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Through-Life Support, Diagnosis and Prognosis in the aeronautical field – A critical literature review

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Author: **Konstantin Tavdishvili**

Student ID: 10662733
Advisor: Prof. Giuseppe Sala
Co-advisor: Ing. Pietro Aceti

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Abstract

The present study provides a comprehensive and detailed definition of structural health monitoring for aircraft, which aims to predict the health status of an aircraft and facilitate condition-based maintenance scheduling to improve through-life support. To ensure effective structural monitoring, the adoption of high-performance data analysis models, including Machine Learning models, is crucial. Additionally, the design of a robust and efficient sensor network for data acquisition plays a vital role in acquiring reliable and accurate data. Furthermore, the study will examine the significance of self-healing systems in improving material performance. It will address novel solutions and applications of self-healing systems, aiming to enhance the durability and reliability of aerospace structures. Overall, this work aims to contribute to the advancement of structural health monitoring, data analysis techniques, sensor network design, and the adoption of self-healing systems in the aerospace field.

Key-words: Through-life Support, Structural health monitoring, Diagnosis and prognosis, Fiber optics, Piezoelectric sensors, Self-healing systems.

Abstract in italiano

La presente ricerca fornisce una definizione completa e dettagliata del monitoraggio strutturale della salute per gli aeromobili, il quale mira a predire lo stato di salute di un aeromobile e agevolare la pianificazione della manutenzione basata sulle condizioni in vista al miglioramento del supporto per la vita. Per garantire un monitoraggio strutturale efficace, è fondamentale adottare modelli di analisi dati ad alte prestazioni, inclusi modelli di apprendimento automatico (Machine Learning). Inoltre, la progettazione di una rete di sensori robusta ed efficiente per l'acquisizione dei dati riveste un ruolo vitale nell’ottenere dati affidabili e accurati. Inoltre, la ricerca esaminerà l'importanza dei sistemi di auto-riparazione nel miglioramento delle prestazioni dei materiali. Saranno affrontate nuove soluzioni e applicazioni di tali sistemi, mirando a migliorare la durabilità e l'affidabilità delle strutture aerospaziali. Nel complesso, questo lavoro mira a contribuire all'avanzamento del monitoraggio strutturale della salute, delle tecniche di analisi dati, della progettazione di reti di sensori e all'adozione di sistemi di auto-riparazione nel settore aerospaziale.

Parole chiave: Supporto per la vita, Monitoraggio strutturale della salute, Diagnosi e prognosi, Fibre ottiche, Sensori piezoelettrici, Sistemi di auto-riparazione.

Contents

Introduction

Aircrafts encompass various systems, subsystems, components, and parts that are continually exposed to thermal, mechanical, aerodynamic, electromagnetic, or other stresses throughout their operational lifespan. Consequently, they are susceptible to degradation and failure. The primary objective is to predict their failure through maintenance procedures to repair or replace components or parts, thereby preventing catastrophic failures and ensuring safety margins. However, maintenance procedures are designed based on different principles, where one approach may incur higher costs while compromising safety to some extent. Hence, there is a need to transition to new maintenance methodologies, such as predictive Condition-Based Maintenance (CBM), which may offer a safer and more cost-effective approach. Chapter 1 will focus on the description of maintenance/support methodologies and on comparison between traditional and more recent maintenance/support methodologies in the aerospace industry embracing the evolving concept of Through-Life Support (TLS).

To ensure the effectiveness of CBM, it is crucial to have internal diagnostic and prognostic systems embedded within aircraft. These systems calculate health and usage parameters and predict their future evolution to establish maintenance schedules. Thus, the design of a reliable and high-performing Structural Health Monitoring (SHM) system becomes essential. A comprehensive SHM system typically comprises a data acquisition sensor network, which collects measurements from various points on the aircraft, and computer models that fuse these parameters, calculate useful indicators, and predict maintenance intervals. Chapter 2 will delve into these subjects.

Section 2.1 will focus on SHM models, classifying them into three categories: data-driven, physics-based, and hybrid approaches. Each class will be described in detail, exploring different models within each category. Special attention will be given to identifying optimal solutions, such as Convolutional Neural Networks (CNN), and an illustrative example of predictive maintenance application will be provided in subsection 2.1.4.

In section 2.2 of the chapter, the focus will shift towards the sensor network used in SHM. A comprehensive description will be provided, encompassing the working principles, novel applications, and future trends of various smart sensors employed in the aerospace industry. Special emphasis will be placed on two key players: Fiber Optics (FO) 2.2.1 and Piezoelectric sensors (PS) 2.2.2.

The discussion will delve into the physics behind these sensors, highlighting their unique characteristics and capabilities. The classification of FO sensors into point, quasi-distributed, and distributed types will be explored, identifying the most prominent solutions and applications such as Extrinsic Fabry-Perot Interferometers and Fiber Bragg Gratings. Furthermore, a novel example of a Distributed Fiber Optic Sensing Textile (DFOST) 2.2.1.3 will be presented, showcasing its immense potential for applications in large-area structures like fuselages or wing components. Similarly, for piezoelectric sensors, the physics will be described, and they will be classified into acoustic emission, guided wave propagation, and electro-mechanical impedance sensors. Best practices utilizing Lead Zirconate Titanate (PZT) or Polyvinylidene Fluoride (PVDF) sensors will be highlighted. Applications of both FO and PS sensors for metallic and composite structures will also be explored.

To further enhance the lifespan and performance of structures, the adoption of self-healing systems presents a promising avenue. Self-healing materials possess the ability to recover and repair themselves after experiencing impacts or failures within a component or system. This self-healing capability can be achieved through intrinsic or extrinsic means.

Intrinsic self-healing involves the utilization of physical or chemical bonds within the material that have the ability to reform and restore their integrity after damage has occurred. On the other hand, extrinsic self-healing relies on external healing agents, such as microcapsules or vascular channels, which can release healing agents to repair the material. Additionally, miscellaneous technologies like Shape Memory Alloys (SMA) can also contribute to achieving extrinsic self-healing.

Chapter 3 will delve into a comprehensive and detailed description of these self-healing approaches. It will focus on identifying novel applications and future perspectives in the field of self-healing materials, highlighting the advancements and potential for further development in this area.

1 Through-Life Support

There seems to be no universally accepted definition for *Through Life Support* (TLS) – in some contexts it refers only to „after-sales support", whereas in other contexts it's a full transfer of technical risk to a contractor (which is known in the United States as "Performance Based Logistics"). It's assumed that "Through Life Support" refers to the performance-based support of the entire aircraft system by the system manufacturer. The concept of ''support'' can encapsulate a wide range of activities in aerospace field. These include deeper aircraft vehicle maintenance/repair/overhaul, major capability upgrades, engineering support, management of spare-parts, technology insertion projects, obsolescence management, reliability and availability analysis, access and use of Intellectual Property such as design drawings and data, training support, and the provision of other products and services which enable an operator to conduct efficient and effective operations [1].

TLS is about „*capability delivery*" – enabling an operations-focused customer to successfully achieve their mission. This implies that any TLS program must ensure that the platform delivers the appropriate capabilities to meet the changing environments of their customers. In the military context, this might mean new weapons and sensors. In the commercial arena, it might mean better cabin experiences, improved fuel-burn performance or else. Capability can be broadly seen as the continuous satisfaction of design/mission requirements and airworthiness, provision of best availability (lowest downtime), adaptation to evolving environment and cost minimization. The International Council on Systems Engineering (INCOSE) defines capability as follows:

"*A measure of the system's ability to achieve the mission objectives, given that the system is dependable and suitable. Examples of capability measures are accuracy, range, payload, lethality, information rates, number of engagements, and destructiveness. Capability measures can be used as performance requirements, design constraints, and/or technical exit criteria. Capability is a system's engineering metric*" [2].

Important parameter for aircraft capability is **Availability.** Availability is the average availability through-life and can be expressed simply as the number of aircrafts. However, when "availability" is used as a forward-looking performance parameter, most definitions imply that it is the probability that an aircraft in a defined group will be fit for operational use immediately or within a defined recovery period whenever tasked. It refers to immediate operational readiness which is of outmost importance both for military and for civil aircrafts to ensure national safety, in the first case, and provide great economic income, in the second. "The most powerful weapon in the world is useless if we can't deploy and use it effectively in the fight…" (Kratz, L.A. (US Assistant Deputy Under Secretary of Defense – Logistics Plans & Programs) [3]. Only available aircraft can deliver capability. Therefore, aircraft availability is an important measure of both effectiveness and readiness in relation to a capability that requires aircraft to help achieve the desired effect. Increase in availability is obtained through minimization of the time taken for aircraft maintenance, known as downtime.

Another important parameter is **Reliability**, also referred as continued availability, of a mission profile. Most definitions of mission reliability imply the probability that an aircraft or equipment that is initially fit for operational use will not fail to complete a given mission profile due to equipment failure. The concept of mission reliability is consistent with the general concept of "reliability". However, mission reliability is assessed against very short intervals of time or usage, while aircraft reliability is assessed over long intervals of time or usage. Also, the definition of failure is not the same in each case. Mission reliability is governed only by the probability of a single mission-critical failure, while (general) reliability is governed by all failures and potential failures that occur over a long interval, regardless of their criticality. Mission reliability is closely allied with flight safety, thus the specified level of mission reliability is the main driver of preventive maintenance.

All engineered objects are inherently unreliable as they degrade with use and time and will ultimately fail if unmaintained. In 2018, around $69 billion was spent by airlines globally on conducting maintenance, repairs, and overhaul, consisting of 9% of their total operational costs [4]. The maintenance phase constitutes a pivotal segment within the chronicles of an aircraft's lifespan, necessitating meticulous optimization and enhancement to minimize expenditures and time investments, all while upholding the paramount importance of aircraft safety and reliability.

The maintenance and support of aircraft platforms has traditionally been carried out using "Time and Materials" (T&M) contracts, whereby the operator pays simply for the level of work undertaken by the contractor (i.e., hours worked), plus the materials used (such as new parts). Nowadays, the aerospace business is changing from a traditionally product driven environment to a more capability driven environment where the product supplier must take responsibility of the serviceability of the product from design, manufacture, operations to disposal. Performance based TLS is related to the concept of ''Power-By-The-Hour'' where a contractor is not paid by the level of activity performed (such as hours spent on maintenance), but rather on the level of defined system availability. It involves a fee paid to a service provider on an hourly operational basis (i.e., the number of flight hours multiplied by a per-hour fee). Such performance-based contracts may stipulate minimum system flight-hour availability where a fee is paid to the service provider for delivery, with penalties for not achieving the availability/delivery targets.

Traditional maintenance ideologies would like to keep the aircraft in the hangar as long as possible, as payments are tied to hours worked. However, Through Life Support concepts dictate „pushing" the aircraft out of the hangar as quick and as long as possible in order to make the operation as profitable for the contractor as possible, by delivering the capability. Maintenance could have been sent to a low-cost provider. However, whilst the labour rate is less, the turnaround times are higher (and thus the aircraft availability is less). When availability means the ability to make money, and downtime means forgone opportunities to make money, there are benefits in paying a higher price for faster maintenance times.

The downtime for servicing can be reduced by designing the aircraft to operate for longer periods without replenishments and other servicing: Routine cleaning to remove damaging atmospheric contaminants can be very beneficial over the long term in reducing the need for corrective maintenance to the structure of airframes and engines; The routine application of corrosion preventive compounds, independently or in conjunction with cleaning, can be beneficial for the same reasons; On occasions when fuel is the only consumable that needs replenishment, in-flight refuelling is a maintenance concept that can significantly reduce the downtime for servicing. The aircraft downtime can further be reduced by extending components lives by: (I) Extra investments with change in technology, (II) extra investments without change in technology and (III) improvements in health and usage monitoring systems.

With regard to the last option, the useful life can be maximised for a given probability of failure by updating the usage input to the estimate of Remaining Useful Life (RUL) as frequently and accurately as possible, and by adjusting the maintenance schedule accordingly. Increasing the accuracy of usage monitoring reduces the uncertainty in the estimate of remaining life. Usage monitoring is essential for determining when to perform preventive maintenance, and improvements in monitoring can reduce downtime and life-cycle costs. In its simplest form, usage monitoring consists of keeping written records of flying hours and elapsed time for the aircraft and its lifed components. With advances in monitoring technologies, including data handling and processing, it has become feasible to monitor the usage of ever more components while improving accuracy and reducing costs. Also, it has in some cases become worthwhile to calculate the RUL and reschedule component replacement using an on-board system rather than a ground-based system. In such cases usage information is fed directly to the on-board system in flight. Such a system is sometimes referred to as a prognostic system. Hence, this work's main purpose is to design efficient and performant usage monitoring system, much more detailed description will be given in the chapter 2.

The various maintenance strategies used across different industries can be broadly split between reactive and proactive methodologies, for rectifying equipment failures immediately and preventing them from occurring, respectively. [5], [6].

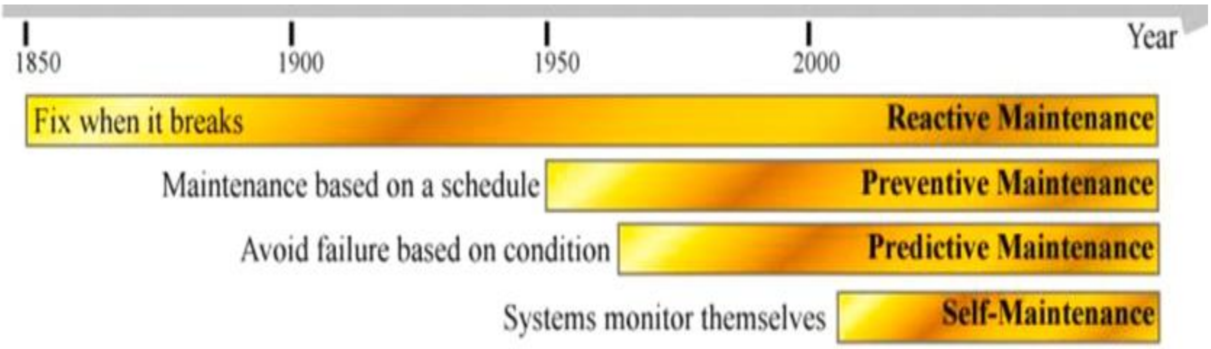


Figure 1. Maintenance strategies [7]

1.1. Traditional Maintenance

Corrective maintenance is a reactive methodology where maintenance is unscheduled and performed immediately after an asset fails. It is based on unexpected events such as pilots' reports, bird strikes, finding during inspection and other. This is the oldest method that best utilizes the maximum lifetime of components and is the easiest strategy to implement for technicians, however, is the most expensive. It is moreover not feasible with safety criteria because the maintenance would trigger only after a failure has occurred which would compromise the safety of a system or of a whole aircraft [8].

Preventive maintenance is a proactive methodology where maintenance is scheduled and performed at predefined intervals which comes in the forms of flight hours, flight cycles or calendar days. Interval periods for preventive maintenance are generated by following maintenance programs, such as the Maintenance Review Board Report, where engineers use their experience to perform experiments and collect data to determine the most appropriate length of maintenance intervals. The goal of such system is to maximize the interval between maintenances and maximize the component usage to exploit its whole useful life. However, this procedure does not guarantee full usage of component and triggers to its substitution/repair long before it exploits its full potential life. This is translated into economical insight: a component that can perform longer is substituted earlier, so the material and maintenance costs are increased [8].

1.2. Condition-Based Maintenance

Condition monitoring entails the systematic monitoring of a defined set of parameters and/or variables that serve as indicators for assessing the state of the system under scrutiny. When these parameters surpass predetermined threshold limits, maintenance actions are triggered, ideally implemented pre-emptively to ensure the safety and integrity of the equipment or system. Overall, condition monitoring offers a multitude of benefits [9], including:

- Reducing aircraft downtime and expenses by eliminating unnecessary maintenance.
- Providing early failure detection to increase availability, safety and reliability.
- Supporting continuous improvement ensuring accurate and consistent response to changing conditions.
- Providing better decision making for operations, engineering and maintenance staff.

However, it also presents some disadvantages as [10], [11]:

- Large initial installation and systems cost.
- Uncertainty associated with monitoring system.

1.3. Prognostics and Health Management

Prognostics and Health Monitoring (PHM) is a comprehensive system endowed with the capability to continually monitor the progressive health and operational usage of a given system, leveraging an extensively distributed sensor network. This network facilitates the acquisition of crucial load and event data, enabling fault diagnosis to effectively identify premature failures and optimize predictive maintenance schedules.

Broadly speaking, a PHM system encompasses both on-board and ground-based components. The on-board system acquires load-related data from various sensors, including but not limited to strain, acceleration, and vibration sensors. It maintains communication with the aircraft system, facilitating the exchange of data. This collected data is subsequently utilized for offline analysis, wherein the load history and life prediction of critical components are assessed post-flight.

Flight record data is downloaded by ground crew members and subsequently processed using damage assessment software. The resulting output encompasses vital parameters such as load and stress history, damage and life management parameters, and graphical user interface prediction tools. Damage and life parameters are often quantified in relation to the ratio of flight damage to the average flight damage recorded within the reference spectrum. The damage and life of each flight are evaluated based on aircraft design method: fatigue crack initiation analysis (for safe-life approach) and crack propagation (for damage tolerance approach) [12].

Condition-Based Maintenance (CBM) is strictly based on PHM system. The selection of an appropriate PHM (and its optimization techniques) is always challenging and highly depends upon the system/component to be monitored. Most generic PHM system consists of three main components [7]:

1. Data acquisition.
2. Data pre-processing and feature extraction.
3. Diagnosis, prognosis and decision-making.

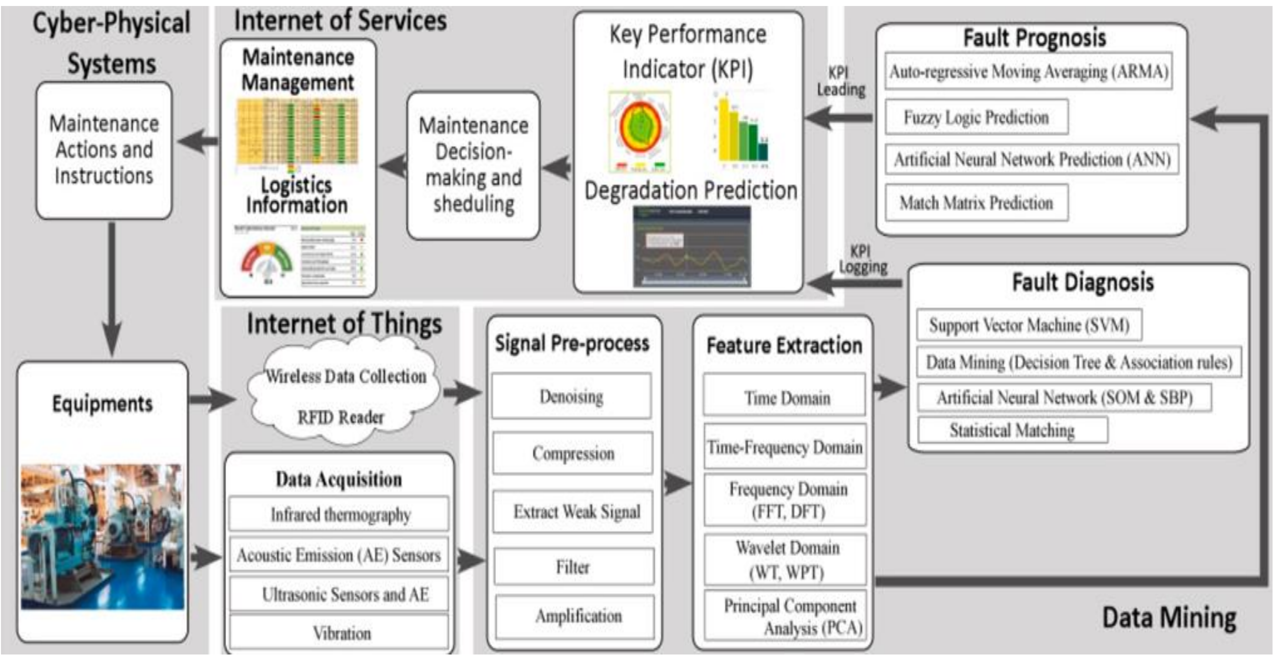


Figure 2. The framework of intelligent maintenance systems [7].

Data are usually acquired by means of various sensors (e.g., electrical, electronic, mechanical, electro-mechanical). The acquired data are then pre-processed (filter, denoising, amplification and etc…) and processed (extraction of entities, evaluation and selection processes to extract features) to determine the health and the usage of the system under investigation.

Numerous techniques are available classified in the time-domain, frequency-domain and time-frequency-based domain [13]. Features extracted from time-domain techniques are suitable for fault detection. The most widely applied technique in this category is the Fast Fourier Transform. Other methods that belong to this category are spectral analysis, higher-order spectra, and envelope analysis. Time-frequency techniques aim at investigating signals in both time and frequency domains. Some of the popular time-frequency techniques are Short Time Fourier Transform, Wavelet Transform, Empirical Mode Decomposition. The latter is a self-adaptive signal processing technique that is suitable for non-linear and non-stationary processes [14]. However, the main weakness of Empirical Mode Decomposition is its high sensitivity to noise.

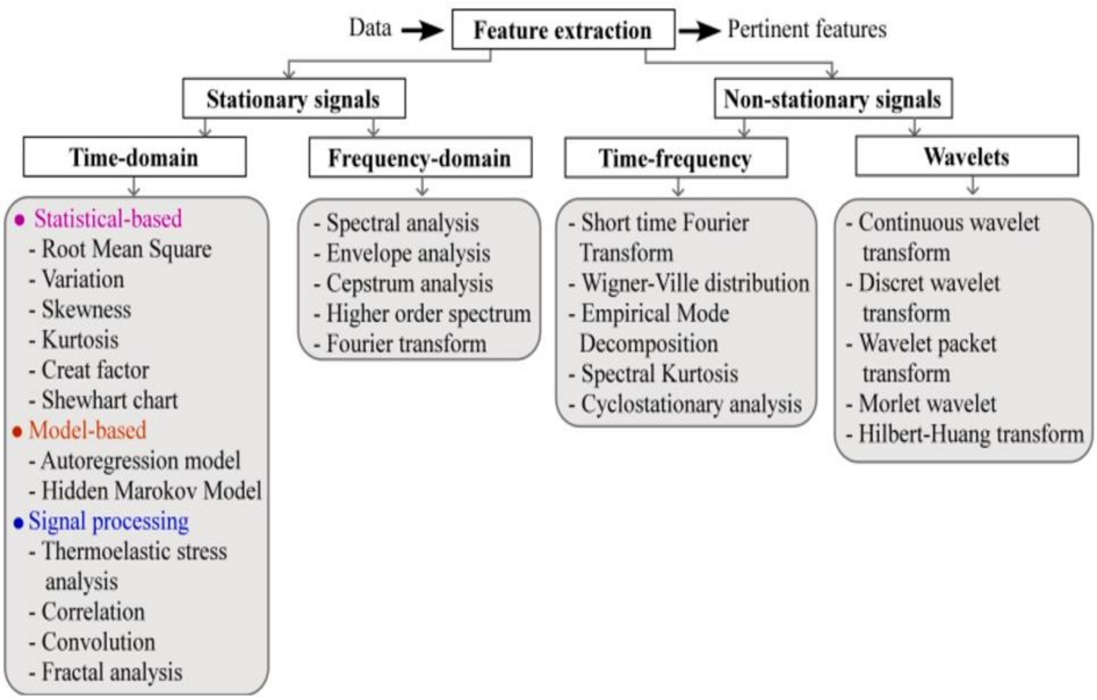


Figure 3. Feature extraction approaches [7] (adapted from [15])

Diagnosis is the phase in which fault detection process includes answers to questions such as [16]:

- Detection: which assembly, sub-assembly or component is defective?
- Identification: What is the cause of defect/failure?
- Assessment: How serious is the problem?

