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Current challenges and future outlooks of pipeline structural health monitoring: A review

Boru hattı yapı sağlığı izlemesinde mevcut zorluklar ve geleceğe bakış: Bir inceleme

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Abstract

This paper presents a comprehensive literature review on data-driven structural health monitoring (SHM) approaches for pipelines. The review explores the common failure modes, driving signals, sensor technologies, and the application of smart techniques in pipeline SHM based on artificial intelligence (AI) and machine learning (ML). The analysis of a significant number of publications reveals that corrosion, erosion, cracks, and deformation are among the most prevalent failure modes, while a diverse range of driving signals, including time series data, vibration, temperature, and acoustic emissions, have been utilized for monitoring. The review also highlights the growing prominence of sensor technologies, such as optical fiber sensors, ultrasound techniques, and piezoelectric sensors. The application of AI and ML techniques, including supervised learning models, deep learning, and ensemble methods, has demonstrated significant potential in enhancing pipeline SHM capabilities, enabling accurate prediction and identification of failures and optimization of service strategies. Furthermore, the review identifies the emergence of promising technologies, such as energy harvesting, the Internet of Things (IoT), robotics, and drones, which offer creative approaches to tackle the issues in pipeline SHM. The review concludes by discussing key challenges, providing recommendations, and outlining future outlooks to guide the advancement of pipeline SHM through collaborative efforts, industry standards, and continued research and development, and to assist researchers, novice students, and practitioners to focus their work on worthy research points in order to avoid repetitions and to present beneficial novel studies.

Keywords: Structural Health Monitoring (SHM), Pipeline anomalies, Data-Driven systems, Artificial Intelligence (AI), Machine Learning (ML), Ensemble Learning

Öz

Bu makale, boru hatları için veri odaklı yapısal sağlık izleme (SHM) yaklaşımlarına dair kapsamlı bir literatür incelemesi sunmaktadır. İnceleme, yaygın arıza modlarını, tetikleyici sinyalleri, sensör teknolojilerini ve boru hattı SHM'sinde yapay zeka (AI) ve makine öğrenimi (ML) tekniklerinin uygulanmasını araştırmaktadır. Önemli sayıda yayının analizi, korozyon, aşınma, çatlaklar ve deformasyonun en yaygın arıza modları arasında olduğunu ortaya koyarken, izleme için zaman serisi verileri, titreşim, sıcaklık ve akustik emisyonlar gibi çeşitli tetikleyici sinyallerin kullanıldığını göstermektedir. İnceleme ayrıca, optik fiber sensörler, ultrason teknikleri ve piezoelektrik sensörler gibi sensör teknolojilerinin artan önemini vurgulamaktadır. AI ve ML tekniklerinin, denetimli öğrenme modelleri, derin öğrenme ve toplu yöntemler dahil olmak üzere, boru hattı SHM yeteneklerini artırmada önemli bir potansiyel gösterdiği, doğru anomali tespiti, arıza tahmini ve bakım stratejilerinin optimizasyonunu sağladığı belirtilmektedir. Ayrıca, inceleme, enerji toplama, Nesnelerin İnterneti (IoT), robotik ve dronlar gibi boru hattı SHM'deki sorunları ele almak için yaratıcı yaklaşımlar sunan umut verici teknolojilerin ortaya çıkışını tanımlamaktadır. İnceleme, anahtar zorlukları tartışarak, önerilerde bulunarak ve boru hattı SHM'sinin ilerlemesini yönlendirmek için işbirliği çabaları, endüstri standartları ve sürekli araştırma ve geliştirme yoluyla gelecekteki beklentileri özetleyerek sona ermektedir; ayrıca araştırmacılara, acemi öğrencilere ve uygulayıcılara, çalışmalarını tekrarlardan kaçınmak ve faydalı yeni çalışmaları sunmak için değerli araştırma noktalarına odaklanmaları konusunda yardımcı olmaktadır.

Anahtar kelimeler: Yapısal Sağlık İzleme (SHM), Boru Hattı anormallikleri, Veriye Dayalı sistemler, Yapay Zeka (AI), Makine Öğrenimi (ML), Topluluk Öğrenimi

1 Introduction

The industrial landscape has evolved significantly, marked by the transition to the highest level where it is now, which emphasizes smart manufacturing and interconnected systems. Key factors driving this development include advancements in automation, a focus on sustainability, and the pursuit of enhanced performance and reliability. Among these innovations, predictive maintenance stands out, utilizing data analytics to anticipate system anomalies before they take place. Besides reducing the downtime and maintenance invoice, this proactive strategy also boosts the overall operational efficiency, ensuring that industrial systems remain reliable and productive in a rapidly changing sector. Unplanned downtime can adversely impact the core business of operators, resulting in significant repercussions. Reports indicate that in oil and gas landscape between 15% and 70% of total production charges are accounted for maintenance costs [1], while the running and upkeep expenses for offshore systems account for 20% to 35% of total revenue [2]. Given this significant percentage, it is crucial for operators to implement a robust maintenance philosophy. Such an approach aims to reduce any sudden

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downtime, enhance the comprehensive system dependability and availability, and ultimately lower running expenses. By prioritizing effective maintenance, companies can better manage their resources and enhance their profitability. High-performance structures are becoming increasingly common across various industries, including aerospace, aviation, automotive, pipelines, and civil engineering. The quality and reliability of these structures are critical for their effective performance in severe, challenging settings. Structural Health Monitoring (SHM) involves the uninterrupted surveillance and assessment of a structural system's performance and behavior over its operational lifespan [3]. The primary goals of SHM are to identify damage through changes in structural behavior captured by measurement information and to assess the operational impacts on structural performance [4]-[6]. SHM employs a range of sensors to monitor the structural response to the applied forces and operational variations [7]. It frequently incorporates sophisticated information analysis approaches like machine learning (ML) models, to manage extensive datasets [8]-[10]. Essential components of SHM, including immediate survilience and non-invasive testing, are crucial for detecting and addressing possible concerns before they develop into serious challenges. By consistently evaluating the condition of these structural systems, their longevity can be enhanced, and the likelihood of anomalies can be scaled down.

1.1 State of the art

Pipeline SHM has become progressively crucial, as pipelines serve an essential function in conveying various fluids, including oil and gas. The monitoring process incorporates various measurement modalities and surveillance techniques to collect information on the pipeline structural integrity. The collected information is analysed leveraging the power of developed models to identify irregularities, foresee possible failures, and enhance the adopted maintenance philosophy. A crucial element of pipeline SHM is the strategic placement of measurement modalities at various locations along the pipeline to observe fluctuations in operational indicators that may signal possible issues. Prevailing measurement modalities in the SHM of pipelines comprise strain sensors, vibration sensors, acoustic emission sensing elements, and optic fibre sensors, which can be affixed to the pipeline surface or entrenched within its walls. Besides sensing elements, pipeline SHM approaches frequently employ sophisticated information analysis techniques, including ML models that recognize patterns in the captured datasets and alert maintenance veterans of possible concerns. Through examining the information gained from several measuring modalities over a span of time, monitoring techniques can recognize trends and forecast future incidents. Another significant component of pipeline SHM is the application of non-destructive testing (NDT) methods, which enable engineers to examine pipelines without inflicting any harm. Radiography, magnetic particle inspection, and ultrasonic testing are widely sued NDT methods. Overall, the pipeline SHM landscape is expeditiously evolving. As innovative techniques and methods are presented, even more sophisticated systems can be expected to emerge, guaranteeing the secure and effective functioning of pipelines worldwide.

1.2 Pipelines and their applications

Pipelines are infrastructure systems used to transport various fluids, including natural gas, crude oil, biofuels, water, and sewage. Pipeline categorization is an essential process that involves classifying pipelines according to several factors, including their dimensions, the material they are made from, their use, and their placement. This classification is critical for implementing appropriate service strategies and surveillance methods. By understanding the different categories and their specific requirements, it ensures that pipelines are installed and operated safely, efficiently, and in accordance with relevant regulations and standards. In terms of the location, the overground pipeline category refers to pipelines that are constructed above ground level. Another category termed 'underground' pipelines. This term refers to pipelines that are installed under ground level. Subsea pipelines category is yet another classification refers to pipelines that installed under sea level. These pipelines are subject to a range of environmental conditions, including extreme pressure, temperature, and corrosive substances, which require robust service strategies and surveillance techniques to ensure their integrity and prevent failures that could lead to to ecological damage or safety risks. Additionally, another pipelines classification is permafrost pipelines whis are usedin regions where the ground remains frozen for at least two consecutive years, typically found in high-latitude and high-altitude regions with cold climates [11]. In permafrost regions, ground stability can be affected by several geological phenomena, including frost heave, thaw settlement, and sliding. These issues can result in pipeline displacement, bending, or deformation, posing significant risks to pipeline integrity and functionality.

1.3 Causes of pipeline failures

Pipeline failures can have various causes, and it's important to note each pipeline failure may have its own specific factors contributing to the incident such as pipeline geometry and material property, transported substance, and surrounding environment. Corrosion of pipeline materials over time can weaken the integrity of the pipeline, leading to leaks or ruptures. According to reports, corrosion has been identified as the cause of approximately 18% of pipeline incidents between 1998 and 2017 [12]. Pipelines can be mechanically damaged by external interference such as excavation activities, accidental damage from construction equipment, or intentional sabotage. Excavation damage can be a significant cause of pipeline incidents. Reports indicate that excavation failure was responsible for about 15% of incidents involving hazardous liquid pipelines and approximately 18% of incidents related to natural gas transmission pipelines during the years 2002 and 2003 [12]. It is important to implement effective damage prevention programs that include education and outreach to excavators, marking of pipeline locations, and safe excavation practices. Subpar materials or manufacturing flaws can also result in pipeline failures. Pipeline failures due to material and weld defects are relatively rare and account for a small percentage of all pipeline failures [12]. However, it is still important to ensure that pipelines are manufactured using high-quality materials and that welding is performed to the highest standards to minimize the risk of defects. Proper inspection and testing during construction and regular maintenance and monitoring can also help identify any potential issues and prevent failures due to material or weld defects. Human errors such as improper installation, maintenance, or operation can also contribute to pipeline failures. Operating errors are responsible for a relatively small percentage of overall pipeline failures [12]. However, it is still important to ensure that pipelines are operated by qualified personnel and that proper procedures are followed to minimize the risk of errors. Regular training and education can help ensure that operators are aware of the potential risks and know how to respond to any issues that may arise. Additionally, implementing effective safety management systems can assist in spotting such problems early on and taking action before they worsen. Finally, extreme weather events, including floods, landslides, earthquakes, and hurricanes, can significantly contribute to pipeline failures. According to reports, in 2002 and 2003, natural force damage was responsible for around 16% of natural gas transmission pipeline failures and about 9% of hazardous liquid pipeline failures [12]. During pipeline design and construction, it is essential to take into account the possible risks from natural forces and to put in place suitable safety measures to reduce damages. From 2010 to 2020, reports indicated that mechanical damages and corrosion each accounted for 27% of pipeline incidents, while natural force damage and material defects represented 16% each of the reported incidents [13].

1.4 Effects of pipeline failures

The ability to effectively monitor the condition of pipelines can help prevent catastrophic failures and ensure that these vital systems operate safely and efficiently. Pipeline failures can lead to various hazards and consequences, including fire or explosion risks, the release of high-pressure gases and liquids, excessive noise, impact hazards, and environmental damage. Fig. 1 illustrates the effects of pipeline incidents on both the community and commercial sectors concerning deaths, injuries, and expenses over the last two decades, as recently reported by the Pipeline and Hazardous Materials Safety Administration (PHMSA) [14].

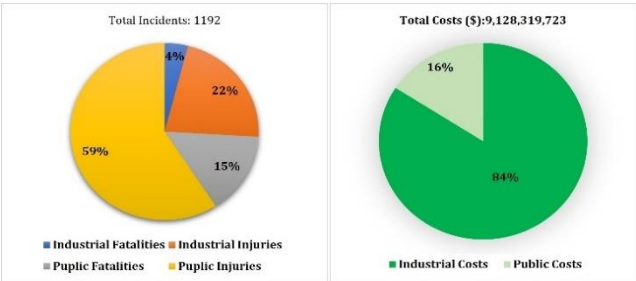

Figure 1. Significant Incident Consequences Statistics [14]

The industry term referred to in Fig. 1 includes anyone involved in the pipeline facility, such as the operator or any employed contractors, while the public term refers to anyone else. It's essential to understand that any injury resulting from a pipeline incident is unacceptable, and efforts should be made to prevent these incidents and minimize their potential consequences.

