Journal of Global Research in Electronics and Communication
Volume 2, No. 06, June 2026
Available Online at: www.jgrec.info
RESEARCH PAPER

# Asset Integrity Management Frameworks for Industrial Facilities: A Survey

Aravindh Balan
*Freelance Post-doctoral scholar*
*Project Manager*
*Inline hydraulics GmbH, Germany*
draravindhbalan@gmail.com

***Abstract*—To optimize assets and the environment, asset integrity is a continuous process of applying knowledge and skills to control risk from facility design, installation, and operation across the course of the asset's existence. The Industrial Facilities are concerned with the safe, dependable, and affordable operation of critical assets throughout their lifecycle. The paper provides a broad overview of the Asset Integrity Management (AIM) by incorporating the lifecycle management principles, risk-based approaches, and data-driven technologies. It addresses the theoretical foundations of AIM, including design and material selection, maintenance planning, inspection and monitoring, and risk assessment and life-extension strategies. An approach based on the lifecycle is highlighted to organize availability, maintainability, and safety requirements with the functional and operational requirements between the conceptual design phase and decommissioning. The unified framework asset criticality and risk categorization with the help of the RBI, FMEA and probabilistic risk assessment. The electrical, mechanical, and electronic integrity of assets is discussed. Finally, the paper has also shown that data-driven prognostics, machine learning, sensor array based on IoT, and advanced signal processing are crucial in predictive maintenance and health-based monitoring. The proposed framework will contribute to the improvement of reliability and regulatory compliance and sustainable industrial activities.**

***Keywords*—Asset Integrity Management (AIM), Industrial Facilities, Condition Monitoring, Machine Learning, Data-Driven Prognostics, Signal Processing, Lifecycle Management.***

## I. INTRODUCTION

The industrial market is radically changing on the basis of mass automation of systems and processes. This has been developing through a couple of decades following the launch of isolated automated systems, which addressed large-scale process issues with relatively little digital infrastructure [1][2]. In contrast, the modern industrial surroundings are characterized by the large variety of interconnected digital resources which operate in complex cyber-physical networks[3]. The increasing volume, rate, and complexity of industrial data currently demand advanced monitoring solutions, more efficient maintenance strategies, and more intelligent analytics to guide engineers, technicians, and operators through real-time decision-making.

The oil and gas industry, being one of the main branches of the world economy, is no exception to this digital transformation[4]. Onshore petrochemical plants are significant in producing high-quality goods like petrol, diesel and petrochemicals from natural gas and crude oil [5][6]. These are the plants that form the foundation of energy chains and industry applications across the globe . These installations, however, being economically significant, work in the worst conditions of all under flammable, toxic, and high-pressure substances.

These are complicated processes in their nature, which is why safety and asset integrity management are required [7]. A major part of the reported cases in refineries and petrochemical plants can be attributed to either equipment wear and tear, mechanical breakdowns, corrosion, operational errors or lack of appropriate maintenance policies. These failures pose threats to human life, nature and economic stability. The effects normally include deaths, major injuries, environmental pollution, factory shutdown, costly repairs, regulatory penalties, legal liability and reputational harm in the long term.

To address those challenges, Asset Integrity and Process Safety (AIPS) Management is presented as an organized and methodical approach that aims to preserve the integrity of dangerous industrial operations . Engineering, operational controls, inspection, and maintenance strategies are the best practice that is incorporated in eliminating the unintended release of hazardous materials or energy in AIPS [8]. Its major goal is to reduce the chances of and the effects of disastrous incidents thus protect the working forces, infrastructure and the environment as well as maintaining a sustainable operation [9]. There has been a growing push to improve AIPS frameworks with resilient system architectures, expert decision support systems, as well as improved data-driven methodologies. Such methods as data mining (DM) and machine learning (ML) are already used to analyze historical databases of incidents, identify patterns and forecast possible failure situations. In addition, recent research points to the possibility of tailoring large language models (LLMs) into specialized AIPS applications [10]. These models are capable of handling a large amount of operational and incident data, categorizing events into predetermined safety types, and coming up with context-specific mitigation measures.