Prognosis refers to the systematic procedure of forecasting the point in time, known as the Residual Useful Life (RUL) [7], [17], at which a component will cease to fulfil its intended function. The RUL signifies the time interval spanning from the current moment to the occurrence of component failure. Accurate prognosis plays a pivotal role in providing valuable insights to facilitate decision-making processes across various domains.

However, it is important to acknowledge that certain failures may manifest intermittently, rendering them challenging to predict with certainty [18]. Consequently, the prognosis process necessitates the consideration of a probability density function to represent the RUL, accounting for the inherent uncertainties and variability associated with failure occurrences.

Finally, it is used in **decision-making** process such as in determining [7]:

- Proactive maintenance steps.
- Cost/benefit analysis.
- Performance improvement.
- Downtime reduction.
- Maintenance scheduling

In certain scenarios, a CBM system may prove ineffective due to various factors. For instance, failure data required for assessing the system's state may be unavailable, or the acquired data may possess qualitative characteristics rather than quantitative, thereby introducing additional complexity to the assessment process. To overcome these limitations stemming from small datasets, several approaches have been proposed.

One prominent approach involves the utilization of data augmentation techniques, which have garnered significant attention for their ability to enhance the size of training datasets by generating synthetic data. Fundamental augmentation techniques such as window cropping and wrapping have been widely employed to generate new data sequences from the original time-series data [19]. Moreover, advanced techniques such as generative algorithms can be leveraged to generate new data that closely resemble real data, further expanding the dataset. By employing data augmentation techniques, CBM systems can address the challenges posed by limited data availability or qualitative data, enabling more robust and comprehensive assessments of the system's condition. [7]

Strategies for performing predictive CBM are being applied to a wide range of different industrial fields and applications, with many novel methods developed in recent years. Many authors have applied different methods to applications, using a mix of data analytics and machine learning. Detailed comparison of different techniques will be presented in section 2.1 Diagnosis, prognosis and decision-making. It is worthy to mention that applicability of one technique or another strongly depends on the equipment/system under consideration. [8]

The following chapter will embrace in-depth study of PHM systems by dealing with different models and current trends for diagnosis, prognosis and decision-making tools. While the remaining part of it will deal with in-depth study of different sensors for data acquisition for PHM of aircraft structures. While chapter 3 will undertake a comparative study of different self-healing systems.

2 Structural Health Monitoring

Structural Health Monitoring (SHM) assumes great significance for structures that are challenging to access for regular maintenance or inspections, such as composite structures. Typically, a safety margin of 2.0 is employed to estimate the ultimate loading capacity that composite structures should withstand [20], resulting in thicker and heavier components, thus increasing costs. However, the implementation of a structural health monitoring system offers a viable solution for real-time monitoring of the health status of composite structures.

Integrating a structural health monitoring system has the potential to alleviate the need for the stringent safety margin imposed by aviation regulations, specifically in the design of composite structures. By leveraging permanently attached sensors for structural health diagnostics, it becomes possible to reduce the safety margin from 2.0 to 1.75. This reduction in safety margin can be assumed with confidence due to the continuous monitoring and real-time assessment facilitated by the structural health monitoring system. [20] assesses the potential fuel savings and direct operating costs (DOC) through a multidisciplinary analysis on a A220-like aircraft quantifying the benefits in fuel saving thanks to SHM. According to the foreseen level of technology, addressed through the number of sensors per square meter, a DOC saving from 2% up to 5% is achievable preserving, at the same time, all the key aircraft performance.

As already mentioned, PHM (or SHM) consists of three main phases: data acquisition, signal pre-processing and diagnosis, prognosis and decision-making.

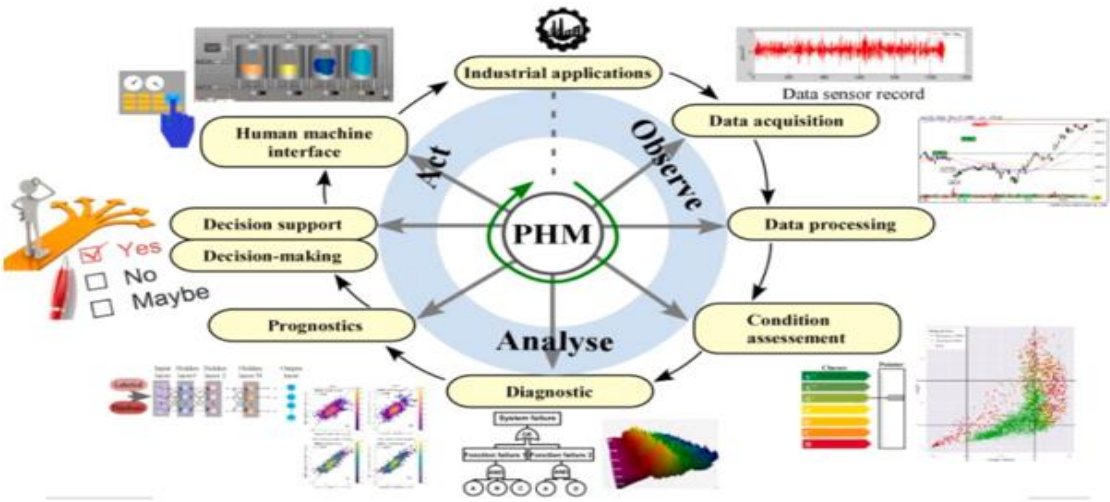


Figure 4. Typical PHM system architecture [7] (adapted from [15]).

The subsequent section will entail an in-depth examination of the field encompassing Diagnosis, Prognosis, and Decision-making, encompassing diverse solutions and identifying forthcoming trends. Ultimately, we will delve into a comprehensive study of sensor networks, highlighting their distinctive characteristics and associated considerations.

2.1. Diagnosis, Prognosis and Decision-Making

Diagnosis and prognosis constitute the fundamental pillars of Health and Usage Monitoring Systems (HUMS). Through the application of data analytics or Machine Learning (ML) techniques, these processes enable the prediction of the Residual Useful Life (RUL) of a machine or subcomponent, thereby facilitating the formulation of effective maintenance schedules. By leveraging diagnostic and prognostic capabilities, HUMS empowers organizations to proactively plan maintenance activities, optimizing resource allocation and minimizing downtime.

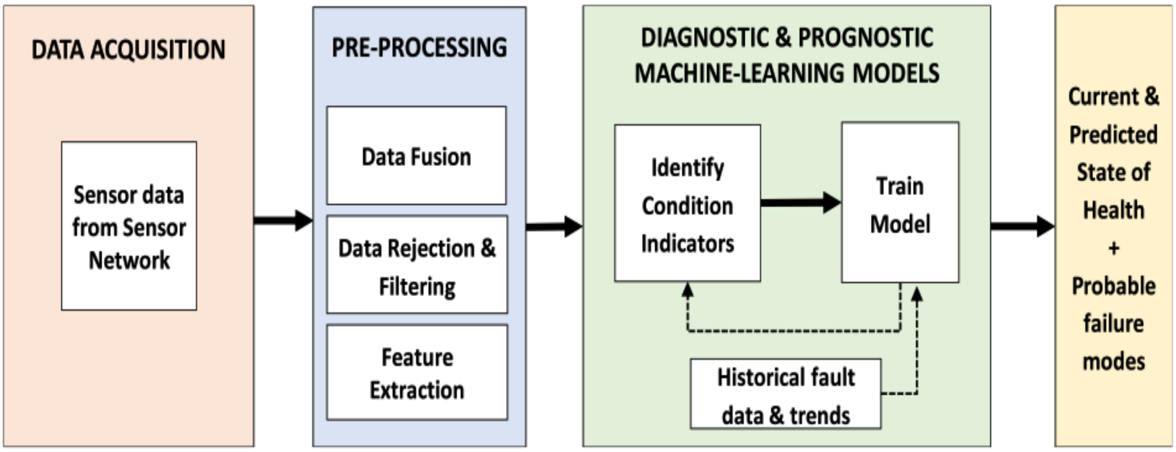


Figure 5. PHM data workflow diagram [21].

In this phase, the parameters acting as condition indicators for faults are identified and monitored to detect, identify and characterize faults and can then be compared to a model "Digital Twin" (DT) of the aircraft.

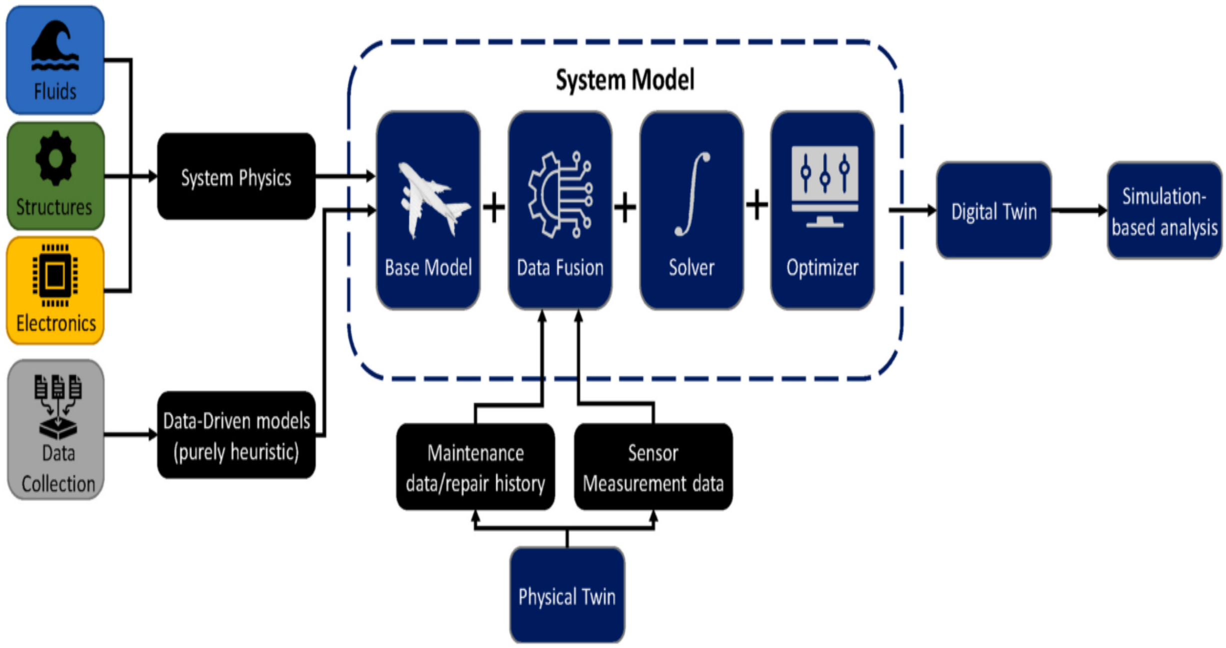


Figure 6. Digital-Twin model process [21].

The concept ''**Digital Twins**'' was coined in a presentation by Grieves in 2003 [22]. A DT is the virtual representation that serves as the real-time digital counterpart of a physical object or process. Real-time contextual and sensor data from the real physical system is incorporated into the digital model to facilitate behaviour analysis of the system's responses to various inputs and external conditions. This integration of the physical and virtual worlds makes digital twins a powerful tool. ''Digital'' refers to the virtual aspect of simulating various scenarios with real-time two-way communication with the physical asset and decision-support functionalities. "Twin" refers to the fact that it is a high-fidelity, exact replica of the physical asset with self-updating functionalities [21].

The interaction between the physical-digital replica is bi-directional, and it is a remarkable feature to distinguish DT and digital model. In the PHM context, the physical-to-digital connection means that the conditional data of the physical entity is transmitted into the virtual environment in real-time. Then, the digital model tunes itself to stay the same as its counterpart, and conditional data are used to fault diagnosis and prognosis. The digital-to-physical connection refers to the transmission of maintenance information that is employed for maintenance decision making.

In the aerospace industry, they play an important role in the reduction of system verification and testing costs within the design and development stages of aerospace systems [23]. However, the maximum potential of digital twin technology lies in its use in health management.

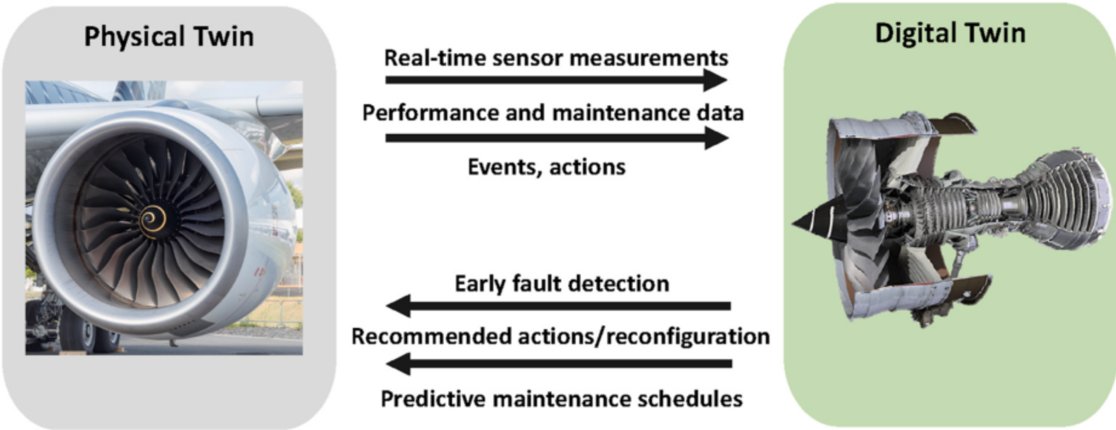


Figure 7. Digital-Twin role in PHM [21].

Using a digital twin, the system would continually adapt to operational changes using collected sensor data of industrial equipment in real time to increase autonomy and guarantee an accurate assessment of a system's state-of-health. The difference between the digital twin and a computer model is that the digital twin updates itself to track the status of the physical twin through data fusion. The digital twin evolves continuously with the physical twin over its life cycle [21].

The utilization of Digital Twins (DT) for complex aircraft components poses certain limitations. One such limitation arises from the requirement of a definitive physical model, making it challenging to accurately model and simulate the physical twin. Additionally, ensuring synchronization and accuracy of data transmission between the physical and digital twin poses another hurdle, as does the processing and storage of large volumes of data.

To overcome these challenges, data-driven methods have emerged as a viable approach, leveraging the mining of connections between variables without relying on prior knowledge or experience. This approach enables effective mitigation of the complexities associated with complex digital twin simulations, which typically demand substantial computational resources. Currently, DT approaches are primarily applicable to a select few complex systems within aviation, such as the engine, environmental control system [24], or electrical power system [25].

Given that engine maintenance costs account for a significant portion, 40% or more, of the total maintenance cost per operator [26], the adoption of DT models holds the potential to reduce engine maintenance expenses and enhance operational efficiency. By leveraging the insights provided by the DT model, organizations can optimize maintenance activities, leading to cost savings and improved overall performance of aircraft engines.

With the improvement of onboard processing capabilities as well as advancement in modelling techniques, we expect to see digital twins deployed broadly across industries in the near future. Nowadays, Digital twin services are being used for aircraft by companies such as Airbus for aircraft using MATLAB and Simulink [27], and Rolls Royce for aero-engines with InteligentEngine [28].

There is a wide range of models available for Prognostics and Health Management ranging from traditional to more recent approaches. However, the general structure of PHM models can be classified into three main branches, as shown in **Figure 8**:

1. Physics-based models
2. Data-driven models
3. Hybrid models

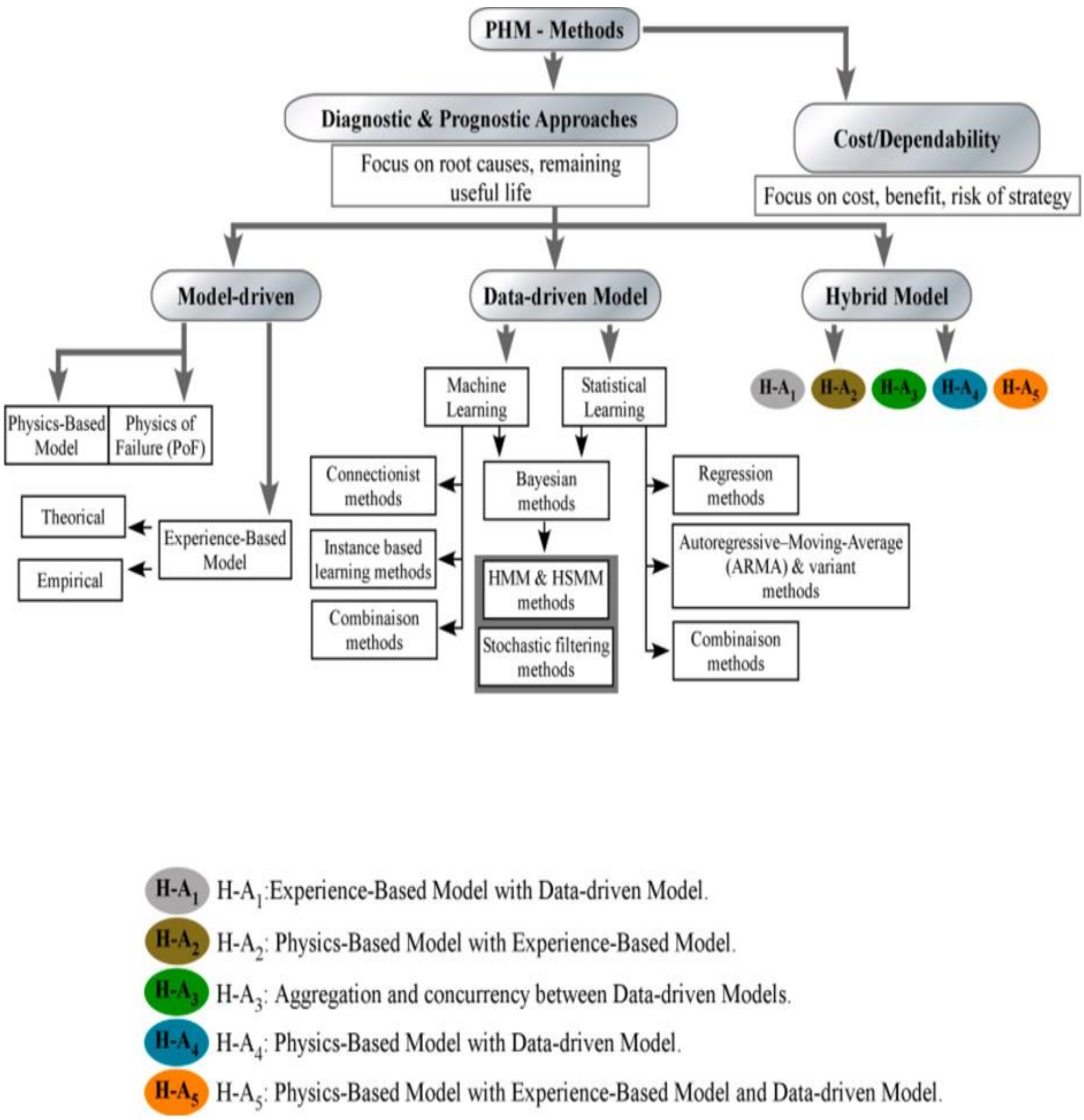


Figure 8. PHM models general classification [7] (adapted from [29]).

2.1.1. Model-Driven Approach

The physics-based or model-driven approach to prognosis involves the utilization of explicit mathematical representations to formalize the physical understanding of a system [30]. This approach incorporates a Physics-Of-Failure analysis to establish failure criteria, drawing upon historical data pertaining to failed equipment [31]. By leveraging this strategy, estimates of the Residual Useful Life can be derived based on knowledge gathered from the system's normal operation, degraded operation, and faulty operation.

In a typical model-driven approach, a physical failure system/model serves as the foundation, and the health monitoring system is designed to collect the necessary sensor data to support the model. The implementation of the physics-based approach follows a series of steps, including Failure Modes and Effects Analysis (FMEA), feature extraction, feature reconstruction, and RUL estimation [32]. These steps are as follows:

1. Failure Modes and Effects Analysis (FMEA): This involves systematically identifying potential failure modes of the system and assessing their effects on system performance and reliability.
2. Feature Extraction: Relevant features are extracted from the sensor data collected by the health monitoring system. These features capture essential information about the system's health condition.
3. Feature Reconstruction: The extracted features are processed and reconstructed to obtain a comprehensive representation of the system's health state. This step involves utilizing statistical techniques or signal processing algorithms to transform the raw sensor data into meaningful information.
4. RUL Estimation: Based on the reconstructed features and historical failure data, algorithms or models are employed to estimate the remaining useful life of the system. These estimation methods leverage the understanding of the system's degradation behavior to predict its future performance.

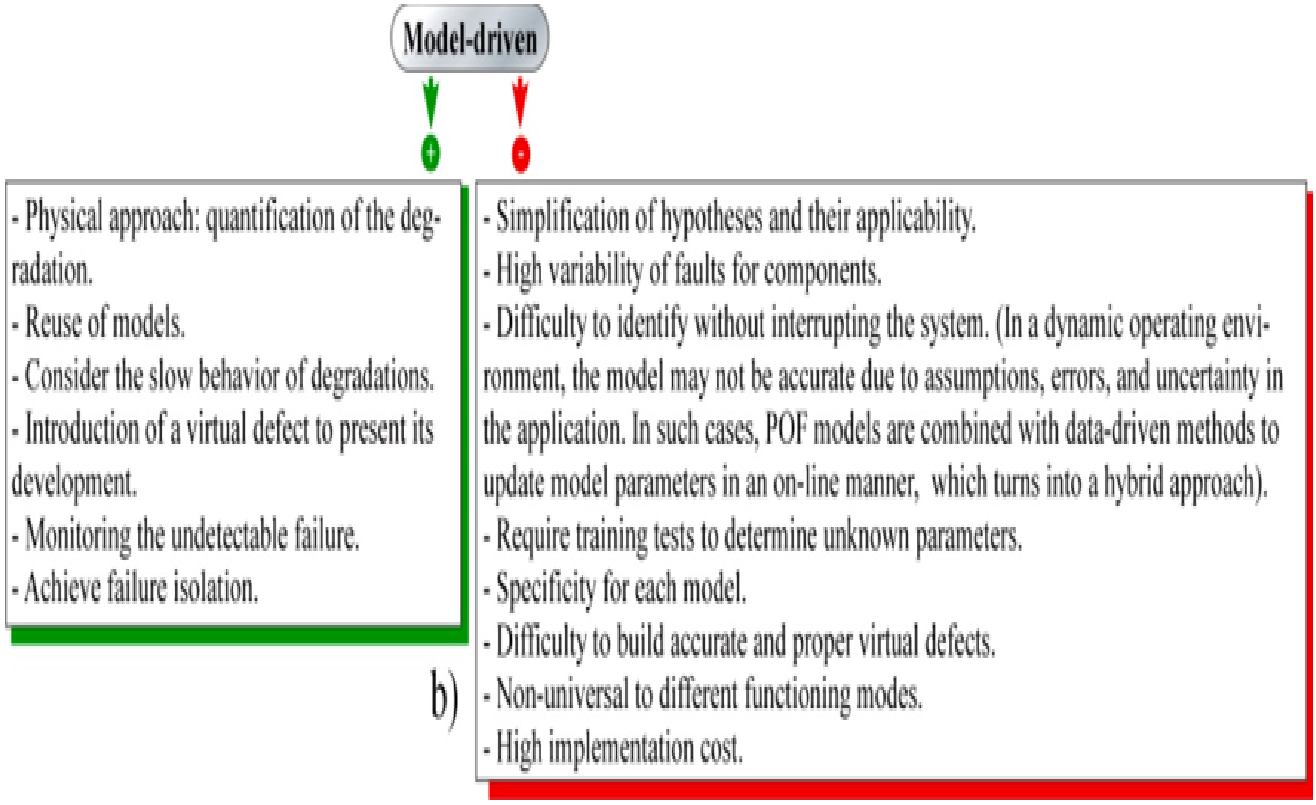


Figure 9. Physics-based model pros/cons [7].