1.5 Maintenance of pipeline systems

Here an overview of three main maintenance philosophies that can be adopted for pipeline systems are provided. The reactive (breakdown) maintenance approach is described as a short-term, cost-effective solution where repairs are only carried out when an asset, such as a pipeline, fails or breaks down. While this approach can be suitable for non-critical assets, it can lead to higher long-term costs due to frequent breakdowns and repairs, as well as increased downtime [15]. In contrast, the preventive maintenance approach is a proactive approach that involves regular inspections, servicing, and repairs to prevent pipeline failure. This approach can reduce downtime and increase productivity by preventing unexpected breakdowns, and, over time, it can save money by prolonging the life of pipelines. But this method can be expensive and time-consuming, and it might not be suitable for every pipeline activity [16],[17]. The predictive (condition-based) maintenance approach is presented as a data-driven approach that gathers information and anticipates malfunctions before they happen by using sensors and monitoring procedures. This approach is considered the most effective for critical pipeline infrastructure, as it is cost-effective, extends the life of assets by identifying and addressing issues early, and ensures the safe, efficient, and smooth functioning of the pipeline system. However, it requires significant investment in monitoring equipment and software, and can be complex to implement [15]-[17]. Taking into account the significant pipeline incident consequences, the predictive (condition-based) maintenance approach is essential and crucial for the safe, efficient, and smooth functioning of pipeline systems.

1.6 Reviewing strategy

This paper presents a comprehensive literature review focused on data-driven SHM approaches for pipelines. The review was conducted to find answers to specific questions regarding the common pipeline failure modes, driving signals, sensor technologies, and machine learning techniques used in this domain. The review process commenced by searching different academic platforms using relevant keywords and search terms as depicted in Table 1

Table 1. Summary of academic platforms and search terms

Academic platforms searched	Keywords and search terms used
• Web of Science • Scopus • Google Scholar • IEEE Xplore	• Pipeline structural health monitoring • Data-driven pipeline SHM • Pipeline failure modes • Signals for pipeline SHM • Sensors for pipeline SHM • Machine learning techniques for pipeline SHM"

A systematic review approach was applied to inform the creation of this paper and to represent the current advancements in the field. The methodology used in this study is illustrated in Fig. 2. The search resulted in a plethora of publications related to the topic. To identify the most relevant and high-quality sources for the current literature review, the list of sources was carefully screened, with titles and abstracts reviewed and manually refined. Sources that were solely focused on SHM of structures other than pipeline systems, such as bridges, buildings, or aerospace structures, were removed. Additionally, studies conducted prior to 2000 were considered outside the scope of the current extensive review. Finally, the review was limited to sources published only in English. The selected relevant publications were then used for a snowballing search to find additional sources through their references or citations, ensuring a comprehensive search for relevant information. The selected sources were then thoroughly read to extract the key findings, recommendations, and conclusions related to the current research questions. The acquired information was then organized into logical themes or categories, such as common pipeline failure modes, driving signals, sensor technologies, and machine learning techniques. Ultimately, the categorized information was analyzed to uncover patterns, trends, and gaps in the literature. The findings were then synthesized to offer a thorough summary of the current knowledge in the area of data-driven pipeline SHM.

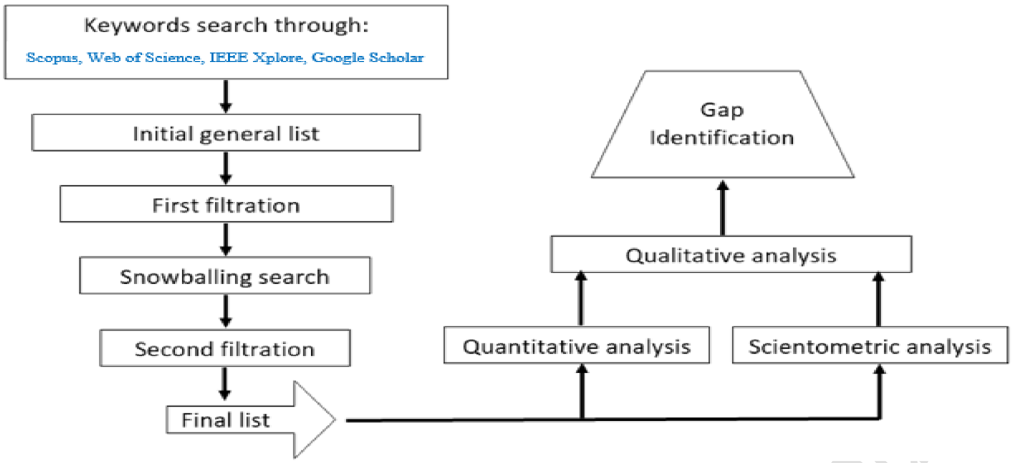

Figure 2. Flowchart of reviewing strategy

2 Pipeline failure modes

Pipeline failures pose a significant threat, leading to ecological damage, safety risks, and substantial economic wastes. A significant instance is the Deepwater Horizon disaster that took place in the Gulf of Mexico in 2010, which led to financial setbacks surpassing 1 billion USD and caused significant harm to oceanic ecosystems [18]. Quantifying the possibility of pipeline damages is challenging due to the extensive network of pipelines, varying operational and environmental conditions, limited data on pipe conditions, and the difficulty of forensic investigation. However, efficient risk management strategies can assist in bringing the total risk of pipeline damages down to a manageable level [19]. Using the combined approach of life cycle and management practices, Figueredo et al. [20] recently discussed the gain of a comprehensive understanding of subsea pipeline incidents, the identification of potential areas for improvement in safety management, and eventually the improvement of subsea pipeline operations' general safety and dependability in the Brazilian petroleum industry. Identifying and addressing the root causes of pipeline failures requires a comprehensive approach that involves careful monitoring, regular maintenance, and effective risk management strategies. Failure to address these issues can lead to serious consequences, including legal responsibilities and harm to the operator's local and international standing. As such, companies operating pipelines are highly recommended to prioritize the prevention of pipeline failures through diligent oversight and proactive measures.

2.1 Pipeline corrosion and erosion

Over time, pipelines can corrode due to either internal exposure to the elements or the substances they transport, or external exposure to their surroundings. Corrosion, illustrated in Fig. 3, is a time-dependent process that, if not treated, can lead to structural damages, leaks, and other issues that can compromise the integrity of the pipeline. Operational corrosion diminishes the capacity of pipelines to withstand both internal and external applied loads [21]. It is important to implement effective corrosion prevention and mitigation strategies to guarantee pipelines operate safely and dependably. Various techniques have been used to prevent or mitigate pipeline corrosion, including coatings, cathodic protection, and monitoring. With an emphasis on heavy water plants, a reliability analysis of pipelines with corrosion defects caused by hydrogen sulfide (H_2S) was presented with the goal of determining failure probabilities for the establishment of a Risk Based Inspection (RBI) program [22]. Two innovative random process corrosion development techniques for underground pipelines were proposed, depicting the rate of corrosion as oscillation of a Poisson square wave procedure [23]. The Poisson square wave technique's suggested linear variant as well as the non-linear version both found to effectively capture the temporal changeability of corrosion development and generate continuous corrosion development records. Other studies discussed corrosion growth model for underground pipelines by incorporating inline inspection (ILI) data and measurement uncertainties in a Bayesian framework [24]-[27]. Dann et al. [28] suggested a system for automatically matching corrosion features found during in-line inspection (ILI) of pipelines, with the goal of replacing the laborious and error-prone manual feature matching procedure. Online corrosion monitoring can aid in preventing structural integrity problems and reducing the effects of corrosion. In this regard, new measuring modalities such as passive wireless devices and optical fiber sensors demonstrate significant potential for ongoing, in-situ monitoring of natural gas and oil infrastructure in real time. Additionally, distributed chemical sensing is recognized as a promising approach for the early detection of corrosion and monitoring corrosive environments. However, ensuring durability and stability under extreme conditions, such as high temperatures and high pressures, poses significant challenges for corrosion sensing [29]. Foorginezhad et al. [30] evaluated the sophisticated sensing systems used for monitoring, and carried out a comprehensive analysis of the elements causing sewer pipeline corrosion, and looked into a number of data analysis methods for evaluating sensor readings for predicting corrosion. Ma et al. [31] additionally examined the existing models for pipeline corrosion growth, examined both probabilistic and deterministic models, and presented the application of ML and deep learning (DL) in modeling corrosion growth. They also presented hybrid approach models, provided suggestions for future development, and addressed the data sources and uncertainties in the modelling process. Taking the advantage of the bimorph sensors, Sheikh et al. [32] proposed an analytical method that uses the piezoelectric effect and vibrational mode shapes to identify and measure corrosion flaws. The method's performance was evaluated both analytically and experimentally, successfully identifying multiple corrosion defects. Another study introduced a probabilistic framework for assessing the reliability of corroded pipeline networks, even when there is limited failure history available. A case study of a buried pipeline network was used to assess the applicability of the method, and the pipeline operator's failure history data was used to confirm the findings [33]. Recent research focused on predicting the maximum depth of pitting corrosion in oil and gas pipelines using DL models, particularly Generalization and Generalization-Memorization models [34]. The study found that the accuracy of DL techniques and deep neural networks (DNNs) in predicting the maximum depth of pitting corrosion significantly exceeded that of empirical and hybrid models. Another recent investigation concentrated on monitoring internal corrosion in pipelines employing a time reversal technique based on piezoelectric active sensing [35]. This study presented a method for assessing the inner surface of the pipeline for any anticipated corrosion by using wavelet packet energy in conjunction with a convolutional neural network (CNN) model. The obtained response signal is inverted in the time domain and retransmitted as an excitation signal using the time reversal method, resulting in a more focused signal.

Pipeline erosion poses a significant challenge for the pipeline industry. It involves the slow deterioration of a pipeline's surface caused by fluid flow and abrasive particles in the materials being transported. This erosion can result in leaks, ruptures, and other failures, leading to serious environmental and economic repercussions. Addressing pipeline erosion is a multifaceted issue that demands careful attention and proactive strategies. Implementing effective monitoring techniques can help minimize the chances of erosion-related events, ensuring safe and efficient transport of materials through pipelines. Elbows in pipelines are designed to alter the flow direction, but they are vulnerable to erosion from the medium being transported. Fig. 3 depicted a typical form of erosion at elbows. Detecting erosion in pipeline elbows is crucial for the pipeline integrity. In this context, several studies were conducted.

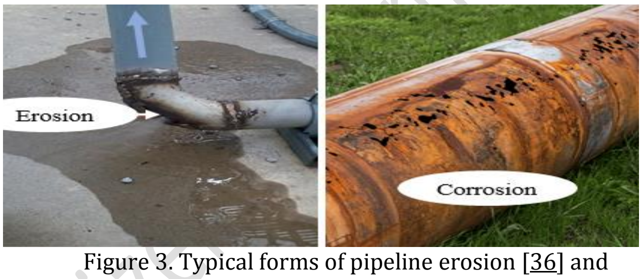

Figure 3. Typical forms of pipeline erosion [36] and corrosion [37].

Nagy et al. [38] discussed the importance of corrosion-erosion detection and monitoring in various industrial infrastructure, such as ships, aircraft, pipelines, etc., and focused on the potential of long-range guided wave inspection using ultrasonic measurements in pipes to detect the damage. The Electromechanical Impedance (EMI) method has become a promising non-destructive approach for early detection of erosion-corrosion. Research has explored the application of the EMI method to identify reductions in wall thickness in pipeline facilities, especially analysing the change in resonance frequency range with decreasing wall thickness. Whether the resonance frequency rises or falls in response to modifications in the system's properties affects the shift of frequency range [39]. The EMI technology has been employed for assessing erosion in steel pipelines and for measuring corrosion through a probe that operates on the concepts of EMI [40]. Muthanna et al. [41] provided information on the erosion-corrosion problems encountered in desalination plants, specifically focusing on the pipe elbow component of the integrated piping system, and highlighted the importance of addressing such issues in desalination plants to enhance energy development in the industry. Meribout et al. [42] conducted a critical review on sensing methods for online integrity monitoring of alloy steel process industry equipment, including tanks, transformers, pipelines, and metallic structural systems in constructure. The authors concluded that while there have been advancements in the sensitivity and accuracy of these monitoring techniques, additional development is necessary for practical field application. They advocated for the use of wireless sensors equipped with ultrasonic technology as a promising alternative for detecting internal erosion-corrosion. Erosion identification approaches usually require constantly contacted sensing modalities affixed on the pipelines, that may be limited by certain environmental factors. To address this limitation, Chen et al. [43] recently introduced an innovative technique for identification of erosion at pipeline elbows, which is simple to execute, economical, and eliminates the need for constantly fixed sensors. This technique integrates percussion, variational mode decomposition (VMD), and DL.

