible signals over hundreds of loading cycles (260, 259, 272).

### 5.2.2 Embedded SHM Sensor Systems and Deployment Gaps

Despite extensive progress documenting fundamental material behavior and process optimization, the practical, long-term deployment of these sensors inside complex, load-bearing structural components remains insufficiently demonstrated. The overwhelming majority of existing studies concerning 3D-printed piezoresistive sensors restrict their scope to the electromechanical characterization of standardized, isolated laboratory coupons, such as standard uniaxial dogbone specimens. Initial integration works have begun to quantify how embedded sensing traces affect the static and dynamic behavior of host

components (258), and some works evaluate component-level cyclic behavior (259). However, comprehensive, field-relevant durability studies on complex geometries subjected to representative operational loads are severely lacking.

A critical review of the current state-of-the-art reveals several remaining practical challenges. First, long-duration fatigue testing and service-life monitoring across realistic environmental spectra (e.g., thermal cycling, humidity) are largely unreported (260, 269). Second, the long-term evolution of the sensor-host mechanical interface, specifically damage initiation around embedded traces and cumulative effects on structural strength under operational loads, has not been comprehensively tracked. Finally, translating lab-optimized parameters into larger-scale production with controlled reproducibility remains a major hurdle (246, 272).

Collectively, the literature provides only limited, short-to-mid-term demonstrations of FDM-printed sensors. While fundamental sensor design and optimization have been successfully established (271), there is a clear and pressing need for real-world application in realistic, geometrically complex structures. Addressing this multifaceted gap requires comprehensive experimental validation combining predictive numerical modeling (FEA), non-contact full-field optical measurements (Digital Image Correlation, DIC), and real-time embedded self-sensing data. Resolving these challenges is imperative to transition 3D-printed embedded sensors from controlled laboratory novelties into highly reliable, system-level diagnostic tools for aerospace and civil SHM applications.

## 5.3 Materials and Methods

### 5.3.1 Overall methodology and workflow.

Figure 5.2 presents an overview of the methodology adopted in this study, which integrates numerical analysis, additive manufacturing, and experimental validation to enable embedded strain sensing in a pylon-type structure.



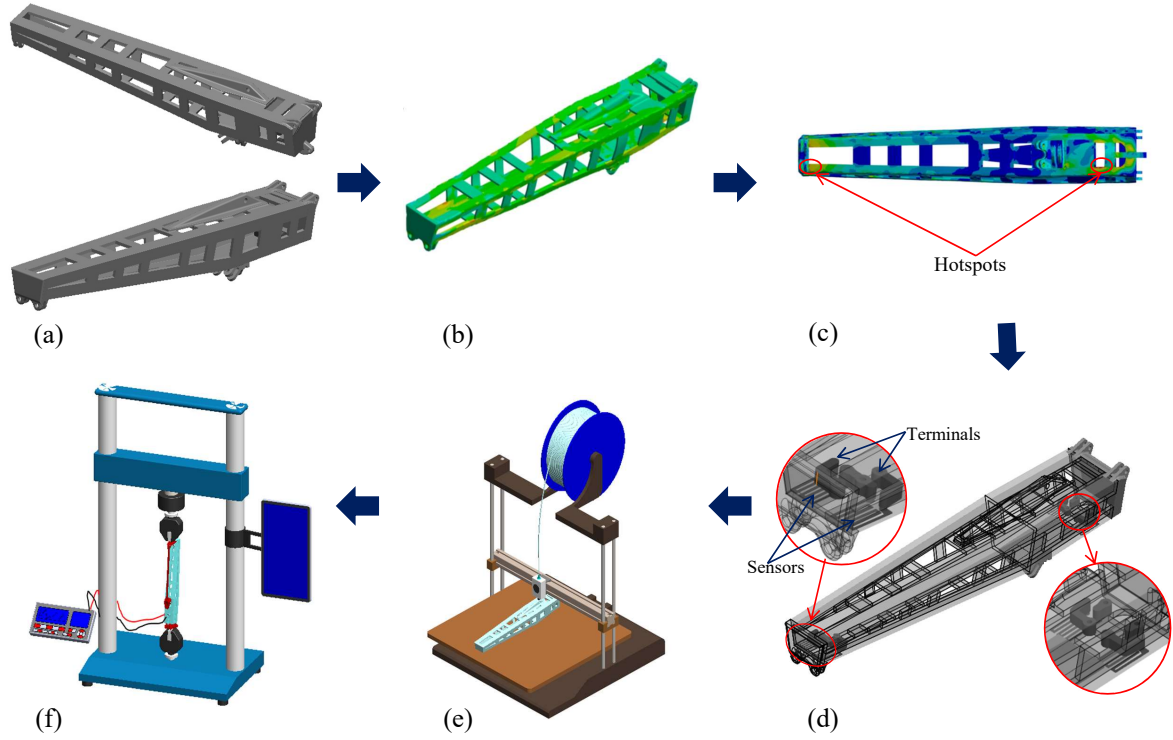


Figure 5.2 – Overview of the methodology: (a) CAD-based geometric modeling of the pylon structure; (b) finite element analysis for structural response evaluation; (c) identification of stress concentration regions (hotspots); (d) sensor embedding and terminal placement strategy within the pylon CAD model; (e) multi-material fused deposition modeling of the pylon structure with integrated sensors; and (f) experimental testing and validation of the self-sensing pylon.

First, a CAD model of the pylon load-bearing structure was developed based on an existing reference design to capture the essential geometric and structural features of the component (Figure 5.2a). The model was subsequently analyzed using finite element analysis to evaluate the structural response under representative loading conditions and to quantify strain distributions within the structure (Figure 5.2b).

Based on the FEA results, regions exhibiting elevated stress and strain levels were identified as candidate locations for sensor integration, enabling targeted monitoring of structurally critical zones (Figure 5.2c). An embedded sensor integration strategy was then implemented within the CAD environment, accounting for sensor placement and terminal routing while preserving the load-bearing functionality of the structure (Figure 5.2d).

The pylon structure with integrated sensors was fabricated using multi-material fused deposition modeling, allowing simultaneous printing of the structural material and conductive sensing elements within a single manufacturing process (Figure 5.2e). Finally, the fabricated prototype was subjected to experimental testing, where DIC and electri-

cal measurements were employed to validate the numerical predictions and assess the performance of the embedded sensors for real-time strain monitoring (Figure 5.2f).

### 5.3.2 Description of the Pylon Structure and Sensor Integration

Aircraft pylons are critical structural components responsible for supporting and attaching the propulsion system to the aircraft, either through direct coupling to the wing as in Figure 5.3 or to the fuselage. The pylon assembly transfers the engine weight, thrust loads, and additional operational loads generated during flight to the primary aircraft structure, thereby playing a vital role in ensuring structural integrity and flight safety (273).

A typical aircraft pylon assembly consists of two main structural subsystems, as illustrated in Figure 5.3: (i) the load-bearing structure (LBS), which carries the primary mechanical loads, and (ii) the non-load-bearing structure, which encloses the LBS and primarily serves aerodynamic and protective functions, such as drag minimization. The present study focuses exclusively on the load-bearing structure due to its direct involvement in load transfer and its critical importance to overall structural reliability.

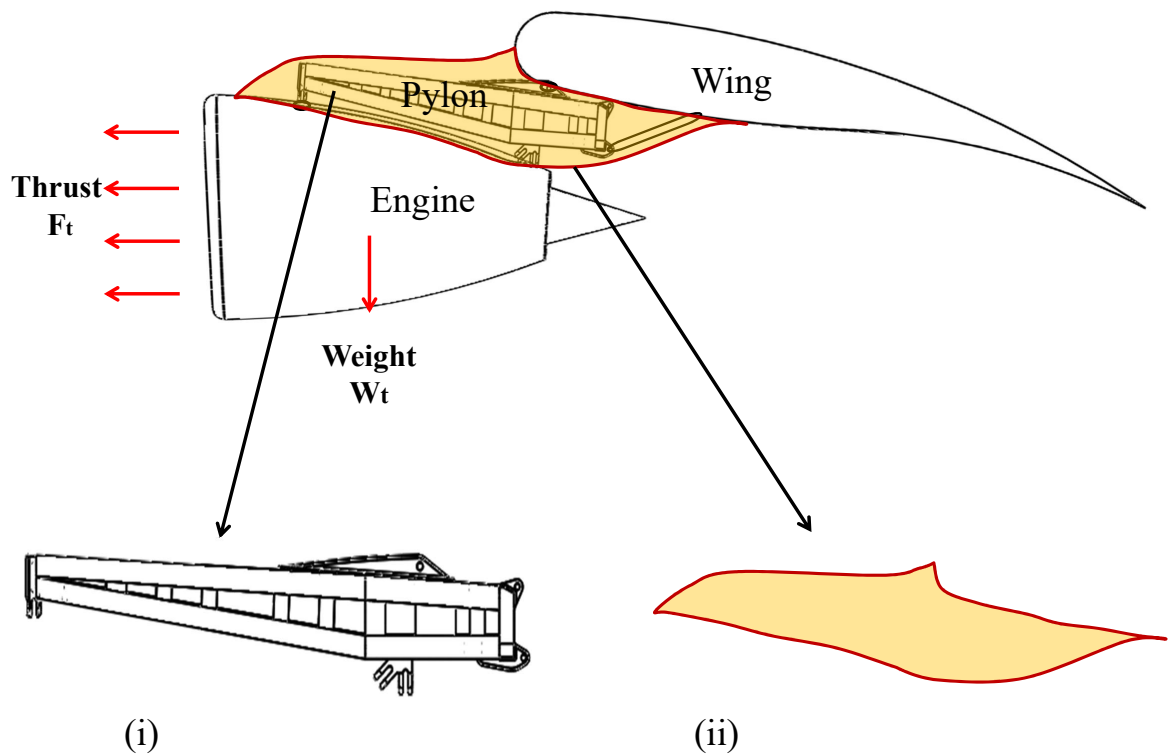


Figure 5.3 – Pylon assembly schematic structure (i) Load Bearing Structure (LBS) and, (ii) Non-load bearing structure (adapted from (15)).



The LBS is subjected to complex loading conditions during service, including engine weight ( $W_t$ ), thrust forces ( $F_t$ ), inertial loads, and aerodynamic effects. These loads, schematically summarized in Figure 5.4, can induce localized stress and strain concentrations, making the LBS a suitable candidate for continuous structural health monitoring. Ensuring the structural integrity of this component is essential, as undetected damage or excessive deformation could have severe safety implications.

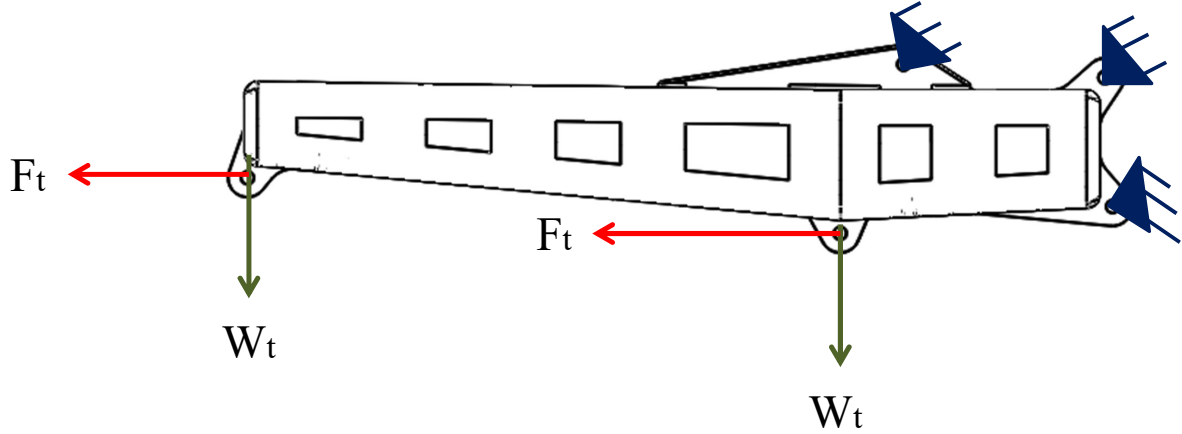


Figure 5.4 – Schematic for the Pylon LBS force diagram (Adapted from (16)).