2.1.2. Data-driven Approach

The data-driven approach in prognosis dispenses with the requirement for prior knowledge of the system or a physics-based model. These approaches offer greater usability in various scenarios, as they do not depend on prior knowledge or expert input. Instead, they leverage recorded historical data to discern system behaviors and subsequently conduct diagnosis and prognosis tasks.

The utilization of data-driven techniques is typically premised on the assumption that the statistical characteristics of system performance remain unaltered until failure occurs. Nevertheless, there are methodologies and procedures available to address this limitation. Accelerated life test [33] and online learning [34], including semi-supervised and unsupervised learning, represent techniques that can be employed to mitigate this drawback. **Figure 10**. reports detailed advantages and disadvantages of data-driven models. While **Figure 11**. contains brief description of novel data-driven models.

The commonly adopted classification for these models is: Machine Learning (ML) models and Statistical Learning models.

- **Machine Learning models**

Its learning phase is based on collections of examples linked by complex relationships which are difficult to describe beforehand. Learning can be achieved using different strategies and depends on the kind of data available. Supervised learning can be used when data is labelled and the desired output is known. Unsupervised learning must be used when the learning database is not labelled. Semi-supervised learning could be used when labelled data is incomplete [35].

Machine learning approaches can be merged, such as: Artificial Neural Networks (ANN), Bayesian methods, support vector machine, state estimation approaches (Kalman filter, particle filter), fuzzy Logic etc.

In traditional Machine Learning approaches, the process of manually extracting features and training algorithms necessitates skilled personnel. However, with deep learning algorithms, the need for manual feature identification is eliminated, and prior knowledge can be automatically learned. Artificial Intelligence (AI) encompasses the broader concept of machines learning and emulating human-like intelligence, with both Machine Learning and Deep Learning falling under this domain.

Currently, the practice of Prognostics and Health Monitoring (PHM) is predominantly carried out by data engineers within the industry, which limits access to inexperienced users who could potentially benefit the most from PHM. Even widely available tools like Microsoft Azure require a certain level of domain knowledge for effective utilization [8]. PHM tools incorporating new technologies, such as AI and Automated Machine Learning, have the potential to introduce greater automation, thereby widening the user base and enhancing safety while reducing costs.

Convolutional neural networks (CNN) reduce connectivity between layers requiring less data pre-processing and therefore cost. [36] shows that trained and validated through experimentation CNN can perform with accuracy above 99% with automatic features extraction and damage type identification for specific beam materials. Moreover, if transfer learning is adopted it performs three times faster than an untrained CNN. Transfer learning helps to deal with small amounts of training data by transferring knowledge from one domain (CNN) to another (the monitored structure).

In general, CNN and Long-Short Term Memory (LSTM) represent the best choices for aircraft systems health diagnosis such as for engines [37] [38], bearings [39] [40] [41] , hydraulics and pneumatics [42].

- **Statistical Learning models**

Even though machine learning methods are much more used and preferred, statistical Learning approaches are sometimes used as they are simple to conduct based on RUL estimation through probabilistic model of collected data. Like machine learning approaches, statistical methods require sufficient data to learn the degradation behavior. We can retain regression-based methods such as Gaussian Process Regression, least squares regression or Hidden Markov models etc. Other methods in this category can be classical methods for predicting time series such as, the autoregressive moving average and variants.

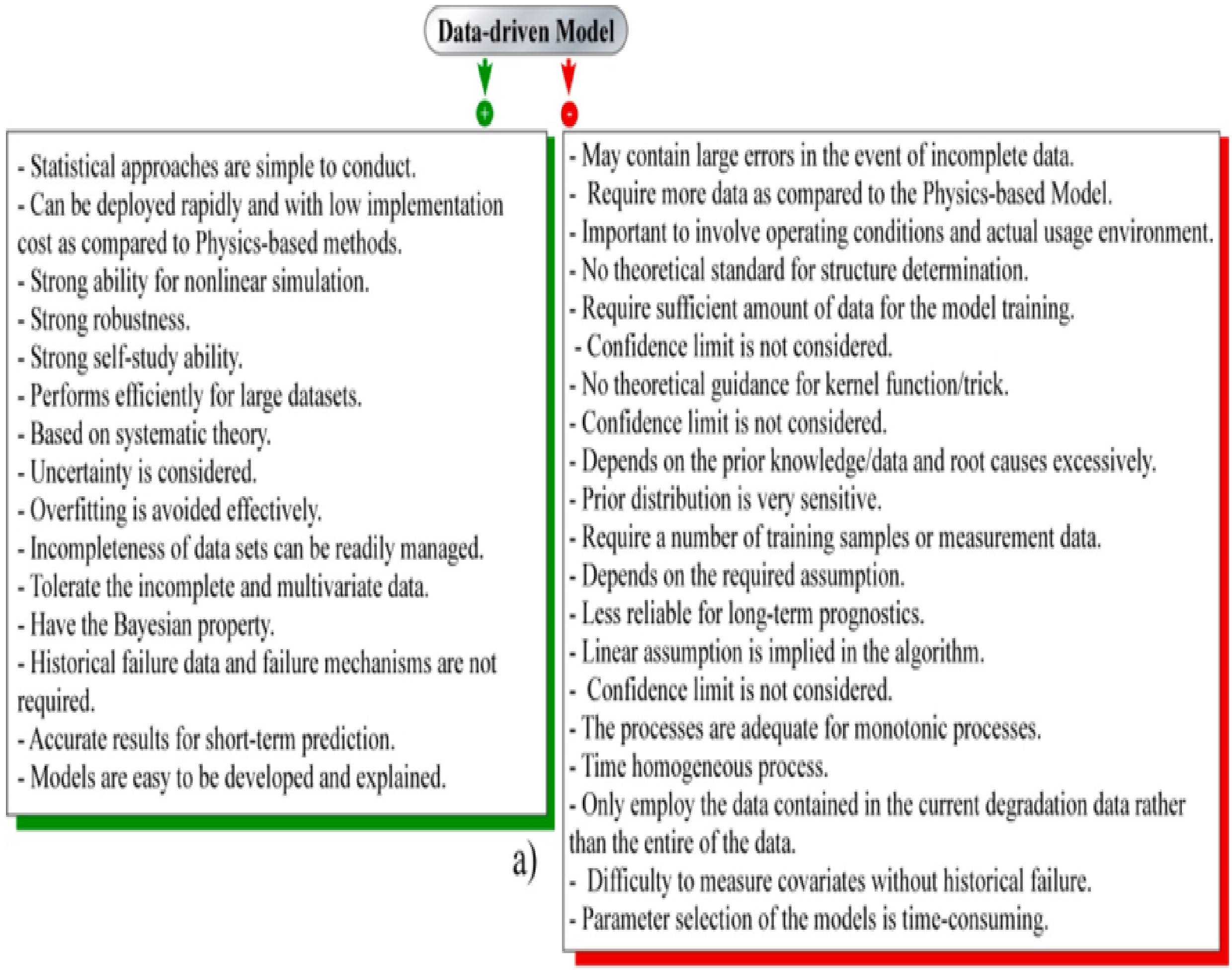


Figure 10. Data-driven models pros/cons [7].

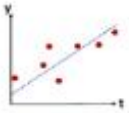
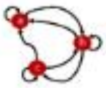
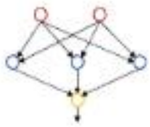
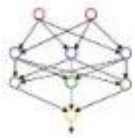
Regression		The relationship between variables is modelled through a curve-fit which is refined iteratively using error measurements in the model predictions. Regression methods include: (1) Ordinary Least Squares Regression; (2) Linear and Nonlinear regression.
Markov Chains		A systematic method for generating a sequence of random variables where the current value is probabilistically dependent on the value of the prior variable. Techniques that use Markov Chains include: (1) Hidden Markov Models (HMM); (2) Markov Chain Monte Carlo (MCMC) algorithms; (3) Simulated Annealing (SA)
Bayesian Algorithms		Bayesian methods tackle regression and classification problems by explicitly apply Bayes' Theorem. The methods in this class of algorithms include: (1) Multinomial Naive Bayes; (2) Averaged One-Dependence Estimators (AODE); (3) Bayesian Network
Classical Artificial Neural Networks		Bio-inspiration from the structure and functioning of naturally occurring neural networks has been a major factor in the development of Artificial Neural Network models. Essentially, they can be described as a type of pattern matching algorithm widely used for classification and regression problems. The methods in this class of algorithms include: (1) Multi-Layer Perceptron (MLP); (2) Radial Basis Function Network (RBFN); (3) Back-Propagation/Feedforward (BPNN/FFNN).
Deep Neural Networks		Deep Neural Networks are an extension of Artificial Neural Networks that exploit the availability of abundant computational resources. They are characterized by a large number of hidden layers in order to deal with highly non-linear problems. The methods in this class of algorithms include: (1) Stacked Auto-Encoders; (2) Deep Boltzmann Machine (DBM); (3) Deep Belief Networks (DBN).

Figure 11. Brief description of novel data-driven models [21].

2.1.3. Hybrid Model Approach

A Hybrid approach is a combination of Data-driven and Physics-based approaches. This approach aims to use the advantages of both categories to obtain more accurate RUL estimates. This model involves the use of a precise mathematical model of the system for the physics-based failure approach, and enough historical data and knowledge of typical operational performance data for the data-driven approach. This approach consists in overcoming the limits and drawbacks of each model to estimate the RUL. Hybrid models are mainly classified in five categories each with plenty of models' combination strategies [43]:

1. H-A_1 - Experience-Based Model with Data-driven Model: These approaches can allow the integration of domain knowledge into Data-driven models to estimate the RUL. The combination of neural network with fuzzy logic to create a back-propagation network and use of wavelet neural network have been adopted by several authors.
2. H-A_2 - Physics-based model and Physics of Failure with Experience-based model.
3. H-A_3 - Aggregation and concurrency between Data-driven models. On the one hand, a Data-driven model is used to estimate the state of the internal system (i.e., crack growth rate). On the other hand, the estimated state of the system health can be used to extrapolate the future state of the system to predict the RUL.
4. H-A_4 - Physics-based model and Physics of Failure with Data-driven model.
5. H-A_5 - Physics-based model and Physics of Failure with Experience-based model and Data-driven model.

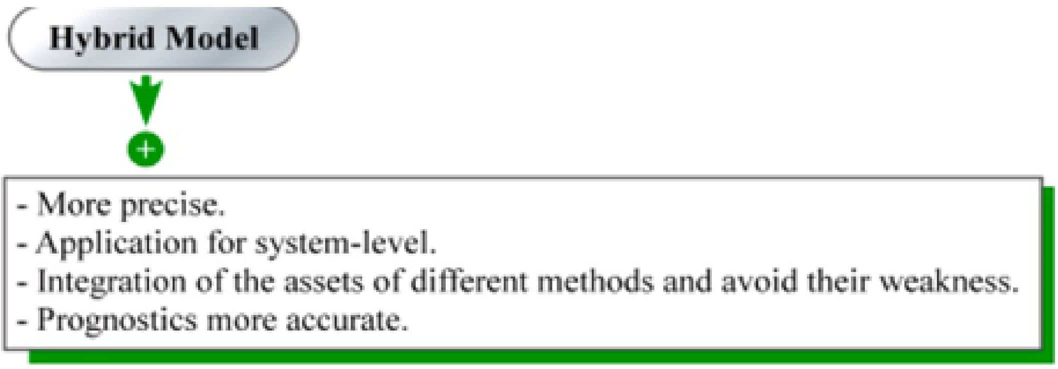


Figure 12. Hybrid model advantages [7].

2.1.4. Predictive Maintenance Planning

The cost of aircraft maintenance represents on average 9-14% of the total airline operating costs [8]. Striving to reduce these costs, aircraft maintenance is shifting to data-driven, predictive maintenance where on-board sensors are increasingly used to monitor the health condition of the aircraft components. Based on these sensor measurements, dedicated algorithms are developed to estimate the Remaining Useful Life of components. Using RUL prognostics, the aim is to anticipate failures and optimize the deployment of maintenance tasks. One of the main challenges in predictive maintenance is to obtain reliable RUL prognostics and to integrate them into maintenance planning. However, when planning maintenance, the errors (e.g., RMSE, false negatives, false positives) of the RUL prognostics are not considered. To account for such potential errors when planning maintenance, one of possible methods for predictive maintenance scheduling can be as described in [44] which proposes a system of alarms to initiate maintenance task scheduling, together with a safety margin that adjusts the moment when maintenance tasks are scheduled.

It proposes a dynamic, predictive maintenance planning framework for a fleet of 20 aircrafts that integrates machine-learning RUL prognostics via CNN. Because the degradation of a turbofan engine is non-linear, many such RUL prognostics models are based on deep learning models, such as CNN. These prognostics are periodically (every day) updated as more measurements become available. Alarms are triggered based on the evolution of the prognostics over time. Triggering an alarm for a component initiates the scheduling of a maintenance task for this component. The ideal time to schedule such a task is determined based on the RUL prognostics and a safety margin, to account for potential errors. The time when alarms are triggered is crucial. Triggering alarms when the predicted RUL is large may result in the initiated maintenance task being re-scheduled several times, as RUL prognostics are updated over time. Triggering alarms when the predicted RUL is small may result in component failures as there may not be enough time and resources left to perform maintenance. The tasks are scheduled using a rolling horizon approach with time windows. In each time window, an integer linear program specifies the slots in which maintenance is scheduled. A more detailed description can be found in [44].

The dataset adopted for this research is C-MAPSS [8]. The C-MAPSS dataset consists of simulated data on the degradation of turbofan engines. This data was generated by NASA using the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS). The dataset contains multi-variate temporal data of 21 sensors. Of the 21 sensors considered, 7 sensors have constant values over time. As such, the remaining 14 sensors with non-constant measurements are taken for the input of the CNNs. There are 4 data subsets, FD001, FD002, FD003 and FD004, each with specific operating and fault conditions. Each subset has one training set where measurements are recorded until the failure of the engine (run-to-failure instances), and one test set. In the test set, the sensor recordings are terminated somewhere before failure, and the aim is to predict the RUL at that moment. Airlines tend to keep their air fleet failure datasets confidential which makes C-MAPSS one of few open-access datasets for testing and for validation of aero-engines.

The results show that alarms are triggered early enough to enable the scheduling of additional tasks such that failures are prevented. By employing this alarm-based maintenance framework, the total cost savings with failure prevention outweigh the costs with potential task rescheduling due to an early alarm and the costs of failures for turbofan engines account for only 7.4% of the total maintenance costs [44]. The results also show that engine failures still occur due to the limited availability of maintenance slots or due to the limited number of maintenance tasks that can be performed per day. The proposed maintenance planning framework is readily applicable to other aircraft components and systems and to industries different from aeronautical as well.

2.2. Smart Sensors

Sensing technology plays a key role in Structural Health-Monitoring systems. Sensors are technological devices that enable the quantification of the physical, chemical, or biological properties of materials, converting them into signals measured by appropriate equipment. The data is then pre-processed to de-noise and filter the signal before reaching machine learning algorithms which will eventually calculate health and usage statuses of aircrafts' components and systems and predict Remaining Useful Life that serves to schedule predictive maintenance windows.

The sensors can be divided into surface sensors and embedded sensors **Figure 13**. The surface sensors are applied and coupled to the surface of components, thereby enabling life cycle monitoring. However, they are susceptible to damage from environmental factors or service conditions, including during the manufacturing process. The embedded sensors are integrated into components, which can result in smart materials or smart components that can monitor themselves during their life cycle and the manufacturing process [45].

Currently, continuous and real-time SHM systems are assisted with the classical Non-Destructive Testing (NDT) techniques, such as ultrasounds, X-rays, infrared thermography, holographic interferometry, eddy currents, and terahertz, among others, which require highly specialized labor along with expensive procedures. Traditional non-destructive ultrasonic inspection techniques suffer from challenges such as acoustic coupling, structural accessibility, and a low signal-to-noise ratio in highly attenuating materials. The use of embedded or attached sensors overcomes some of these difficulties as they remain permanently attached or embedded in the structure or structural component throughout its life cycle, including during its manufacturing process [45].

Sensing technology can lead to two monitoring methodologies, i.e., depending on how the sensors are implemented, either **passive monitoring** or **active monitoring.** As shown in **Figure 14**, in passive monitoring, the information for the analysis comes from the variation of the component's physical properties under inspection, a variation that is caused by interactions that the component suffers from throughout its life cycle. This type of monitoring requires that the components under inspection have certain physical properties, such as piezoelectricity, pyroelectricity, and thermoelectricity or other.

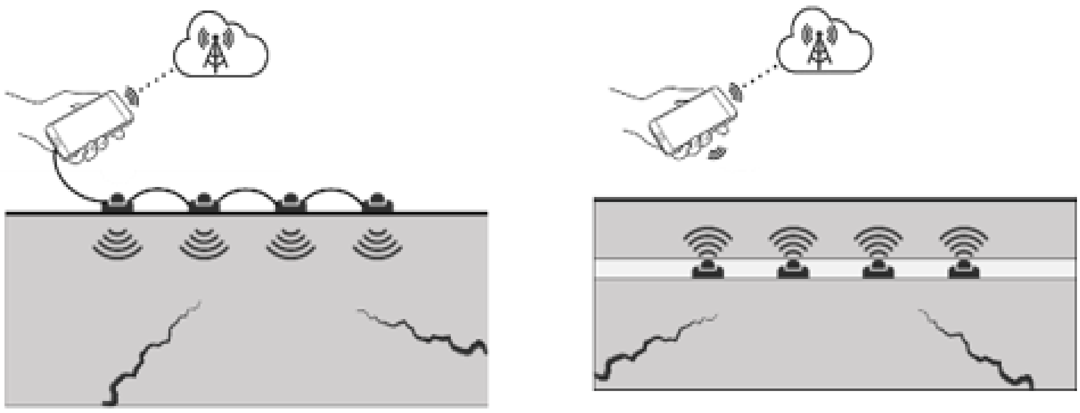


Figure 13. Surface sensors (on left) and embedded sensors (on right) [45].

In active monitoring, the information for analysis comes from the application of stimuli from an embedded actuator. The capture of the response caused by stimulus is achieved by a set of sensors, embedded or on the surface. This type of monitoring requires that the components to be inspected have certain physical properties, such as piezo-resistivity, pyro-resistivity, and thermos-resistivity or other.

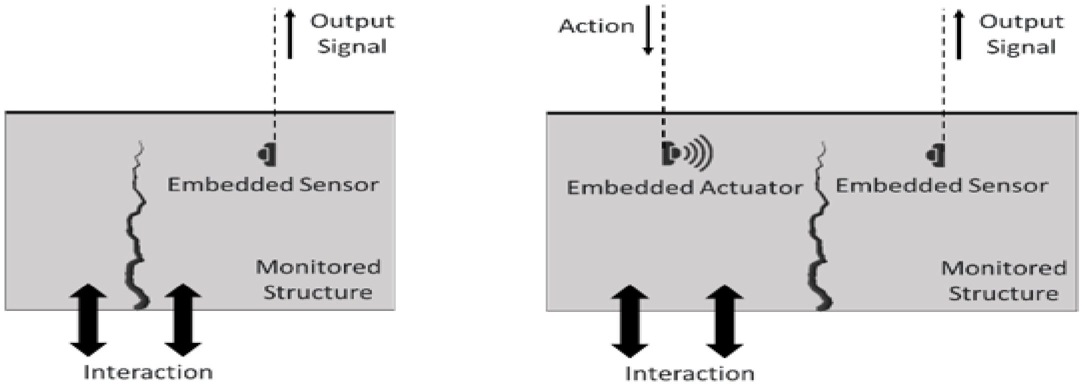


Figure 14. Passive (on left) and active monitoring sensors (on right) [45].

Fiber Optic (FO) sensors [46] and Piezoelectric (PS) sensors [47] are some of the most widely used technologies for the development of these types of materials, although there are other technologies, such as vibration-based methods [48], electrical resistance techniques [49], eddy currents techniques [50], electromagnetic techniques [51], capacitive methods [49] and micro-electro-mechanical systems [52].

Vibration-based techniques, also known as modal analysis techniques, which analyze the dynamic response of a structure or structural component when excited by a spectrum of frequencies, are the most widely used type for civil engineering applications such as wooden and composite structures [53] [54].

The **Electrical Resistance techniques** can use a particular material or structural component as a sensitive material, i.e., this technique is based on the variation of the resistance of a given material. An example of the application of this technique is the monitoring of carbon fiber-reinforced polymers (CFRP), since carbon fibers are electrical conductors incorporated in an insulating matrix. The measurement of global electrical resistance appears to be a valuable technique for monitoring fiber cracking in unidirectional arrangements as well as in the delamination process.

Inspections by **Eddy currents** are one of the NDT techniques that are based on the principle of electromagnetism. The electric current of a coil creates the primary magnetic field, which in the presence of a conductive material, induces alternating electrical currents in the component. Consequently, these create a secondary magnetic field, contrary to the primary field, which is measured using another coil. Induced currents circulate in planes perpendicular to the magnetic flux. Damage changes materials' conductivity, thereby affecting eddy currents and modifying the secondary magnetic field. These techniques can be used to measure electrical conductivities and magnetic permeabilities, detect defects, detect and analyse corrosion in the materials. [50], [55].

Other techniques that make use of the component's electrical properties are the **Low-Frequency Electromagnetic Techniques**, which monitor the integrity of a given component by measuring the electrical conductivity and dielectric signature of the components [56], as well as **Capacitive Methods**, in which electrodes are placed on the outer surface of the sample and electric tension is applied between them, creating a condenser system, wherein capacity changes are indicative of internal properties (such as the materials' nature or their humidity content) [51].

In addition, **Continuous Wave Terahertz Imaging** was found to be especially interesting for imaging water infiltrations and composite materials that contain conductive wires [57]. **Thermography** techniques have also been used to monitor the health of systems, such as the innovative variant of active transient thermography known as double active transient thermography, which increased the temperature contrast for delamination defects at different depths and locations [58]. Some of these techniques and their applications are presented in the tables below:

Author	Types of sensors	Methodology of integrating sensors	Measurements	Applications
Sebastian et al. **[59]**	Glass fibre coated with carbon nanotube	Open contact moulding process	strain	Carbon-reinforced plastic composites
Pinto et al. **[60]**	Shape memory NiTi alloy	Open contact moulding process	Strain distribution Damage	Carbon-reinforced plastic composites
Cougnon et al. **[61]**	Thin films	Magnetron-Sputtering deposition and open contact-moulding process	Heating elements	Fabrication of heating elements
Meoni et al. **[62]**	Carbon nanotubes	Mounted on reinforced concrete	Strain	Reinforced concrete structures
Gino et al. **[63]**	PZT powder	Resin Infusion processes	Loads (Through the electrical signal)	Glass fibre-reinforced polymer

Table 1. Overview of some sensors' applications for composites.

Author	Types of sensors	Methodology of integrating sensors	Measurements	Applications
Zhang et al. **[64]**	Micro ring sensor	Laser-assisted metal deposition	Temperature	Monitoring of manufacturing processes
Hahnlen et al. **[65]**	Shape memory NiTi alloy	Ultrasonic additive manufacturing	Temperature	Monitoring of manufacturing processes
Juhasz et al. **[66]**	Passive sensor-printed	Hybrid manufactured metal structure	Strain	Metal structural components
Stoll et al. **[67]**	Eddy current sensors	Laser powder bed fusion	Crack propagation	Metal structural components

Table 2. Overview of some sensors' applications for metals.