2.2 Pipeline scale formation

Pipeline scale formation, shown in Fig. 4, refers to a buildup of deposits on the inner walls of pipelines. Theses deposits can reduce the flow capacity of the pipeline and elevate the vulnerability to failures such as corrosion or complete rupture. Scaling can be caused by a variety of factors, including the molecular structure of the substances being transferred, the pipeline temperature, the applied pressure, and the existance of impurities in the substances. In addition to chemical treatment and mechanical cleaning, regular monitoring and services help recognise and tackle scaling issues before they develop into major concerns. Pipeline scale formation is a significant challenge within the petroleum landscape. However, with the implementation of effective prevention and control strategies, operators can minimize the impact of scale deposits on pipeline operations. Regarding monitoring scale deposit formation, Almutairi et al. [44] discussed the capability of Distributed Temperature Sensor (DTS) systems to provide real-time downhole data for various aspects of production engineering, including inflow profiling and monitoring of fluid temperature to prevent wax and hydrate formation. They also focused on the analysis of scale deposition on the temperature profile of a conventional producing well using DTS. Shar et al. [45] highlighted the effectiveness of the Cased Hole Gamma Ray measurement in detecting scale presence and emphasized that the measurement can be a crucial indicator of scale buildup, especially with the absence of other indicators. Alhammadi et al. [46] introduced three distinct methods for detecting scale deposition utilizing a light sensing technique. They highlighted the issue of scale buildup in oil pipelines, which can result in sensor malfunction and decreased oil production, ultimately affecting well integrity.

Rostron [48] conducted a thorough literature review on scale detection, creating a thorough compilation of all possible techniques for detecting pipeline scale deposit. He examined the formation of calcite scale and the significant economic risks posed by uncontrolled scale accumulation. Askari et al. [49] emphasized the necessity for precise measurement of wax thickness inside pipelines used in oil and gas landscape to manage the flow of transffered substances through pipelines, introducing an innovative method that employs artificial neural networks (ANNs) for this measurement. Stuewe et al. [50] investigated the efficacy of two non-destructive testing (NDT) methods - contact ultrasonic testing (UT) and impact-echo (IE) testing - for identifying scale growth in geothermal facilities, acknowledging the necessity of a scale monitoring solution under high-temperature conditions in geothermal plants to improve service and cleaning strategies. Another successful measurement of scaling growth by conducting resonance tests at regular time intervals during a descaling process has been recently presented [51].

Figure 4. Typical form of pipeline scale deposit [47].

2.3 Pipeline deformation

A major problem for pipeline networks is pipeline deformation, which is the bending or warping of pipelines as a result of a variety of variables, including temperature, pressure, stress variations, and natural forces like landslides, soil erosion, and seismic activity. Pipeline deformation can have serious consequences, including risks to the environment, financial losses, and worker and community safety. The development of cutting-edge technologies for the real-time detection and control of pipeline deformation is essential to reducing these risks. Surface loads from construction and automobiles, as well as ground movements like earthquakes, have an impact on buried infrastructure, such as pipelines for gas and water supplies. To monitor pipeline conditions and prevent deflection and deformation, Qiu et al. [52] examined regular monitoring of pipeline deflection to estimate stress levels and maintain them below critical thresholds. Glisic et al. [53] explored lifeline systems and geotechnical hazards from earthquakes, addressing permanent and transient ground deformations, and proposed a health assessment method for buried pipelines using distributed Optical Fiber Sensors (OFSs). Wenkai et al. [54] investigated the relationship between oil-gas pipelines and landslides, paying particular attention to patterns of stress and deformation during landslide events, highlighting the importance of this understanding for pipeline design and remediation. Additionally, the necessity of monitoring changes in pipeline diameter to prevent accidents and ensure quality testing was discussed [55]. Wong et al. [56] showed a method for enhancing pipeline SHM utilizing transient hydraulic pressures from water hammer as a natural stimulus, leveraging distributed OFSs. A deformation monitoring approach for long-distance pipelines was developed, combining distributed OFSs with the conjugate beam method, and confirmed using a pipeline's finite element model [57]. This approach evaluated pipeline deformation using both continuous and discrete strain signals, confirming the efficacy of the monitoring method. Traditional methods for monitoring pipeline deformation, such as periodic inspections by skilled technicians or robots, are inadequate for real-time assessment, prompting researchers to explore more efficient techniques like the inverse finite element method (iFEM) [58]. Cheng et al. [59] highlighted the significance of monitoring pipeline deformation due to human activities and geological disasters, studying how to convert measured structural strain from distributed OFS into pipeline deflection while addressing the challenges of accurately reflecting pipeline deformation. The structural integrity of buried warm pipelines is at risk due to thawing permafrost in harsh environments. Ground temperature distributions surrounding buried warm pipelines and their reaction to differential thaw settlement in cold regions were among the recent studies that concentrated on the differences in engineering characteristics of pipeline foundation permafrost and their influence on pipeline mechanical behavior [60]. Permanent ground displacement (PGD) caused by fault shifts poses a serious threat to pipeline safety and operation. Calculating the strains caused by fault effects in the pipeline is necessary for assessing the health of the pipeline near fault lines. In order to achieve this, simplified computational methods have been created to examine the mechanisms underlying fault-action-related pipeline failures, accounting for variables such as pipeline elongation, soil passive pressure, and the pipeline's interaction with the surrounding soil [61]. Fig. 5 illustrates a typical form of landslide causing pipeline deformation.

2.4 Pipeline cracks and leakage

Pipeline crack and leakage detection is a crucial component of ensuring the pipelines integrity and safety. Cracks - leading to leakages – may take place because of different reasons including corrosion, stress, fatigue, and manufacturing defects. Cracks in pipelines, as depicted in Fig. 5, can have devastating consequences, including environmental damage, loss of product, and even human fatalities. Leakage is a serious global issue as well, with some countries experiencing water loss, for instance, due to leaks exceeding 40% of the total water supply system [62]. As precautional measure, there has been a growing need for effective methods for detecting, diagnosing, and monitoring pipeline cracks and the accompanying leakages. To aid in accident prevention and guarantee the safe and efficient functioning of pipelines across various industries, various technologies and methods have been used or combined to create a comprehensive system that can detect cracks or leakages early, diagnose their severity and location accurately, and monitor their progression over time. Utilizing fiber geometry and optical time domain analysis for information localization, the use of optical fiber sensors (OFSs) to monitor temperature profiles over long distances for leakage detection in various applications, including pipelines, was presented [63], [64]. Additionally, a thorough method utilizing distributed OFSs based on Brillouin scattering for in-line and real-time monitoring of long-distance pipelines was covered [65]. This method could detect ground movement, leaks, and third-party intrusions in addition to measuring temperature and strain over distances greater than 150 km. Myles [66] described the theoretical underpinnings and real-world uses of a fiber optic technique that uses Brillouin acoustic scattering to locate pipeline leaks underground and monitor strain changes within the pipes. The author emphasized the potential of fiber optic technology to address significant issues with current pipeline monitoring systems and mentioned that fiber optic cables can be used to monitor strains, measure temperatures, and find leaks over long distances. The assessment of underground pipelines can be challenging due to their complex nature and the many factors that can impact their condition. To overcome these challenges and with great help of the continuous revolution of technology, many researches have presented different underground pipeline assessment techniques. Mirzaei et al. [67] explored the application of brillouin optical time domain amplifier (BOTDA) and raman optical time domain reflectometer (ROTDR) measurement modalities as accurate systems for detecting oil pipeline leaks, focusing on the environmental temperature changes resulting from oil leaks. By resolving the mass, energy, and heat transfer equations in the fiber cable and soil, they demonstrated the transient response of these sensors. Another study looked at the difficulties and methods of detecting and localizing pipeline leaks, with a focus on hardware-based approaches that make use of specialized sensing devices like vapor sampling, soil monitoring, optical fiber sensors, cable sensors, acoustic monitoring, and ultrasonic flow meters. Additionally, software-based approaches that rely on applications that continuously monitor pipeline parameters like temperature, pressure, and flow rate were covered [68]. Likewise, subsea pipeline assessment can be challenging because of the hostile and corrosive surroundings in which the pipelines are located. Seawater can cause deterioration and corrosion of the pipeline's components, which can lead to leaks, cracks, and other defects. In addition, subsea pipelines are subject to damage from marine growth, marine life, and other environmental factors. Subsea pipelines were reported to have relatively lower deterioration rate compared to the other categories of pipeline systems [69]. However, maintaining these structures has become a focus of research and development, with new methods being developed to improve integrity management efficiency [70]. A mathematical model and experimental validation were used in another study to examine the accuracy and viability of using distributed optical fiber temperature sensing for leak detection in subsea oil pipelines. The results showed that the optical fiber cable detection system could quickly and accurately determine the location and scale of leaks along a subsea pipeline [71]. An alternative innovative approach for the swift detection and identification of pipeline leak locations was proposed, employing lead zirconate titanate (PZT) sensors, with an emphasis on its effectiveness and accuracy [72].

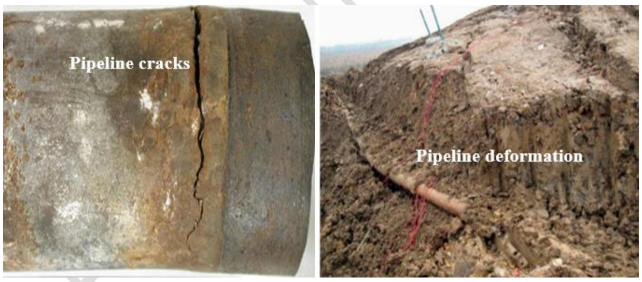

Figure 5. Typical forms of pipeline cracks [73] and deformation [54].

Real-time crack monitoring has garnered significant research interest, leading to the development of various methods, including computer vision methods, in-situ sensing modalities, and non-destructive assessment. Roberts et al. [74] explained the recent evolvement and implementation of Acoustic Emission (AE) monitoring as a non-invasive method for detecting, locating, and the surveillance of fatigue cracks in metal structures and emphasized how the Paris-Erdogan equation, which correlates crack length, fatigue cycle count, applied stress intensity factor range, and material constants, can be used to characterize the crack growth rate during fatigue. Another study provided important insights into the full fatigue acoustic emission (AE) characteristics of piping prior to cracking [75]. The analysis of AE data showed that variations in amplitude and energy were sensitive to the microscopic structure of the pipe, offering valuable information on the progression of fatigue and aiding in leak prediction. Additionally, a novel method for detecting and localizing cracks in high-pressure fluid pipelines using AE signals was introduced [76], which leveraged changes in AE activity in relation to applied load to indicate irregularities in the material's structure. This technique demonstrated improved accuracy in fault diagnosis compared to traditional methods. Moreover, the recent discussion on using distributed OFSs for crack monitoring highlighted their unique ability to monitor spatially distributed cracks over large areas or long distances [77].

3 Data-driving signals

Continuous monitoring of pipeline behavior offers valuable insights into its performance under various operating conditions, aiding in the optimization of design and maintenance strategies. Multiple parameters can be monitored for data-driven diagnostics and prognostics to assess the current condition and potential issues affecting pipeline integrity, as well as to predict future behavior and remaining useful life. Strain measurements reveal the deformations and stresses that the pipeline undergoes, helping to identify potential structural problems. Monitoring temperature variations along the pipeline can also detect anomalies or unusual conditions that may compromise its structural integrity. Additionally, data from vibration sensors provides important information about the behavior and condition of the pipeline structures. Keeping track of pressure levels and fluid flow rates within the pipeline can help identify leaks or changes in operating conditions that may impact structural performance. Furthermore, monitoring corrosion levels is essential for assessing the degradation of the pipeline material and ensuring its long-term integrity. Beyond these parameters, time itself can be a valuable signal for pipeline SHM.

3.1 Time series

A statistical technique for analyzing and interpreting data points gathered over time is time series analysis. Finding patterns, trends, and connections in a series of chronologically arranged data is its main goal. Time series modeling is a potent statistical technique for evaluating data obtained from sensors mounted on structures in the context of SHM. Sohn et al. [78] explored the SHM process through a statistical pattern recognition framework, utilizing statistical process control (SPC) techniques for vibration-based damage diagnosis. Harley et al. [79] introduced the Time Reversal Change Focusing (TRCF) monitoring technique, which offers a metric for assessing the extent of damage in pipes. They demonstrated how to reduce multimodal and dispersive effects in a low-power SHM system for pipelines by using time reversal processing techniques, highlighting that TRCF alleviates the limitations on excitation frequency and bandwidth found in many other non-destructive testing methods. Gul et al. [80] investigated statistical pattern recognition methods in SHM for detecting structural changes, particularly in damage detection, and validated these methods through various test structures and replicated damage scenarios. De Lautour et al. [81] discussed the implementation analytical time series techniques in SHM for damage classification and estimation, addressing the challenges of applying these methods to real structures due to the need for a substantial number of training samples. Vamvoudakis-Stefanou et al. [82] examined the use of unsupervised statistical time series techniques for vibration-based failure identification across a collection of ostensibly identical structures. Additionally, Graph Tools can be employed to visualize signal patterns and time evolution in response to different fault scenarios, simulating and analyzing fault propagation through structural graphs, which aids in identifying critical points and potential failure modes, thereby facilitating fault pattern recognition and validation [83].