Real-time monitoring of such critical structural components necessitates robust and reliable sensing solutions. Conventional surface-mounted sensor networks can suffer from limitations related to installation complexity, debonding, environmental exposure, and long-term durability, particularly in complex geometries and load-intensive regions, as reported by (249). These challenges motivate the integration of sensing elements directly within the structure.

In this work, an optimized 3D-printed piezoresistive strain sensor is embedded within the load-bearing structure at strategically identified high-strain regions. This embedded sensing approach aims to enable real-time strain monitoring while preserving the structural integrity and aerodynamic profile of the pylon-type component.

To enable effective strain monitoring while preserving the structural functionality of the pylon load-bearing structure, an embedded sensing strategy was adopted in this study. Rather than relying on externally mounted sensors, which are prone to debonding and environmental degradation, the sensing elements were integrated directly within the structure. Sensor placement was guided by the need to monitor critical load paths and regions expected to experience elevated strain levels under operational loading. The integration approach was designed to ensure mechanical compatibility between the sensor and host material, minimize disruption to the structural load transfer, and maintain manufacturability using additive manufacturing techniques. Detailed sensor geometry, placement, and orientation considerations are presented in 5.3.2.3

### 5.3.2.1 Adopted pylon design

Aircraft pylon configurations vary significantly depending on aircraft size, propulsion system, and installation architecture. In this study, a pylon load-bearing structure based on a reference design reported in open literature by Stefanovic (15) was adopted to serve as a representative structural case study. The selected design captures key geometric and load-transfer characteristics typical of aircraft pylons, making it suitable for investigating embedded sensing concepts in a realistic structural context.

The objective of this work is not the design or structural optimization of the pylon itself, but rather the deployment and evaluation of an embedded strain sensing system within an existing load-bearing component. To facilitate experimental implementation at laboratory scale, a geometrically scaled version of the reference pylon model was employed. Correspondingly, the applied load levels were selected to be consistent with the scaled prototype while preserving the underlying load paths and deformation mechanisms of the original structure.

By adopting an established pylon design, this study isolates the sensing and monitoring aspects from structural design considerations, enabling a focused assessment of the proposed self-sensing approach. Consequently, detailed structural design development of the pylon is outside the scope of this manuscript.

### 5.3.2.2 CAD modeling

The three-dimensional CAD model of the pylon load-bearing structure was developed using SolidWorks (Dassault Systems, version 2024). The geometry was constructed to faithfully represent the adopted reference design while maintaining a level of geometric simplicity suitable for numerical analysis and experimental realization. The completed CAD model was exported in STEP format and subsequently imported into ABAQUS (version 2024) for finite element analysis.

To enable laboratory-scale testing while preserving the dominant structural response characteristics, several modeling assumptions were introduced. The reference geometry of the adopted pylon load-bearing structure used in this study, is shown in Figure 5.5, illustrating the main structural configuration and load support locations. The applied loading was simplified to focus on the primary thrust-related load component, which represents the dominant contribution to the structural stress state of the pylon under operational conditions. The contribution of engine self-weight was neglected, as it constitutes a comparatively smaller fraction of the total loading, by a factor of 4 - 6 (274) and does not significantly alter the overall strain distribution pattern relevant to this study.

In addition, vibrational loads were not considered in the present analysis. Such loads are typically characterized by high-frequency, low-amplitude responses that are more suitably captured using dynamic sensing techniques, including accelerometers and piezoelec-

tric transducers. Since the primary objective of this work is to evaluate the quasi-static strain monitoring capability of embedded piezoresistive sensors, the exclusion of vibrational effects enables a clearer assessment of sensor performance under dominant load-bearing conditions.

These simplifications allow isolation of the strain response associated with primary structural loading, thereby facilitating a focused evaluation of the embedded sensing approach without introducing unnecessary complexity. The adopted assumptions and boundary condition definitions are consistent with the scope of the present investigation and are further detailed in the subsequent finite element analysis section.

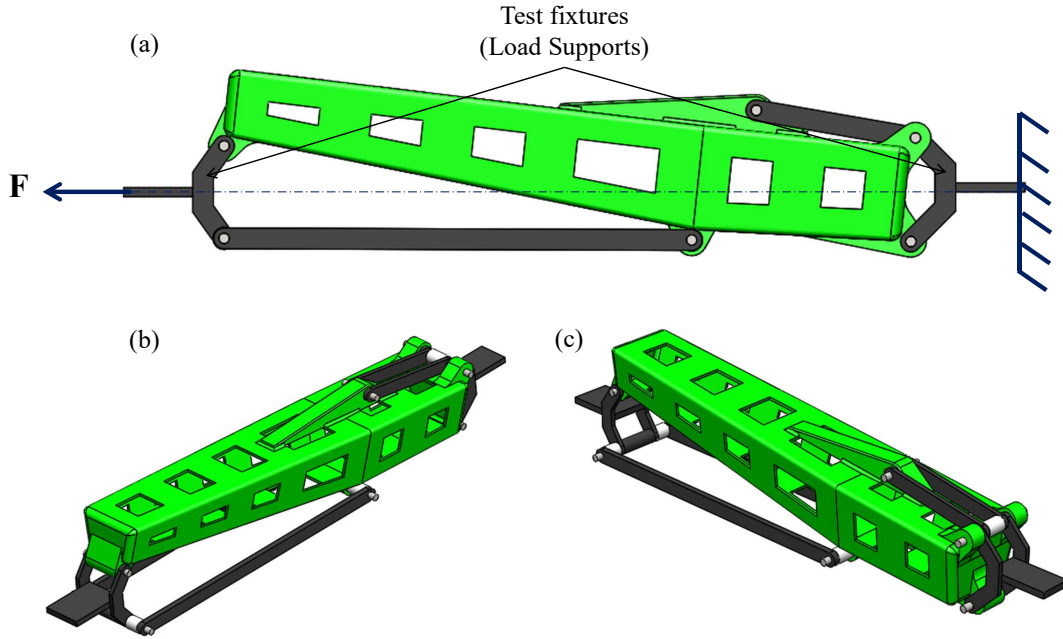


Figure 5.5 – Reference geometry of the adopted pylon load-bearing structure used in this study, (a) the main structural configuration and load support locations, (b) and (c) are the 3D front and rear views of the geometry assembly respectively.

### 5.3.2.3 Embedded sensor geometry

The sensor geometry embedded in the pylon-like structure in this study is based on an optimized 3D-printed piezoresistive strain sensor design previously reported by Musa et al. (271). That study demonstrated that the optimized geometry provides enhanced piezoresistive sensitivity relative to alternative configurations, making it suitable for strain-based structural health monitoring applications.

While the optimized geometry exhibited high sensing performance, a reduction in structural stiffness was identified as a potential drawback. Musa et al. (271) showed that this limitation could be effectively mitigated by uniformly scaling the sensor geometry by a factor of 0.5, without compromising its piezoresistive response characteristics. Accordingly, the present study adopts this scaled variant of the optimized sensor design. The geometric configuration of the sensor is illustrated in Figure 5.6.

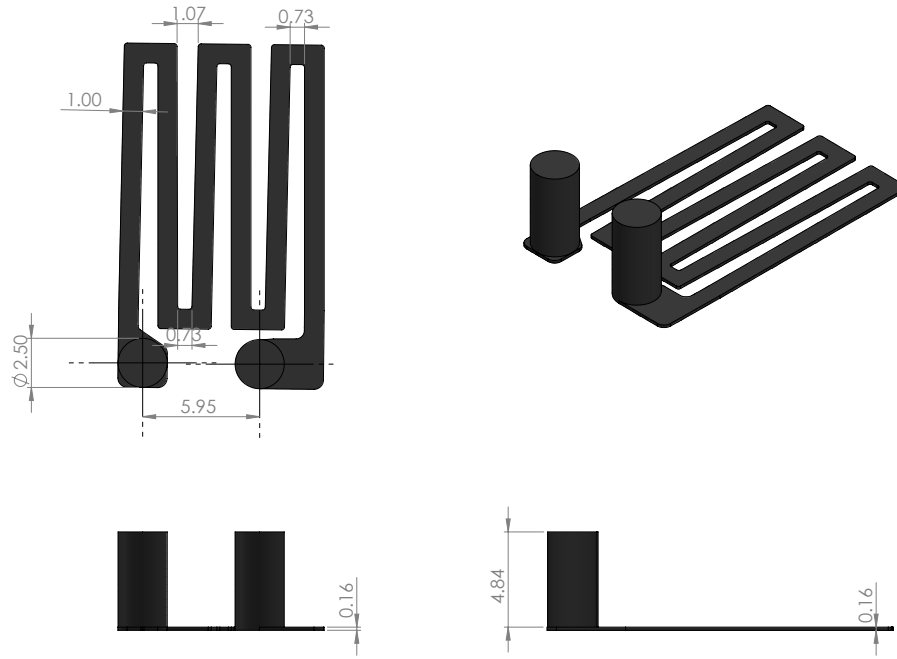


Figure 5.6 – Geometry of the optimized 3D-printed piezoresistive strain sensor embedded within the pylon structure.

The sensor was embedded at strain hotspot locations identified from the finite element analysis, as described in Section 5.4.1. At each selected location, the sensor was positioned within the mid-plane of the local structural region to ensure effective strain transfer between the host material and the sensing element. To maximize sensitivity, the sensor trace was oriented along the principal longitudinal stress direction of the pylon structure, thereby enabling enhanced capture of the dominant strain signature under applied loading.

### 5.3.3 Finite Element Analysis

#### 5.3.3.1 Material Properties

To computationally determine the optimal locations for sensor integration, a predictive finite element model was developed using Abaqus/explicit solver. The physical prototype consists of a structural host printed from standard Polylactic Acid (PLA) and embedded piezoresistive sensing elements fabricated from a commercial carbon-black doped conductive PLA (Proto-pasta CPLA). However, for the specific objective of mapping the macro-level global stress and strain distribution prior to sensor embedding, the pylon was mathematically simplified and modeled as a single homogeneous, isotropic, linear-elastic continuum. This standard approximation is highly effective for identifying macro-strain topologies without the computational overhead of modeling multi-material micro-interfaces. The effective isotropic mechanical properties assigned to the finite element

model included a Young's Modulus ( $E$ ) of 2.309 GPa, a Poisson's ratio ( $\nu$ ) of 0.354, and a density ( $\rho$ ) of 1149.929 kg/m<sup>3</sup>.

### 5.3.3.2 Boundary Conditions and Loading

The structural geometry was designed to represent an aerospace wing pylon, a critical load-bearing component responsible for transmitting engine thrust to the aircraft's main wing structure. To accurately simulate true in-service boundary conditions during physical validation, customized metallic load fixtures were incorporated into both the experimental and numerical models, preventing localized polymer crushing at the loading zones.

The boundary conditions implemented for the numerical analysis replicate this physical tensile test configuration. The CAD model for these load fixtures as well as the physical model as manufacture and assembled are illustrated in Figures 5.7(a) and 5.7(b) respectively.