While **Figure 15** and **Figure 16** present common sensor integration techniques for composites and for metals:

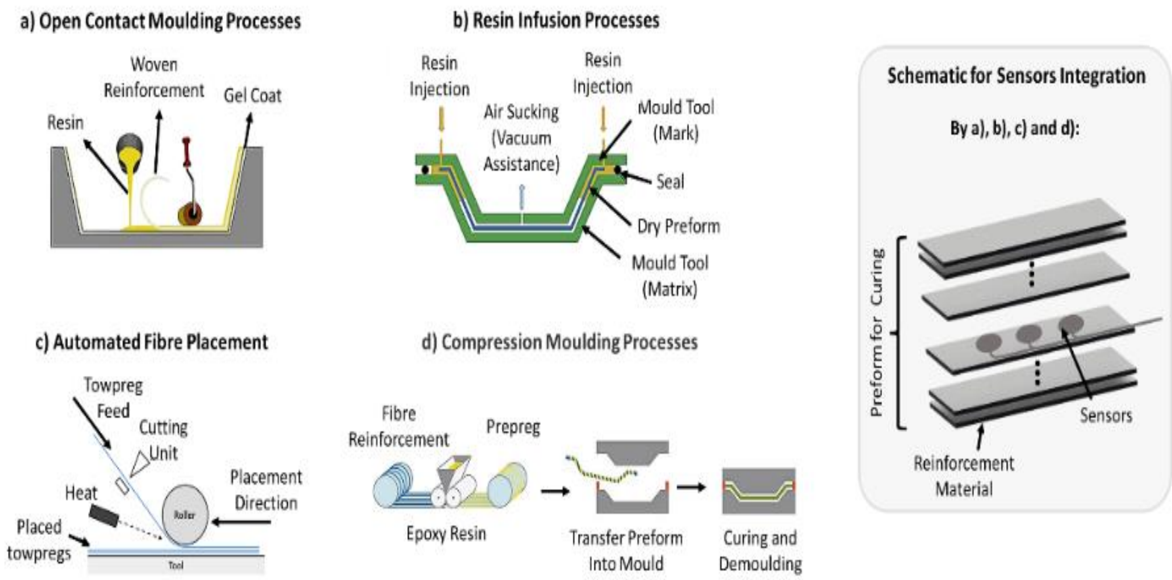


Figure 15. Sensor integration techniques for composites [45].

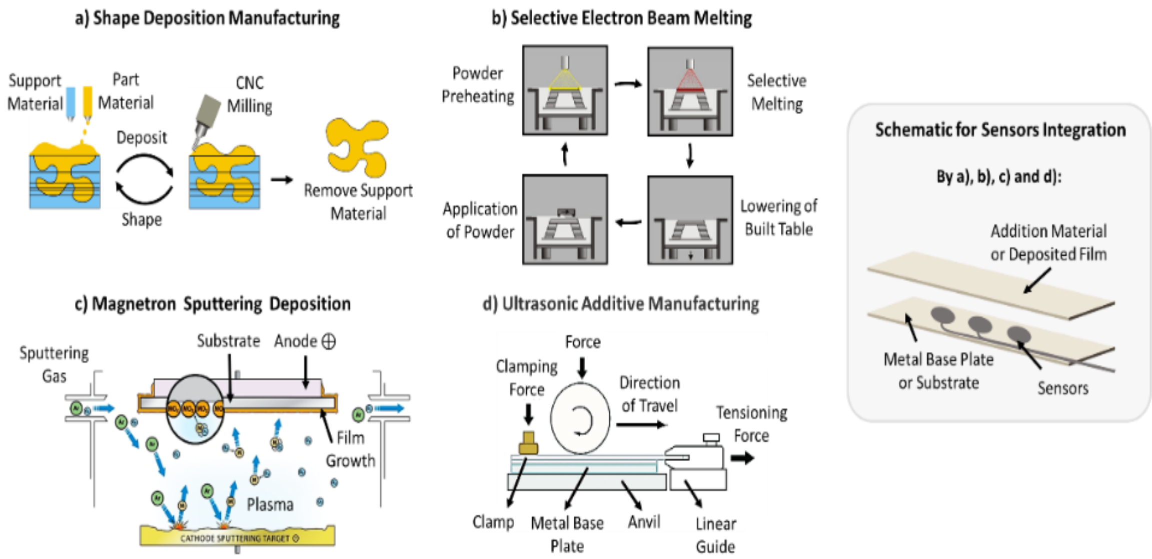
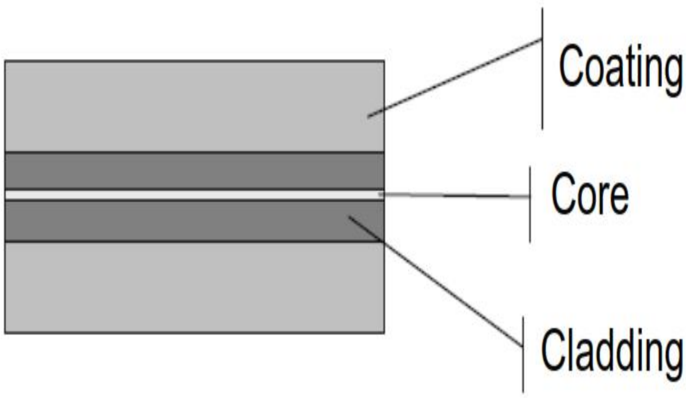


Figure 16. Sensor integration techniques for metals [45].

As Fiber Optic and Piezoelectric sensors are the most widely used technologies for structural monitoring in the aircraft industry, the focus will be placed on them in the following sections.

2.2.1. Fibre Optics

Fiber optics have recently emerged as a highly promising technological solution for integration into structures or structural components [36], [45], [68], [69] and many others. By utilizing FOs as embedded sensors, it becomes feasible to monitor crucial structural parameters in locations that are typically inaccessible for traditional sensor deployment. Optical sensors are particularly well-suited for structural health monitoring in aircraft due to their lightweight nature, absence of electromagnetic interference, non-conductive properties, corrosion resistance, long lifespan, and ability to be seamlessly embedded within composite structures.



FO is a flexible, transparent fiber made by drawing glass (Silica) and generally consists of three parts: core, cladding and coating. The core and the cladding are of the same material but with different refractive indices (difference is very small in modern FO) so that the light is kept and guided within the core bouncing back and forth off the boundary between the core and cladding by the total internal reflection phenomenon **Figure 17**.

Because the light must strike the boundary with an angle greater than the critical angle, only light that enters the fiber within a certain range of angles can travel down the fiber without leaking out. This range of angles is called the acceptance cone of the fiber. The coating has protective nature for fragile core-cladding material and can be made of different materials, such as polyacrylate or polyimide, the last one guaranteeing better performance in terms of larger temperature resistance, thinner coating and other. The external diameter of FO can range between 140-250 µm (microns) which is slightly thicker than human hair.

One fiber optic can be utilized to multiplex tens or hundreds of optic load sensors, thus significantly reducing the wiring problem. Glass optical fibers are almost always made from silica, but some other materials, such as fluor zirconate, fluor aluminate, and chalcogenide glasses as well as crystalline materials like sapphire, are used for longer-wavelength infrared or other specialized applications. Silica and fluoride glasses usually have refractive indices of about 1.5, but some materials such as chalcogenides can have indices as high as 3. Typically, the index difference between core and cladding is less than 1%.

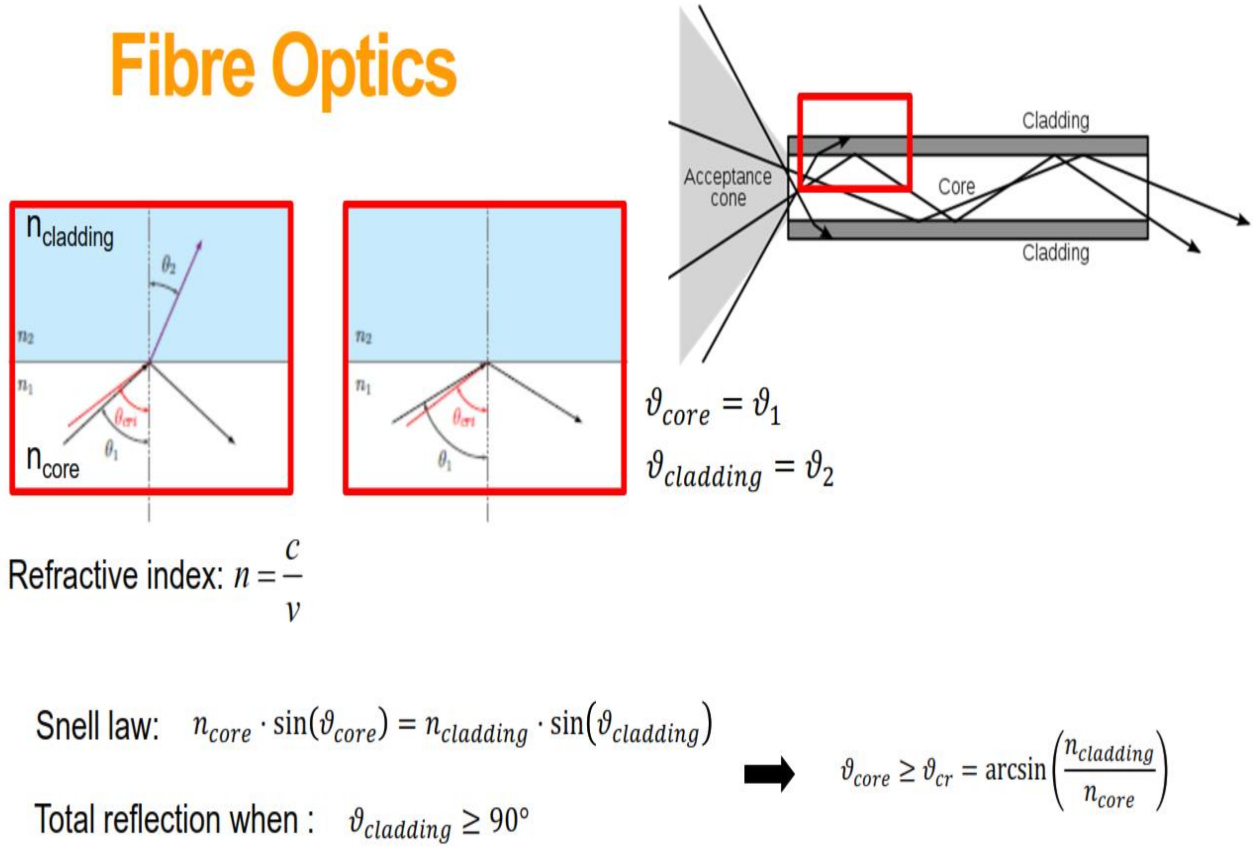


Figure 17. Reflection phenomenon inside FO

FOs are resistant to corrosion and high tensile loads, and possess elongations up to 5%, leading to long life cycles. These sensors' resistance to high temperatures enables the measurement of temperatures from 200 to 800 ◦C with a silica core, and up to 1500 ◦C with a sapphire core, wherein the measurement resolutions are on the order of 0.1 ◦C. Another important feature is the flexibility that these sensors have because they can be applied to complex surfaces that are difficult to access, as well as perform local or distributed measurements, which can range from 1 mm to tens of kilometres [70].

They can monitor several parameters such as temperature, pressure, vibration, corrosion, and strain-induced in the structures. Each FO is based on the propagation of the optical wave and its physical properties. FOs can undergo geometrical (size and shape) and optical (refractive index) changes due to various environmental disturbances, while transmitting light from one place to another [71]. The changes in amplitude (intensity), phase, frequency and polarization of the optical properties of transmitted light can be measured and correlated to relative mechanical, thermal or other external stimuli which creates these changes in transmitted light's parameters.

2.2.1.1. Fibre Optics classes

The fiber optic sensors are classified in three main domains of:

1. Point sensors.
2. Quasi-distributed sensors.
3. Distributed sensors.

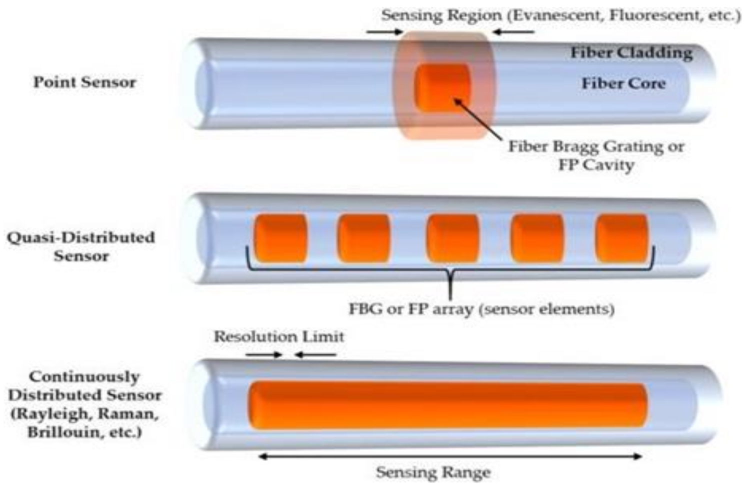


Figure 18 and **Table 3Error! Reference source not found.** Contain detailed description of different types of FO technologies:

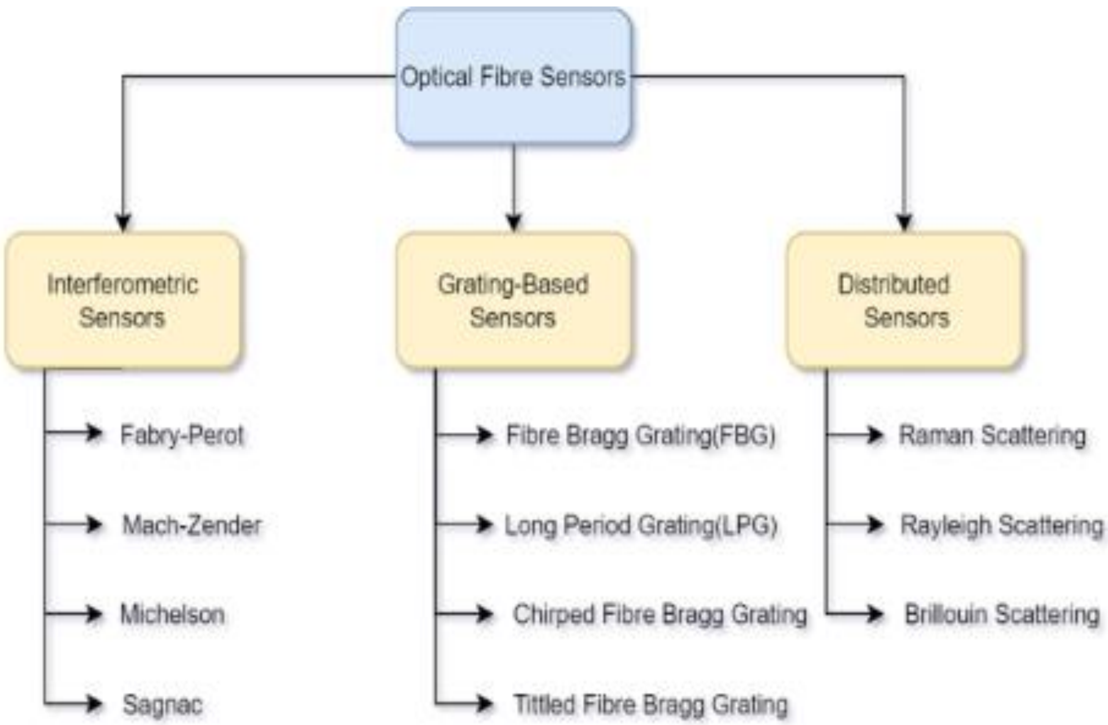
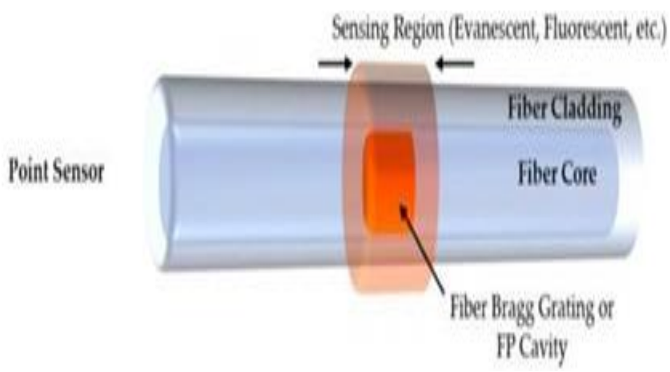


Figure 18. FO classes [68].

TYPES OF SENSORS PARAMETRS	FIBRE BRAGG GRATING SENSORS	FABRY-PEROT INTERFEROMETRIC SENSORS	SOFO INTERFEROMETRIC SENSORS	RAMAN OPTICAL TIME-DOMAIN REFLECTOMETRY	BRILLOUIN OPTICAL TIME-DOMAIN REFLECTOMETRY
Sensor type	Point Semi-distributed	Point	Long gauge	Distributed	Distributed
Main sensing parameters	-Temperature -Strain -Rotation -Pressure	-Temperature -Strain -Rotation -Pressure	-Deformation -Strain -Force	-Temperature	-Temperature -Strain
Multiplexing	-Quasi distributed -Wavelength division	-Parallel -Time-division	-Parallel -Time-division	Distributed	Distributed
Spatial resolution	0.1	0.1	0.1	1	1
Advantages	-Linearity in response -Accurate -High resolution -Inherent Wavelength Division Multiplexing (WDM) encoding	-High sensitivity -Accurate	-Long gauge -High spatial resolution	-Infinite sensing points -Fibre integrated	-Infinite sensing points -Fibre integrated
Disadvantages	Cross sensitivity	Single point	Low speed (10s)	-Temperature only -High cost	Cross sensitivity
Companies	Micron Optics Fibresensing	Luna Osmos	Smartec	Halliburton Co. Sensornet Ltd. AP Sensing	OZ Optics, Omnisens SA, Neubrex

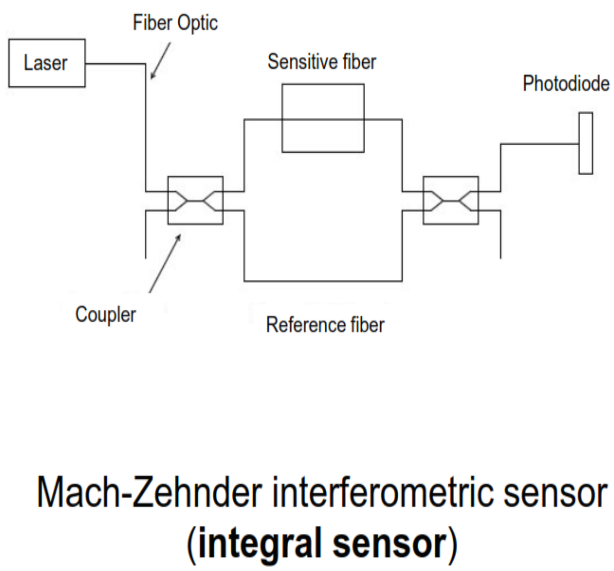
Table 3. Brief description of FO sensors [68].

➢ Point sensors.



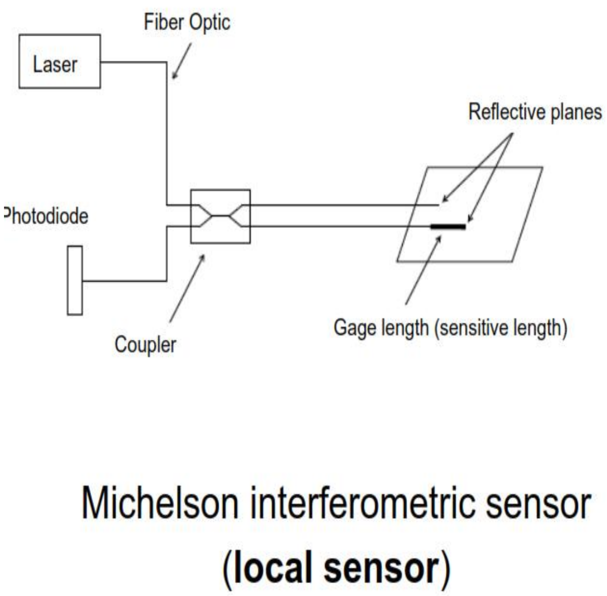
Point based sensors, or interferometric sensors, are local sensors based on light's phase change that enable the measurement of changes at specified locations in a structure. Interferometric FOs are by far the most used local sensors because they offer the best sensitivity. However, point-based sensors cannot provide complete monitoring of a large structure. This is because point base sensors can only provide information from one location, which does not contain enough information to assess the complete structure. Multiple sensors can be installed, but this will require a longer installation time and multiple signal cables to transmit the information of any single sensor, making it too bulky for large structures.

The light from a source is equally divided into two fiber-guided paths: one reference path and one analysis path. In the interferometric sensors, two mirrors are used that are adjusted to mix the wave and form a "fringe pattern", which is directly related to the difference in the phase of optical waves caused by the two mirrors. The most common configurations of interferometric sensors are Mach–Zehnder, Michelson and Fabry–Perot:



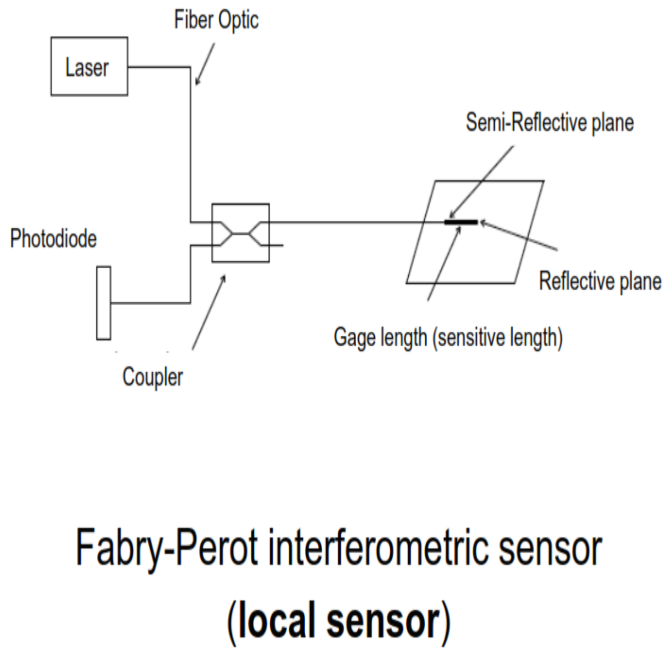
Pros	Cons
Easy working principle	Difficult to insulate reference fibre from outside
High sensitivity	NO local measurements

Figure 19. Mach-Zehnder interferometric sensor



Pros	Cons
Local measurements (quasi)	Difficult of fibres coupling (fibres have to be parallel)
High sensitivity (twice respect of the one of Mach-Zehnder because the light passes 2 times through gauge length)	Invasivity (in composites)

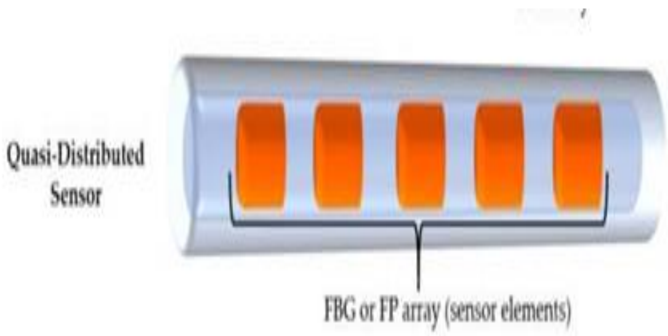
Figure 20. Michelson interferometric sensor



Pros	Cons
High sensitivity	Difficult to restore the continuity of the fibre (extrinsic sensors)
Low invasivity (intrinsic sensors)	Low robustness (extrinsic sensors)
High robustness (intrinsic sensors)	

Figure 21. Fabry-Perot interferometric sensor

➢ Quasi-distributed sensors.



A Fiber Bragg Grating (FBG) is a permanent periodic modulation of the refractive index in the core of a single-mode optical fiber and it is frequency/wavelength–based sensor. It reflects certain wavelengths of light and transmits all others. This is achieved by creating a periodic variation in the refractive index of the fiber core which reflects a narrow spectral band centered around the so-called the Bragg wavelength. Any change in FBG under strain or temperature is followed by changes in the wavelength of reflected light, which can be monitored in real-time [45].

Bragg wavelength is given by equation:

$$\lambda_B = 2\, n_{eff} \Lambda$$

Where λ_B is Bragg wavelength, n_{eff} is effective refractive index and Λ is average grating period (i.e., distance between two consecutive gratings).