3.2 Vibration

In SHM, Vibration-driven surveillance is a widely used as it can identify hidden incidents within the internal components of structures by analyzing changes in their structural characteristics [84]. In the field of pipeline SHM, vibration signal processing involves analysing and interpreting signals produced by vibrating pipelines. Important details regarding the pipeline's performance, condition, and possible flaws are contained in these signals. Both frequency-domain and time-domain analysis techniques are used in the process. Instead of converting the signal waveform to the frequency domain, time-domain analysis techniques analyze it directly in the time domain. This approach offers insights on the amplitude, phase, and time characteristics of a signal, enabling the identification of patterns and anomalies. Techniques such as auto-regressive (AR) [85], auto-regressive with exogenous input (ARX) [86], auto-regressive integrated moving average (ARIMA), vector auto-regressive (ARV) [87], auto-regressive moving average (ARMA) [88], and auto-regressive moving average with exogenous inputs (ARMAX) [89] are widely applied in time series analysis. On the other hand, a method for analyzing signals in the frequency domain is called frequency-domain analysis. Frequency-domain analysis offers insights into the phase and amplitude of different signal frequency components, helping to identify specific vibration patterns or anomalies. Techniques like Fourier transform (FT) [90], frequency response function (FRF) [91], strain frequency response function (SFRF) [92], frequency domain decomposition (FDD) [93]], and multiple signal classification (MUSIC) [94] are employed in frequency domain analysis. Vibration-based fault identification techniques are growing in popularity due to their technical and financial advantages. They offer global sensitivity to damage, outperforming localized techniques like ultrasonic and radiographic methods. The location and extent of damage can be predicted using changes in modal parameters, such as natural frequencies, mode shapes, and modal damping [95]. Depending on the length of the pipeline, underground pipelines may respond differently to seismic activity, which can result in different displacements and strains, particularly at the boundary points [96]. These differences may have an impact on the pipeline's performance and structural soundness during seismic activity. Furthermore, changes in displacements and strains are caused by variations in the coefficients of elastic and viscous interaction between the pipeline and soil along its length. Displacements can range from 0 to 15%, while strains can vary from 0 to 18% when compared to a scenario where these coefficients remain constant. The pipeline's response to seismic forces also differs based on its length.

3.3 Temperature

Temperature measurements are commonly employed in pipeline SHM to assess the thermal behavior of the structures. Temperature variations may have an effect on pipelines' structural integrity, causing the material to expand or contract. By tracking temperature changes along the pipeline, abnormalities or deformations that may signal damage or wear can be identified, allowing for timely preventive measures. Temperature-based monitoring techniques are currently a focal point of research in SHM due to their ease of distributed sensing, lack of pollution, stability, sensitivity, and low cost [65]. Zhao et al. [97] unveiled a new scour monitoring system for submarine pipelines' nearshore and landfill segments that relies on temperature measurements. They presented the three-index estimator (TIE) methodology, which distinguishes between the heat transfer behaviors of sediment and water using active thermometry. Another system was suggested in relation to scour monitoring that uses temperature readings to extract consistency, spatial continuity, and amplitude as three characteristics from temperature time records. This system can distinguish between areas exposed to water flow and those buried in sand by analyzing the excess temperature gap and time instability during the heating process [98]. Experimental tests were conducted to confirm that the system is effective in monitoring scour conditions. The temperature-based pipeline scour monitoring approach is regarded as low-cost, highly precise, flexible in construction, and a promising method for offshore pipeline scour monitoring, especially in nearshore areas [99]. Madabhushi et al. [71] emphasized the use of temperature measurements for near real-time leak detection in subsea oil pipeline networks through optical fiber cables. This technology employs optical time domain reflectometry to detect temperature gradients along the fiber, helping to pinpoint the location and extent of a leak. The optical fiber temperature measurement system's precision and spatial resolution were assessed through mathematical modeling and experimental studies. Ukil et al. [100] provided insights and solutions for gas pipeline leaks and water ingress issues, particularly focusing on the application of distributed temperature sensing (DTS) systems for monitoring and detecting abnormal events like pipeline leaks. They also discussed the application of the temperature tracer method (TTM) across various engineering fields, including oil and gas pipeline safety. TTM is a technique for monitoring the structural health of pipelines and has gained popularity as a low-cost, non-invasive way to evaluate the integrity of subsea pipelines and find leaks of gas and oil [63], [66], [67]. In a newly conducted study, He et al. [101] thoroughly reviewed the TTM, which indirectly assesses the health of a structure by monitoring effective temperature signals and employing a mathematical model that links temperature with measured physical quantities. The authors also noted the method's application in SHM due to its advantages, including ease of use, low cost, continuous monitoring, and minimal environmental impact.

3.4 Ambient noise and acoustic transient

Ambient noise serves as a baseline for normal operating conditions and aids in detecting changes or anomalies in noise levels, while acoustic transients are crucial for identifying specific events that could damage the pipeline. Monitoring both ambient noise and acoustic transients is essential for thorough pipeline SHM. Several researchers have developed various non-intrusive technologies that utilize ambient noise and acoustic transients to enable cost-effective and large-scale pipeline inspection and condition assessment. In this context, three experimental case studies were conducted on plastic pipes to demonstrate the monitoring of multiple anomalies, material loss, and leaks, particularly regarding transient hydraulic pressures caused by water hammer [56]. Furthermore, a novel technique utilizing acoustic emission signals for crack identification and localization in high-pressure fluid transport pipelines was presented [76]. Recognizing that transient wave-based methodologies are promising for estimating pipeline failures, Ahadi et al. [102] discussed how acoustic emission (AE) methodologies are used for identifying and localizing leaks in gas or liquid pipelines. They examined the challenges associated with interpreting and classifying AE signals, emphasized the effectiveness of correlation-based methods for identifying leakage signals, and highlighted the benefits of the Wavelet Transform (WT) for time-frequency analysis of AE signals while addressing the drawbacks of the Short Time Fourier Transform (STFT) in AE analysis. Jing et al. [103] suggested using a rough inverse scattering method to reconstruct variations in cross-sectional area along water pipelines, enabling the deduction of the size and location of blockages. Zeng et al. [104] presented a pipeline condition assessment technique utilizing the concept of "Inverse Wave Reflectometry". The technique is based on hydraulic transients and discussed the challenges associated with evaluating aging and deteriorating underground pipelines in water distribution systems. This method analyzes pressure wave reflections within the pipeline to detect the position of the anomalies and how severe they are. The authors noted several advantages of this approach, including its non-destructive nature, capability to assess multiple pipelines at once, and potential for real-time monitoring. Wang [105] tackled the problem of leaks in water supply systems and proposed an active transient wave-based methodology to estimate leaks in pipe networks, highlighting the significance of measurement quality and quantity for accurate leak detection, particularly in real-world settings where noise frequently affects signals. Inspired by passive imaging techniques from oceanography and geology, which use ambient turbulence noise and correlation-based functions to estimate parameters, Wang et al. [106] explored the utilization of passive acoustic noise for identifying pipeline degradation and faults within water supply sensor systems. They emphasized the need for high-powered acoustic sources and the possible stresses on the water system caused by active detection methods, in contrast to passive techniques that take advantage of existing noise. Their suggested technique estimates average wave speed, reflections, and the scattering characteristics of anomalies by extracting the impulse response (IR) or time-domain Green's functions between sensors. This passive method, utilizing correlation functions of flow-induced turbulence noise, provides a non-destructive and long-range solution for asset management, capable of detecting leaks, blockages, air pockets, and deterioration, with measurement accuracy and detection performance comparable to conventional active methods [107]. Addressing the challenges of water loss in supply networks and the need for non-intrusive technologies for pipe inspection and condition assessment, the last reference suggested a compressive sensing-based technique that uses ambient noise signals to identify pipe faults in water pipelines. This technique seeks to decrease correlation sidelobes and increase the noise bandwidth, which can cause ambiguities and false alarms in fault detection [108].

3.5 Stresses and strains

The generated stresses and strains are also crucial factors in the SHM of pipelines, enabling timely maintenance and repair. Stresses in pipelines are caused by various factors, including changes in pressure and temperature, and external loads. Strains, on the other hand, refer to the deformation of the pipeline due to the applied stresses. The measurement and monitoring of these stresses and strains can assist engineers in pinpointing problematic areas and take the necessary action to avoid catastrophic failures. The use of advanced sensors has made it possible to accurately design monitoring systems capable of capturing real-time data on the current behaviour of pipelines, analysing these data, and predicting future behaviour. One such study by Amirat et al. [22] focused on the Lifecycle oversight of underground pipelines for the safe conveyance and delivery of hydrocarbons. They highlighted the significance of reliability analysis as a strategic approach for risk-informed design and upkeep of pipelines. Additionally, they experimentally characterized the spread of residual stresses in pipes of large diameter, and integrated this with a corrosion model to evaluate the effects of aging throughout the pipeline's lifespan. Inaudi et al. [109] discussed the unique features of a monitoring technology that was rarely found in conventional techniques. The discussed technique allowed for the measurement of strain to detect pipeline leakages and prevent pipeline failure in landslide areas. Li et al. [110] reviewed cutting-edge strain sensors that are expected to play a significant role in the creation of intelligent tools and next-generation smart components. In terms of technology readiness levels (TRLs), they focused on industrial strain sensing technologies that have advanced to a mature stage. The creation of damage indices to identify and pinpoint damage in a structure under simulated environmental conditions was another topic covered by the writers. Liu et al. [111] provided insights into real-time, early-warning monitoring of landslides and slope stability, along with the development of strain sensing and visualization modules for SHM. Li et al. [112] suggested a multi-sensor surveillance system for buried metallic pipeline performance assessment and SHM under sophisticated stress conditions. They addressed the challenge of measuring and identifying substantial axial bending stresses that arise from surface loads, uneven pipe trenches, and ground subsidence during construction. The authors also presented a field application that demonstrated the effectiveness of their proposed monitoring scheme, supporting the rationale behind their proposal. Recently, Cheng et al. [59] employed a long short-term memory (LSTM) neural network in conjunction with distributed fiber optic strain sensing to translate the measured strain in optical fibers into deflection of pipelines. Their intelligent transformation model proved effective and accurate in translating strain to deflection, making it applicable in practical engineering scenarios. In the context of pipeline fault detection, it was observed that strain drops, measured by sensors near the pipe extremities, provided the most informative data for analyzing strain measurements and determining pipe flow properties and leakage. These strain drops remained stable regardless of other flow and leakage conditions [113]. He et al. [114] introduced a novel stress wave communication networking method for SHM of pipelines, utilizing sensor networks. This technique creates multiple-access stress wave channels for data transmission between multiple sensors using piezoelectric transducers and orthogonal variable spreading factor (OVSF) codes. The feasibility of this method was experimentally validated, showcasing the benefits of stress wave communication, including the removal of the need for additional cables or communication devices.

4 Instrumentation and measurement

Measurement and sensing methods are crucial for SHM of pipelines as they deliver instantenous information on their structural integrity. By employing accurate and reliable measurement and sensing techniques, SHM can effectively identify damage at an early stage, facilitating timely repairs or maintenance, which helps prevent catastrophic failures and enhances safety. Numerous studies have focused on either developing new SHM measurement and sensing techniques or assessing the effectiveness of existing and emerging methods. Warsi et al. [115] reviewed electronic techniques used for SHM in civil and mechanical systems, highlighting the significance of instantenous surveillance to avert structural damages and economic setbacks. A recent study presented a technique that uses the Euclidean distance method to determine the best location of sensors in a pipeline network for damage detection. In order to categorize damage locations and facilitate quick detection using a small number of sensors, this methodology was combined with a support vector machine (SVM) [116].