### A. *Structured of the paper*

The paper is organized in the following way: Section II introduces asset integrity management in industrial plants, Section III categorizes Integrated Framework for Asset Criticality and Risk Classification, Section IV is a review of Data-Driven and AI-Based Asset Integrity Frameworks, Section V summarizes literature review, and Section VI gives conclusions and future research perspectives.

## II. ASSET INTEGRITY MANAGEMENT (AIM) IN INDUSTRIAL FACILITIES

The strategic method known as Asset Integrity Management (AIM) guarantees the safe, dependable, and economical functioning of vital assets over the course of their lifetime. AIM maximizes reliability, availability, maintainability, and safety (RAMS) to reduce operating costs and minimize hazards. Such a strategy is especially crucial in high-risk industries like manufacturing and oil and gas, where asset failure might lead to significant financial losses, safety hazards, and damage to the environment [11][12]. As assets deteriorate and systems become more complex, the traditional reactive maintenance techniques are no longer effective in assuring long-term performance. In order to decrease downtime, extend asset life, improve safety, and ensure regulatory compliance, active maintenance approaches and techniques have been developed to identify and address potential issues before they become failures.

### A. *Fundamental Principles of Energy Asset Integrity*

Asset Integrity Management is a lifecycle-based, broad-based process of maintaining the functional capability of the critical infrastructure [13]. Its area cuts across several engineering fields of mechanical, electrical, civil, and systems engineering and all phases of an asset life, including design and manufacturing through decommissioning.

**Key pillars of AIM include:**

- **Design and Material Selection:** The construction and design of assets should have the ability to withstand the operation needs as well as environmental effects and material degradation. The process needs the correct modeling that should be based on industry norms and use the past performance metrics to make material and design decisions.
- **Maintenance Planning:** The organization has abandoned the old model of maintenance that it applied to determine the maintenance state through scheduled maintenance in favor of maintenance systems that forecast the future maintenance requirements based on the state of equipment . The system contributes to better allocation of resources and reduction of interruption in the operation and eradication of unexpected failures on equipment.
- **Inspection and Monitoring:** The inspection process entails advanced methods that involve Non-Destructive Testing (NDT) alongside permanent monitoring mechanisms that detect faults and the degradation and unforeseen actions in advance before the problems become deep-rooted system failures.
- **Risk Assessment:** The use of risk-based inspection (RBI), failure mode and effects analysis (FMEA) as tools to rank interventions in terms of probability and consequence of failure[14].
- **Life Extension:** The process involves analyzing existing asset lifespan through integrity checks which lead to the application of rehabilitation and retrofitting and structural improvement technologies that enable equipment to operate safely while meeting safety regulations and performance criteria.

### B. *Life-Cycle Approach to Asset Integrity*

The life cycle management (LCM) strategy guarantees that resources, information, and technology are shared and coordinated effectively, and that the techniques employed throughout projects are consistent [15][16]. It is necessary to take into account every stage of a system's life cycle, from ideation to system retirement. LCM outlines the procedures for obtaining and providing system goods and services that are configured from the hardware and human system components within the context of the process industry [17]. The life-cycle stages of process asset systems start with the identification of needs and continue through conceptual design, preliminary design, detailed design, development, acquisition phase, manufacturing, and construction. The system moves into its operational stage which consists of three parts operation and support and final disposal which leads to system retirement. Fig. 1 shows that asset integrity assessment needs to be conducted from the beginning of a project until the time of equipment decommissioning.

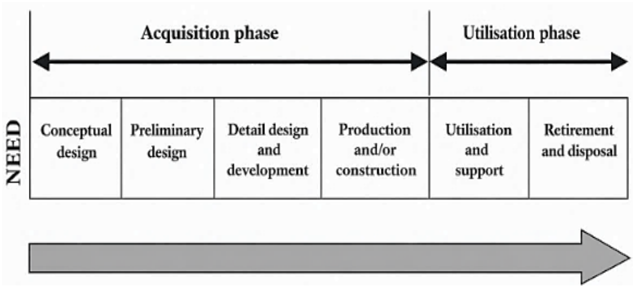


Fig. 1. Life cycle phases of process asset systems.