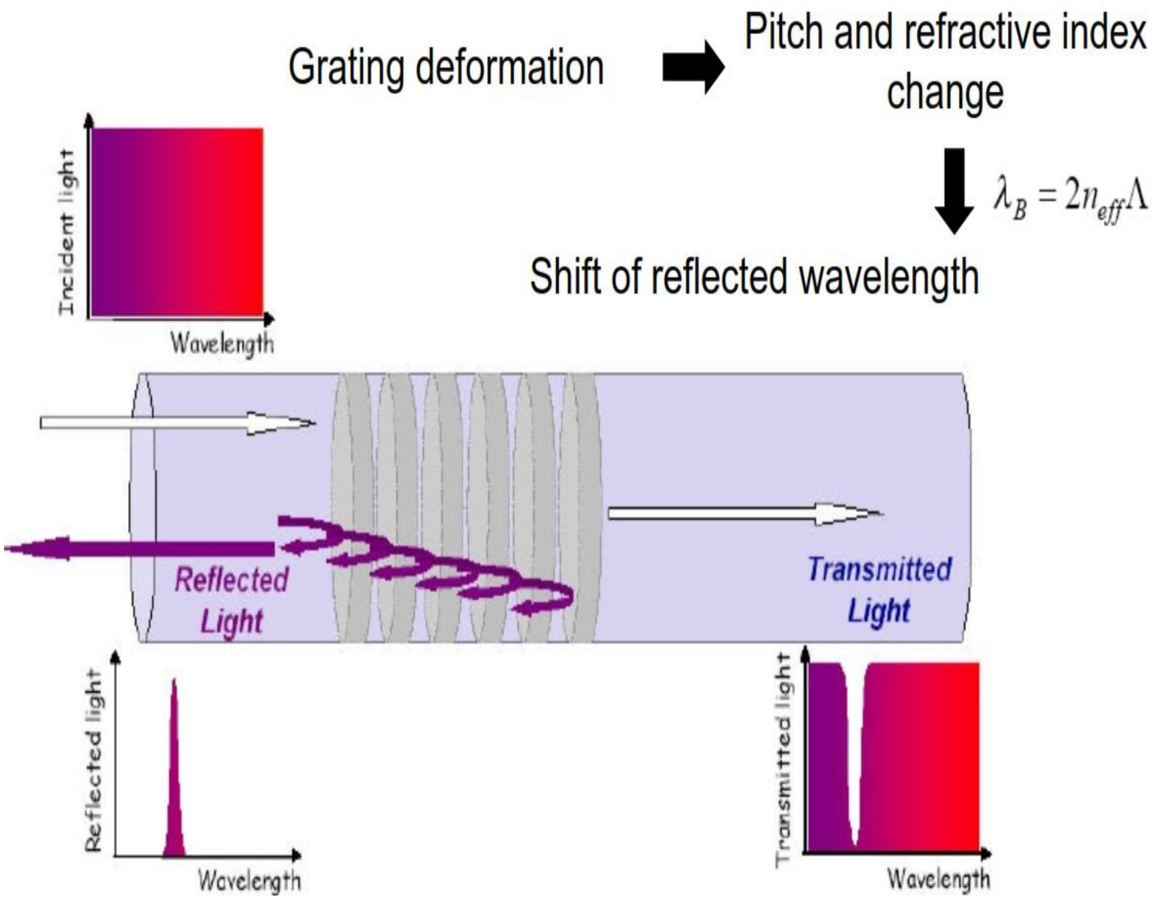


Figure 22. FBG operating principle

However, the previous equation does not provide information about wavelength shift due to strain or temperature effects. To get more useful representation of Bragg equation, it can be derived with respect to strain and temperature as follows:

$$\Delta\lambda_B = 2\left(\Lambda\frac{\partial n}{\partial l} + n\frac{\partial \Lambda}{\partial l}\right)\Delta l + 2\left(\Lambda\frac{\partial n}{\partial T} + n\frac{\partial \Lambda}{\partial T}\right)\Delta T$$

$$\Delta\lambda_B = \lambda_B\,(1-p_e)\,\varepsilon + \lambda_B\,(\alpha+\zeta)\,\Delta T \longrightarrow \Delta\lambda_B = K_\varepsilon\,\varepsilon + K_T\,\Delta T$$

ε	axial mechanical strain
ΔT	Temperature change
p_e	Photo-elastic constant
α	Coefficient of Thermal Expansion (CTE)
ζ	Thermo-optical coefficient

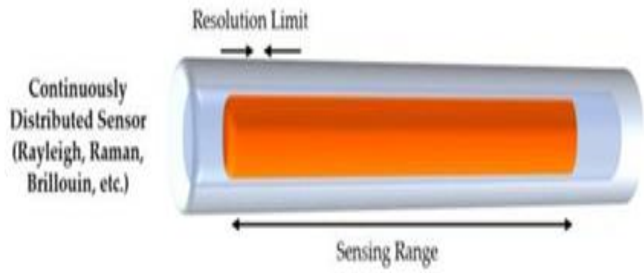
Figure 23. Bragg equation derivation

Finally, strain representation is retrieved from spectral domain of reflected light through numerical tools. FBGs can monitor transversal as well as axial strains and provide local measurements.

FBG has the advantages of high sensitivity and resolution (3-5 με), lightweight, small size, strong anti-electromagnetic interference capability, corrosion resistance etc. They can monitor temperature, humidity [72], strain [73] and other parameters.

However, there are several important concerns in FBGs' selection. First, FBG should be designed to guarantee a measurable wavelength range of the interrogation system and no spectra overlapping in the measurable wavelength domain [74]. Secondly, the number of FBG in a single-fiber cable is limited by the maximum strain value the fiber sensor will experience [75]. Lastly, FBG fabrication also entitles high labour costs because of the required equipment and personnel, limiting the mass production and the cost-effectiveness [76].

➢ Distributed sensors.



The distributed fiber optic sensors (DFOS) have shown great potential and are best suited for large structural applications since all fiber optic segments act as sensors and as it enables the replacement of thousands of traditional strain gauges with the use of a single fiber cable [77]. Additionally, DFOS not only can monitor strain values but also can monitor other physical properties such as temperature [78], pH changes [79], vibration [80], displacement, and shape. (DFOS) have improved some of the drawbacks of quasi-distributed sensors. The main advantage is removing the limitation in the number of sensors the fiber cable can carry [69].

This type of sensor is based on the modulation of light intensity; therefore, fractures or local damage in a structure cause variation in light's intensity. There are multiple interrogation methods used in DFOS. They are all based on the scattering process inside the fiber core and can be classified as Rayleigh, Brillouin, and Raman distributed sensing [69].

Rayleigh scattering is an elastic process in which the scattered photons have the same wavelength and frequency as the incident photons. The Rayleigh backscatter is caused by random fluctuation in the index profile along the fiber. The applied strain on the fiber sensor will cause changes in the reflected spectrum similarly to FBGs [81].

The Brillouin method is an inelastic scattering process that occurs because of light propagation through fibers with material density fluctuation. Its frequency shift depends on the acoustic velocity and the fiber's refraction index, which is affected by changes in temperature and strain. For this reason, Brillouin-distributed sensors have been used widely to monitor strain and temperature [82], [83].

Raman scattering is also an inelastic scattering, and it is due to the molecular vibration whereby the incident light interacting with optical phonon is scattered. The intensity of the stokes is only dependent on temperature. Hence, Raman scattering is only used for temperature monitoring [84].

Nevertheless, the main disadvantages of the DFOS system are insufficient resolutions, weak signals, heavy and expensive interrogation systems as well as the labour cost for the fiber installation. Therefore, a solution to mitigate such disadvantages will be presented in section 2.2.1.3 under the name of Distributed Fiber Optic Sensing Textile (DFOST) [69].

2.2.1.2. Fibre Optics applications

This section deals with the presentation of different techniques of applications for FO sensors. Classification is done according to two possible materials where sensors could be embedded in: composites or metals.

- **Fiber Optics applications for composites.**

When referring to the SHM mechanism of composite components, this includes the real-time monitoring of the manufacturing and curing processes of composites and the in-situ non-destructive evaluation of in-service structural components. So, it is difficult to perform conventional NDT methods, thus giving rise to the possibility of using FOs embedded in the composite component's matrix. Most applications of embedded FOs focus on polymer matrix composites [85], [86].

In the composite production phase, FOs can be embedded in the matrix or between the laminates of the composite to monitor certain conditions, such as the composite-stacking sequence, the resin flow during processing [87], the curing process of the laminates [88], or the misalignment of the fibers, which can lead to a significant reduction in the mechanical strength of the laminates [89]. During the post-production phase, these sensors allow for the simultaneous monitoring of strains and temperatures to which the component is subjected during its life cycle, and, in special cases, they can also be used to detect acoustic waves [85]. During the production process, misalignment, gaps, or overlaps of the laminates or fibers may arise. Such defects may endanger the component's integrity when it is in service; therefore, the use of embedded FOs ensures great control over the possible spread of defects during the component's life cycle [90].

In most applications of the monitoring of composite components, sensors such as Extrinsic Fabry–Perot Interferometers (EFPI) and FBGs are implemented since these types of sensors can be easily distributed throughout a real structure with a single fiber. In addition, FBG sensors enable the identification of strains on dynamic requests, while extrinsic Fabry–Perot interferometers enable the identification of transient events [85]. [45] presents the different types of FOs used and the methodologies of the integration of sensors for each of the applications developed.

During the process of integrating FOs into the polymer matrix, many authors [91], [92] reported challenges regarding sensor fastening or FOs breakages. To solve these issues, FOs complemented with textile reinforcements have been implemented and studied [69], [93].

Regarding the correlation between FBG sensors and EFPI, each has a preferred application, which is why these types of FOs are used simultaneously, regardless of the loading type or life phase of the structural component, mixed and completed monitoring are guaranteed.

Following figures report the applications of FBGs only and EFPI integrated with FBGs:

Author	Methodology of integrating processes	Measurements	Sensitivity	Applications
Bremer et al. **[94]**	Open contact moulding	Strain and crack	0.0033 mm/N	
Oromiehie et al. **[95]**	Automated fibre placement	Defects	-	Composite components for aerospace
Kousiatza et al. **[96]**	Fused filament fabrication	Residual strain	-	Complex lightweight structures
Hurtado et al. **[97]**	Resin transfer moulding	Strain	Up to 7500 μ	Fibre-reinforced polymer structure Failure

Table 4. Novel FBG applications for composite structures.

Author	Methodology of integrating sensors	Measurements	Sensitivity	Applications
Leng et al. **[98]**	Open contact moulding processes	Strain	-	Carbon fibre-reinforced polymer
Oliveira et al. **[99]**	Compression moulding processes	Strain	2.6 με/N	Carbon fibre-reinforced polymer

Table 5. Novel FBG and EFPI applications for composite structures.

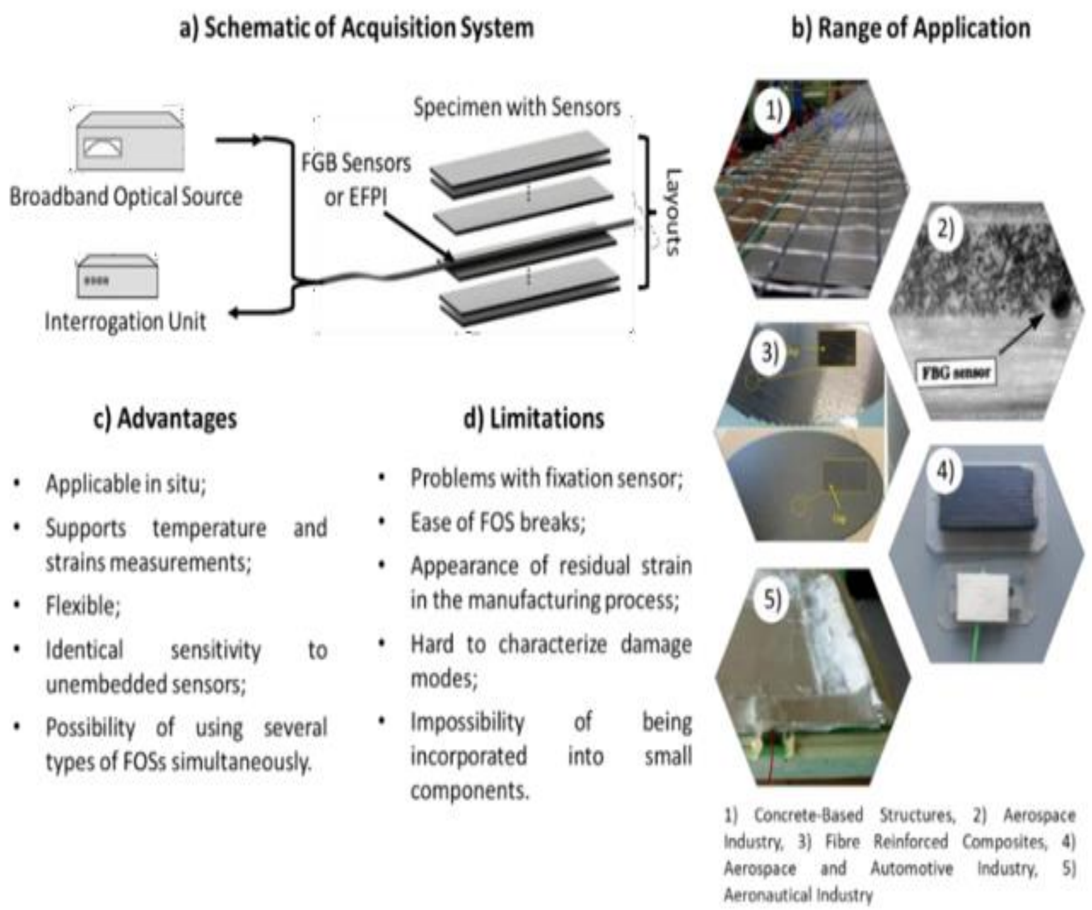


Figure 24. Scheme of embedded FO in composites [45].

❖ Fiber Optics applications for metals.

FOs are also attractive for in-situ structural monitoring of metallic structural components since the sensors that use optical properties provide silent monitoring, greater sensitivity, good accuracy and high-temperature capacity. Metals such as steel, nickel, iron, and titanium have high melting points. In this sense, metal-processing technologies involving the melting of metals will lead to the destruction of FOs, which is undesirable. Therefore, to avoid the damage of FOs, it is necessary to resort to a set of material-processing technologies that does not involve the fusion of a base metal, such as shape deposition manufacturing, ultrasonic additive manufacturing, Magnetron Sputtering, electroplating or others [45].

Once again, FBG sensors are main actors for metals using FO sensing. FBG sensors incorporated into components manufactured, for example, with nickel and stainless steel [100], [101] provide high sensitivity, good accuracy, and high-temperature capacity for temperature measurements. Embedded FBG sensors in metals were capable of high sensitivity, precision and linearity for strain and temperature measurements compared to surface sensors. It was also shown that the embedded FBG sensors accurately track the strain for temperatures above 400°C [102].

Table 6 reports FBG applications for metallic parts and **Figure 25** reports FO general scheme for metals.

Author	Methodology of integrating sensors	Measurements	Sensitivity	Applications
Alemohammad et al. **[103]**	Magnetron sputtering and electroplating	Residual stress Temperature	21 pm/°C.	Metal cutting tools
Grandal et al. **[104]**	Laser cladding	Strain Temperature	29 pm/°C–23 pm/°C. 0.9 pm/με–1 pm/με.	High-temperature environments
Jinachandran et al. **[105]**	Metal packaging using stainless steel and tin	Strain Temperature	0.4456 με/N 11.16 pm/°C	Iron pipelines and other ferromagnetic components
Chilelli et al. **[106]**	Ultrasonic additive manufacturing	Cracks	Length of 0.286 ± 0.033 mm	Complex systems
Hehr et al. **[107]**	Ultrasonic additive manufacturing	Residual stress Temperature Delamination	-	Fibre-routing designs and alloy systems

Table 6. FBG applications for metals.

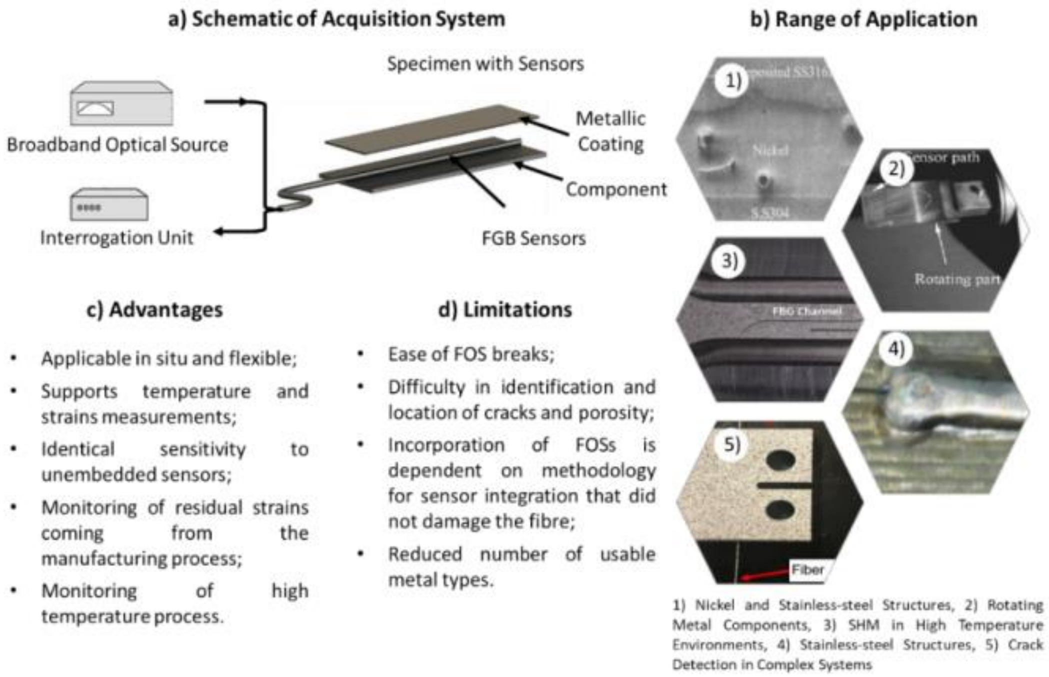


Figure 25. Scheme of embedded FO in metals [45].

2.2.1.3. Distributed Fibre Optic Sensing Textile (DFOST)

This part presents a description of the work performed in [69] , in particular about the fully distributed fiber optic sensing through textiles. As previously mentioned, fully distributed FO removes the limitation in the number of sensors the fiber cable can carry and the entire fiber becomes a sensor with multiple sensing locations, allowing the measurement of large amounts of information. However, the main disadvantage of the fully distributed FO system is the high cost of the interrogation system as well as the labor cost for the fiber installation process.

For this reason, [69] aims to explore a new process to reduce the time and complexity of the fiber installation process. In fully distributed FO, the fiber layout process could take a couple of hours, and special care is required due to the fiber breakage that could occur during the routing of the fiber. Different approaches have been developed, but they presented some non-neglectable disadvantages.

In this article, fully distributed fiber optic sensing textile (DFOST) was designed to detect different strain directions by using one single line of fiber cable. Thanks to the ability to draw fiber patterns [83], it can be tailored to measure strain and/or temperature in locations where it is difficult to install conventional sensing systems. For example, the textile can be embedded into airplanes' wings to monitor its structural status. With the use of smart textiles, it aimed to demonstrate the ability to use this technique not only for installation on the surface of a structure but also its ability to be embedded into materials such as composites which is done via autoclave process. Additionally, the advantage of using DFOST in comparison with other techniques, such as fiber tape and manual installation, was demonstrated by its fast implementation and the ability to design fiber patterns.

To validate the performance of the proposed textile sensor, the fabric was embedded into composite material and subjected to different laboratory experiments (e.g., cantilever test). Optical Frequency Domain Reflectometry (OFDR) was used as the interrogation method to measure strain responses. For further validation, the strain measurements collected by the smart textile were compared with strain gauges and fiber optic sensors installed on the surface of the composite panel.

OFDR provides a high spatial resolution of a few millimeters for tens of meters of measurable fiber length [108]. It is based on Rayleigh's backscatter which is caused by random fluctuation in the index profile along the fiber. Similar to a standard Bragg grating, the Rayleigh backscatter responds to changes in the refractive index or physical length created by variation in strain. The relationship between spectral shift ($\Delta\nu$) and strain (Δc) and temperature (ΔT) is linear, similarly to FBGs: $\Delta\nu = K_T\Delta T + K_C\Delta c$.

Before embedding the fiber into the textile, two different fiber sizes were investigated to explore how the size affects the sensor sensitivity. Both fibers with the same core size (9 µm). However, the coating material and coating diameter were different. One fiber had an acrylate and jacketed coating with a 650-µm diameter, and the second fiber had a more expensive polyimide coating with a 145-µm diameter. Polyimide coating allows the fiber to survive up to 350 ◦C whereas the acrylate and jacketed last between 130 ◦C and 200 ◦C depending on temperature–time exposure [69].

Both fibers were embedded into a cost-effective reinforcing fabric provided by ADFORS- Saint Gobain (XP414 laid scrim), which was made by chemically bonding continuous filament yarn in open mesh construction. The fiber was stitch-bonded onto the fabric by using an embroidery machine. This equipment can perform a "roll to roll" function, which allows to produce long-length samples. A calibration test was conducted to observe the strain transfer ratio. To investigate the response, fibers stitched in the textiles were stretched by using a tensile machine, and strains were measured by using optical frequency domain reflectometry (OFDR) from LUNA Innovation. The tension on the fiber was controlled by using an AGS-X Shimadzu 10KN test frame. The sample size was 45 cm x 6 cm, and the tensile machine was set up to run for three cycles. Each cycle included the stretch and release of the textile [69].

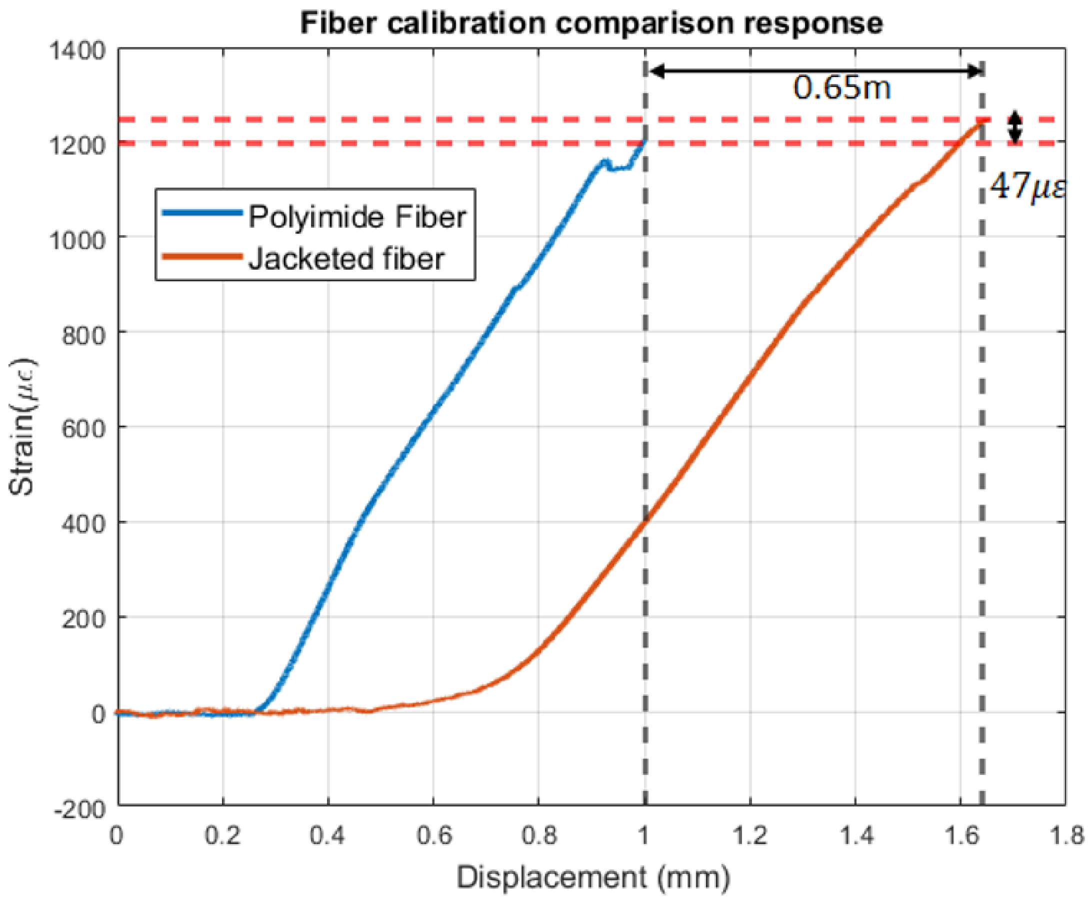


Figure 26. Calibration results of strain vs displacement [69].