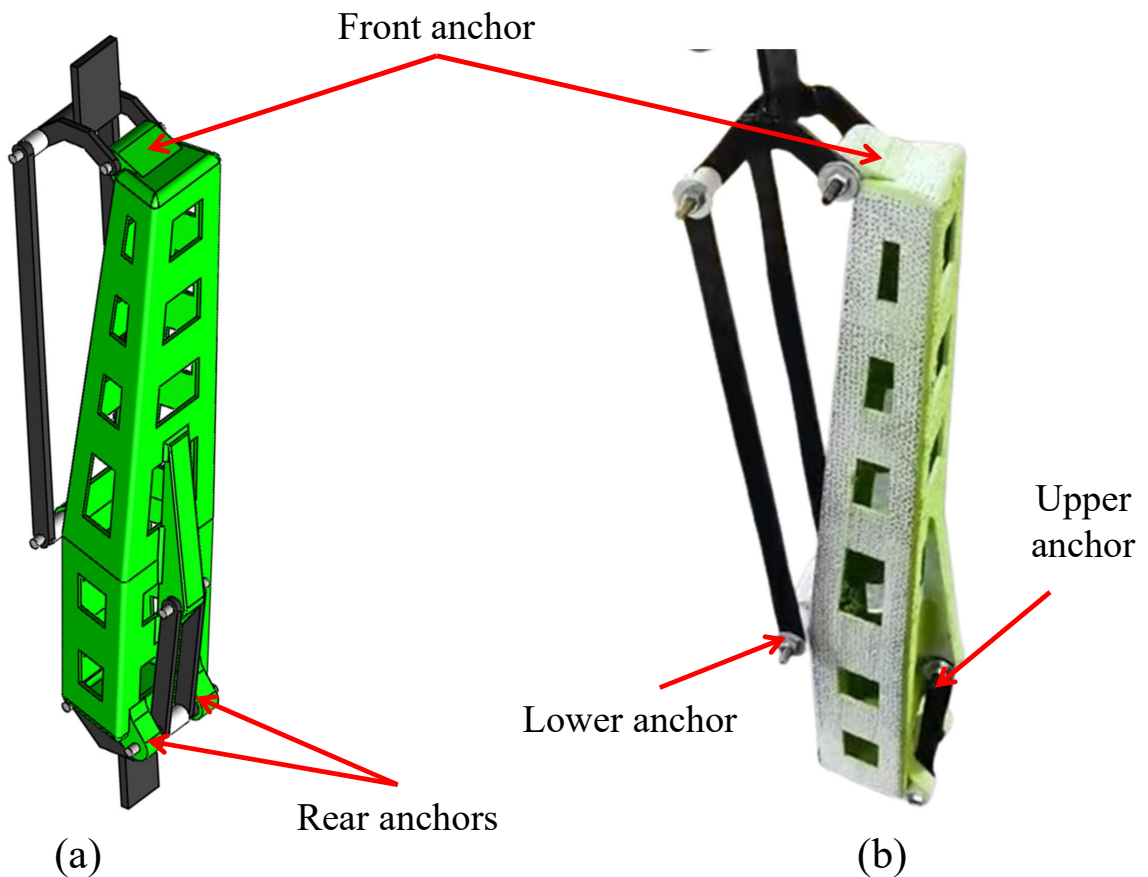


Figure 5.7 – Pylon structure with customized load fixtures: (a) the CAD model, and (b) the FDM-printed structure.

The lower anchor fixtures, which nominally interface with the fixed assembly, were fully constrained in all degrees of freedom to simulate a rigid attachment. Conversely, an operational longitudinal displacement ( $u$ ) of 20 mm was prescribed at the upper loading

fixtures to simulate the structural demands of the theoretical engine thrust force ( $F_t$ ) as illustrated in Figure 5.8.

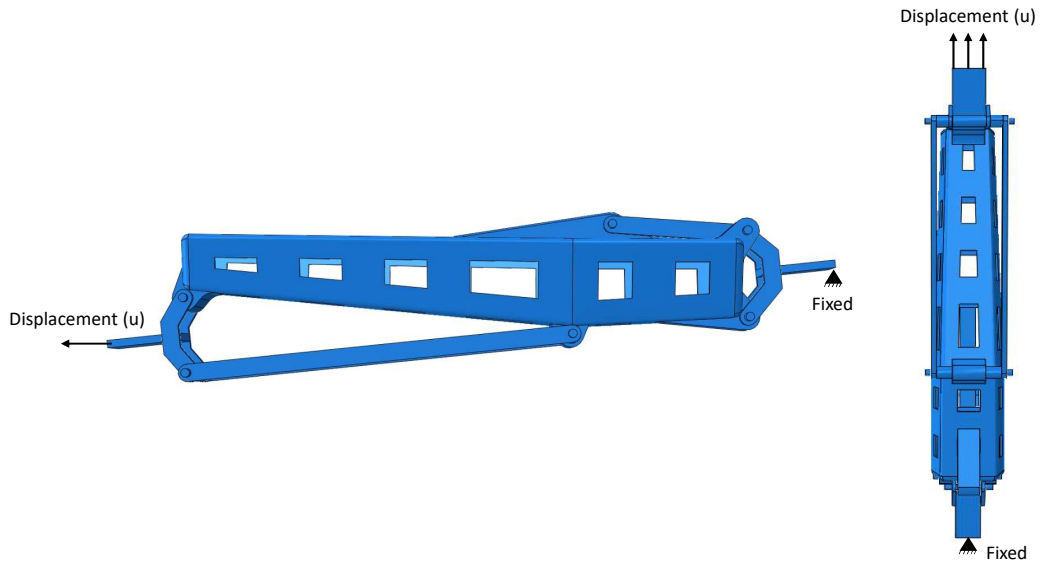


Figure 5.8 – Numerical boundary conditions of the Pylon model.

To ensure a true quasi-static response and minimize undesirable inertial effects during the explicit simulation, this displacement was controlled using a smooth step amplitude curve.

### 5.3.3.3 Numerical Modeling and FEA Setup

The structural behavior and stress distribution of the pylon were evaluated through FEA using the Abaqus/Explicit solver. The continuous domain was discretized using 10-node modified quadratic tetrahedral elements (C3D10M), selected for their superior performance in capturing acute stress concentrations, resisting volumetric locking, and handling complex geometric transitions under severe deformation. To determine the optimum spatial discretization, a comprehensive mesh convergence study was performed. Based on this evaluation, a global element size of 1.0 mm was selected, with localized mesh refinement implemented around the anchor points, providing an optimal balance between numerical accuracy and computational efficiency (Figure 5.9). To maintain numerical stability under large localized strain fields, both distortion control and enhanced hourglass formulations were activated.

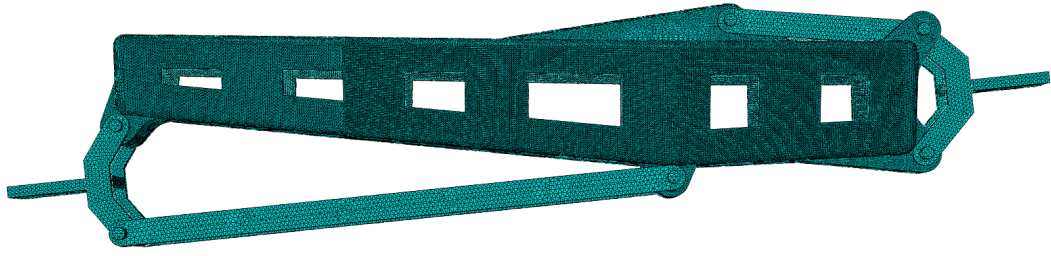


Figure 5.9 – Computational mesh of the Pylon structure discretized with 10-node quadratic tetrahedral elements.

Numerical interactions between the independent parts were governed by the General Contact algorithm. The contact interfaces between the metallic support fixtures and the polymer pylon structure were defined using a "hard" contact relationship in the normal direction to prevent element interpenetration. Tangential behavior was regulated via a penalty friction formulation with an isotropic friction coefficient ( $\mu$ ) of 0.2, ensuring realistic load transfer across the structural interfaces during displacement.

#### 5.3.3.4 Strain Hotspot Identification

The primary objective of the numerical simulation was to pinpoint the structural "hotspots" regions exhibiting the highest concentration of mechanical deformation under the applied operational load. The selection criteria for optimal sensor placement were strictly dictated by the localized principal strain fields.

Crucially, while the sensors needed to be placed in high-strain zones to maximize the piezoresistive signal-to-noise ratio, sharp internal corners and abrupt geometric transitions were deliberately avoided. This precaution ensured that the sensors were not embedded in zones susceptible to numerical stress singularities or highly localized, non-linear plastic yielding, which could prematurely fracture the internal conductive traces.

Once the optimal high-strain, uniform-gradient regions were identified, they were evaluated against the physical spatial requirements of the 3D-printed sensing elements. The customized sensors were designed with a classic continuous strain-gauge topology featuring three end-loops, a trace width of 1.0 mm, an inter-trace distance of 1.07 mm, a layer thickness of 0.16 mm, and an effective active length of 15 mm. The FEA successfully confirmed that the identified primary structural hotspots provided a sufficient macro-strain footprint to fully encapsulate this sensor geometry, directly informing the toolpath generation for the subsequent multi-material FDM fabrication.

#### 5.3.4 Fabrication of the Embedded Sensor Structure

The transition from a virtual CAD model to a physical self-sensing pylon prototype was achieved utilizing a multi-material FDM process. This approach enabled the simultaneous fabrication of the load-bearing polymeric structure and the embedded piezoresistive



sensing elements within a single, continuous manufacturing cycle, thereby eliminating the need for post-fabrication sensor bonding and ensuring perfect mechanical coupling.

#### 5.3.4.1 Additive manufacturing setup

The pylon prototype was fabricated using an Ultimaker S7 3D printer, equipped with an Independent Dual Extruder (IDEX) system and a Material Station. The structural body of the pylon was printed using a commercial poly-lactic acid (PLA) filament (Ultimaker Green PLA, 2.85 mm diameter), selected for its dimensional stability and ease of printability. The embedded strain sensors and their corresponding terminal tracks were fabricated using a carbon-black-doped conductive PLA filament (Protopasta Conductive PLA, 2.85 mm diameter).

The slicing process and G-code generation were performed using Ultimaker Cura (version 5.11.0). To ensure a highly dense load-bearing structure and mitigate the effects of internal voids on the structural stiffness of the 2 mm thick pylon walls, the component was sliced with an infill density of 100%, effectively rendering the structure solid. Both the structural and conductive materials were extruded through 0.4 mm brass nozzles at a constant layer height of 0.1 mm. The thermal parameters were maintained uniformly across both materials, with the nozzle temperatures set to 210°C and the heated build plate maintained at 60°C to ensure optimal first-layer adhesion and minimize thermal warping during the fabrication process.

#### 5.3.4.2 Multi-material/embedded printing strategy

To ensure the piezoresistive sensors were perfectly encapsulated within the identified strain hotspots, a specific multi-material embedding strategy was employed. The conductive PLA sensors were assigned to the secondary extruder, allowing the IDEX system to automatically alternate between the structural and functional materials layer-by-layer without cross-contamination. To maintain a consistent thermal history and uniform material deposition across the complex cross-section, the print speed for both the host structure and the embedded sensors was maintained at a constant 30 mm/s. Figure 5.10 presents the FDM-based manufacturing process adopted for fabricating the smart pylon prototype.