4.1 Optical fiber sensors

Before discovering the optical fiber sensors (OFS) in the the middle of the 1970s, electrical-based measurement were the predominant technology in the market. However, due to the susceptibility of electrical sensors to electromagnetic interference and their need for frequent calibration, researchers began investigating alternative sensing methods beyond electronics. This exploration ultimately brought OFS to the forefront, highlighting their potential in a diverse array of uses [117]. OFSs are measurement technologies that can identfy changes in physical features including temperature, pressure, strain, and others, by using optical fibres. These sensors are extensively utilized in various applications, including pipeline SHM. One specific type of OFSs is the Fiber Bragg Grating (FBG) measurement modality, which operates by employing regular changes in the core fiber's refractive index to reflect particular wavelengths of light. FBG sensors are favored for their straightforward sensing principle, resistance to electromagnetic interference (EMI), compact size, and ability to measure strain [109]-[111], temperature [109], [118], force [118], [119], flow rate [120], pressure [121], torque and displacement [122], and vibration [123], and their capability of multiplexing [124]; FBG sensors have emerged as promising sensing elements and have demonstrated significant potential for monitoring the health of pipeline structures [125]. Numerous studies have been conducted over the last 20 years to investigate the use of OFS technology in the prognosis and diagnosis of pipeline failures. For pipeline deformation, section 2.3, for instance, the technology or its derivatives have proven to be reliable and accurate solutions for monitoring such a damage, allowing engineers and operators to detect and track any changes in the shape or position of pipelines. This technology has been shown to be a non-invasive and economical way to keep an eye out for pipeline leaks, as discussed in Section 2.4. It enables immediate responses in the event of a leak, greatly lowering the possibility of environmental harm and improving pipeline operations safety. Additionally, the technology provides excellent accuracy and precision in identifying cracks by identifying even minor changes in strain or temperature, ensuring that no cracks are overlooked and preserving the pipeline safety and integrity. OFS technology is easily installable and can be incorporated into current pipeline infrastructures, making it an increasingly popular choice for monitoring across various industries. Moreover, several studies have been conducted to propose new monitoring techniques or to review and evaluate existing ones. Leng et al. [126] highlighted the significance and application of embedded OFSs like extrinsic Fabry-Perot interferometer (EFPI) and FBG sensing modalities, for real-time survweilance of the curing process and damage detection in high-performance structures. Inaudi et al. [109] discussed the application of distributed OFSs for SHM of large structures including pipelines. The same authors [127] reviewed the OFS technologies and systems that have reached commercial exploitation and routine application in SHM and presented significant application examples of OFSs in the sector. Majumder et al. [128] conducted an in-depth analysis of research and development efforts in SHM utilizing FBG sensors, highlighting their advantages over electrical sensors, their suitability for comprehensive sensing systems, and their applications in structural sensing, while also identifying areas that require further investigation. Tan et al. [129] offered a non-destructive technique to detect corrosion by using changes in the Bragg wavelength brought on by strains on the FBG due to mechanical elongation and variations in the pipeline coating materials. They explored and experimentally validated the relationship between wavelength shifts, corrosion rates, and induced strain. Feng et al. [130] explained the evolvement and implementation of multiple core optical fiber and spatial-division-multiplexing sensors for monitoring the integrity of steel pipes. The authors demonstrated the feasibility of their approach through experiments on a scaled model of a steel pipe, utilizing spatial-division-multiplexing method compined with a 7-core fiber to monitor deformation and vibration responses, emphasizing the precision and dependability of their findings and showcasing the method's effectiveness in detecting the resultant structural strains as well as modal frequency. They also noted the promising applications of their proposed technique in the SHM of underground pipelines and other infrastructures. Wang et al. [131] proposed a high-sensitivity interrogation system for FBG sensors using a composite cavity fiber laser, designed to measure wavelength changes in the FBG sensor by converting these changes into arm length variations and ultimately into shifts in the fiber laser beat frequency signal (BFS). This system is characterized by its simple structure, low cost, and high sensitivity. Li et al. [132] introduced a methodology employing OFS to create an intelligent system for underground pipelines, facilitating quantitative assessments, predictions, and automated safety evaluations, with its feasibility validated through experiments in a real pipe network. Wu et al. [133] proposed a non-intrusive structure utilizing FBG sensing for detecting pipeline pressure deterioration to ensure safety, featuring a ditrigonal strain beam that amplifies strain on the pipeline wall, benefiting from its simple design and ease of installation. Jiang et al. [134] recently addressed the challenges of traditional pipeline health assessment methods, such as complexity and cost, by integrating distributed OFS and proposing a framework that combines this technique with semi-supervised learning for pipeline health assessment. Additionally, Bertulessi et al. [135] briefly discussed the applications of distributed OFS in Pipeline Health Monitoring (PHM), mentioning technologies like distributed acoustic sensing (DAS) as well as stimulated brillouin scattering (SBS) in pipeline systems.

4.2 Piezoelectric sensors

Piezoelectric sensors are essential in SHM applications, particularly for assessing a structure's performance and integrity. Recently, their application in pipeline SHM has attracted considerable interest from researchers. Leveraging the unique properties of piezoelectric sensors, researchers have been able to create effective monitoring systems that identify and diagnose structural problems early, facilitating proactive maintenance and reducing the likelihood of costly pipeline incidents or environmental hazards. In the early 2000s, the feasibility of distributed health monitoring for identifying and locating structural damage was demonstrated using wired piezoelectric accelerometer arrays in conjunction with black box technology [136]. Numerous studies and research articles have underscored the effectiveness of piezoelectric sensors in SHM applications [137]-[139]. These references offer in-depth insights into various facets of piezoelectric sensor use in SHM, including their design, how they are installed, how they process signals, and pertinent case studies. They explain how the piezoelectric effect is used to convert mechanical phenomina such as stresses or vibrations into useful electrical signals, carrying beneficial information for SHM purposes. The cited bibliographies also emphasize how high sensitive the piezoelectric sensing modalities are, enabling them to identify minor variations in structural resposes. Furthermore, the cited references highlighted the capability of the piezoelectric sensors to effectively record dynamic responses, enabling the early detection of structural failures. This promotes proactive maintenance and helps prevent catastrophic consequences. In section 2.1, novel method for monitoring pipeline corrosion ware presented, which employed piezoelectric sensors affixed to the pipeline's outer surface as both actuators to produce ultrasonic signals and sensing elements to detect the produced signals as they travel across the pipeline wall. Piezoelectric sensors are frequently utilized in electromagnetic interference (EMI)-based techniques to detect and monitor pipeline deterioration. In this application, sensors attached to the pipe's surface measure changes in their electrical impedance over time, demonstrating a high level of accuracy and sensitivity in detecting corrosion. Section 2.4 discussed approaches for identifying pipeline leaks using piezoelectric sensors, emphasizing their ability to accurately detect and locate leaks. Additionally, these sensors have been employed to monitor pipeline structural behaviors, including vibration and strain. Cheraghi et al. [140] and Fu et al. [141] introduced SHM techniques that focus on the surveillance of the vibration signals of pipes utilizing piezoelectric measurements, achieving improved damage location and localization accuracy compared to conventional methods. In the pipeline monitoring system, a particular kind of piezoelectric material called lead zirconate titanate (PZT) was used as a transmitter and sensor to create and identify stress waves, owing to its strong piezoelectric properties, rapid response, and broad bandwidth, making it ideal for stress wave-based SHM systems [114]. To address the limitations of existing SHM measurement technologies, such as the reliance on adhesives or couplants for sensor mounting - which can compromise consistency and reproducibility - discrete piezoelectric ultrasonic transducers are employed. These transducers facilitate adhesive-free and rapid prototyping, enhancing measurement accuracy [142]. While fiber Bragg gratings (FBGs) have drawbacks in frequency bandwidth, thermal sensitivity, and cost, piezoelectric sensors are lightweight, offer high-frequency bandwidth, and have been extensively utilized in SHM through EMI-based techniques [143]. Leveraging their accuracy, high sensitivity, and immediate surveillance capabilities, A smart corrosion sensing node and cloud-based wireless impedance monitoring systems that use piezoelectric technology are examples of recent developments for online quantitative monitoring of pipe corrosion [144]. Overall, the application of piezoelectric sensors in pipeline SHM has yielded promising outcomes. As researchers continue to investigate new applications and methodologies, these sensors are expected to become increasingly valuable, advancing the field of structural engineering by providing reliable data for maintenance, safety assessments, and decision-making processes.

4.3 Micro-electro-mechanical sensors

Micro-electro-mechanical sensors (MEMS), including accelerometers, are widely utilized in various fields, notably in pipeline SHM. These sensing modalities are embedded devices, usually sub-micrometer to millimeter in size, that combine mechanical and electrical components [145]. MEMS accelerometers are specifically engineered to measure acceleration and find applications across many industries, including pipeline SHM [146]. In this context, they can monitor the structural integrity of pipelines by detecting vibrations, changes in acceleration, and other mechanical parameters that may signal potential issues or damage. Continuous monitoring of these parameters enables pipeline operators to identify and resolve problems such as leaks, corrosion, stress concentrations, deformations, displacements, or other anomalies before they worsen, thereby guaranteeing the safety and dependability of the pipeline systems [147]. MEMS accelerometers are essential for real-time vibrational analysis in SHM. A complementary metal-oxide-semiconductor (CMOS) MEMS procedure can be used to fabricate them, resulting in compact, high-performance, and cost-effective accelerometers [115]. These miniaturized sensors employ real-time monitoring to detect changes in acceleration within structures. By incorporating MEMS accelerometers into SHM systems, non-invasive and retrofittable monitoring solutions become feasible. It is significant to remember that research and development in the use of MEMS accelerometers for SHM is ongoing, with efforts focused on enhancing their sensitivity, accuracy, and reliability for improved pipeline monitoring. Sabato et al. [148] explored the application of MEMS accelerometers in SHM, particularly their integration within Wireless Sensor Networks (WSN) for wireless data transmission. They underlined the need for sensors that can pick up low-amplitude and low-frequency vibrations, which traditional low-cost sensor boards might not be able to do. The authors also discussed the ShakeNet system, a vibration sensing system developed to address existing systems' limitations in capturing low-frequency vibrations. While pointing out the dearth of research on the real-world use and comparison of commercially available low-cost accelerometers under SHM conditions, Ribeiro et al. [149] carried out an experimental performance evaluation of inexpensive MEMS accelerometers for determining the natural frequencies and damping ratios of civil structures as well as evaluating their noise characteristics. Recently, Manikandan et al. [150] evaluated and evaluated the effectiveness and suitability of accelerometers based on MEMS for measuring vibration, providing guidance on selecting the appropriate MEMS accelerometer based on specific needs.

4.4 Attenuated total reflectance spectroscopy

In pipeline SHM, attenuated total reflectance (ATR) spectroscopy is a commonly used measurement method for examining the characteristics and makeup of pipeline materials. This method is a useful tool for assessing pipeline conditions because it enables direct sample measurement without the need for significant preparation. A sample is brought into contact with a high-refractive-index crystal, like zinc selenide or diamond, in order to perform ATR spectroscopy. There are several internal reflections in the crystal as a result of the angled infrared light being directed onto its surface. An evanescent wave created by these reflections enters the sample and makes it easier to analyze its molecular makeup and structure [151]. ATR spectroscopy is capable of detecting and characterizing various substances that may be found in pipelines, including corrosion products, contaminants, and degradation by-products. By examining the spectral data obtained from ATR measurements, it becomes possible to identify and monitor alterations in the chemical composition and condition of pipeline materials, aiding in the assessment of their integrity and the prediction of potential failures [152]-[154]. While ATR spectroscopy is a powerful analytical tool for pipeline materials, it is frequently employed alongside other measurement and sensing methods in pipeline SHM to offer a more thorough assessment of the structural integrity of pipelines.

4.5 Magnetic flux leakage

Another widely employed technique in pipeline SHM is thw magnetic flux leakage (MFL). This technique is for identifying failures and evaluating the pipeline integrity. This non-destructive testing (NDT) technique utilizes sensing elements that are sensitive to magnetism to identify the magnetic leakage field generated by flaws on the pipeline's inner and outer surfaces [155]. In MFL technology, a magnetizing device generates a magnetic field within the pipeline. As the magnetized pipeline moves through the sensor array, any structural defects or irregularities in the pipeline cause the magnetic field to be disrupted, which allows magnetic flux to leak out. The sensors then capture this leakage, providing data that can be analyzed to identify and characterize the defects [156]. The MFL technique is particularly advantageous for inspecting operational pipelines, as it does not necessitate taking the pipeline out of service for assessment. As a result, it is an economical and effective method of pipeline integrity monitoring [157]. Furthermore, this valuable technique can be integrated with other sensing methods, such as ultrasonic testing or visual inspection, to obtain a more thorough comprehension of the pipeline's state [155].