A linear response was observed for both samples **Figure 26**. The polyimide and jacketed fiber strain coefficients were 1746 με/mm and 1308 με/mm, respectively. These results demonstrated that polyimide fiber has a better response to strain changes. The added jacketed coating reduces the strain transfer to the fiber's core. Additionally, polyimide fiber started detecting strain changes at a 0.2mm displacement while the jacketed was at 0.4 mm. This further confirms that polyimide has a better strain response; hence, it is better suited for the application. In addition, the polyimide fiber had a size comparable to the fiber present in the composite sample. Therefore, it did not affect the structure of the composite. However, for displacement greater than 0.8 mm, it seems the linearity response no longer holds. This response was observed on each of the six cycles.

The final sensor pattern was fabricated by using the polyimide fiber textile combination. The pattern design used for the smart textile is shown in **Figure 27**. The fabric was 0.91m long and 0.30m wide. The fiber was routed by using a U-shape format with a 5cm space between each fiber. There were a total of three curvature points and four straight sections.

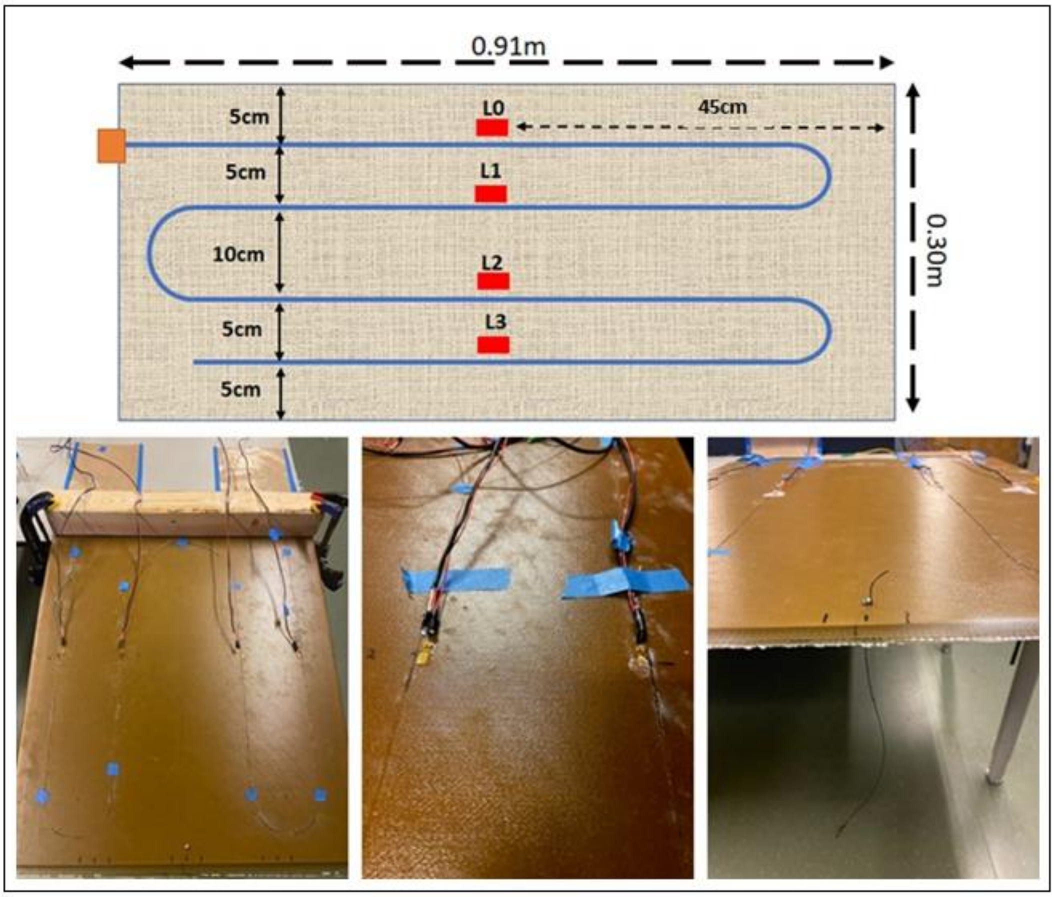


Figure 27. Cantilever test setup and textile layout [69].

The Boeing team in St. Louis fabricated composite panels for testing while incorporating the XP414 textile with the fiber provided by ADFORS-Saint-Gobain and the University of Massachusetts. The sensing textile was embedded in the composite sample, which was cured by using an autoclave process. The composite material (BMS8-276) is commercially available but has proprietary Boeing specifications.

The DFOST embedded in the composite was tested by using a cantilever test approach both against static and dynamic loads. In addition to the DFOST sensor embedded in the composite, two additional sensors were added to the surface of the composite. One sensor corresponds to a second distributed fiber sensor placed in the surface and the other corresponds to four strain gauges. More detailed description of static and dynamic test analysis can be found in section 4 of [69].

In conclusion, the article demonstrated the integration of distributed fiber optic sensing into a textile by using the embroidering method. By using this approach, the overall installation time of the DFOST sensors can be reduced. Additionally, different sensor patterns can be designed to be customized for the customer application. The paper also studied the sensor's response when the strain was applied. It explored the strain transfer between a polyimide coating and jacketed fiber. As demonstrated during the calibration process, polyimide fiber had a better response when the strain was applied. In addition, the DFOST was embedded into a composite sample. Static and dynamic tests were performed by using a cantilever setup. The sensor measured the strain inside the composite with the largest standard deviation (0.57) when no load was applied and the minimum (0.01) was at 3 kg. The DFOST also measured dynamic vibration with the minimum strain difference recorded value of 3 με and a fundamental frequency of 2.11 Hz. The measurement values were compared with a fibre sensor located at the surface of the composite panel. It was observed a constant strain difference of 8.7 times greater across all loading values from the measurement performed by the surface sensor which is because the surface sensors are more loaded than embedded sensors since bending has increasing impact for points distancing from neutral axis [69].

Distributed Fiber Optic Sensing Technology (DFOST) can be utilized to monitor structures that are challenging to access, as it employs distributed sensors capable of providing a vast number of measurements from various locations. Nevertheless, the primary drawback of DFOST continues to be the considerable cost associated with the interrogation system, as well as the availability of having an autoclave for curing processes.

2.2.2. Piezoelectric Sensors

The piezoelectric effect was discovered in 1880 by the Curie brothers and was first used by Paul Langevin in the development of ultrasounds, based on quartz crystal transducers, during the first World War [45]. Piezoelectric materials can become electrically polarized upon the application of external stress or deform in response to electrical stimuli. Therefore, sensors based on piezoelectric effect could be used as multipurpose sensors to realize the SHM systems. Compared with other monitoring sensors or techniques, piezoelectric sensors have numerous advantages, such as small size, light weight, low cost, availability in a variety of formats, high sensitivity, and so on.

The development of piezoelectric ceramics, such as Lead Zirconate Titanate (PZT) [109] was revolutionary. Moreover, to obtain better properties than crystals after being polarized, they also offered flexible geometries and dimensions because they could be manufactured through sintering. Currently, piezoelectric ceramics of the PZT type are the predominant ceramics in the market.

Other materials can also be found, such as PT (PbTiO3) [110] and PMN (Pb (Mg1/3 Nb2/3) O3) [111], that are used in devices that require special and very specific properties. These are inorganic piezoelectric materials. However, there can also be organic ones [45].

PVDF (polyvinylidene fluoride) [112] is the most typical organic piezoelectric material, which is versatile and lightweight compared to piezoelectric ceramics [113]. In consequence, thin films of any desired form can be drawn into them, giving them an advantage in designs of complex geometries. Despite organic piezoelectric materials having lower electromechanical coupling, other characteristics that make them attractive are their low electrical permittivity, low acoustic impedance, high voltage sensitivity, and relatively lower cost.

Composite piezoelectric materials (piezopolymers) and sensors integrated with simultaneously high piezoelectricity and decent flexibility show unprecedented opportunity to improve the performance of SHM systems, such as working range, complex mechanical loadings, etc. Moreover, composite fiber piezoelectric sensors have high compatibility with composite structures, unlike PZTs [113].

The working principle of a piezoelectric sensor depends on the **''Piezoelectric Effect''** of piezoelectric materials discovered by Curie brothers in 1880. They found that, when an external force (pressure or tension) is applied in a specific direction of some dielectric crystals, the surface of both ends of the crystal will generate positive and negative bound charges of equal amount of electricity, and the density of bound charges is proportional to the magnitude of the applied stress, which is called the "positive piezoelectric effect".

Lately, the existence of ''inverse piezoelectric effect'' was demonstrated. The material with piezoelectric effect will produce corresponding deformation under a certain electric field, and the deformation of the material will be restored when the applied electric field is removed. The direct piezoelectric effect is used for sensing applications while inverse piezoelectric effect is exploited for actuation applications. The schematic diagram is shown in **Figure 28** :

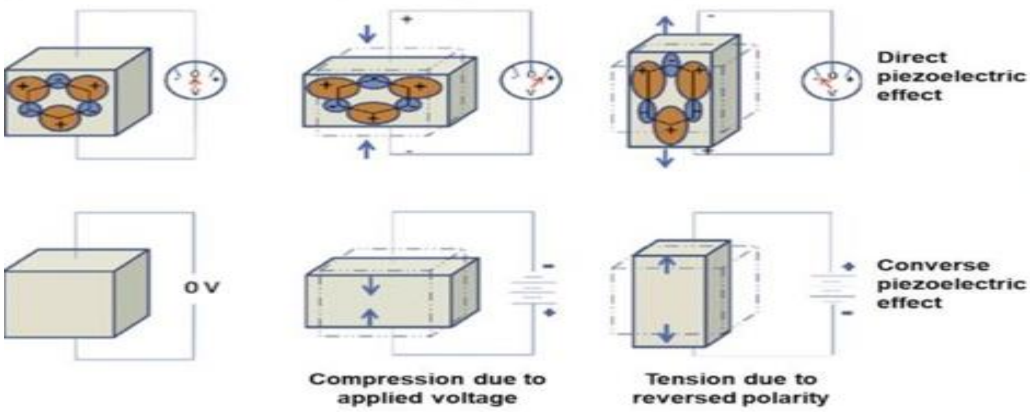


Figure 28. Piezoelectric effect [113].

2.2.2.1. Piezoelectric Classes

The most significant defect or damage inspection techniques based on piezoelectric transducers can be grouped into three classes, wherein their behaviors can be passive or active. These main classes are:

1. Acoustic Emission.
2. Guided Wave propagation.
3. Electro-Mechanical Impedance (EMI).

The technique based on **Electro-Mechanical Impedance** is considered one of the most promising methods for the development of SHM systems. The electromechanical impedance based SHM utilizes the electromechanical property of piezoelectric materials and the coupling of piezoelectric sensors and target structure. The EMI sensors can be attached to the surface of the structure or embedded into the structure. In this active monitoring method, the piezoelectric EMI sensors can work as actuators, converting the electric voltage signal into a mechanical stress solicitation. Meanwhile, the piezoelectric sensors can act as the sensors, converting the structure's mechanical response to an electric signal. To ensure immunity to ambient noise and vibrations commonly present in practical applications, variable high frequencies (typically larger than 30 kHz) are preferred which brings the issues of weak signals limiting the sensor monitoring application to local damages only. The sensitivity of detecting damage through EMI is closely related to the selected frequency band of the excitation signal, which is emitted by the EMI sensor. The size of PZT piezoelectric sensor affects ZS/ZT (ratio of host structures' mechanical impedance to the PZT transducer's mechanical impedance), which is equivalent to the sensitivity. For using the frequencies below 125 kHz, the sizes (length and width) of sensors should fall into the range of 5 mm to 20 mm and thickness of sensors of 0.1 mm to 0.3 mm [114]. The EMI methods are used for continuous monitoring and early detection of structural defects, such as joint looseness, debonding, and crack detection. This technique is simple to implement and uses small and inexpensive piezoelectric sensors.

Guided wave propagation refers to waves that are confined or guided within a structure or a medium. It is used for damage detection both in metallic and composite materials. There are mainly four modes of the guided wave propagation [115], as shown in **Figure 29**:

1. Pitch-catch mode
2. Pulse-echo mode

3. Thickness mode
4. Impact detection mode

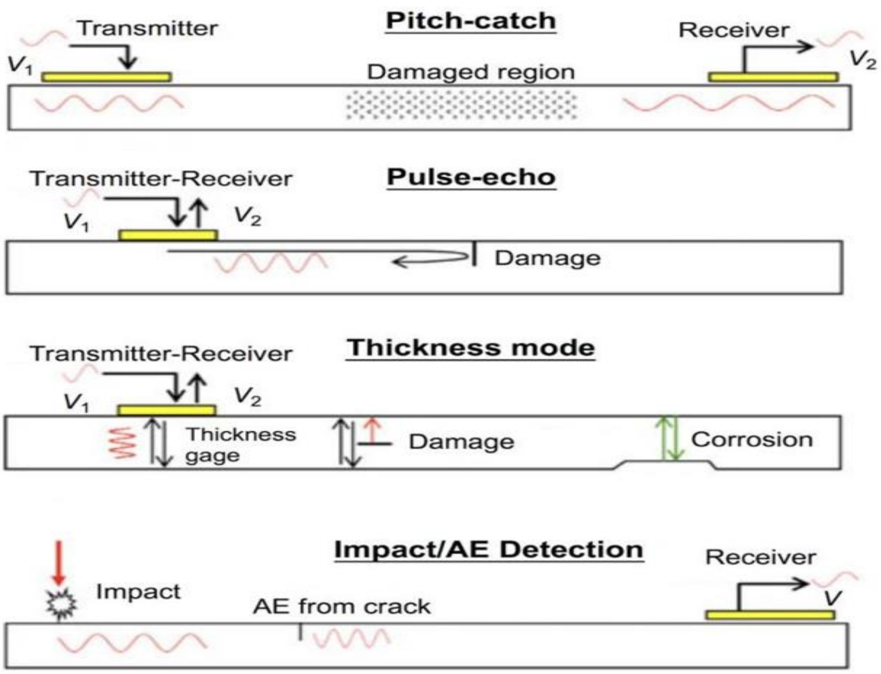


Figure 29. Guided waves operational modes [113].

Taking the typical pitch–catch mode as an example, a pair of piezoelectric transducers are attached on the plate-like structures. Firstly, ultrasonic guided waves are induced by the piezo-actuator attached to the surface of a flat plate-like structure. Secondly, ultrasonic disturbances occur and propagate radially to the around in the structure. Finally, the piezo sensor around receives the electric charge signal, owing to the induced mechanical strains and output voltage signals (sensing waveform). While there is even damage existing in the structure, the guided wave (such as lamb wave) would incur dispersion and energy would attenuate during the propagation in the pitch–catch mode, pulse–echo mode, and thickness mode. The thickness mode can be used for the detection of corrosion thickness loss. In the impact detection mode, the piezoelectric sensors would receive a signal of acoustic guided wave, while impact events on the structure and advancing cracks occur.

Compared with the local electro-mechanical, the guided wave monitoring technology can both realize local damage monitoring and global monitoring. In the case of local damage monitoring, the guided waves could be used to monitor the hybrid bonded joints [116]. To realize the global monitoring using a lower quantity of transducers, piezoelectric transducers exciting high purity of shear horizontal wave are preferred [117].

Acoustic emission based SHM is monitoring internal elastic waves of components that are generated to release strain energy after the damage or impact. When the structures are under low-frequency dynamic loadings, elastic waves would generate and propagate to the piezoelectric materials. The stress variation of structures can be reflected by analyzing the output voltage of piezoelectric sensors based on the direct piezoelectric effect. This method is a passive monitoring technique, unlike the other two methodologies. Acoustic emission method is available only for damage initiation and propagation, such as impact event, crack initiation, fiber breakage, debonding, and delamination. For example, when a sudden crack occurs in the structure, piezoelectric sensors can catch the signal of acoustic emission from the crack. The acoustic emission based SHM is a local monitoring. Piezoelectric sensors should be placed near the key objects where damages or defects are prone to occurring [113].

In some practical applications, only passive monitoring is not enough. For example, the impact events on airplane or aerospace structures might cause damage to the structures and the damage could also worsen or become extended with time due to the operational fatigue. In this scenario, active monitoring is needed to continuously monitor the damage progression. In analogy, purely active monitoring also has its drawbacks. Piezoelectric transducers need to send out inspect waves continuously, resulting in useless work when they are not demanded. Therefore, it is desirable to integrate the passive and active sensors to overcome each other's disadvantages.

However, piezoelectric components face some difficulties. An accurate sensor self-diagnostic is of paramount importance as sensor failures without self-identification will lead to false results in damage detection. Moreover, for the long-term monitoring, sensor failure or debonding failure tends to occur which must be well accounted for. Additionally, lots of properties of piezoelectric materials would vary when the operating temperature changes, such as piezoelectric properties, dielectric constant, coupling constant, and Young's modulus. For the guided wave based SHM systems, the temperature would make an impact on the guided wave baseline comparison and an optimal baseline selection method for the environment temperature range should be adopted. Furthermore, the environmental effect of ambient induced noises, vibrations, and external loads also should be dealt with appropriately in the practical engineering SHM systems.

A self-powered wireless sensor network is highly demanded, particularly for the case of structural health monitoring. The direct piezoelectric effect enables the piezoelectric devices to harvest electrical power from ambient mechanical and vibrational energies, such as structure vibration, airflow, etc. The piezoelectric energy harvesters can be integrated to the wireless sensor network for structural health monitoring to provide an unbounded power source for the system.

2.2.2.2. Piezoelectric Applications

Regarding polymer matrix composites, there is a small range of manufacturing processes that allow for the incorporation of piezoelectric materials due to the Curie temperature that limits the applicability of these sensors. Few techniques can be adopted for that purpose such as open contact-moulding [118] and the vacuum-assisted resin transferring [119]. However, piezoelectric materials find their vast application in concrete structures of civil engineering structures [120], [121].

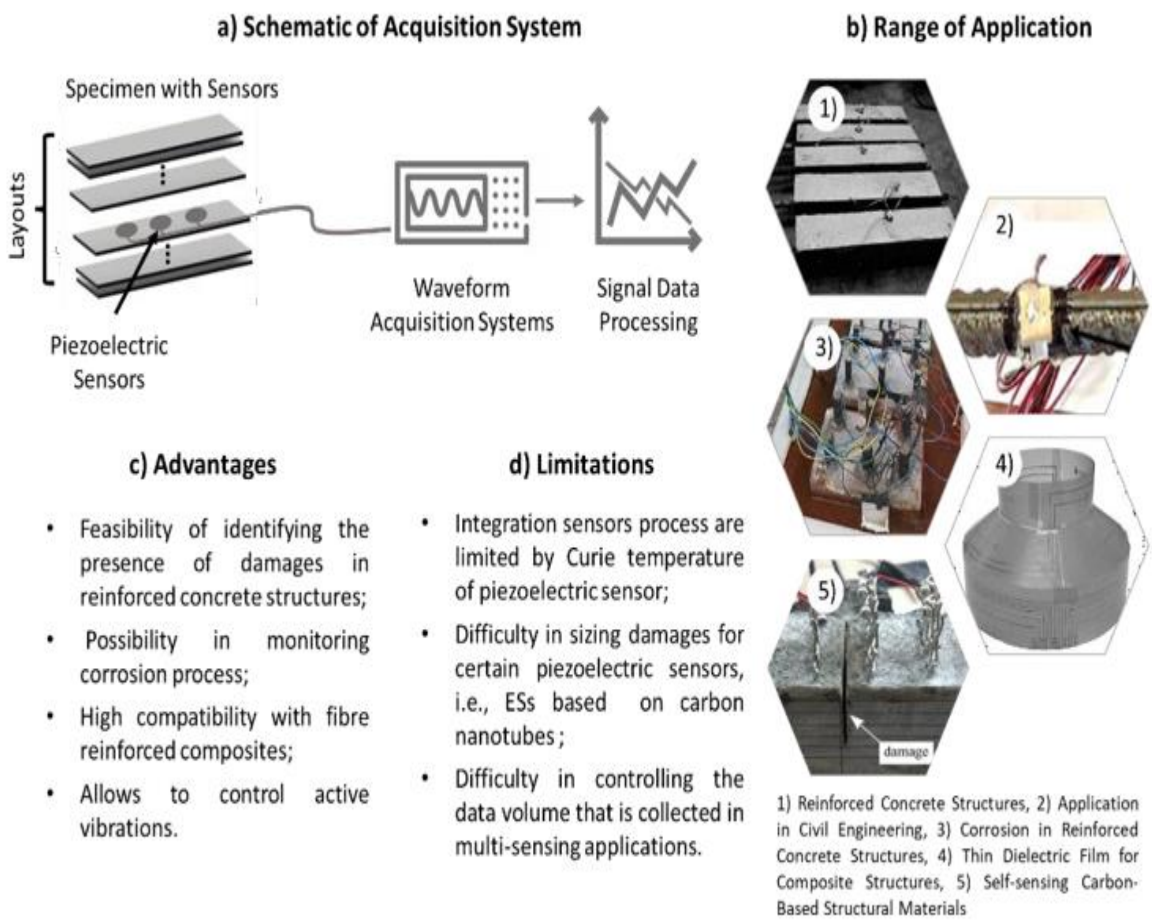


Figure 30. PZT embedment in composites [45].

Currently, the applications for metal components use sensitive ceramic and polymeric piezoelectric sensors, more specifically PZT sensors [122] and Piezoelectric Polyvinylidene Fluoride (PVDF) sensors [123]. Traditional manufacturing approaches for incorporating piezoelectric materials into metals can be problematic due to their high temperatures during production or the long curing times of the adhesives used to connect the sensor to the metal. To bridge the challenges that technological processes present, the scientific community has carried out a set of developments, among which is their focus on the development of a process of “stop and go”, which consists of taking a break in the manufacturing process of a given component to allow for the inclusion of embedded sensors [122] or through the joining of metal components in the solid-state, i.e., by ultrasonic additive manufacturing [123] . In any case, the processes to incorporate piezoelectric sensors into metal matrices are based on the additive manufacturing process, allowing greater control of the sensors' positioning and avoiding their damage.