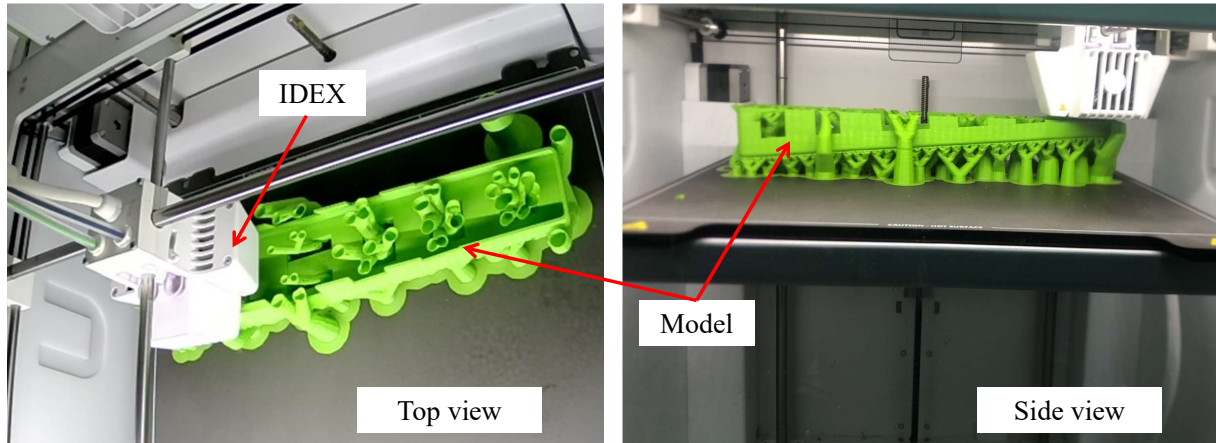


Figure 5.10 – FDM process employed in the fabrication of the smart pylon prototype using Multimaker s7, showing the top-view and side-view configurations of the Independent Dual Extruder (IDEX) printing setup.

Furthermore, facilitating a robust electrical interface with the external Data Acquisition (DAQ) system without damaging the soft polymer sensors is a recognized challenge in 3D-printed electronics. To address this and minimize parasitic contact resistance, the conductive PLA traces were designed with out-of-plane terminals projecting directly from the external surface of the host structure. These projecting terminals featured enlarged geometries with integrated through-holes. Post-fabrication, steel screws were threaded into these specific cavities to anchor the external lead wires. This mechanical fastening approach provided a high clamping force, ensuring a stable, low-resistance electrical interface for the 2-wire measurements during mechanical testing.

### 5.3.5 Experimental Setup

To physically validate the numerical model and evaluate the performance of the embedded 3D-printed piezoresistive sensors, a comprehensive experimental testing campaign was conducted. The self-sensing pylon prototype was securely mounted in a customized test fixture (load supports) within an EMIC DL-30000 Universal Testing Machine (UTM). The UTM was equipped with a 50 kN load cell and operated via the Tesc control software program, configured to apply a uniaxial tensile load representative of the operational thrust force  $F_t$ .

The experimental setup used for the piezoresistive response measurement for the embedded sensor is shown in Fig. 5.11.

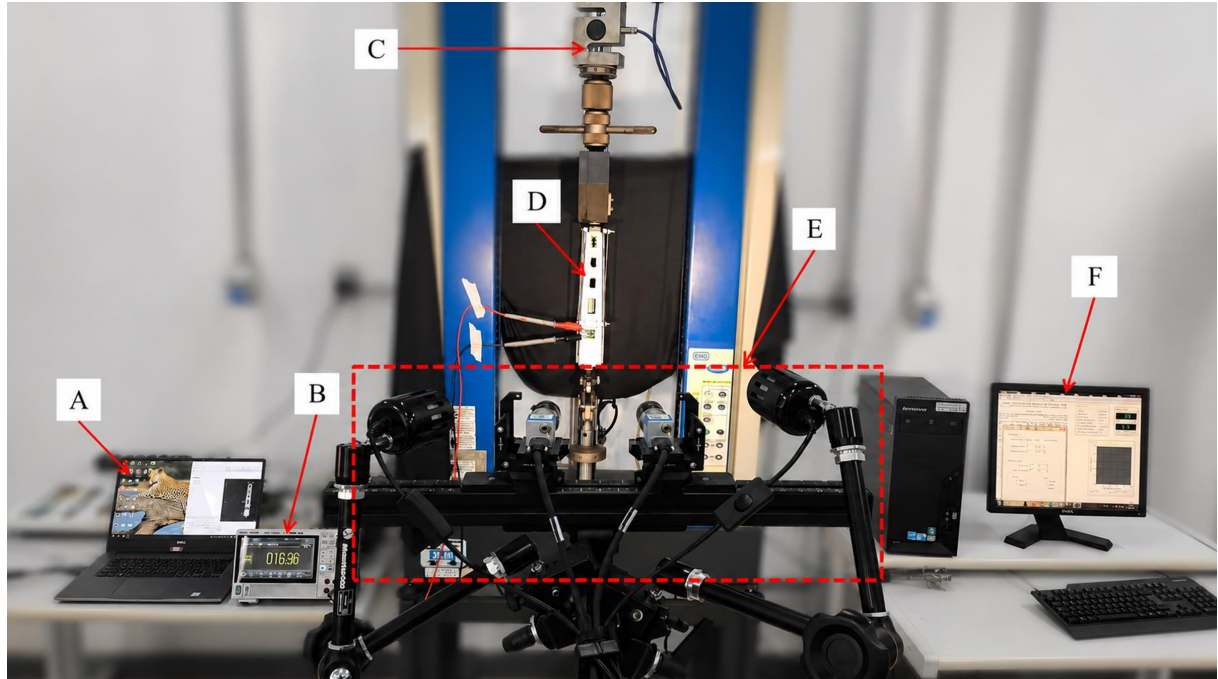


Figure 5.11 – Experimental setup for piezoresistive response measurement of the sensor under tensile loading. (A) Data acquisition and control laptop; (B) resistance measurement unit; (C) load cell; (D) test specimen with mounted sensor; (E) digital image correlation (DIC) cameras and illumination system; (F) data processing workstation. The dashed region highlights the optical measurement zone.

The experimental setup required the strict synchronization of three independent data streams: the mechanical load/displacement from the UTM, full-field strain measurements from a DIC system, and the electrical resistance response from the embedded sensors.

#### 5.3.5.1 Digital Image Correlation (DIC)

To provide a non-contact “ground truth” measurement for both the FEA validation and the sensor calibration, a 3D-DIC system comprising two CSI Ace 5.0 MP digital cameras ( $2448 \times 2048$  pixels resolution) fitted with 8 mm f/1.4 lenses was employed. Image synchronization and the subsequent post-test full-field strain correlation analysis were executed using Vic-3D software. Prior to testing, a high-contrast stochastic speckle pattern was applied to the surface of the pylon prototype, specifically targeting the identified strain hotspot regions.

To prevent thermal degradation or localized heating of the FDM-printed PLA structure during prolonged testing, cold LED light diffusers with polarizing filters were utilized to illuminate the specimen evenly while eliminating reflective glare. The DIC camera acquisition rate was set to 5 Hz (200 ms interval). This frame rate was strategically selected to maintain highly manageable data volumes during prolonged constant-load and cyclic

tests, while providing sufficient temporal resolution to capture the quasi-static structural deformation behavior.

#### 5.3.5.2 Electrical measurement system

The piezoresistive response of the embedded sensors was continuously monitored using a RIGOL DM858E digital multimeter. Because the 3D-printed conductive PLA sensor features a two-terminal connection design and typically exhibits a high baseline resistance, a standard 2-wire resistance measurement configuration was utilized. Given the multimeter's extensive measurement capability (up to 50 M $\Omega$ ), the parasitic contact and lead-wire resistances are considered negligible relative to the sensor's intrinsic resistance and piezoresistive response.

To overcome typical data acquisition bottlenecks and ensure high-speed synchronization with the DIC system, a custom multi-threaded Python data acquisition script was developed. The script decoupled the instrument communication from the live graphical user interface, running a dedicated background thread that directly queried the multimeter via USB. Furthermore, the multimeter's internal integration time was optimized by reducing the Number of Power Line Cycles (NPLC) to 0.02. This configuration allowed the electrical resistance to be sampled at approximately 30 - 50 Hz, ensuring multiple electrical data points were captured for every single DIC frame, thereby facilitating highly accurate post-test temporal interpolation and synchronization.

#### 5.3.5.3 Loading protocol

The experimental evaluation was divided into a structured loading protocol designed to thoroughly characterize the sensor's static calibration, dynamic reliability, and real-time operational capability within the linear elastic limit of the structure.

1. **Quasi-Static Calibration Ramp:** The structure was subjected to a continuous, low-speed tensile load at a rate of 2 mm/min up to a maximum load of 200 N. This baseline test was used to establish the mathematical relationship between the relative change in resistance ( $\Delta R/R_0$ ) and the physical strain ( $\epsilon$ ) extracted from the corresponding DIC hotspot, thereby determining the intrinsic Gauge Factor (GF) of the embedded sensor.
2. **Operational Step-Loading Protocol:** Finally, to validate the system-level SHM applicability for real-time monitoring, a precisely timed incremental step-loading profile was applied. The protocol was governed by a constant crosshead displacement rate of 2.0 mm/min during the active loading phases, interspersed with distinct constant-displacement holds. Specifically, the loading sequence consisted of an initial tensile ramp for 15 seconds, followed by a 10-second steady-state hold. A secondary

loading ramp was then applied for 5 seconds, followed by another 10-second hold, before a final loading ramp was maintained for the remainder of the 50-second test duration. This specific sequence was designed to evaluate both the dynamic tracking fidelity during transient mechanical events and the short-term viscoelastic stability (drift resistance) of the sensors during steady-state operations. The real-time electromechanical response derived from the embedded sensor network was continuously recorded against the DIC ground truth to demonstrate temporal synchronization and to evaluate the fault-tolerance of the redundant sensor architecture.

## 5.4 Results and Validation

### 5.4.1 Numerical vs. Experimental Full-Field Validation

To ascertain the predictive fidelity of the structural model and formally validate the targeted locations for sensor embedding, a rigorous comparative analysis was conducted between the numerical simulations and the experimental full-field optical measurements. Figure 5.12 juxtaposes the experimental Digital Image Correlation strain distribution with the corresponding finite element analysis strain contours generated via Abaqus/Explicit. By directly comparing the numerical strain field to the experimental ground truth, a robust qualitative and topological validation of the sensor embedding locations is achieved.

The numerical model (Figure 5.12b) clearly identifies highly localized strain concentrations, designated as the primary structural hotspots, situated near the clamped boundary constraints and specific geometric transitions of the pylon architecture. Governed by mathematically perfect boundary conditions and a flawlessly aligned axial load vector, the FEA naturally predicts a perfectly symmetrical strain distribution across the longitudinal plane of symmetry. Notably, the contour scale of the numerical model bounds the functional structural strain at 10% ( $1.0 \times 10^{-1}$ ), with localized mathematical singularities naturally occurring near the idealized infinitesimal point-load application nodes.

Crucially, the experimental DIC strain map (Figure 5.12a) physically corroborates the spatial localization of these predicted hotspots. The regions experiencing the maximum strain in the physical prototype, peaking locally at approximately 1.93% before failure, perfectly align topologically with the high-strain domains mapped by the numerical solver. This spatial agreement conclusively validates the methodology used to determine the optimal embedding coordinates for the piezoresistive sensor network.