4.6 Radio-technical methods

Another method that is frequently used to evaluate the integrity of pipelines is radiography. It employs X- or gamma rays to generate images of the pipeline's internal structure, enabling the detection of defects and anomalies. In this method, a source of radiation is placed over one of the pipeline sides, while a radiographic receiver is positined on the opposite side. The source emits X- or gamma rays that travel through the pipeline material, and the receiver captures the radiation that passes through, converting it into an image. This image can reveal issues such as corrosion, cracks, wall thinning, or other defects within the pipeline [158]. Radiography offers several benefits in pipeline structural health monitoring (SHM). It produces detailed, high-resolution images of the internal condition, facilitating accurate identification and characterization of defects. This technique is applicable to both onshore and offshore pipelines and is effective for a variety of pipeline materials [158]. However, there are limitations to consider. Radiography requires access to both sides of the pipeline, which can be problematic for buried or submerged pipelines. Additionally, radiographic inspections may necessitate temporarily taking the pipeline out of service, potentially disrupting operations [158]. To address these challenges, researchers investigate the likes of computed digital radiography and tomography (CT) scanning as alternative methods. These methods provide enhanced imaging capabilities and can offer three-dimensional insights into the internal structure of the pipeline [159]. Radiography is an important technique in pipeline SHM as it enables non-destructive evaluation of the internal conditions of pipelines. It produces detailed images that assist in detecting and characterizing defects, thereby helping to maintain the safety and integrity of pipeline infrastructure. Another emerging technology in pipeline SHM is Radio Frequency Identification (RFID). RFID-based sensing systems provide wireless and remote monitoring capabilities, enabling the acquisition and analysis of data in real time [160]. RFID sensors can monitor various parameters relevant to pipeline SHM, such as strain, temperature, pressure, and corrosion. These sensors are typically passive, meaning they do not require an external power source and can be powered by the energy emitted from an RFID reader or scanner. They can be affixed to the pipeline surface or embedded within it, enabling continuous health monitoring of the pipeline [161]. One significant advantage of RFID devices in pipeline SHM is their wireless and remote monitoring capabilities, which eliminate the need for physical connections or wired systems, simplifying deployment and maintenance. Moreover, RFID sensors can be integrated with other sensing technologies, such as fiber optic sensors or acoustic emission sensors, to create a comprehensive monitoring solution [162]. However, it's essential to recognize that the use of RFID devices in pipeline SHM is still in its infancy, and more studies and advancements are required to improve their dependability and performance. Challenges such as signal interference, communication range limitations, and sensor durability must be addressed for successful implementation in pipeline monitoring applications [163]. In summary, RFID devices show promise as a wireless and remote monitoring solution in pipeline SHM, offering the potential for Instantaneous data acquisition and assessment that facilitates proactive maintenance and early detection of potential pipeline issues. However, more study and advancement are needed to get past technical obstacles and guarantee their efficient application in pipeline SHM.

4.7 Pigging and visual inspections

Pigging and visual inspections are two significant methods employed in pipeline SHM. Pigging involves the use of devices known as "pigs" to inspect and clean pipelines. These cylindrical devices are placed inside the pipeline and driven by the flow of the material being transported. Pigs can be equipped with various sensors and tools to gather information on the structural health of pipelines, such as detecting defects, determining the pipeline wall's thickness and locating any areas that are eroding or corroding. This method enables in-line inspection of pipelines without the need for excavation or shutting down the system [164]-[168]. In contrast, visual inspections entail a physical examination of the pipeline's external surface to spot any visible defects or anomalies. This can be conducted through direct observation or with the aid of remote inspection tools like cameras or drones. Visual inspections are particularly effective for identifying external corrosion, coating damage, leaks, and other visible signs of deterioration. They provide critical information about the pipeline's condition and can help determine if further inspection or maintenance is necessary [169], [170]. Both pigging and visual inspections are essential for pipeline SHM. Pigging offers a thorough evaluation of the pipeline's internal condition, while visual inspections deliver important insights into external surface conditions. These methods can be used in conjunction with other strategies like radiography, magnetic flux leakage, or ultrasonic testing, to achieve a more comprehensive understanding of the pipeline's structural health [171]. It is crucial to remember that variables like pipeline age, location, operating conditions, and regulatory requirements affect the frequency and extent of pigging and visual inspections. Pipeline operators typically create inspection plans that specify the intervals and methods for inspections, guided by these factors and industry best practices [172], [173].

4.8 Ultrasound techniques

Ultrasound methods are crucial in pipeline SHM as they provide a non-destructive testing approach for assessing pipeline integrity. One notable technique is ultrasonic guided wave testing, which has gained popularity for pipeline defect screening [174]-[176]. This method employs guided ultrasonic waves to detect defects without requiring direct contact with the pipeline surface [177]-[179]. Experimental evaluations have shown that it is effective in identifying cracks, corrosion, and various other types of damage in pipelines [142], [180], [181]. Ultrasonic guided wave technology and its uses in identifying pipeline flaws have been thoroughly described in the literature [182]. Ultrasonic testing provides in-depth information about the defect size, position, and severity, facilitating targeted maintenance and repair efforts [182]. The idea behind this method is to send ultrasonic signals into the pipeline material and then look at the reflected signals to find any irregularities or flaws. To enhance defect identification and classification, the data gathered from ultrasonic inspections can be processed and examined using a variety of signal processing methods and machine learning algorithms [183]. It's crucial to remember that also ultrasound techniques are commonly combined with other methods of inspection, such as radiography or magnetic flux leakage, to provide a comprehensive evaluation of pipeline integrity. Each method has unique benefits and drawbacks, and the choice of technique depends on factors like pipeline characteristics, accessibility, and the specific types of defects being examined [183]. While the guided wave technique is effective for monitoring the health of tubular structures, interpreting elastic wave signals for damage detection can be challenging due to factors such as mode conversion, mode mixing, refraction, dispersion, and attenuation [184].

4.9 Electrochemical techniques

In pipeline SHM, electrochemical sensing methods such as electrochemical impedance spectroscopy (EIS) and electrochemical corrosion potential (ECP) monitoring have attracted a lot of interest because of their effectiveness in detecting and monitoring corrosion-related problems [185]. These electrochemical sensors utilize the principles of electrochemistry to assess and analyze corrosion processes within pipelines. EIS evaluates the impedance of the pipeline's protective coating, enabling the detection of coating degradation or corrosion. This method provides an understanding of the electrochemical response of pipelines, enabling the early identification of possible issues. Meanwhile, ECP monitoring assesses the corrosion potential of the pipeline, which can indicate the likelihood of corrosion occurring. By monitoring changes in the ECP over time, it is possible to identify areas of the pipeline that are at risk of corrosion. These electrochemical sensing techniques offer the advantage of being non-destructive and can provide real-time monitoring of pipeline conditions. They can help in detecting corrosion, coating degradation, and other potential issues, allowing for timely maintenance and preventing pipeline failures [186].

4.10 Eddy current techniques

One popular non-destructive testing (NDT) method for pipeline SHM is eddy current testing [187]. This technique produces eddy currents in the pipeline material through the use of a coil-generated magnetic field. Consequently, an opposing magnetic field is produced by these eddy currents, and the interaction between these fields is employed to identify anomalies and defects in the pipeline material [173]. Eddy current testing is particularly effective for accurately detecting damage in both ferrous and non-ferrous materials, making it ideal for pipeline inspection and monitoring. This technique is essential for identifying damage before a pipeline develops a pathway that could lead to leakage, thus boosting the comprehensive integrity and protection of pipelines. Existing in-line inspection (ILI) techniques, like electromagnetic acoustic transducer methods, magnetic flux leakage, and ultrasonic testing, have drawbacks in terms of detection sensitivity and inspection time. A unique pulsed eddy current (PEC) sensing technique has been put forth to identify and distinguish between inner and outer diameter flaws in steel pipes in order to overcome these difficulties. This method makes use of the induced eddy current distribution patterns at the inner diameter surface, which are influenced by permeability and conductivity. High inspection speed, a large detection depth, remarkable sensitivity, good linearity, low power consumption, simple implementation, and crack identification capabilities have all been demonstrated [188].

5 Data analysis and monitoring methods

In the realm of pipeline SHM, data analysis is crucial for deriving meaningful insights from the extensive amount of collected data. Important elements of SHM systems include sensor accuracy, data volume, and data analysis algorithm performance [189]. It can be especially difficult to analyse high-dimensional data, which has many variables. Data mining (DM) methods can be applied in these circumstances to uncover patterns and hidden relationships in the data [190]. Using a combination of statistical, mathematical, artificial intelligence (AI), and machine learning (ML) approaches, DM entails extracting useful knowledge, insights, and information from massive datasets [190]. For monitored pipelines to remain reliable and intact, diagnostic and prognostic techniques are essential. There are many uses for the benefits of monitoring, recognizing, and quantifying features of interest from structural responses that can reduce expenses, improve safety, and save time [191]. In this context, AI and ML techniques are increasingly employed in pipeline SHM to improve monitoring system capabilities and offer intelligent solutions to the challenges faced in this field [192], [193]. Kudelina et al. [194] reviewed ML-based fault diagnostic techniques, while Huang [195] summarized the advancements of AI in mechanical fault diagnosis. ML algorithms for analysing structural integrity are developed via supervised training approaches using a database of labelled attributes, whereas DL models have gained traction for their capability to analyse raw datasets and determine the damage state or remaining useful life (RUL) [196]. Conventional SHM methods that rely on site inspections are tedious, time-consuming, costly, and pose dangers to field experts. Integrating DL and smart devices in civil engineering applications has shown promise in mitigating these challenges [197]. ML and DL techniques have been extensively researched in SHM, with algorithms being trained on diverse datasets to enhance their accuracy [198]. Artificial neural networks (ANNs) improve predictions of pipeline performance by establishing relationships between various input parameters and the target parameter. The use of ANNs allows for the consideration of complex interactions between uncertain variables such as operating conditions and pipeline properties [199]. Noroznia et al. [200] proposed a novel pipeline age evaluation model using an ANN based on measured data. Various types of artificial neural network (ANN) technologies and their applications in mechanical engineering, including mechanical fault diagnosis, structural analysis, geometric modelling, and design optimization, have been explored [201], [202]. Convolutional neural network (CNN)-based methods have also been studied for SHM. Specifically, guided wave NDT using ultrasonic sensors has been employed to identify and track pipeline irregularities in crucial regions that are prone to flaws. CNN models have been developed to differentiate among a total of six different types of pipeline signals, with the goal of enhancing event recognition in pipeline monitoring [203]. Recently, a CNN-based corrosion monitoring technique demonstrated an impressive classification accuracy of over 99.01%. This indicates the capability of the technique to quantitatively evaluate the pipeline corrosion condition and accurately detect the severity of internal corrosion, highlighting its potential applicability to various pipeline types with differing levels of corrosion [36]. Another novel diagnosis strategy utilizes a one-dimensional CNN to extract spatial information and a Bidirectional Gated Recurrent Unit (Bi-GRU) for temporal information fusion, demonstrating robustness in fault identification accuracy, particularly for noise and variable pressure signals, with an accuracy of approximately 95.9% [204]. Support Vector Machine (SVM) algorithms have also been employed in pipeline SHM. Driven by a network of FBG sensors and aided by SVM algorithms, the structural condition of a pipeline was predicted by evaluating the measurements sensitivity of pipeline pressure, flow variations, and leakage detection and localization, where great accuracies achieved by the SVM classifiers [113]. A Recurrent Neural Network (RNN)-based model was found effective and accurate to predict a pipeline's life condition, contributing to better decision-making for maintenance and safety [205]. Unsupervised learning techniques, including autoencoders, have been investigated in the context of pipeline SHM. Autoencoders, a form of ANNs, are frequently utilized for unsupervised learning applications like reduction of dataset dimensionality, extraction of most reliable features, and compression of data [206]-[211]. Variational autoencoders (VAEs) serve as a powerful method for probabilistically representing high-dimensional datasets, as they can extract latent parameters from the data's probabilistic distribution and create a compact representation that facilitates the reconstruction of unseen data [212], [213]. Unsupervised data clustering techniques, including K-means and principal component clustering analysis (PCCA), have garnered attention in pipeline SHM. By utilizing the clustering capabilities of these algorithms, pipelines can enhance data analysis, recognize damage patterns, detect outliers, optimize sensor placement, and extract features, thereby improving the overall effectiveness of structural health monitoring and assessment [214]. Additionally, analysing pipeline incident datasets indicates the potential for developing a causal model that could identify key factors and predict future failures in pipeline systems [215]. Fuzzy logic has also been explored in the context of pipeline SHM, as it can better handle the inherent uncertainties and ambiguities present in structural data, resulting in decision-making procedures that are stronger and more trustworthy for monitoring, maintenance, and asset management [216]-[218]. The progress in SHM systems is influenced by various elements, such as the creation of novel materials and intricate constructions, and the necessity to enhance safety protocols. A key focus in SHM is the advancement of innovative measurement methodologies, which enhance the recorded signals' quality and facilitate the investigation of material properties via novel approaches [219]. To minimize the reliance on skilled technicians for conducting in-situ NDT on high-pressure pipes transporting hazardous substances, a pole-climbing robot (PCR) designed for inspecting industrial-sized pipelines has been developed [220]. Diverse robotic systems, including mobile and climbing robots as well as aerial drones, can be employed for pipeline SHM [221]. Multiple mode robotic platforms, including aerial and roosting drones, hybrid ground-water robots, hybrid sky-water robots, and hybrid sky-ground robots, hold significant capability for executing various inspection duties when integrated with NDE approaches. Additionally, soft robotics utilizing smart materials are being created for inspection tasks in confined spaces due to their lightweight nature, high adaptability, and reduced reliance on electric motors compared to traditional rigid robotics [221]. Advanced SHM technologies, such as Optical Fiber Sensors (OFS) for detecting corrosion and distributed OFS for physical and chemical sensing, have been developed but remain in the early stages of implementation. There are still challenges in applying SHM techniques that rely on acoustic methods and unmanned aerial vehicles (UAVs), particularly due to the difficulty of monitoring deformations from both sides using a single technique. This highlights the necessity for the development of newer technologies to accurately identify errors and damages in the pipeline industry [222]. Emphasizing the importance of integrating multiple sensors to enhance monitoring accuracy, Sharma et al. [223] explored the possibilities of multi-sensor frameworks and sensor data fusion for predictive maintenance, pointing out how important advances in electrical and computer engineering, electronics, sensor technology, and information science have been to the development of new pipeline SHM technologies. The concept of the Internet of Things (IoT) has transformed lifestyles by enabling greater efficiency, convenience, and automation across various industries, including pipeline monitoring techniques that leverage IoT capabilities [224]. Energy harvesting methods are crucial for pipelines ongoing surveillance using Wireless Sensor Networks (WSNs), with various approaches and sensors proposed in the literature for detecting leaks and corrosion. These techniques for WSN-based Pipeline Monitoring Systems (PMS) can be categorised as invasive energy harvesting techniques (IEHTs) and non-invasive energy harvesting techniques (NEHTs). The former category necessitates modifications to the pipeline structure, while the latter one does not require significant alterations. In this context, Virk et al. [225] offered an extensive review on WSN-based energy harvesting technologies for pipeline SHM systems in the water, oil, and gas sectors.