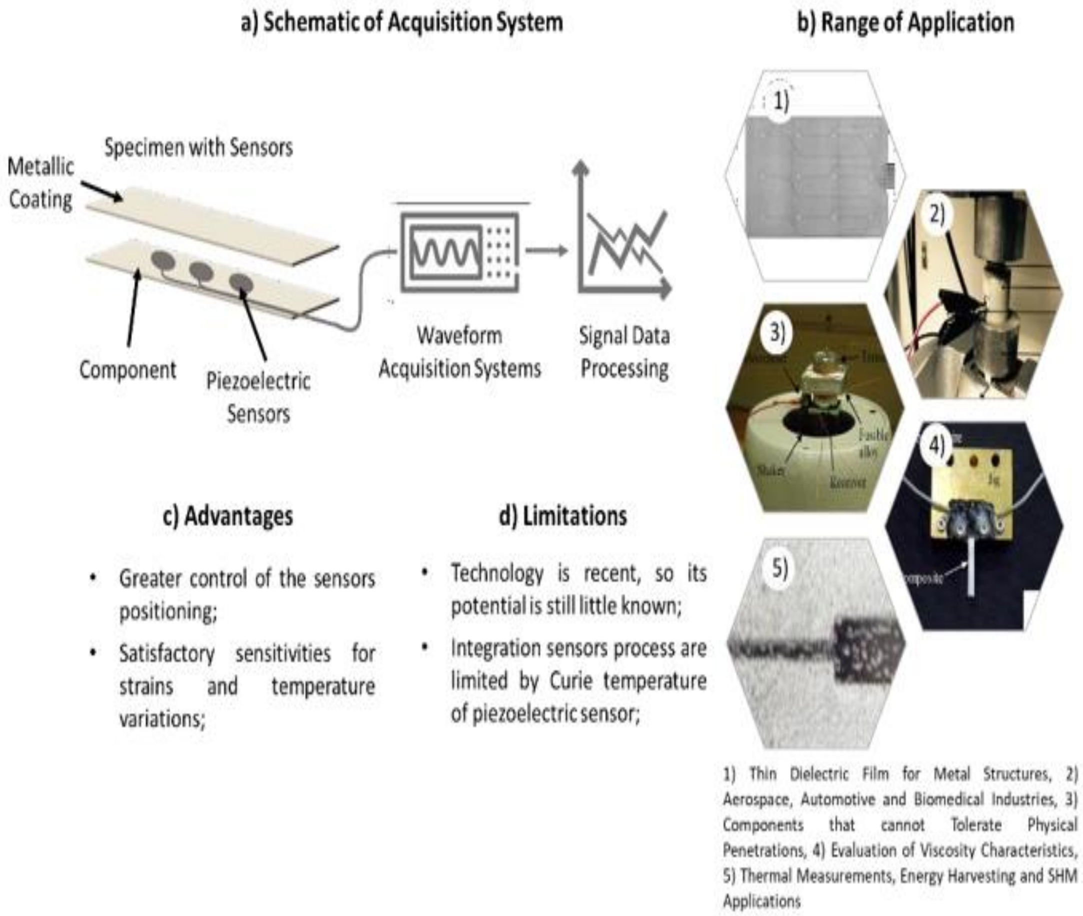


Figure 31. PZT embedment in metals [45].

Energy harvesting technology has also received extensive attention and research in recent years to tackle the problem of energy supply for large and numerous amounts of sensors within aircraft structures. The fundamental idea behind energy harvesting technologies is to convert a wide spectrum of fugitive or external energy into electrical energy through appropriate sensors and store it. An energy harvesting system usually consists of three parts: target harvesting energy, energy converter and load. The large-scale target energy includes solar energy, wind energy, tidal energy, geothermal energy, etc., and the small-scale energy includes thermal energy, mechanical energy, electromagnetic radiation. [124] Systematically discussed the potential of piezoelectric materials to harvest wind and mechanical energy in the environment as energy harvesting devices and claimed that this technology has important significance for wireless health monitoring technology in complex working environments. Because mechanical energy is the easiest to obtain in the aerospace industry, mechanical forced vibration or fugitive energy during active work are frequently expressed by mechanical energy, and the piezoelectric effect of piezoelectric materials can convert this mechanical energy into electrical energy, mechanical energy is usually regarded as the most efficient input energy among all the sources of energy that are currently available. Therefore, most research directions have focused on the collection of mechanical energy. Compared to other materials, piezoelectric polymers (PVDFs) are a more desirable material choice for piezoelectric effect-based mechanical energy harvesting [125]. So, it is a common scheme to collect environmental mechanical energy by nanotechnology assembling PVDF into piezoelectric nanogenerators. To solve the problem of low output current density of piezoelectric nanogenerators when collecting environmental mechanical energy, [126] proposed a new piezoelectric nanogenerator design based on piezoelectric materials with high-voltage electric coefficient, which achieved significant improvement.

Piezoelectric sensors, in conjunction with fiber optics, form the foundational sensor technology for Structural Health Monitoring. These sensors prove especially valuable in scenarios demanding precise measurements for dynamic processes. In comparison to alternative sensor types, piezoelectric sensors exhibit distinctive attributes such as a wide frequency range with high amplitude, rapid response time, and a high modulus of elasticity. Moreover, piezoelectric sensors possess a straightforward structure, offer high resolution, and necessitate minimal installation space.

3 Self-Healing Systems

As evident, the eventual degradation and time-dependent failure of materials and structures necessitate the implementation of methodologies and remedies to address aircraft system failure issues. Structural monitoring serves as a means to observe the system; however, decisions are typically made during maintenance phases. Thus, to preserve materials from failure, extend their operational lifespan, and uphold mechanical properties, the adoption of self-healing techniques emerges as a prominent solution [127]. The capacity of a material to heal (recover/repair) from damages naturally and autonomously without any external or superficial interference is described as self-healing.

Self-healing materials were first developed 2000 years ago [128]. The Romans found self-healing in concrete structures where microcracks were resisted due to intrinsic crystallization of minerals in concrete.

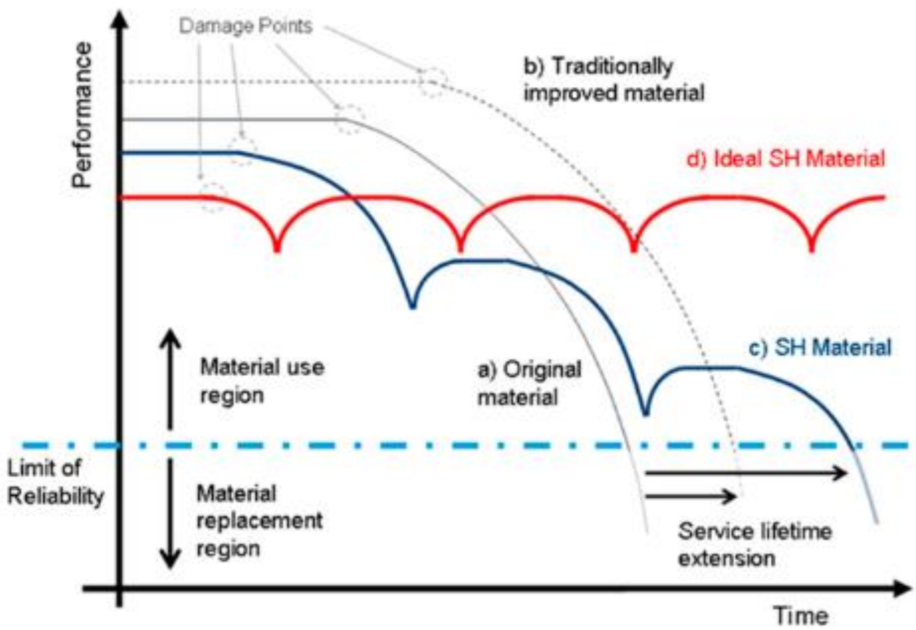


Figure 32. Lifetime extension of engineered materials via self-healing principles [127].

In the search for improved self-healing materials, researchers have looked to nature for inspiration because it is well known that many organisms and body parts can repair damage, thus improving their durability and resilience. Normally, the aim is to repair small defects that arise due to fatigue, surface damage, or overload which would otherwise compromise the structural integrity of the material [129]. Various self-healing methods have recently been developed and tested. These bioinspired engineered materials, i.e., materials that "self-heal" after external damage, have been studied since the early 1990s [130].

Self-healing mechanisms can be divided into two types, extrinsic and intrinsic healing. Furthermore, classification of self-healing systems can also be made on autonomic healing or non-autonomic healing (i.e., with or without external stimuli).

In **extrinsic healing**, the healing agent is used as an additive to fill up the cracks in the matrix. Extrinsic healing depends on external healing agents in the form of capsules or vascular channels. Thus, extrinsic self-healing involves the development of materials relying on healing agents and catalysts **Figure 33**. For such healing agents, microcapsules or hollow fibers have usually been filled with liquid compounds. When any damage occurs to a structure, these microcapsules or channels break down to release the encapsulated healing agent and catalyst. Most common healing agent is Dicyclopentadiene (DCPD), while the catalyst is the Grubbs catalyst. The released healing agent not only heals the existing cracks but also prevents further crack growth through its action. However, the healing agents released from the containers can only act a single time and then containers become empty. So, further healing of structures is not possible if there is repeated damage [131].

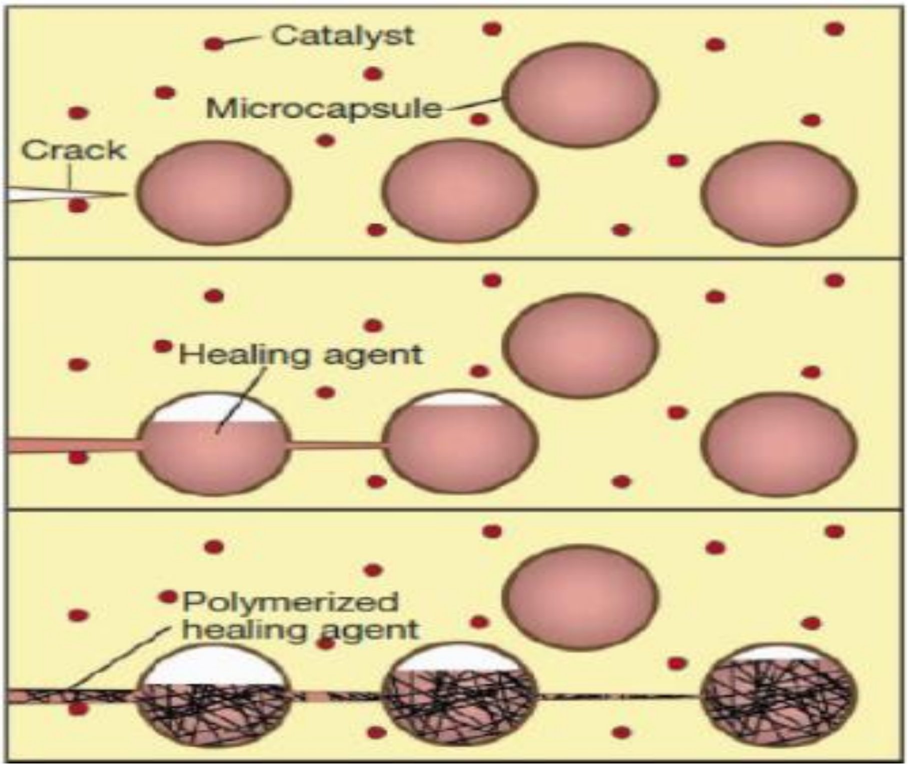


Figure 33. Extrinsic self-healing polymer via microcapsules [132].

Agents	Agents functioning
Microcapsule	The healing must be chemically inactive to the polymer shell; the capsule must have a long shelf life. It must be compatible with the dispersed polymer region. The shell walls must be weak to allow for rupture. The catalyst must be close to the capsule. Thematrix and the capsule must have a high interfacial attraction.
Monomer polymerization	Less volatile for the required time to complete polymerization. No cure-inducedshrinkage and stress relaxation. Polymerization at atmospheric temperature
Catalysts	Dissolves in monomer, clustering does not occur in polymer matrix
Coatings	Microcapsules have a strong influence on the physical and chemical characteristics of the matrix; Microcapsule's size will be smaller than the thickness of the coating and clustering does not occur in the matrix
Healing	Low economy, must be quicker, multiple cycles

Table 7. Considerations for microcapsules embedded in composites [131].

The vascular channels found in animals and plants for transporting fluids have been reproduced in the form of hollow channels containing healing agents in a variety of materials, including polymer, metal and ceramic composites **Figure 34**. The existence of vascular channels may allow for the continuous supply of larger amount reactive agents into the material compared to capsules, giving the capacity for repeated repair in the same area. [133] developed a method for optimizing the manufacturing of hollow fiber glasses to be used as a liquid curing agent and dye container. Borosilicate glass fiber has a diameter of 30 to 100 micrometers and a 55% hollow. They prepared hollow fibers using composite panels and recovered up to 97% of the original flexural power by containing repair agents.

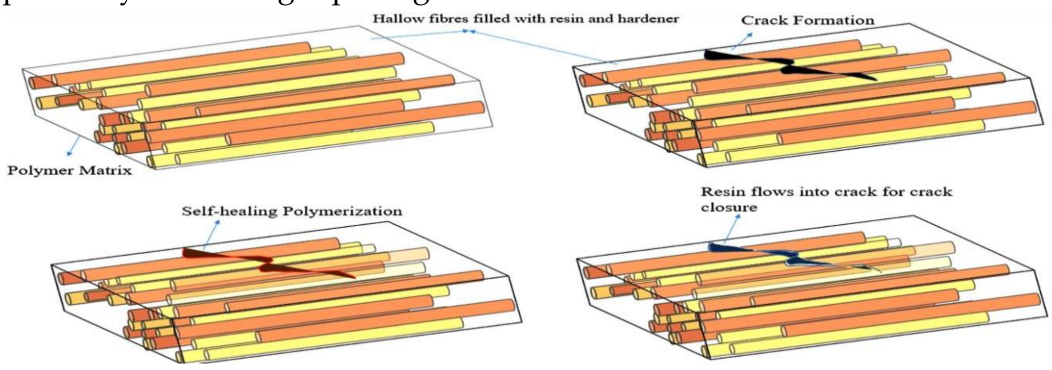


Figure 34. Self-healing via hollow fibers [131].

In **intrinsic healing** a reversible crosslinking bond (supramolecular chemistry) is used to bind the monomers and fill the cracks. It is absent of any healing agent and catalyst as it is based on reconstruction of chemical (covalent and non-covalent), physical or supramolecular bonds. Covalent interactions usually involve Diels Alder reactions while non-covalent interactions mainly comprise ionomers, hydrogen bonds, Van Der Waals forces [134]. Upon damage, self-healing occurs by reformation of interactions and damage recovery. Thus, the general mechanism of intrinsic self-healing works based on reversible interactions in the polymers or nanocomposite structures. Usually, the more dynamic the reversible chemistry, the better the self-healing ability of the material. Low association strength of reversible chemistry causes good self-healing ability of polymers. However, the low association strength of a reversible self-healing network does not allow it to resist external forces. Therefore, reversible chemistry endows polymers with fine self-healing capability, but less resistance to external forces. Accordingly, better reversible chemistry decreases the attainment of high tensile strength of materials during potential applications. Consequently, producing self-healing materials that not only have high mechanical properties, but also high self-healing efficiency is challenging. In this regard, different extrinsic self-healing approaches must be preferred such as nanofiller addition in the nanocomposites. Nanofillers such as graphene [135] and carbon nanotube [136] might be adopted.

Graphene is a two-dimensional nanostructure consisting of sp^2 hybridized carbon atoms. In 2004, Andre Geim and Konstantin Novoselov prepared and reported single-layer graphene [137]. [138] studied the self-healing effect in vitrimer/graphene oxide nanocomposites. The self-healing effect was studied at 60 ◦C. Recovery occurred in 5 min. Inclusion of 0.5–1 wt.% graphene oxide caused 80–88% self-healing of the nanocomposites.

While the nanocomposite with a carbon nanotube nanosheet revealed an average healing efficiency of 107.7% for fracture energy and 96.22% healing efficiency for peak load. The maximum healing efficiency (fracture energy) was 141% for a carbon nanotube nanosheet-based sample [134]. An enhanced self-healing effect of the epoxy/carbon nanotube nanocomposite was observed owing to the matrix–nanofiller interactions and interface formation [139]. Inclusion of nanoparticles such as carbon nanotube and graphene may further enhance the impact resistance of epoxy/fiber nanocomposites particularly useful for aircraft fuselage applications. Relative to metal alloy-based structures, a healing efficiency of >90% has been observed for self-healing polymer nanocomposites. Consequently, metal-based space fuselage has been successfully replaced with the composite structures with superior damage-healing properties [140].

Figure 35 shows the classification of self-healing technologies based on three main branches of: healing agents, reversible crosslinks and miscellaneous technologies.

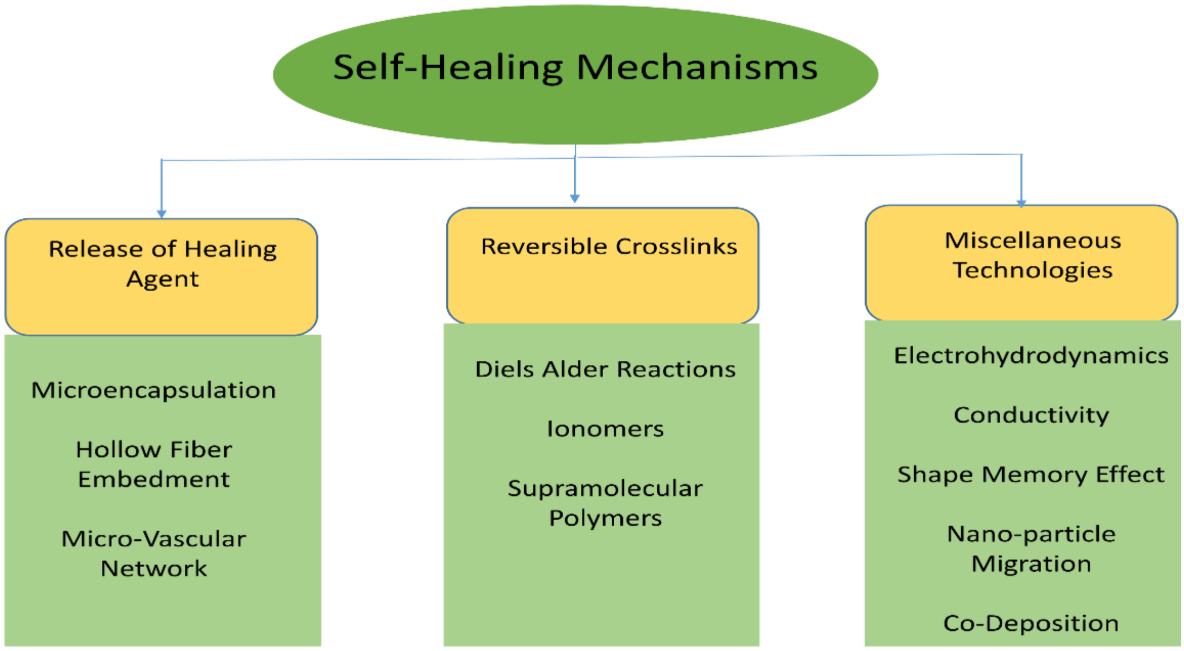


Figure 35. Self-healing mechanisms [131].

To further improve impact properties of self-healing epoxy/glass fiber or epoxy/carbon fiber composites for aerospace applications, super-elastic self-healing NiTi alloy (most common SMA) wires were used along with carbon or glass fiber fillers. Inclusion of self-healing wires enhanced the damage tolerance of aerospace composites under repeated impacts. Self-healing polymer composites have been investigated as an alternative to metal alloys for protecting space structures from space debris [141].

Shape Memory Alloy (SMA) is made of shape memory material. Shape memory material is a kind of smart material with unique shape memory effect and super elastic effect because it can respond to changes in temperature, pressure and other changes to produce recoverable deformation, so it is considered to have a similar role to "memory", mainly divided into shape memory alloys and shape memory polymers. In **Figure 36**, stress–strain–temperature curves for shape memory effect and super-elasticity can be found. SMA has the advantages of a large driving force per unit volume and a direct actuation of the material itself, thereby reducing system complexity and improving system reliability and low-motion noise. The requirements for smaller size, lighter weight and robustness pursued by the aerospace field make them widely used in aerospace. SMA material is a material that is mainly affected by temperature and stress and achieves solid–solid phase conversion in the two states of martensite and austenite. *Austenite* is a state in which metals are characterized by cubic crystal structures that are stable at relatively high temperatures. *Martensite* is a state in which metals are characterized by monoclinic or tetragonal crystal structures that are stable at relatively low temperatures or under high stress [142].

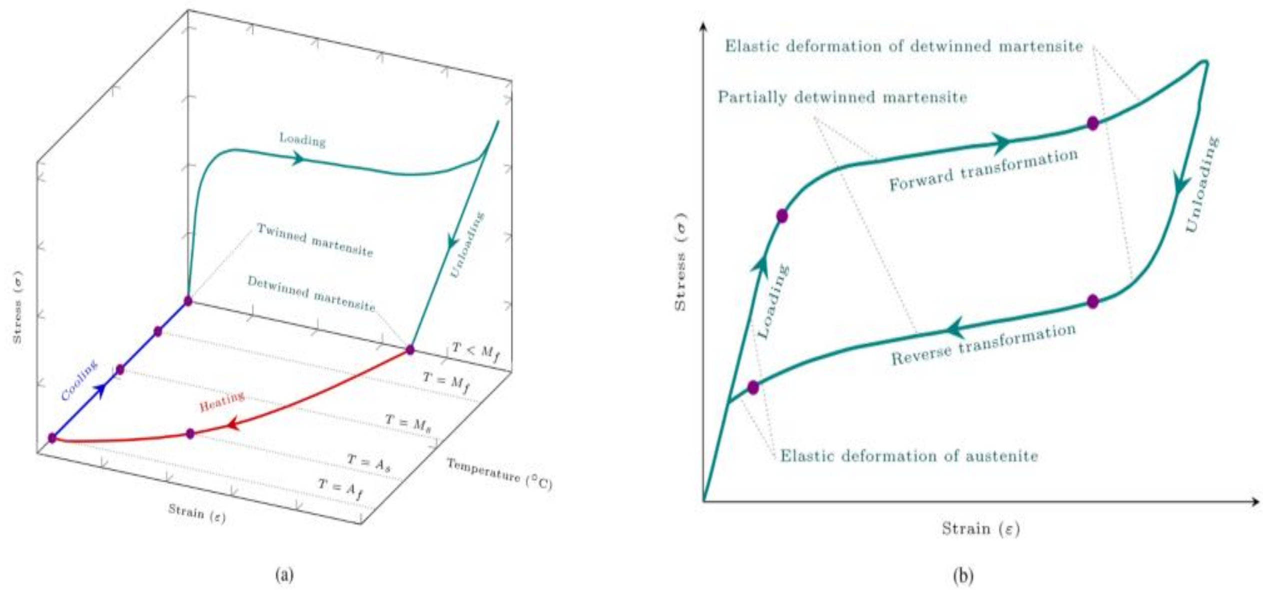


Figure 36. Stress-strain-temperature curves for (a) shape memory effect and (b) super-elasticity [143].

The *one-way memory effect* refers to the deformation of SMA at lower temperatures, i.e., in the martensitic state, and when the temperature rises to the austenitic state, the metal returns to its undeformed shape.

The *two-way memory effect* refers to the fact that the metal returns to the austenitic phase at a higher temperature austenitic state and returns to the martensite phase when cooled to the martensite state. In general, the shape memory effect means that when SMA is in a low-temperature twin martensite structure, it is transformed into a detwinned martensite by loading, and when the temperature rises, the SMA will be converted to austenite and produce corresponding deformation recovery.

The *Super-elasticity* refers to the characteristic that SMA converts austenite into detwinned martensite and deforms by loading and then quickly returns to austenite recovering its initial shape after unloading. It is characterized by the fact that it does not produce permanent deformation even under large loads and is an important characteristic that SMA material structures can replace springs and other structures. Super-elasticity allows structures made of SMA materials to withstand enormous strains and still return to their initial shape, which is very suitable for some applications where vibration energy absorption or extreme deformation recovery is restored.

The elastic modulus and yield stress of shape memory alloys are higher at high temperatures and lower at low temperatures, but the opposite in shape memory polymers. So, shape memory materials have a different elastic modulus and stiffness coefficient at different temperatures. Using this property, it is possible to exploit SMA in passive vibration control: By changing the stiffness coefficient of SMA, natural frequency of the whole structure changes therefore resonance peak is modified [144].

Shape memory alloys have the critical property of super-elasticity, which prevents permanent deformation even when subjected to large loads and allows for speedy recovery after unloading. These materials have a large hysteresis loop area and can produce high intrinsic material damping [145]. NASA utilized a shape memory alloy to develop a Mars rover tire that is woven from super-elastic shape memory alloy wire, which can not only achieve adaptive ability to road surface unevenness input during mission execution but also overcome the plastic deformation problem of traditional spring tires [146]. Moreover, shape control is one of the main application directions of shape memory materials in the aviation industry. The main purpose of shape control is to adapt to different environments by changing the shape of structures, such as aircraft skins (as for example, to adapt to different flight speeds within different flight phases to improve performance).