However, a high-resolution examination of the experimental DIC map reveals a distinct deviation from the numerical model regarding the overall field symmetry. While the right and left structural nodes are geometrically identical, the experimental strain field exhibits a pronounced asymmetry, with one lateral domain experiencing a higher magnitude of localized deformation than its symmetric counterpart. As discussed subsequently

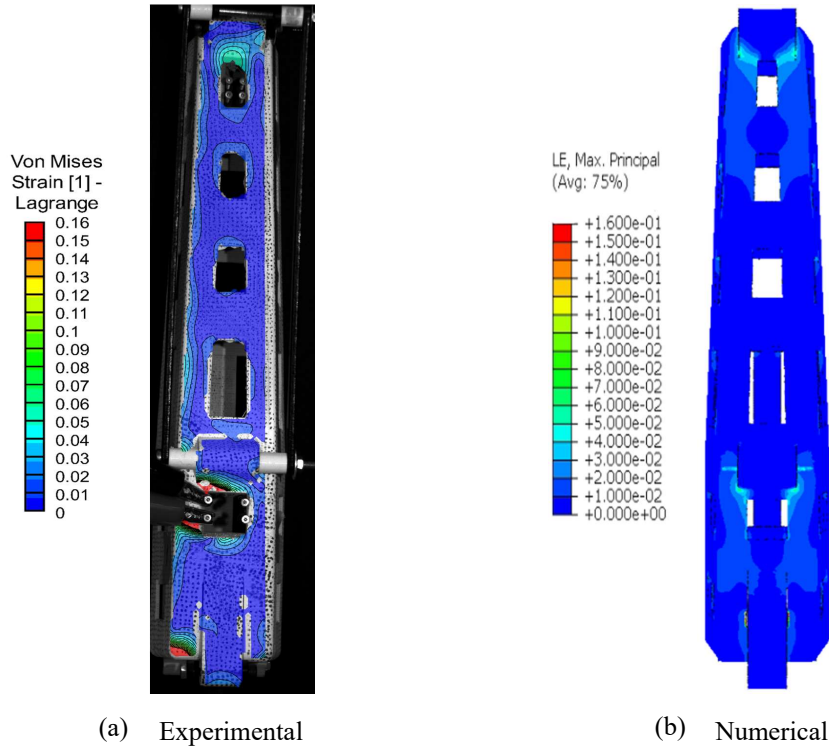


Figure 5.12 – Comparative full-field structural analysis under quasi-static tensile loading. (a) Experimental DIC strain map showing actual surface deformation (Von Mises Strain [%]), and (b) numerical strain distribution (Logarithmic Max. Principal Strain). While the FEA predicts a perfectly symmetrical response based on idealized boundary conditions, the DIC captures the physical realities of the test setup, validating the precise spatial locations of the strain hotspots while highlighting an operational load misalignment.

in Section 5.5, this phenomenon is attributed to the complex physical boundary conditions and slight off-axis misalignment inherent to the experimental test fixture, a reality that the embedded sensors successfully detected in real-time.

#### 5.4.2 Spatiotemporal Evolution of the Experimental Strain Field

To gain deeper insights into the macro-mechanical behavior and progressive deformation history of the self-sensing wing pylon, full-field optical data capturing the chronological evolution of the strain field was compiled. Figure 5.13 illustrates the sequential development of the experimental Von Mises strain field across twelve successive loading stages, spanning from initial grip engagement to the pre-failure limit. This visual timeline permits a high-fidelity assessment of how strain propagates across the complex 3D geometry and progressively localizes at the designated sensor positions.

The evolution profile can be categorized into three distinct mechanical phases:

1. **Elastic Initiation Phase (Stages 1–4):** Stage 1 represents the initial reference state under minimal preload conditions. As tension scales through Stages 2 to 4, the

pylon undergoes uniform macro-elastic strain distribution. During this early stage, the maximum recorded local Von Mises strain values remain exceptionally low, shifting slightly from 0.114% at Stage 2 to 0.170% at Stage 4. This phase primarily captures the baseline structural compliance and the physical seating dynamics of the FDM polymer within the UTM test fixtures.

2. **Hotspot Development & Asymmetry Manifestation (Stages 5–8):** As the tensile load intensifies through Stages 5 to 8, the global strain uniformity breaks down, giving rise to distinct topological concentrations. The peak local Von Mises strain climbs progressively from 0.270% (Stage 5) to 0.495% (Stage 6), eventually reaching 0.795% at Stage 8. Crucially, it is during this intermediate phase that the loading misalignment and subsequent parasitic bending moment become visually prominent. The strain field begins to show clear lateral asymmetry, with a disproportionately higher strain gradient accumulating along one side of the structural architecture than its symmetric counterpart.
3. **Progressive Localization & Pre-Failure Saturation (Stages 9–12):** In the final stages leading up to structural testing limit, severe strain localization becomes tightly bounded within the intended primary structural hotspots. The maximum localized Von Mises strain spikes rapidly, escalating from 0.940% at Stage 9 to 1.330% at Stage 10, before climbing to 1.800% at Stage 11. At Stage 12, just prior to test limit, the peak localized strain field saturates at a maximum value of 2.100% (0.021 strain).

Importantly, this chronological full-field mapping demonstrates that the high-strain zones do not shift or migrate macroscopically during the loading lifecycle. Instead, they remain strictly stationary, progressively intensifying at the precise coordinates predicted by the numerical models and monitored by the embedded piezoresistive sensor network. This continuous spatial convergence firmly establishes that positioning smart sensor networks based on early-stage predictive stress topologies remains completely valid throughout the entire operational and progressive loading profile of the integrated structure.



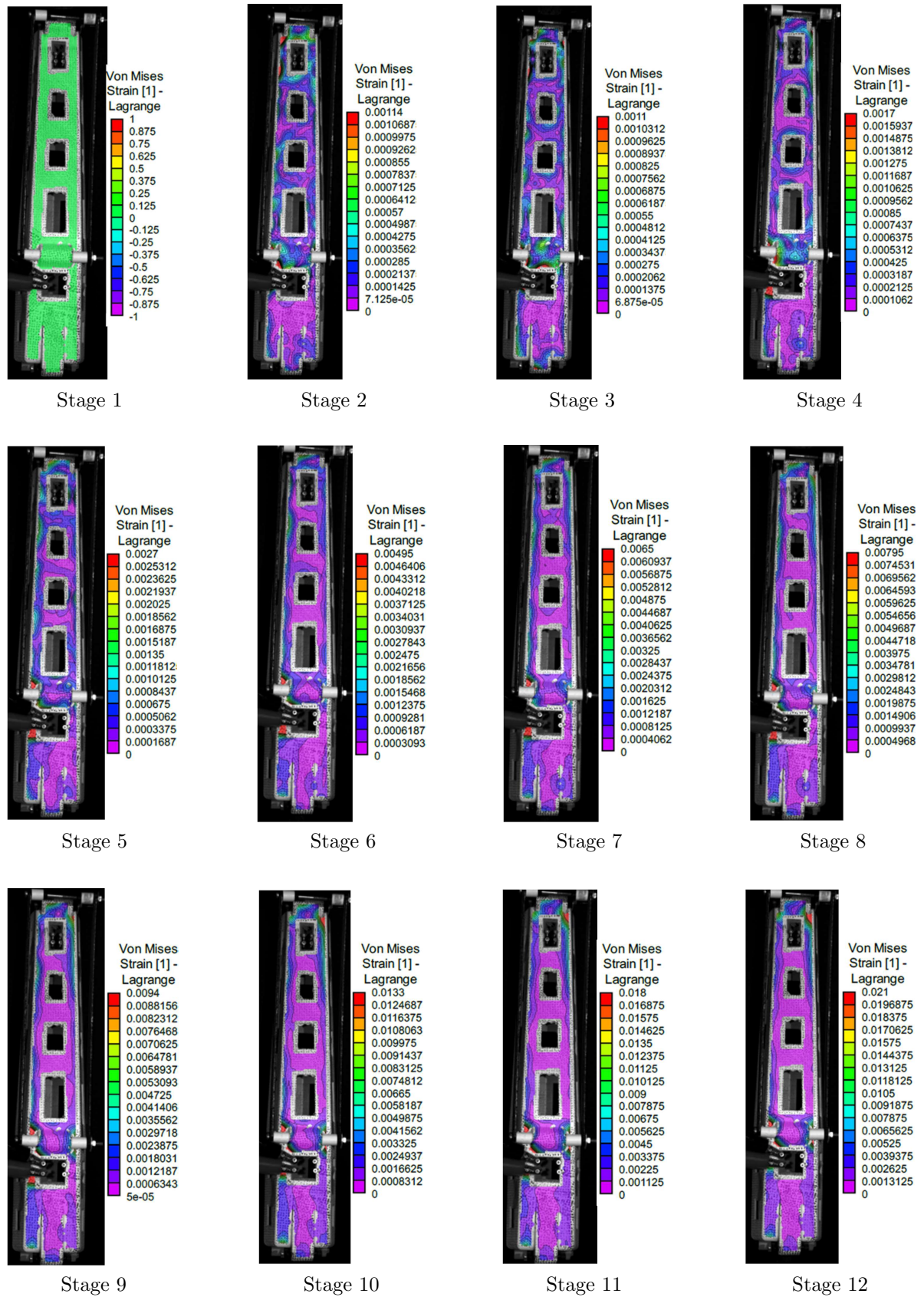


Figure 5.13 – Evolution of the Von Mises strain field obtained from DIC during the progressive loading period of the experiment.



### 5.4.3 Embedded sensor response

Following the validation of the structural response via DIC, the piezoresistive behavior of the embedded 3D-printed strain sensors was characterized. To establish the intrinsic sensitivity of the sensing elements within the linear elastic regime of the host structure, the relative change in electrical resistance ( $\Delta R/R_0$ ) was continuously monitored and correlated with the localized principal strain extracted from the DIC analysis.

As detailed in the methodology, the sensor network architecture was designed with built-in redundancy to enhance system reliability. Sensors 1 and 2 were embedded at the rear pylon hotspots, positioned symmetrically opposite each other relative to the loading axis. Similarly, Sensors 3 and 4 were symmetrically integrated at the front pylon strain hotspots. Under ideal theoretical conditions, each symmetric pair should experience identical strain fields, allowing one sensor to serve as a fail-safe redundancy for the other. Figure 5.14 illustrates the nomenclature adopted for the embedded sensors used throughout the data acquisition process.

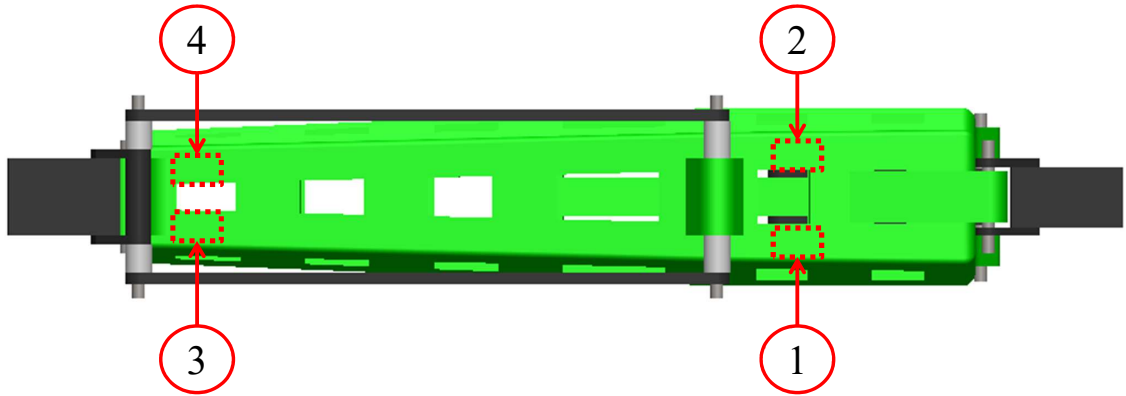


Figure 5.14 – Sensor nomenclature adopted for the embedded sensing network used during data acquisition. The numbering scheme identifies the spatial locations of the embedded sensors within the monitored structure.

Figure 5.15 presents the electro-mechanical correlation for all four embedded sensors. A discernible linear trend is observed in all cases, confirming the piezoresistive viability of the conductive PLA within the tested elastic strain range. However, the experimental data reveals varying degrees of sensitivity and linearity, as reflected by the extracted Gauge Factors (GF) and coefficients of determination ( $R^2$ ).

The rear-positioned sensors (Sensors 1 and 2) exhibited highly comparable sensitivities, yielding Gauge Factors of 1.64 and 1.80, respectively. Their linearity was also consistent, with  $R^2$  values of 0.9017 and 0.8916. This close agreement in performance validates the redundancy strategy for the rear hotspot, demonstrating that localized structural strain can be reliably captured even if one sensor were to fail.