6 Results and discussion

This comprehensive review examined a substantial number of publications related to pipeline SHM. It focused on the evolution of pipeline SHM, investigating the various types of pipeline failures highlighted in the literature, as well as the sensor technologies and the latest approaches for fault prognostics and diagnosis. The selected papers represented contributions from numerous authors across different countries, primarily over the past 20 years, starting from the year 2000. Through this cutting-edge evaluation and the synthesized insights from the analyzed research papers, a considerable amount of information regarding the context of pipeline SHM has been systematically extracted and categorized. This provides a solid foundation for future innovations and developments in this field. Fig. 6 depicts the percentage of publications related to pipeline SHM per year, illustrating an increasing trend of publications in a yearly basis. This increasing trend indicates a positive growth in research activities and publications centered on pipeline SHM. It reflects a sustained effort to enhance knowledge, technologies, and practices aimed at ensuring the integrity and reliability of pipelines, highlighting the significance and complexity of pipeline SHM as a field of active exploration.

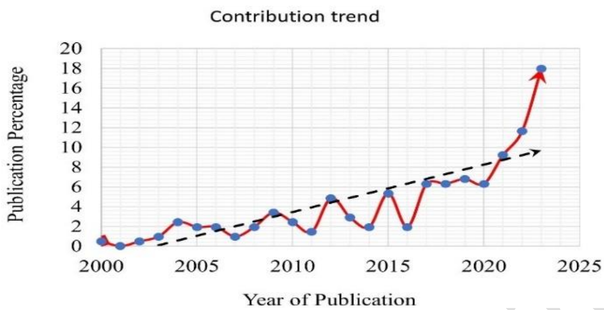

Figure 6. Trend of publication in pipeline SHM

The literature review, as depicted in Fig. 7, revealed that corrosion and erosion combined represented the highest percentage of discussed failures at 44%. This indicates that issues related to corrosion and erosion were the most prevalent among the identified failure modes in the reviewed publications. Following that, cracks and leakages accounted for 26% of the discussion, highlighting their significant presence in the literature. Pipeline deformation was also a notable concern, representing 18% of the discussions. Scale formation, although with a lower percentage of 12%, was still a recognized issue in pipeline SHM discussions. However, scaling is indeed an important issue encountered in oil and gas pipelines that deserves more consideration, and the fact that was not as prominently featured in the literature review findings suggested that it might not be receiving the same level of focus or research attention as the other major failure modes like corrosion, cracking, and leakage because scaling issues may be more localized or system-specific, whereas the other failures tend to be more universal pipeline problems. However, it should not be overlooked, as it can still have a considerable effect on pipeline performance and dependability, particularly in the oil and gas sector. Additionally, it is essential to recognize that there are other potential failure modes and causes that can impact the pipeline's integrity and performance. Joint failure, for instance, such as bolt looseness in flanged connections, is an important consideration that should be addressed in pipeline SHM. Flanges and bolted joints are critical points of potential failure that need to be monitored for any loosening or degradation that could lead to leaks or other issues. Incorporating monitoring of these components into the overall pipeline SHM strategy is a valuable recommendation.

The presented review also revealed that a variety of driving signals has been monitored in pipeline SHM as discussed across the viewed publications. Datasets of time series, vibration, temperature, ambient noise, acoustic transients, stresses and strains, pressure, corrosion rate, flow rate, chemical composition, as well as electromagnetic field, all have been incorporated into pipeline SHM strategies, facilitating the early identification of problems and proactive upkeep to guarantee the long-term dependability and safety of the infrastructure.. However, the choice of best monitoring signals is influenced by various factors, including pipeline material and design, pipeline environment, failure modes, operational requirements, monitoring technology availability, and data integration and analysis. Considering these selection factors and conducting a thorough assessment of the pipeline system, knowledgeable choices regarding the selection of monitoring signals in pipeline structural health monitoring can be made to efficiently oversee and preserve the structural integrity and operational reliability of the infrastructure.

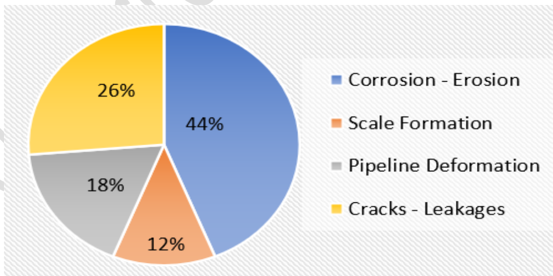

Figure 7. Percentages of most pipeline failures discussed

The state-of-the-art review also displayed different instrumentation and measurement technologies discussed in the literature. The methods include radiographic techniques, pigging and visual inspection, Eddy current techniques, electrochemical techniques, ultrasound techniques, magnetic flux leakage, attenuated total reflectance (ATR) spectroscopic techniques, micro-electro-mechanical sensors (MEMS), piezoelectric sensors, and optical fibre sensors. Optical fibre sensors have the highest discussion percentage at 27.5%, while electrochemical techniques have the lowest at 2.5%. Fig. 8 depicts these methods along with their corresponding discussion percentages in reviewed papers. Generally, the percentages indicating the discussion of various instrumentation and measurement technologies in the context of pipeline SHM are significant. They offer insights into the degree of emphasis and consideration afforded to each technology in the examined papers concerning the state of the art. The current review indicates that higher percentages imply that specific technologies, like OFSs, ultrasound methods, and piezoelectric sensors, have garnered more attention and discourse in the realm of pipeline SHM. This may suggest that these technologies are viewed as significant, effective, or promising for assessing the structural health of pipelines. On the other hand, lower percentages, like those for electrochemical techniques, may suggest that these methods are less commonly discussed or perceived as less significant in the considered topic. Overall, the percentages offer a glimpse into the current trends, preferences, and research emphasis on different instrumentation and measurement technologies for pipeline SHM, helping researchers and practitioners understand which technologies are gaining traction and which may require further exploration or development.

With the vast diversity of instrumentations and measurement technologies, the selection of the suitable technology for pipeline SHM is influenced by several factors, including the monitoring objectives, cost, accuracy and reliability, sensitivity and resolution, ease of installation and maintenance, compatibility with pipeline material, data management and analysis, environmental conditions, regulatory requirements, and scalability. Table 1 provides some advantages and limitations of various measurement and sensing technologies used in pipeline SHM, offering valuable insights for a thorough evaluation when selecting the most suitable technology for pipeline SHM that aligns with specific needs and requirements.

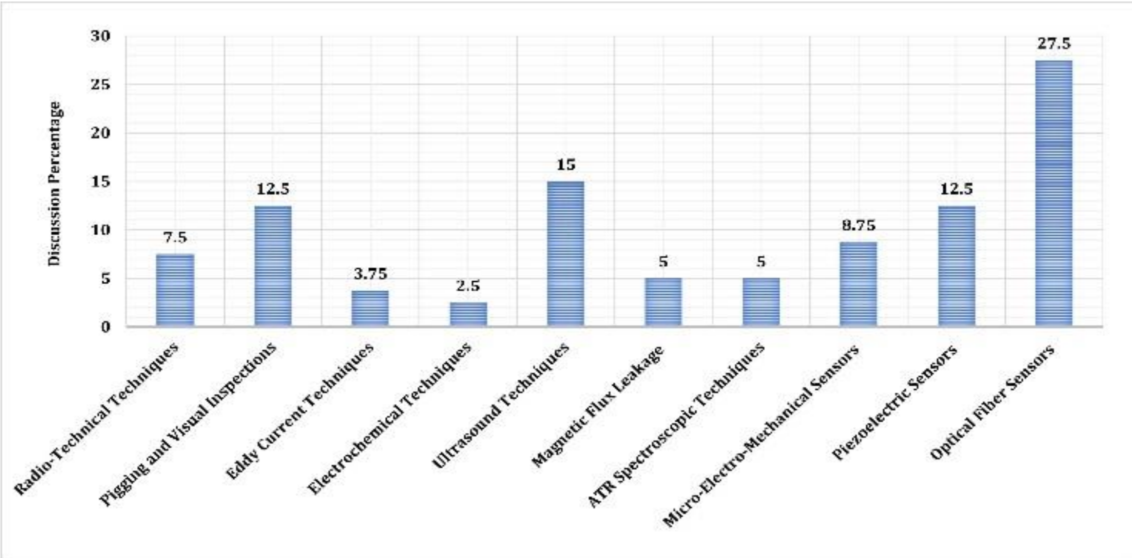

Figure 8. Percentages of most sensing technologies discussed

Additionally, the reviewed papers discussed various AI and ML techniques utilized in pipeline SHM to enhance monitoring capabilities, provide intelligent solutions, and improve decision-making processes. The extensive review emphasized the contribution of AI and ML techniques, including Deep Learning (DL) models, in processing raw data and determining the damage state or remaining useful life (RUL) of pipelines. These models enhance accuracy, efficiency, and the processing of complex data sets, leading to informed decision-making in pipeline maintenance and safety. Techniques such as supervised learning artificial neural network (ANN) models, convolutional neural network (CNN) models, support vector machine (SVM) algorithms, recurrent neural network (RNN)-based models, as well as unsupervised learning autoencoders, variational autoencoders (VAEs), clustering algorithms like K-means, fuzzy logic, and principal component clustering analysis (PCCA) were prominently featured in the literature. The review highlighted the importance of applying multi-sensor condition monitoring in pipeline SHM, paving the way for the utilization of more ML techniques, including ensemble learning that leverages the robustness of model boosting, bagging, majority voting, and stacking techniques to improve the precision and dependability of pipeline srveillance methods. By combining multiple sensors and leveraging ensemble learning methods, researchers can improve the detection of anomalies, predict failures, and optimize maintenance strategies in pipeline infrastructure. While the discussed AI and ML methods offer significant benefits in pipeline SHM, it is essential to acknowledge that each method has its own set of pros and cons as outlined in Table 2. The selection of the most suitable method for a specific pipeline monitoring application should consider various factors, including monitoring objectives, data quality, operational requirements, and cost-effectiveness. The continuous innovation and exploration of more effective methods by combining different AI and ML models to leverage their positive capabilities highlight the dynamic nature of research in pipeline SHM. This integration of various techniques not only addresses the limitations of individual methods but also enhances the overall monitoring and assessment processes, leading to more efficient and reliable pipeline health monitoring systems. Furthermore, the current in-depth survey revealed that the introduction of promising technologies like energy harvesting, monitoring robots and drones, and the cocept of Internet of Things (IoT), is vital in the domain of pipeline SHM. These technologies offer innovative solutions to enhance the monitoring, inspection, and maintenance of pipelines, addressing challenges and improving the efficiency and effectiveness of SHM systems. Energy harvesting techniques enable continuous monitoring of pipelines using Wireless Sensor Networks (WSNs) without the need for external power sources, ensuring uninterrupted data collection and surveillance, reduce the need for frequent battery replacements or external power supply, leading to cost savings in the long run for pipeline monitoring systems, and promote sustainability by utilizing renewable energy sources to power monitoring devices, reducing the environmental impact of traditional power sources. Similarly, IoT technologies enable remote monitoring and real-time data transmission from sensors installed along pipelines, allowing for quick detection of anomalies and timely interventions, facilitate the integration of sensor data, enabling comprehensive analysis and visualization of pipeline health metrics for informed decision-making and predictive maintenance, and automate data collection, analysis, and reporting processes, improving operational efficiency and enabling proactive maintenance strategies. Robots and drones, on the other hand, offer enhanced inspection capabilities for pipelines, including accessing hard-to-reach areas, performing non-destructive testing (NDT), and capturing high-resolution imagery for detailed analysis, reduces the need for manual intervention in hazardous environments, enhancing safety for technicians and mitigating risks associated with pipeline monitoring, and can adapt to various pipeline environments and conditions, providing flexibility in inspection tasks and expanding the coverage area for SHM. Overall, the combination of energy harvesting, IoT, robots, and drones enables comprehensive and multi-modal monitoring of pipelines, covering a wide range of parameters and ensuring thorough assessment of structural health, enhances the quality and precision of monitoring data through real-time data collection, integration, and analysis, which results in more accurate anomaly detection and predictive maintenance. Additionally, it promotes innovation in SHM modeling, resulting in the creation of advanced monitoring systems that are efficient, reliable, and adaptable to changing pipeline condition