However, shape memory materials also have important applications in the assisted self-healing of material structures. **Figure 37** shows a representation of self-healing through SMA by applying signals like temperature, magnetic field, current etc. This allows the damaged structure to first attain the physical macroscopic level of fit (closed state) before relying on the inherent qualities of the material to cure itself (healed state). [147] utilized thermo-reversible polymers as a matrix, along with the integrated SMA reinforcement material to develop a new self-healing composite material. This structure can activate SMA by heating to provide auxiliary force, while activating the chemical reaction of the thermo-reversible material itself to realize self-repairing. This actively enhanced structure has an average healing efficiency of 92%.

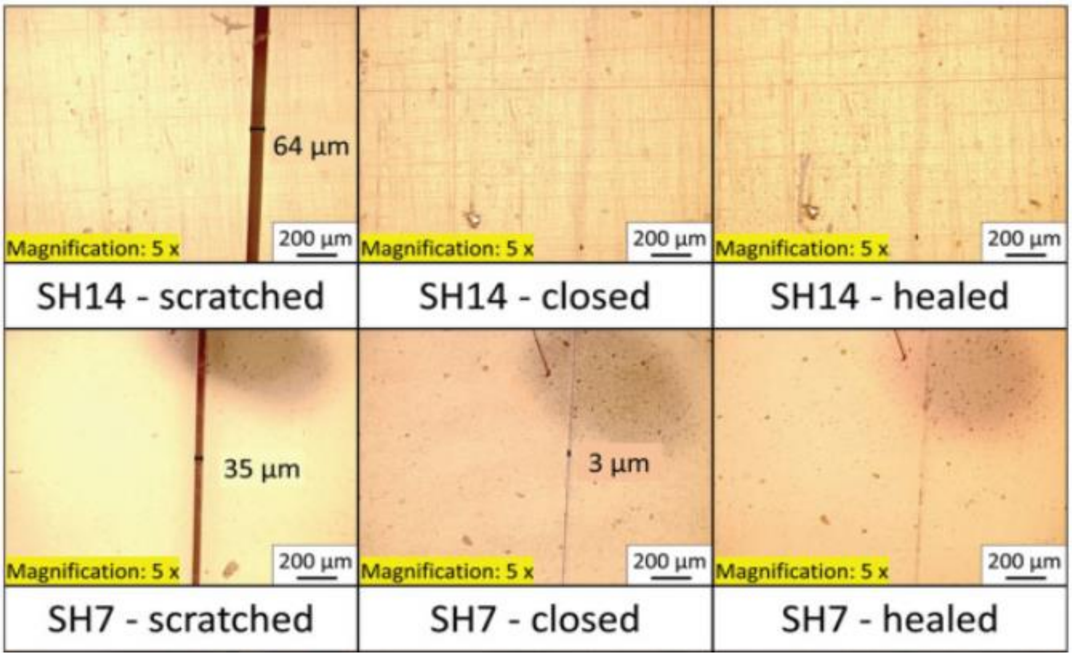


Figure 37.
Morphological investigation of the SMA performance of the selected networks via optical microscopy. The samples were monitored as scratched, recovered (closed), and after healing at 180 °C for 5 h [148].

3.1. Self-healing in composites

Focusing on aerospace, the most widespread polymers used as matrices are epoxies. A molecule with numerous epoxide groups is called epoxy resin. Epoxy resin is utilized as a matrix in aerospace composites for two reasons: first, it has excellent technical features, and second, it can be produced with low curing temperature and viscosity. The low curing temperature combined with the low viscosity allows for the inclusion of discrete and rather poor microcapsules and their dispersion without premature capsule collapse. Better characteristics with respect to other thermosetting polymers in terms of mechanical properties (strength and modulus), adhesion to substrates and fibers, resistance to moisture absorption and to corrosive environments make epoxies remarkably suitable for aerospace applications. An additional advantage is their good performance at elevated temperatures owing to high glass transition temperatures [127]. **Table 8** Reports properties of epoxy resins.

Property	Value
Viscosity (cP)	12000-13000
Density (g/cm^3)	1.16
Tensile strength (MPa)	73
Elongation (%)	4
Flexural strength (MPa)	60

Table 8. Properties of epoxy resin [149], [150].

Commonly adopted solutions for polymers are extrinsic self-healing techniques via microcapsules or vascular channels exploiting healing agents and catalysts **Figure 38**, as described in previous section. However, intrinsic techniques still play an important role in self-healing of composite structures. **Table 9** and **Table 10** report some novel applications of chemical and physical interactions of self-healing techniques. For detailed description of each technology and related references the reader is addressed to [127].

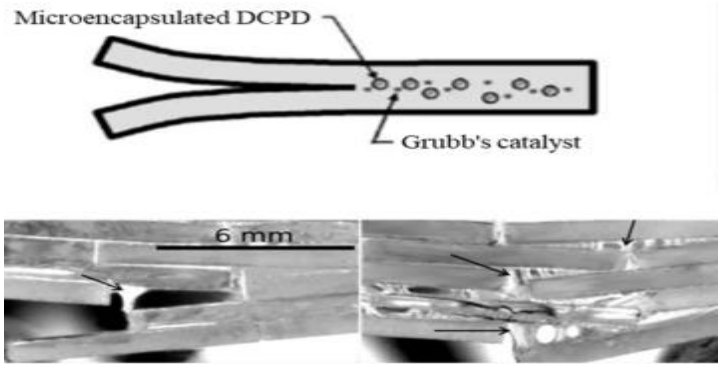


Figure 38. Composites self-healing via microcapsules [151].

Healing mechanism	**Formulation**	**Healing conditions**	**Tg (◦C)**	***η (%)***	**Test (specimen)**	**Notes**
Interdiffusion +DA/rDA	DGEBA-FGE-PACM + BMI in DMF	10 µL gel on cracked surfaces, RT, 12 h, ~4.7 kPa	56	70 ± 22	P_C (CT)	0.58 M of BMI in DMF
DA/rDA	*GNS* + FDB-OGE-D230	~0.2 W cm^{-2}, ~20 min (IR)	57	93	Lap shear strength	0.5 wt% GNS
DA/rDA	*CFs*-BMI + DGEBA-FGE-IPD	90◦C, 1h and RT,24h	63	82	Microdroplet single fiber pull-out test	CFs oxidized w/HNO_3, reacted w/TEPA, immerged into BMI
Tetrasulfides	ER-OMAS	70 ◦C, 10 min, air, 30 kPa	-11	100	Gap closure efficiency	~600 µm-thick film
Vitrimer	DGEBA-di/tricarboxylic acid	240 ◦C, 3 min	~15	~100	σ_T (dog-bone)	10 mol% $Zn(acac)_2$ catalyst
Bio-vitrimer (transesterification)	TEP-MHHPA	220 ◦C, 5 min	187	70	Crack width reduction	$Zn(acac)_2$ catalyst
Bio-vitrimer (disulfide exchange)	IS-ECH-4AFD	100 ◦C, 60 min	41	100	Optical microscopy	Multiple reprocessing cycles

Table 9. Intrinsic self-healing via chemical interactions [127].

Healing mechanism	Formulation	Healing conditions	Tg (◦C)	*η (%)*	Test (specimen)	Notes
Mech. Interlocking + polyetherification-homopolymerization	DGEBA-PACM	185 ◦C, 1 h, 8–13 MPa	118	178 ± 56	P_C (CT)	Excess of epoxy groups
Differential expansive bleeding	DGEBA-DDS + PCL	190 ◦C, 8 min, 18.7 kPa	203	>100	P and U at failure (SENB)	15.5 wt% PCL, non-brittle behavior
Epoxy particles	Glass fiber + coldsetting epoxy + thermosetting epoxy particles	120 ◦C, 10 min	n.a.	>100	Fatigue (SENT)	Fatigue life extension
Pressure delivery of healing agent	CFs + DGEBA-TETA + EMAA	150 ◦C, 30 min	n.a	221 ± *17*	Failure energy (DCB)	15 vol% EMAA particles
Pressure delivery of healing agent	CFs + DGEBA-TETA + EMAA	150 ◦C, 30 min	n.a	223	G_{IC} (DCB)	2-layers EMAA mesh
Thermoplastic melting and viscous flow into cracks upon heating	CFs + DGEBA-TETA + EVA	150 ◦C, 30 min, 25 kPa	97	103	G_{IC} (DCB)	10 wt% thermopl. agent

Table 10. Intrinsic self-healing via physical interactions [127].

Intrinsic self-healing is typically restricted to a small damage zone. These materials can heal microcracks before any crack growth leading to catastrophic failure, but damage due to high energy impacts can not be healed. This issue can be overcome by including into self-healing polymers a shape memory capability so that the shape memory will bring the fractured surfaces in contact and the intrinsic healing mechanisms will occur by so-called close-then-heal strategy [147], [152]. However, with current progress extrinsic self-healing via micro/nano capsules and channels still shows most promising results because of better mechanical properties.

[153] addresses the synthesis of a nano-fiber network by coaxial electrospinning, embedding the healing agent dicyclopentadiene (DCPD) in polyacrylonitrile (PAN)

fiber. Compared to other encapsulation methods, the use of nano-fiber filled with healing agent has no effect on the mechanical properties of the matrix and can address a larger healing area. Additionally, carbon nanotubes were added as nanofillers to enhance the molecular reactivity between free radicals of the repair agent (DCPD) and the epoxydic matrix. The use of carbon nanotubes also improves the electrical conductivity of the material, which once transformed into thermal conductivity, speeds up the repair process. This could represent a major benefit for aerospace structures, especially at aircraft control surfaces (slats, spoilers, aileron, flaps) and fuselages. As most of these structures are electronically maneuvered, electric impulses can trigger the healing mechanism within the composite. The use of a microvascular self-healing system can be extremely beneficial in manufacturing thermosetting polymeric composite materials, as it has no negative effect on the nominal properties of the epoxydic matrix material and can be applied between each layer of the laminate, without causing delamination. This is since the matrix encloses the microvascular system during the curing process, and it can also attach to the reinforcing fibers. The self-healing capability of the nano-fiber network was carried out by flexural tests, at epoxy resin level and composite level. Results obtained from Fourier transform infrared spectrometry, thermogravimetric analysis and scanning electron microscopy confirmed the successful encapsulation of DCPD healing agent in PAN fibers. Flexural tests indicate that after 48 h, the epoxy resin has recovered 84% of its flexural strength while the composite material recovered 93%.

Other examples are the nanocomposite with a carbon nanotube nanosheet which revealed an average healing efficiency of 107.7% [134], as described in previous section, and sandwich panels self-healing with a polymer foam and glass fiber/epoxy skins through a biomimetic vascular system [154]. Sandwich panels consist of two thin sheets made from relatively rigid material, separated by a softer core. Such panels provide resistance to bending with relatively low weight.

3.2. Self-healing in metals

The number of publications on self-healing in metals is clearly lower than the number of reports on other materials, but the interest has been rapidly increasing in recent years. It is a difficult assignment to build self-healing metallic materials. Repair procedures tend to occur at higher temperatures or in extreme conditions because of the high melting temperatures of metals which easily form oxides on surfaces through bonding with oxygen molecules. In comparison with the fast and efficient reactions in polymers, the atomic bonding is strong in metals; thus, a high energy is required to transport the healing agent to the cracks.

The capability of self-healing in metals lies in this basic concept for various methods, including impregnated capsules, alloy atoms, coatings or electro-heating. The self-healing procedures of revolutionary metallic materials are classified according to **Figure 39**. Additional actuation, such as applying heat or electricity, is essential as autonomous self-healing metals have yet theoretical basis.

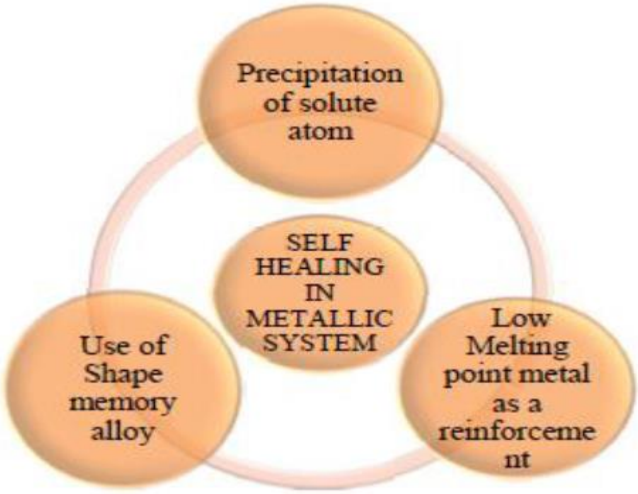


Figure 39. Self-healing methods in metals [155].

The **precipitation of supersaturated solute atoms** at high temperature is most intensively studied in this concept. For this reason, the temperature should be sufficiently high (around half of the melting point) to promote the diffusion of solute atoms which is directly connected with crack repair and performance restoration. Strong metal materials are required to recover their mechanical strength not only by filling cavities but also via chemical bonding.

[156] reports supersaturated solute materials adoption for metallic alloys' healing in particular: Austenite stainless steel healing via Boron Nitride (BN) precipitation on creep surfaces. as shown in **Figure 40** boron and nitrogen atoms aggregate on the cavity surface, thus suppressing cavity growth. Importantly, the healing efficiency depends on the mobility of healing materials, which can be accelerated under high pressure or temperature. Generally, this is performed at a temperature range of 0.4-0.65 Tm (melting temperature).

[157] studied Fe–Au alloys that induced gold-rich precipitates at 0.52 Tm for the autonomous filling of cavities. The gold precipitates were found at the cavity surfaces, causing a change in the crack morphology. The model predictions were in good agreement with the experimental results. From the abovementioned studies, it is expected that the supersaturated solute materials in the alloy can provide an

opportunity to heal metal materials and further extend their creep lifetime. However, it must be pointed out that the physical properties may not be fully recovered with a healing material weaker than the original metal and the composition of the alloy may change during the heating process and that this healing mechanism happens on nanometre scale level and it can't fix heavy cracks.

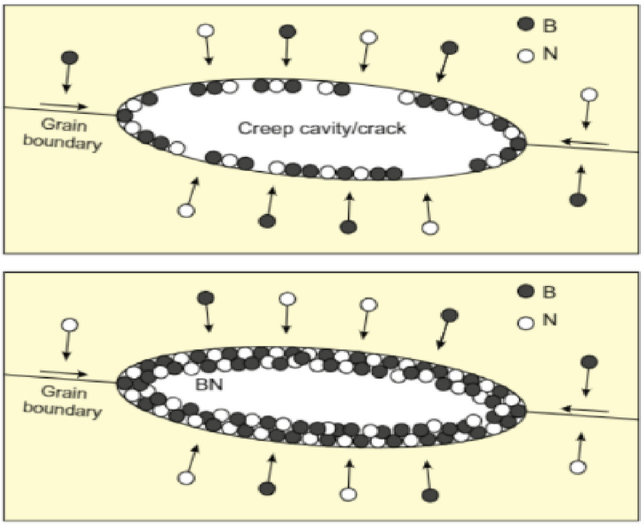


Figure 40. Illustration of BN precipitation on the creep cavity surface in stainless steel [129].

More attention should be placed on **Encapsulated Healing Agents**. **Error! Reference source not found.** shows the healing performance of capsule-based self-healing materials mainly in epoxy resins. Microcapsules containing dicyclopentadiene (DCDP), a monomer curing representative, were embedded inside a polymeric epoxy matrix, including a catalyst to achieve the self-healing of autonomous polymers. Self-healing happens when capsules that discharge the agent (a monomer) are propagated and broken by a break in polymeric materials. Encapsulated agents' treatments, such as polymer healing agents, have been utilized to create self-healing metal matrix composites. Based on most important performance metric adopted for personal needs, it is possible to prefer one technology over another. For instance, in aeronautical field it is of outmost importance to reduce the time of any process therefore the solutions based on seconds (epoxy + antiamony) or few hours (Epoxy+ CuBr(2)(2-Melm)4) are most likely to be preferred to other solutions.

In **self-healing SMA** materials, heating at a high temperature helps to achieve substantial recovery by constraining shape recovery, which can lead to geometric reconstruction and crack closure. SMA has been enhanced to aid the healing process; nevertheless, the services and products remain essentially non-autonomous and need external actuation (typically heating). The primary challenges encountered by self-healing SMA-reinforced materials, are (I) maintaining the bond between the SMA and matrix. (II) Synthesis affinity between SMA and the steel matrix; (III) The characteristics and recovery kinetics of SMA-reinforced matrix. (IV) SMA-metal matrix compatibility during synthesis [131]. Therefore, more research has to be undertaken for embedment of SMA into metal matrix composites.

Mechanism	Healing percentage (%)	Time for healing (hours)	Conditions for healing	Matrix
DCPD+Grubbs	75-100	10-48	Room temperature	Epoxy
ENB/DCPD+Grubbs	85	48	Room temperature	Epoxy
Epoxy+Mercaptan	104	24	Room temperature	Epoxy
Epoxy + CuBr(2) (2-Melm)4	111	1.5	130-180 ◦C	Epoxy
Epoxy+Antiamony Pentafluoride	70	20 sec	Room temperature at 0.2 MPa	Epoxy

Table 11. Novel self-healing technologies for metal matrix composites [158].

Apart from the specified areas, the self-healing concept can also be applied to **coatings** for metallic alloys such as aluminum, titanium and magnesium for corrosion protection for commercial applications. The authors created the facet of the titanium alloy with a thickness of 2.03 mm, a 60% indium (In) – 40 % tin (Sn) self-healing coating with a melting temperature of 124 ◦C and a thickness range of 0.005–0.0015 mm. If a surface break appears, these devices may be heated through the In–Sn alloy's melting point. As soon as the specimen is heated, the break in the titanium alloy is covered by molten area alloys [159], [160]. The self-healing coating could be activated repeatedly, indicating the chance of multicycle heating in inert conditions.

Generally, the advancement of self-healing capabilities in metals is still in its nascent stages. Consequently, extensive research and development efforts are necessary to effectively implement this technology in metal structures, while ensuring optimal performance and cost-effectiveness, while also prioritizing safety and reliability considerations.

4 Conclusions and future research

The presented work focused on defining a Structural Health Monitoring system specifically tailored for monitoring the health and usage of aircraft, with the ultimate goal of facilitating condition-based maintenance and improving through-life support performance of aircrafts. The study conducted an extensive analysis of SHM subsystems, beginning with the examination of analysis and prediction models.

Given the present state of technology and understanding, the methodologies of Convolutional Neural Network (CNN) and Long-Short Term Memory (LSTM) persist as the prevailing approaches in data analysis and modelling for aerospace systems, specifically in applications concerning engines [37], [38], bearings [39], [40], [41] , hydraulics and pneumatics [42]. A pioneering utilization of the CNN model in the context of engines has been introduced [44], focusing on a fleet comprising 20 aircraft. The approach revolves around triggering alarms to determine maintenance windows using a rolling horizon methodology. The findings demonstrate that this technique enables a remarkable reduction in engine maintenance expenses, accounting for merely 7.4% of the overall maintenance costs, while highlighting its seamless adaptability to various aerospace components.

However, hybrid physics-data driven approach offers the most advantageous solution, as it effectively addresses the limitations of each individual approach. However, the development of hybrid approaches is still in its early stages, and further research is required to ensure their seamless integration into aircraft systems from both technical and economic perspectives.

The design of the sensor network is equally critical for the success of SHM systems. Smart sensors for aeronautical applications are mostly based on Fiber optics and Piezoelectric sensors. Concerning **Fiber optics**, discussions have initially revolved around Fiber Bragg Gratings (FBGs) and Extrinsic Fabry-Perot Interferometers (EFPI), which have revealed limitations in their application to large structures as point or quasi-distributed sensors alone cannot adequately sample parameters from the entire structure unless they are extensively distributed across multiple positions, resulting in significant cost escalation. Consequently, a novel solution known as Distributed Fiber Optic Sensing Textile (DFOST) has been developed [69], specifically tailored for large surface and hardly accessible structures like wings or fuselage components, providing lower installation times compared to other embedding techniques and allowing customized sensor patterns design according to customers' needs. Nonetheless, the primary limitations of this system revolve around the significant expenses associated with the interrogation system and the requirement for an autoclave for the curing process. Consequently, future developments should prioritize addressing these drawbacks and exploring potential solutions to mitigate these challenges.

Piezoelectric sensors are the preferred choice in situations that demand restricted installation space, high-resolution dynamic process monitoring, and rapid response. For composite and metal components, the commonly utilized piezoelectric sensors are inorganic lead zirconate titanate (PZT) and organic polyvinylidene fluoride (PVDF). These sensors have demonstrated their effectiveness in a variety of applications within the aerospace industry, showcasing their versatility and reliability. In addition to their monitoring capabilities, PVDFs can be effectively utilized in energy harvesting technology. This opens up possibilities for developing wireless and self-powered sensor networks, thereby reducing complexity, space requirements and costs. Consequently, further research efforts can be directed towards exploring and enhancing energy harvesting strategies as well as for monitoring purposes.

Finally, the paper explores the potential of **Self-healing systems** in the aerospace field. An effective solution for self-healing systems in composites involves the utilization of a nanocomposite comprising a carbon nanotube nanosheet, which has demonstrated an impressive average healing efficiency of 107.7% [134]. This nanocomposite is suitable for application in fuselage parts. To enhance both the self-healing performance and the range of capabilities, the incorporation of super-elastic self-healing NiTi alloy into the matrix can be considered. This addition enables the healing of substantial impact damages using the "close-then-heal" strategy. [147] adopted integrated SMA within thermo-reversible polymer matrix based on intrinsic chemical self-healing and achieved 92% of healing efficiency. Given that intrinsic healing offers the advantage of numerous self-healing cycles when compared to the limited cycles of external healing agents, further research should focus on exploring the potential of integrating shape memory alloy (SMA) wires to enhance this technology. Therefore, it is crucial to direct efforts towards improving this combined approach by reducing the required heating temperature and enhancing healing efficiency, thereby unlocking its full potential.

Currently, the number of publications on self-healing for metals is quite limited. However, the most commonly employed technology in this field involves the precipitation of supersaturated atoms, such as Boron Nitride (BN) [156] and Fe-Au [157] strategies, interesting for small defects. While for large defects healing agents-based solutions can be employed. In this regard, the ideal system would consist of the room temperature-based process with minimal healing time required, still ensuring healing efficiencies over 90%. Hence nowadays, the smaller healing time is achieved via heating mechanisms, extensive work and research are still required to design more performant self-healing systems for metals.

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Abbreviations

Artificial Intelligence	AI
Artificial Neural Network	ANN
Boron Nitride	BN
Condition-Based Maintenance	CBM
Carbon Fiber Reinforced Composite	CFRP
Commercial modular aero-propulsion system simulation	C-MAPSS
Convolutional Neural Network	CNN
Dicyclopentadiene	DCPD
Distributed Fiber Optic Sensor/Sensing	DFOS
Distributed Fiber Optic Sensing textile	DFOST
Direct Operational Cost	DOC
Digital Twin	DT
Extrinsic Fabry-Perot Interferometers	EFPI
Electro-Mechanical Impedance	EMI
Fiber Bragg Grating	FBG
Failure Modes and Effects Analysis	FMEA
Fiber Optic	FO
Failure Modes and Effects Analysis	FMEA
Health and Usage Monitoring System	HUMS
Long-Short Term Memory	LSTM
Machine Learning	ML
Non-Destructive Technique	NDT
Optical Frequency Domain Reflectometry	OFDR
Polyacrylonitrile	PAN
Prognostics and Health Management	PHM
Piezoelectric Sensor	PS
Polyvinylidene Fluoride	PVDF
Lead Zirconate Titanate	PZT
Residual Useful Life	RUL

Structural Health Monitoring	SHM
Shape Memory Alloy	SMA