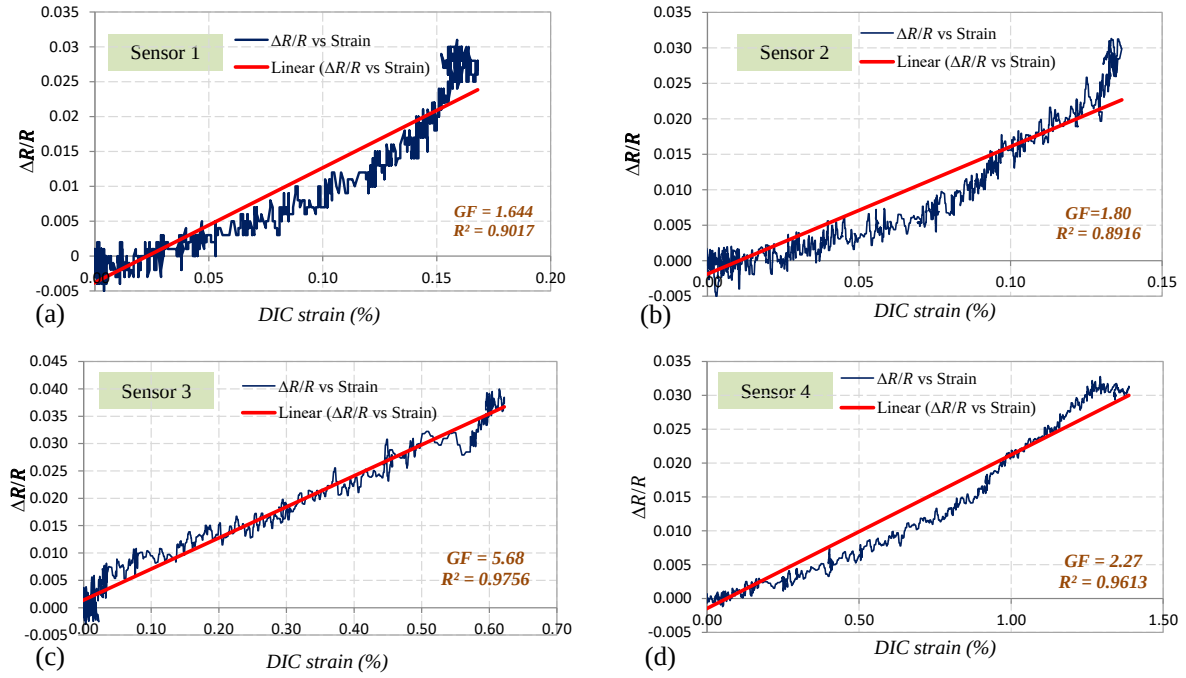


Figure 5.15 – Relationship between normalized resistance change ( $\Delta R/R$ ) and DIC strain (%) for the four embedded sensors. Sensors 1 and 2 (a, b) correspond to the rear structural hotspots, while Sensors 3 and 4 (c, d) correspond to the front hotspots. The extracted gauge factors (GF) and coefficients of determination ( $R^2$ ) highlight the sensitivity and linearity of each redundant pair.

Conversely, the front-positioned sensors (Sensors 3 and 4) displayed a notable divergence in sensitivity. While Sensor 4 yielded a GF of 2.27 ( $R^2 = 0.9613$ ), Sensor 3 exhibited a significantly higher sensitivity with a GF of 5.68 ( $R^2 = 0.9756$ ). Despite the variance in the absolute GF values, both demonstrated excellent linearity. While slight variations in the carbon-black percolation network or contact resistance at the terminals contribute to baseline sensitivity differences, this significant asymmetry between theoretically symmetric sensors strongly suggests a deviation from the idealized loading axis. As corroborated by the full-field DIC strain maps, minor misalignments introduced by the load supports created an asymmetrical strain field across the physical prototype, an anomaly that the embedded sensors successfully detected and which is discussed exhaustively in Section 5.5.

#### 5.4.4 Real-time monitoring capability

To evaluate the practical applicability of the embedded sensing system for operational Structural Health Monitoring, it is imperative to verify that the sensors can capture transient structural events without significant temporal lag. Therefore, the self-sensing pylon was subjected to an incremental step-loading protocol. This profile evaluates both the dynamic tracking during load ramps and the signal stability during constant-load hold

periods.

Figure 5.16 illustrates the time-series evolution of the localized mechanical strain and the corresponding electrical response for the redundant sensor pairs over a 50-second test duration.

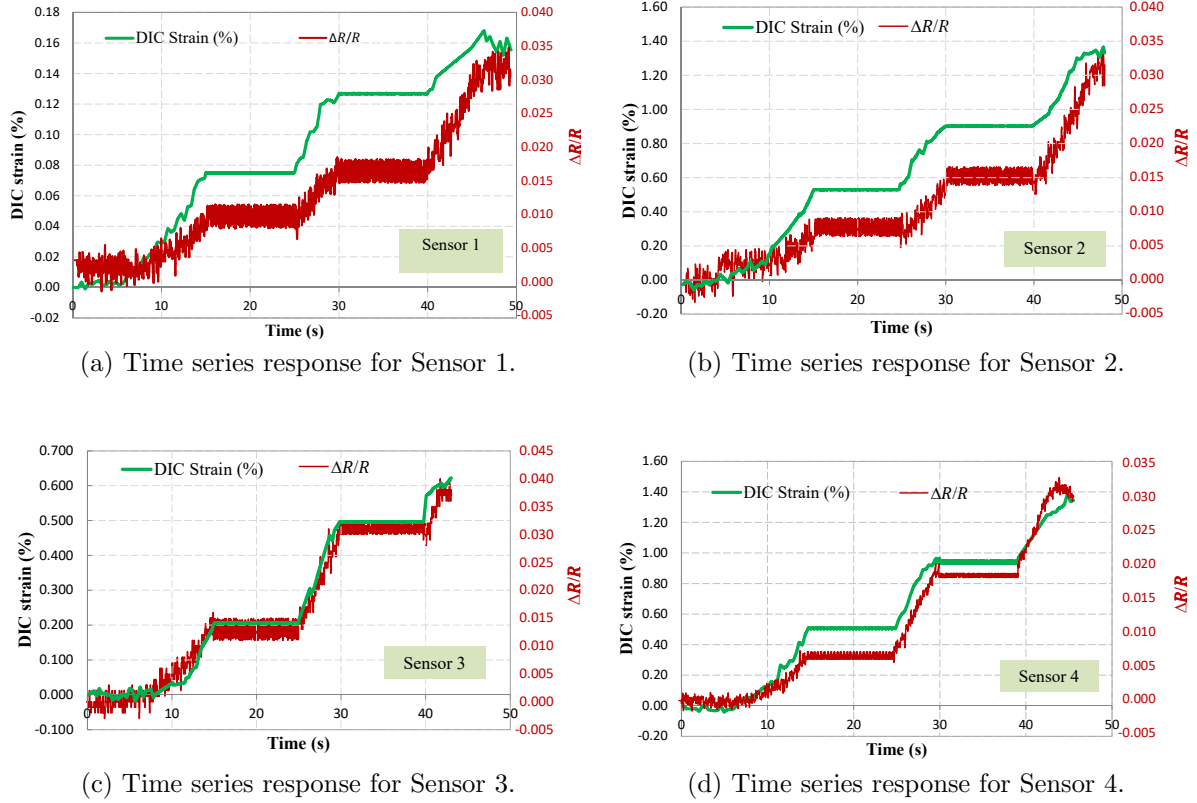


Figure 5.16 – Time-series evolution of the localized mechanical strain and the corresponding electrical response (a) Sensor 1 (b) Sensor 2 (c) Sensor 3, and (d) Sensor 4.

As observed in Figures 5.16(a) and 5.16(b) for the rear-positioned sensors (Sensors 1 and 2), the piezoresistive output ( $\Delta R/R$ ) faithfully tracks the ground-truth DIC strain profile. Every distinct loading ramp and subsequent plateau is clearly mirrored in the electrical data stream. Critically, there is no discernible phase shift or temporal lag between the mechanical deformation and the resistance change, confirming that the multi-threaded DAQ setup and the intrinsic piezoresistive response of the 3D-printed conductive PLA are sufficiently rapid for real-time monitoring applications.

Similarly, Figure 5.16(c) and 5.16(d) demonstrates the dynamic tracking capabilities of the front-positioned sensors (Sensors 3 and 4). While the absolute strain and  $\Delta R/R$  amplitudes differ between these two sensors, a consequence of the off-axis load misalignment discussed previously in Section 5.4.3, the dynamic *shape* of the transient response is perfectly preserved across both nodes. During the flat hold periods (e.g., between 10–20 seconds and 30–40 seconds), the resistance signals remain highly stable with minimal observable viscoelastic drift.

This successful real-time demonstration confirms that the fully integrated FDM-printed sensing architecture is highly capable of detecting discrete loading events, quantifying load severity, and monitoring sustained stress states, thereby fulfilling the core prerequisites for an integrated aerospace SHM system.

## 5.5 Discussion

### 5.5.1 Influence of Experimental Boundary Conditions on Strain Symmetry and Sensor Response

A critical observation from both the full-field optical validation and the static calibration phase was the divergence from idealized structural symmetry. In the finite element framework, the anchor points were modeled with perfectly rigid constraints and subjected to a purely axial tensile load, naturally predicting a perfectly symmetrical strain distribution across the longitudinal plane. However, physical boundary conditions in experimental setups rarely achieve perfect theoretical alignment.

As clearly revealed by the experimental DIC analysis (Figure 5.12a), the actual strain distribution across the pylon was noticeably non-symmetrical. The integration of the prototype into the UTM relied on customized mechanical grips and structural supports designed to transmit the tensile force. The inherent machining tolerances of these fixtures, combined with the seating dynamics of the FDM-printed polymer within the test rig, introduced a slight off-axis misalignment to the applied tensile load vector. Consequently, the structure was subjected not to a mathematically perfect uniform tension, but rather to a complex stress state that incorporated a subtle parasitic bending moment.

Crucially, this physical asymmetry perfectly explains the divergence in the extracted Gauge Factors between the symmetrically placed front sensors (Sensor 3 and Sensor 4) observed during the static calibration. Because one side of the pylon's geometry absorbed a disproportionate fraction of the mechanical energy due to the off-axis tensile pull, the localized strain experienced at the Sensor 3 hotspot was physically distinct from the strain at the Sensor 4 hotspot. The discrepancy in the calculated GF values and dynamic signal amplitudes is, therefore, not a byproduct of inherent variability or signal noise in the 3D-printed piezoresistive material. Rather, it is an accurate measurement of the true, asymmetric structural deformation.

This finding highlights a significant advantage of the proposed multi-material SHM architecture. The predictive FEA successfully defined the macro-level load paths and optimal sensor placement regions, but the embedded sensors, validated by the optical ground truth of the DIC, proved their operational superiority by measuring the *actual* mechanical state of the structure. They successfully diagnosed an unexpected loading anomaly that a purely theoretical model could never anticipate, proving the system's

high reliability for real-world diagnostic applications.

### 5.5.2 Piezoresistive Synchronization and Dynamic Tracking Fidelity

The real-time step-loading results (as presented in Section 5.4.4) validate the operational viability of the embedded 3D-printed piezoresistive sensors for dynamic SHM. A pervasive challenge with additively manufactured polymeric sensors is their susceptibility to viscoelastic lag and delayed piezoresistive response, which can render them unsuitable for transient load detection. However, the temporal profiles extracted from the incremental step tests demonstrated negligible phase shifts between the applied mechanical strain (DIC ground truth) and the resultant piezoresistive output ( $\Delta R/R$ ). This high-fidelity synchronization confirms that the optimized multi-threaded Data Acquisition (DAQ) architecture, combined with the intrinsic piezoresistive properties of the carbon-black doped PLA, is sufficiently responsive to capture discrete structural events instantaneously.