Table 2. Measurement and sensing technologies discussed

Method	Advantages	Limitations
Fiber optical Sensors	▪ High sensitivity to parameter changes ▪ Capability of distributed sensing ▪ Immunity to electromagnetic interference ▪ Long-term stability and reliability ▪ Capability of real-time monitoring	▪ Necessity to appropriate expertise and maintenance due to sensor fragility ▪ Sensitivity to environmental factors. ▪ Sensitivity to installation method and calibration ▪ Limited measurement range
Piezo-electric Sensors	▪ High sensitivity to parameter changes ▪ Wide operational frequency range ▪ Compact size and lightweight ▪ Capability of real-time monitoring	▪ Sensitivity to ambient temperature variations ▪ Limited measurement range ▪ Sensitivity to external noise or interference ▪ Sensitivity to installation method and position
Micro-Electro-Mechanical Sensors	▪ High sensitivity to parameter changes ▪ Small size and placement flexibility ▪ Ability to integrate multiple sensing elements for simultaneous multi-measurements ▪ Cost-effective ▪ Capability of real-time monitoring	▪ Limited durability and reliability in harsh environmental conditions ▪ Necessity to regular calibration and maintenance ▪ Limited measurement range or sensitivity for certain parameters
Attenuated total reflectance spectroscopic techniques	▪ Saving in time and resources as it provides direct analysis of samples in their natural state ▪ Versatility in the analysis of a wide range of materials	▪ Surface sensitivity and may not be suitable for detection of anomalies located deep within the pipeline ▪ Necessity to sample preparation. ▪ Incapability of real-time monitoring
Magnetic Flux Leakage	▪ High sensitivity to parameter changes ▪ High sensitivity to pipeline anomalies ▪ Versatility in above-ground and underground pipeline monitoring ▪ Comprehensive detection due to comprehensive coverage of the pipeline's surface ▪ Capability of real-time monitoring	▪ Limited to ferromagnetic materials. ▪ Necessity to surface preparation ▪ Limited to surficial defects and may struggle for deeper defects within pipeline wall. ▪ Necessity to regular calibration and maintenance
Radio-Technical techniques	▪ Hogh resolution (Radiography). ▪ Non-destructiveness (Radiography). ▪ Capability of detecting internal and external defects (Radiography). ▪ Cost-effective and large-scale deployment (RFID). ▪ Passive operation (FRID) ▪ Maintenance-free (FRID).	▪ Safety concerns (Radiography). ▪ High cost and necessity to appropriate expertise and maintenance (Radiography). ▪ Challenging accessibility for buried or hard-to-reach pipelines (Radiography). ▪ Limited operational range (RFID). ▪ Sensitivity to external interference (RFID).
Pigging	▪ Improved flow and reduced blockages. ▪ Prevention of corrosion and damage. ▪ Increased safety. ▪ Cost-effectiveness	▪ Limited accessibility. ▪ Operational complexity. ▪ Sensitivity to Pipeline Conditions.
Visual/physical inspections	▪ Direct inspection. ▪ Low cost. ▪ Flexibility	▪ Limited detection range. ▪ Operator subjectivity. ▪ Safety risks.
Ultrasound techniques	▪ Comprehensive detection. ▪ High detection sensitivity.	▪ Limited detection depth. ▪ Necessity to surface preparation.

	▪ Non-destructive. ▪ Capability of real-time monitoring. ▪ Versatility in above-ground and underground pipeline monitoring.	▪ Necessity to appropriate expertise.
Electrochemical techniques	▪ Selectivity and Sensitivity. ▪ Non-destructive. ▪ Cost-effectiveness. ▪ Capability of real-time monitoring.	▪ Limited detection range. ▪ Sensitivity to environmental factors. ▪ Necessity to regular calibration and maintenance.
Eddy Current	▪ Non-destructive Testing. ▪ Sensitive to Surface Defects. ▪ Suitable for Ferrous and Non-Ferrous Materials. ▪ Rapid Inspection.	▪ Depth limitation. ▪ Surface condition sensitivity. ▪ Necessity to appropriate analysis and assessment personnel.

Table 3. Detection and monitoring algorithms discussed

Type	Advantages	Disadvantages
▪ Bayesian Interference	▪ Allows the integration of prior information into the analysis. ▪ Allows for a clear interpretation of results in terms of probabilities. ▪ Can be versatile for different applications. ▪ Enables continuous updating of beliefs as new data becomes available, facilitating real-time decision-making. ▪ Can help mitigate overfitting by incorporating prior distributions.	▪ Not suitable for high-dimensional problems or complex models. ▪ Sensitive to the choice of prior distributions and may lead to subjectivity or bias if not chosen carefully. ▪ Can lead to unreliable estimates, particularly if the prior is not well-informed. ▪ Interpreting results and understanding the implications of prior distributions can be difficult for new users.
Neural Networks	▪ Can of learn and identify intricate patterns in data that are challenging for other algorithms to detect. ▪ Able to generalize from examples and provide accurate predictions for new, unseen data. ▪ Extremely versatile, applicable to a broad array of predictive modelling tasks. ▪ Can manage large volumes of data and perform parallel processing, making them ideal for big data applications.	▪ May be computationally intensive and demand significant computing resources for training. ▪ Can be challenging to interpret, making it hard to understand the reasoning behind their predictions. ▪ Overfitting is a frequent issue with neural networks, where the model closely fits the training data but performs poorly on new data. ▪ Require substantial amounts of labelled data for effective training, which can be time-consuming and costly to acquire.
Support Vector Method	▪ Beneficial in high-dimensional environment. ▪ Performs well when there is a distinct margin of separation. ▪ Less prone to overfitting as compared to other algorithms. ▪ Suitable for both linear and non-linear data.	▪ Not ideal for large datasets due to the lengthy training time required. ▪ Choosing the right kernel function can be tricky. ▪ Sensitive to the selection of kernel function and hyperparameters. ▪ It can be difficult to interpret the results of SVM.
Principal Component	▪ Reduces dimensionality. ▪ Detects patterns and correlations that might not be obvious in the original dataset. ▪ Improves data accuracy by reducing noise and redundancy in the data. ▪ Increases efficiency by speeding up computation time.	▪ Loss of information. ▪ Requires domain knowledge. ▪ Sensitive to outliers. ▪ May not work for all datasets, particularly those with highly complex or nonlinear relationships between variables.
K-Means	▪ Easy to implement and computationally efficient. ▪ Works well with large datasets. ▪ Highly scalable and can manage a vast number of variables.	▪ Requires the number of clusters to be specified in advance, which can be difficult if the optimal number is not known. ▪ Sensitive to initial cluster assignments.

	▪ Simple and straightforward algorithm.	▪ Assumes that clusters are spherical, of equal size, and have similar densities, which may not hold true in real-world datasets. ▪ Not suitable for datasets with a high degree of noise or outliers.

7 Review outcomes

Based on the comprehensive review and discussions of valuable results obtained, several key current challenges, recommendations, and future outlooks can be identified in the considered research field.

7.1 Key challenges

- The seamless incorporation of the promising techniques including energy harvesting, IoT, robots, and drones into existing pipeline monitoring systems. Ensuring compatibility, interoperability, and data integration among these technologies can be complex.
- Managing the vast amount of data generated by various sensors and technologies poses a challenge. Ensuring data quality, accuracy, and effective analysis methods are essential for deriving meaningful insights and making informed decisions.
- The lack of standardized practices and regulations for pipeline SHM can hinder the implementation and adoption of advanced monitoring technologies. Establishing industry standards and guidelines is crucial for ensuring consistency and reliability in monitoring practices.
- Implementing advanced SHM technologies, such as AI, ML, drones, and robotics, may require significant investments in infrastructure, equipment, and expertise. Cost-effectiveness and resource optimization are key challenges for widespread adoption.
- With the increasing use of IoT and data-driven technologies, ensuring the security and privacy of sensitive monitoring data becomes a critical challenge. Protecting data from cyber threats and unauthorized access is essential.

7.2 Recommendations

- Emphasis on the importance of integrating multi-sensor condition monitoring in pipeline SHM to enhance the identification of structural issues and refine the adopted condition-based mainyenance strategy.
- Exploring the application of ensemble learning techniques, such as model boosting, bagging, majority voting, and stacking, to leverage the robustness of multiple ML models for more accurate and reliable monitoring systems.
- Highlighting the need for addressing a wider range of pipeline failures, including joint failures such as bolt looseness in connection flanges. Incorporating monitoring of critical points like flanges and bolted joints into the overall pipeline SHM strategy is crucial for maintaining the structural health and dependability of pipelines.
- Advocating for the establishment of standardized practices and regulations in pipeline SHM to ensure consistency, reliability, and interoperability of monitoring technologies across the industry.
- Encouraging the investment in emerging technologies such as energy harvesting, IoT, robotics, and drones to enhance monitoring capabilities, improve efficiency, and ensure sustainable and reliable pipeline infrastructure.
- Fostering the collaboration among industry stakeholders, researchers, and regulatory bodies to share knowledge, best practices, and innovations in pipeline SHM, promoting continuous improvement and advancements in the field.

7.3 Future outlooks

- Continued advancements in AI and ML techniques to drive innovation in pipeline SHM, enabling more accurate anomaly detection, predictive maintenance, and real-time monitoring.
- The development of innovative sensor technologies, including optical fibre sensors, MEMS, piezoelectric sensors, and smart materials, to enable more precise and comprehensive monitoring of pipeline health, leading to early detection of issues and proactive maintenance.
- The integration of robotics and drones for inspection and maintenance tasks to improve efficiency, safety, and coverage in pipeline monitoring, enhancing overall reliability and safety of pipeline infrastructure.
- Focus on data analytics, predictive maintenance, and condition-based monitoring to continue to grow, enabling predictive insights, optimizing maintenance schedules, and improving the overall reliability and safety of pipeline infrastructure.
- Incorporating environmental monitoring capabilities into pipeline SHM systems to assess the impact of pipelines on the environment, ensuring compliance with regulations, and promoting sustainability in the pipeline industry

8 Conclusion

This comprehensive literature review makes several novel contributions to the field of pipeline structural health monitoring (SHM):

- Systematic Analysis of Failure Modes: The review provides a detailed examination of the most prevalent pipeline failure modes, including corrosion, erosion, cracks, and deformation. This in-depth analysis helps identify the critical areas that require effective monitoring and maintenance strategies.
- Emerging Sensor Technologies: The review highlights the growing prominence of innovative sensor technologies, such as optical fiber sensors, ultrasound techniques, and piezoelectric sensors. This insight into the latest advancements in sensing capabilities can guide the development of more comprehensive and accurate pipeline SHM systems.
- Advancements in Data-Driven Approaches: The review extensively covers the application of artificial intelligence

(AI) and machine learning (ML) techniques, including supervised learning models, deep learning, and ensemble methods. The demonstrated potential of these data-driven approaches in enhancing anomaly detection, failure prediction, and maintenance optimization is a significant contribution to the field.

- Integration of Emerging Technologies: The review identifies the promising integration of energy harvesting, Internet of Things (IoT), robotics, and drones into pipeline SHM. These advancements enable continuous, remote, and automated monitoring, improving the overall performance and efficiency of pipeline integrity assessment and maintenance.
- Comprehensive Recommendations and Future Outlooks: The review provides a well-structured set of recommendations and future outlooks that address the key challenges and guide the future progress of pipeline SHM. These strategic directions can serve as a roadmap for researchers, industry professionals, and regulatory bodies to drive the advancement of this critical field.

9 Author contribution statements

In the scope of this work, the Author 1 in the comprehensive literature search, data analysis, writing - original draft, and writing - review & editing; Author 2 in the subject matter knowledge, revision, and supervision; the Author 3 in the revision and supervision; Author 4 in the revision and supervision of the article in terms of content were contributed.

10 Ethics committee approval and conflict of interest statement

The authors declare that there is no need to obtain permission from the ethics committee for the review paper prepared.

The authors also declare that there is no conflict of interest with any person / institution in the review paper prepared.

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