Furthermore, the step-loading profile provided critical insights into the short-term viscoelastic stability of the FDM-printed sensing elements. During the constant-load hold periods (the plateaus of the stepwise increments), the electrical resistance signals remained remarkably stable, exhibiting only minimal drift. This suggests that within the tested linear elastic regime, the fully dense (100% infill) structural host effectively constrained excessive polymer chain relaxation, thereby mitigating the severe piezoresistive creep that typically plagues soft conductive polymers.

Finally, the dynamic tracking response of the front-positioned sensors (Sensors 3 and 4) reinforces the robustness of the embedded architecture under non-idealized conditions. As established in Section 5.4.3, these sensors experienced asymmetrical strain magnitudes due to an off-axis load misalignment. Crucially, however, their temporal dynamic response (the precise shape of the signal tracking the loading and unloading ramps) remained perfectly synchronized with the local strain field. This proves that while the baseline sensitivity (Gauge Factor) is inherently sensitive to local load paths and microstructural variations, the temporal tracking fidelity of the embedded sensors is highly resilient. Consequently, the sensing network can reliably identify the exact onset and cessation of structural loading events, regardless of spatial loading anomalies, making it a robust diagnostic tool for unpredictable, real-world operational environments.

### 5.5.3 Manufacturing Challenges and Prototype Limitations

The transition from standardized laboratory coupons to a complex, load-bearing structural prototype introduced distinct manufacturing challenges inherent to the multi-material FDM process. During the initial fabrication phases, the pylon's structural load anchors experienced premature mechanical failure during the removal of the sacrificial support structures. Root-cause analysis revealed that the geometric scaling of the original aerospace

pylon design reduced the anchor cross-sections to a thickness that, when combined with the inherent brittleness of the standard PLA host material, could not withstand the localized shear stresses associated with support removal. Consequently, the anchor geometries were redesigned and reinforced. To maintain the validity of the structural analysis, these localized amendments were carefully restricted to the boundary interfaces, ensuring that the macroscopic load distribution and stress paths across the active sensing regions remained fundamentally unaltered.

Furthermore, embedding the piezoresistive sensors within a complex 3D structural geometry highlighted a critical piezoresistive limitation driven by FDM print anisotropy. In previous foundational studies by the authors, identically optimized sensor geometries achieved exceptionally high Gauge Factors ( $GF \approx 59$ ). In those controlled coupon tests, the planar nature of the specimens allowed the conductive traces to be deposited in continuous layers perfectly aligned with the primary axis of the applied load. However, the complex spatial orientation of the pylon prototype dictated that the embedded sensors could not be printed in this optimal, continuous-trace orientation. Instead, due to the global toolpath requirements of the host structure, the conductive elements were manufactured as fragmented layers stacked successively. As extensively documented in the literature, this cross-layer anisotropy significantly disrupts the continuous carbon-black percolation network and introduces higher inter-layer contact resistance (21). While the embedded sensors still successfully delivered reliable and highly responsive dynamic diagnostic data, this physical manufacturing constraint fundamentally explains the reduced absolute sensitivity scores observed in the component-level prototype compared to the theoretically optimized, directionally printed coupons.

#### 5.5.4 Future Applications Illustration

To visually summarize the potential applications of 3D-printed embedded piezoresistive sensors in engineering polymers, an illustrative infographic is provided in Figure 5.17. This figure highlights applications in aerospace, automotive, and industrial polymer components, demonstrating how embedded sensors can monitor structural health in real time.



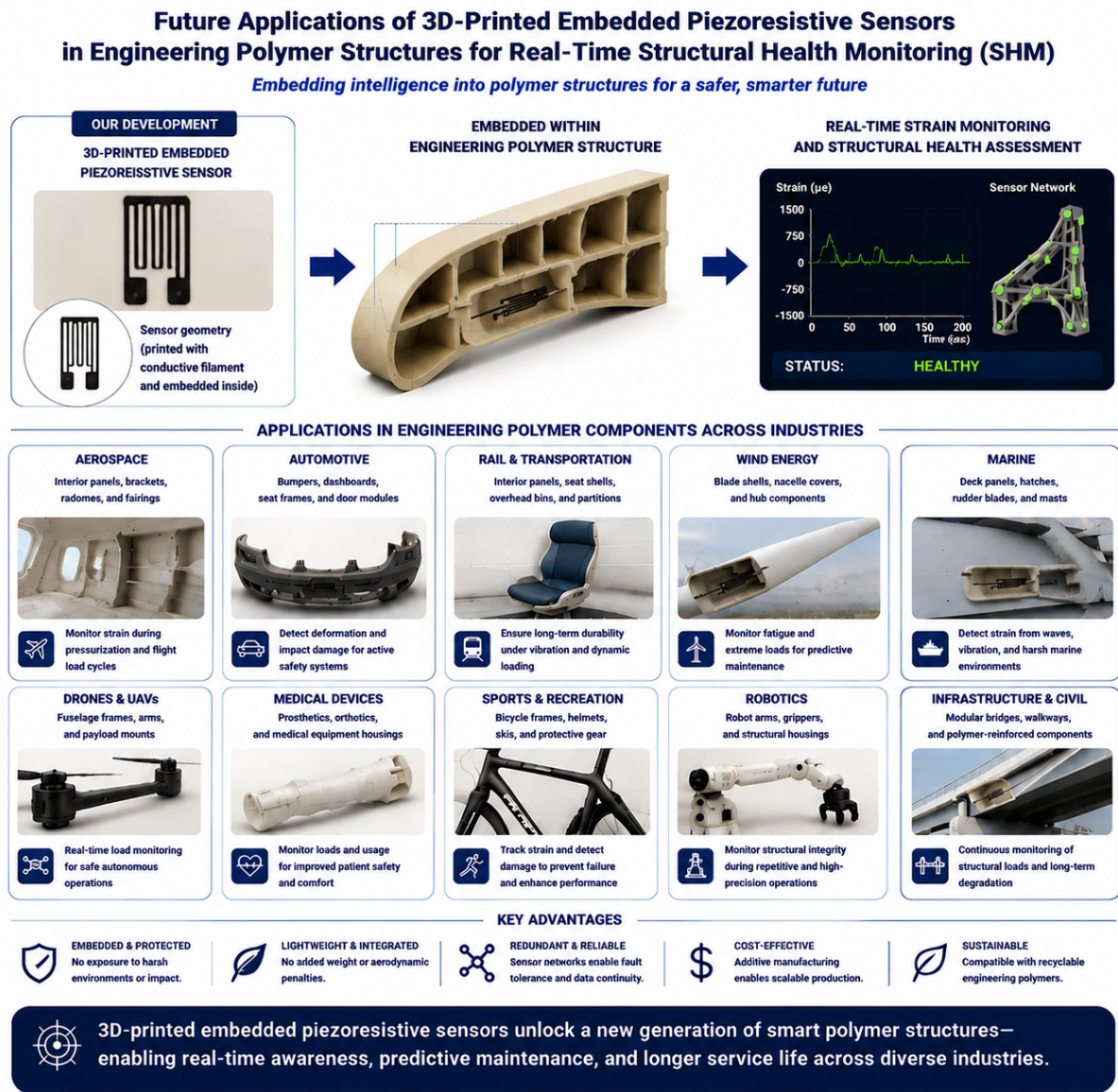


Figure 5.17 – AI-generated illustration of potential applications of 3D-printed embedded piezoresistive sensors in engineering polymers. This image is provided solely for illustrative purposes.

## 5.6 Conclusion

This study successfully demonstrated the practical deployment and comprehensive experimental validation of a fully embedded, 3D-printed piezoresistive sensor network within a realistic, load-bearing aerospace wing pylon prototype. By leveraging multi-material Fused Deposition Modeling (FDM) to directly encapsulate conductive PLA sensing elements within a structural PLA host, the inherent limitations of traditional retrofitted SHM systems, such as adhesive debonding and environmental degradation, were effectively mitigated.

A rigorous numerical-experimental framework was established to validate the self-



sensing architecture. Predictive Finite Element Analysis successfully mapped the macro-strain topologies of the structure under a nominal tensile load, pinpointing the optimal spatial coordinates for sensor placement while deliberately avoiding geometric stress singularities. Subsequent full-field optical validation via Digital Image Correlation physically corroborated these predictive models, confirming the spatial accuracy of the identified strain hotspots and validating the multi-material design methodology.

The most critical finding of this research emerged from the structural response to complex experimental boundary conditions. While the idealized numerical model predicted a perfectly symmetrical strain distribution under purely axial tension, the physical UTM test fixtures inherently introduced a slight off-axis misalignment, inducing a subtle parasitic bending moment. Crucially, the embedded sensor network independently detected this physical asymmetry in real-time. Symmetrically paired sensors exhibited distinct, localized responses that perfectly matched the optical ground truth captured by the DIC.

This behavior highlights the profound diagnostic sensitivity of the proposed embedded SHM system. The integrated sensors proved their operational superiority by measuring the *actual* mechanical state of the structure, successfully diagnosing an unexpected, real-world loading anomaly that a mathematically idealized theoretical model could not anticipate.

Ultimately, this research bridges the critical gap between laboratory-scale coupon characterization and component-level structural deployment. By proving that 3D-printed, embedded piezoresistive sensors can reliably monitor complex stress states and detect physical loading deviations in realistic geometries, this study establishes a robust foundation for the future of functionally integrated, self-sensing aerospace components. Future investigations will build upon this framework by subjecting the self-sensing pylon architectures to long-term cyclic fatigue and diverse environmental spectra to further assess their life-cycle durability.

## 6 Final Remarks

This dissertation has presented a systematic and comprehensive exploration into the development, optimization, and practical application of embedded 3D-printed piezoresistive sensors for Structural Health Monitoring. By progressively advancing from a fundamental literature review to rigorous computational optimization, and culminating in the validation of a complex physical prototype, this research bridges the critical gap between laboratory-scale coupon testing and system-level structural implementation.

The initial comprehensive review underscored the dominance of piezoresistive sensors, particularly those utilizing carbon-based nanomaterials, due to their seamless compatibility with additive manufacturing. However, it also revealed that the reliability of SHM systems is frequently bottlenecked by the sensor-material interface, highlighting the need to carefully manage the physical integration process to prevent structural degradation.

Addressing this fundamental trade-off, the geometric optimization phase of this research provided a robust computational and experimental methodology. Through the deployment of Gaussian Process Regression (GPR) and MOPSO, the inherent conflict between sensor sensitivity and structural stiffness was navigated. The study definitively showed that while a fully embedded sensor configuration achieves superior piezoresistive sensitivity (achieving a Gauge Factor of  $\approx 59$ ), it inherently compromises host stiffness. Crucially, the research proved that applying a deliberate geometric scaling factor to the embedded design can restore the host structure's stiffness to near-native levels ( $\approx 2.18$  GPa) without sacrificing piezoresistive performance.

In the final phase, the thesis successfully demonstrated the transition of these optimized sensor topologies into a functional, load-bearing aerospace pylon prototype. By integrating predictive Finite Element Analysis to pinpoint structural hotspots, the sensors were embedded with high precision using a single-step, multi-material FDM process. Experimental testing combined with full-field Digital Image Correlation (DIC) confirmed highly accurate temporal synchronization between the applied mechanical strain and the sensor's electrical response, exhibiting negligible viscoelastic lag during dynamic loading. Furthermore, the implementation of a redundant sensor architecture provided critical fault tolerance, enabling the system to diagnose asymmetrical loading anomalies that theoretical numerical models could not anticipate.

In conclusion, this work has successfully formulated a highly scalable "Experiment-Model-Optimize-Validate" framework. By proving that additively manufactured self-sensing structures can reliably detect, quantify, and dynamically track mechanical loads in real-time, this thesis pushes the boundaries of current sensing technology. It lays a validated foundation for the future deployment of intelligent, self-aware composite structures in

safety-critical aerospace and civil engineering environments.

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# Appendix

# APPENDIX A – Experimental DoE data

Table A.1 – Design Variables and DoE Responses Data.

| Design Variables |       |      |     | Responses |        |                      |       |       |        |                      |       |       |        |                      |       |
|------------------|-------|------|-----|-----------|--------|----------------------|-------|-------|--------|----------------------|-------|-------|--------|----------------------|-------|
|                  |       |      |     | DoE 1     |        |                      |       | DoE 2 |        |                      |       | DoE 3 |        |                      |       |
| $w_1$            | $w_2$ | $t$  | $N$ | GF        | $R^2$  | $\varepsilon_{\max}$ | $E$   | GF    | $R^2$  | $\varepsilon_{\max}$ | $E$   | GF    | $R^2$  | $\varepsilon_{\max}$ | $E$   |
| [mm]             | [mm]  | [mm] | -   | -         | -      | [%]                  | [MPa] | -     | -      | [%]                  | [MPa] | -     | -      | [%]                  | [MPa] |
| 2.0              | 0     | 0.2  | 2   | 2.83      | 0.9704 | 3.02                 | 1831  | 2.85  | 0.9849 | 3.04                 | 2041  | 55.87 | 0.9845 | 2.76                 | 1855  |
| 0.8              | 2     | 0.2  | 2   | 2.85      | 0.9881 | 2.10                 | 1796  | 2.13  | 0.9890 | 2.63                 | 1963  | 46.01 | 0.9732 | 3.00                 | 1872  |
| 0.8              | 0     | 1.2  | 2   | 0.50      | 0.9851 | 1.83                 | 2010  | 0.80  | 0.9915 | 2.26                 | 2088  | 50.23 | 0.9931 | 2.76                 | 1852  |
| 2.0              | 2     | 1.2  | 2   | 0.43      | 0.9872 | 1.19                 | 2006  | 0.81  | 0.9873 | 3.55                 | 2098  | 59.99 | 0.9942 | 2.69                 | 1841  |
| 0.8              | 0     | 0.2  | 4   | 2.24      | 0.9841 | 1.75                 | 2124  | 2.29  | 0.9709 | 2.33                 | 2116  | 26.65 | 0.9853 | 2.66                 | 1862  |
| 2.0              | 2     | 0.2  | 4   | 4.12      | 0.9773 | 3.23                 | 1790  | 3.37  | 0.9955 | 3.32                 | 1932  | 63.02 | 0.9864 | 2.83                 | 1871  |
| 2.0              | 0     | 1.2  | 4   | 1.02      | 0.9931 | 2.44                 | 1794  | 2.08  | 0.9332 | 1.75                 | 2058  | 61.17 | 0.9737 | 2.93                 | 1885  |
| 0.8              | 2     | 1.2  | 4   | 1.54      | 0.9910 | 2.54                 | 1841  | 1.61  | 0.9935 | 2.42                 | 2086  | 65.49 | 0.9878 | 2.44                 | 1870  |
| 1.4              | 1     | 0.7  | 3   | 2.96      | 0.9935 | 2.45                 | 1972  | 1.94  | 0.9892 | 3.03                 | 2040  | 57.50 | 0.9721 | 2.32                 | 1803  |
| 1.4              | 1     | 0.7  | 3   | 2.93      | 0.9935 | 2.47                 | 1972  | 1.96  | 0.9892 | 3.03                 | 2040  | 57.50 | 0.9721 | 2.34                 | 1803  |
| 0.8              | 0     | 0.2  | 2   | 3.85      | 0.9854 | 2.80                 | 1884  | 3.04  | 0.9873 | 2.25                 | 2071  | 57.59 | 0.9855 | 2.43                 | 1844  |



Table A.1 – continued from previous page

| Design Variables |       |      |     | Responses |        |                      |       |       |        |                      |       |       |        |                      |       |
|------------------|-------|------|-----|-----------|--------|----------------------|-------|-------|--------|----------------------|-------|-------|--------|----------------------|-------|
|                  |       |      |     | DoE 1     |        |                      |       | DoE 2 |        |                      |       | DoE 3 |        |                      |       |
| $w_1$            | $w_2$ | $t$  | $N$ | GF        | $R^2$  | $\varepsilon_{\max}$ | $E$   | GF    | $R^2$  | $\varepsilon_{\max}$ | $E$   | GF    | $R^2$  | $\varepsilon_{\max}$ | $E$   |
| [mm]             | [mm]  | [mm] | -   | -         | -      | [%]                  | [MPa] | -     | -      | [%]                  | [MPa] | -     | -      | [%]                  | [MPa] |
| 2.0              | 2     | 0.2  | 2   | 2.51      | 0.9891 | 2.94                 | 1800  | 5.54  | 0.9912 | 3.72                 | 1937  | 50.14 | 0.9940 | 2.76                 | 1846  |
| 2.0              | 0     | 1.2  | 2   | 1.21      | 0.9980 | 2.77                 | 1975  | 0.25  | 0.9322 | 2.12                 | 2046  | 51.37 | 0.9966 | 2.76                 | 1809  |
| 0.8              | 2     | 1.2  | 2   | 0.55      | 0.9776 | 1.63                 | 2061  | 1.74  | 0.9815 | 2.69                 | 1928  | 50.23 | 0.9931 | 2.76                 | 1845  |
| 2.0              | 0     | 0.2  | 4   | 4.00      | 0.9866 | 2.95                 | 1797  | 2.99  | 0.9887 | 2.65                 | 2042  | 59.63 | 0.9734 | 2.34                 | 1882  |
| 0.8              | 2     | 0.2  | 4   | 2.52      | 0.9875 | 2.63                 | 1794  | 3.31  | 0.9817 | 2.69                 | 2129  | 45.84 | 0.9867 | 2.43                 | 1875  |
| 0.8              | 0     | 1.2  | 4   | 0.82      | 0.9857 | 2.07                 | 2029  | 1.33  | 0.9899 | 2.83                 | 1956  | 49.15 | 0.9717 | 2.79                 | 1832  |
| 2.0              | 2     | 1.2  | 4   | 0.57      | 0.9841 | 1.89                 | 1926  | 0.85  | 0.9663 | 2.20                 | 2009  | 75.73 | 0.9748 | 2.21                 | 1838  |
| 1.4              | 1     | 0.7  | 3   | 2.93      | 0.9836 | 2.47                 | 1972  | 1.96  | 0.9793 | 3.00                 | 2040  | 56.93 | 0.9624 | 2.30                 | 1803  |
| 1.4              | 1     | 0.7  | 3   | 2.93      | 0.9836 | 2.45                 | 1972  | 1.96  | 0.9892 | 3.06                 | 2040  | 58.08 | 0.9624 | 2.32                 | 1803  |
| 0.8              | 1     | 0.7  | 3   | 2.12      | 0.9844 | 2.64                 | 2013  | 1.63  | 0.9860 | 2.87                 | 2082  | 50.70 | 0.9907 | 2.56                 | 1958  |
| 2.0              | 1     | 0.7  | 3   | 1.14      | 0.9985 | 2.82                 | 1964  | 2.07  | 0.9838 | 3.07                 | 1985  | 66.98 | 0.9797 | 2.89                 | 1903  |
| 1.4              | 0     | 0.7  | 3   | 0.77      | 0.9821 | 1.85                 | 2039  | 2.13  | 0.9854 | 2.90                 | 2058  | 68.70 | 0.9667 | 2.43                 | 1927  |
| 1.4              | 2     | 0.7  | 3   | 1.69      | 0.9951 | 3.03                 | 1912  | 1.97  | 0.9827 | 3.14                 | 2080  | 63.03 | 0.9697 | 2.80                 | 1900  |
| 1.4              | 1     | 0.2  | 3   | 5.35      | 0.9879 | 2.84                 | 2063  | 3.67  | 0.9850 | 3.10                 | 2001  | 56.86 | 0.9867 | 2.66                 | 1935  |
| 1.4              | 1     | 1.2  | 3   | 0.80      | 0.9934 | 2.83                 | 2009  | 0.80  | 0.9908 | 2.77                 | 2091  | 67.13 | 0.9703 | 2.24                 | 1921  |

Table A.1 – continued from previous page

| Design Variables |       |      |     | Responses |        |                      |       |       |        |                      |       |       |        |                      |       |
|------------------|-------|------|-----|-----------|--------|----------------------|-------|-------|--------|----------------------|-------|-------|--------|----------------------|-------|
|                  |       |      |     | DoE 1     |        |                      |       | DoE 2 |        |                      |       | DoE 3 |        |                      |       |
| $w_1$            | $w_2$ | $t$  | $N$ | GF        | $R^2$  | $\varepsilon_{\max}$ | $E$   | GF    | $R^2$  | $\varepsilon_{\max}$ | $E$   | GF    | $R^2$  | $\varepsilon_{\max}$ | $E$   |
| [mm]             | [mm]  | [mm] | -   | -         | -      | [%]                  | [MPa] | -     | -      | [%]                  | [MPa] | -     | -      | [%]                  | [MPa] |
| 1.4              | 1     | 0.7  | 2   | 2.46      | 0.9798 | 2.94                 | 1947  | 1.33  | 0.9734 | 2.77                 | 2056  | 81.16 | 0.9808 | 2.21                 | 1914  |
| 1.4              | 1     | 0.7  | 4   | 1.86      | 0.9838 | 3.46                 | 1955  | 2.44  | 0.9882 | 3.21                 | 2082  | 56.16 | 0.9973 | 2.66                 | 1944  |
| 1.4              | 1     | 0.7  | 3   | 2.96      | 0.9935 | 2.45                 | 1972  | 1.94  | 0.9892 | 3.06                 | 2040  | 58.08 | 0.9624 | 2.34                 | 1803  |
| 1.4              | 1     | 0.7  | 3   | 2.93      | 0.9935 | 2.47                 | 1972  | 1.96  | 0.9892 | 3.03                 | 2040  | 56.93 | 0.9721 | 2.32                 | 1803  |

## APPENDIX B – Full Pareto front

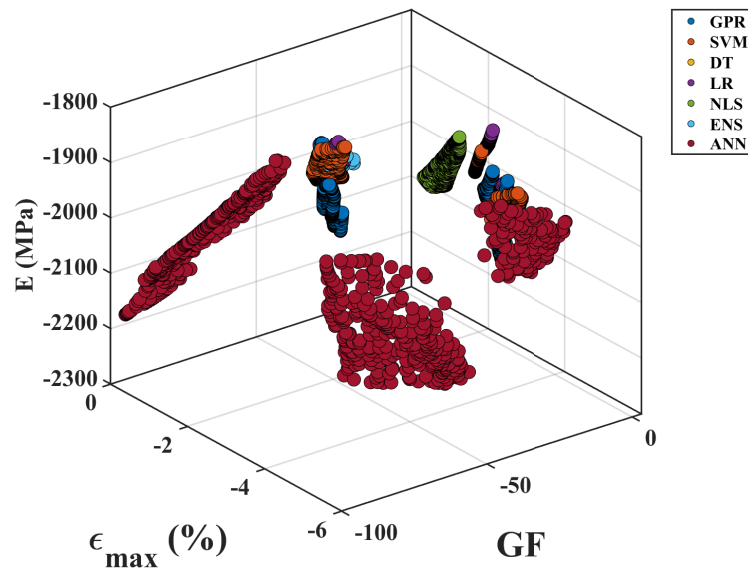


Figure B.1 – Comparison of Pareto fronts generated by all eight surrogate models. The scattered and inconsistent fronts from models like ANN and DT highlight the superiority of the GPR model for this optimization problem.