- The discovery of an operational or market requirement marks the start of a system, industrial plant, or facility's development cycle.
- In order to continue meeting the defined demand, the system, industrial plant, or facility needs maintenance and support throughout its operational lifespan.
- Therefore, a life cycle approach is necessary to save operating and maintenance expenses and maximize plant efficiency, and maintenance and support design should be developed in tandem with system design.
- The functional requirements of throughput, quality, capital cost, schedule, etc. are equally important as the criteria for system effectiveness in terms of availability and maintainability.

## III. INTEGRATED FRAMEWORK FOR ASSET CRITICALITY AND RISK CLASSIFICATION

Asset Criticality Assessment and Frameworks on Risk Classification are aimed at prioritizing the criticality of industrial assets in a systematic and measured way with regard to the risk exposure, importance to the functioning, and consequences of failure. Hierarchy and criticality ranking of the assets are used to group systems based on the plant level, component level up to component level through risk matrices and scoring models. RBI is a method of assessing the risk in terms of probability and consequence of failure to streamline the process of planning the inspection. The FMEA recognizes and prioritizes possible failure modes by the Risk Priority Number (RPN). Probabilistic Risk Assessment (PRA) uses statistical methods such as fault tree and event tree analysis to quantify uncertainty and risk at the system level.

The necessity of AIM occurs when stakeholder expectations and internal expectations diverge, harming the business or its operations and resulting in integrity violations [18]. The organizational structure might have several levels where integrity infractions can take place. For example, some of them include discrimination, power abuse, leaking private information to competitors or the media, and careless use of the company's resources . Integrity infractions can also result from intentionally selling subpar goods, concealing financial difficulties, extorting suppliers, spying on rivals, dodging environmental regulations, etc. This is achieved at the plant level in an asset-centric organization by enhancing three different kinds of interactions from an AI perspective, notably:

- The organization's interaction with its stakeholders (i.e., when the stakeholders' expectations and interests (financial and HSE) conflict with the company's) via the improvement of plant plans, policies, etc.
- The workforce-organization interaction (i.e., When the functional interests of managers, employees, departments, and units clash) by resolving the discrepancy between employee comprehension and organizational expectations.
- The functional link between workforce and activities (i.e., when employees' personal interests conflict with what should occur at the operational or activity level of the business).

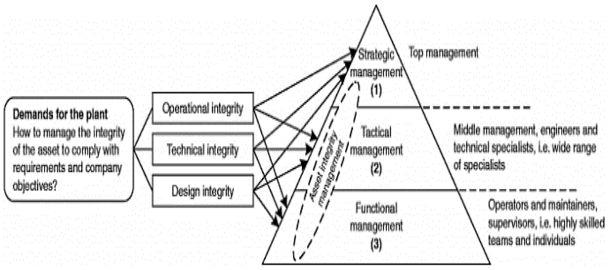


Fig. 2. Asset Integrity Management Across Organizational Levels.

Fig. 2 presents a strategy to the alignment of asset integrity management at organizational levels between design, technical, and operational integrity and strategic, tactical, and functional management [19]. The pyramid structure emphasizes the way top management sets strategic goals, middle management conveys these goals to technical and operational controls, and functional teams implement daily integrity activities. It underscores the seamless nature of task assignments for seeing the plant assets meet regulatory requirements and business goals.

### *A. Integrity Management of Mechanical Assets*

An important tool for achieving the objective of having a high penetration of renewable energy sources (wind and solar photovoltaic) in the contemporary grid is energy storage systems, particularly PHS, CAES, and FES. However, reaching the aforementioned objective may be hampered by the incredibly high cost of energy storage devices.

This entails integrating several energy storage technologies in order to execute many network functionalities [20]. The technical features of the various technologies, including their power and energy capacity, response and discharge times, and so on, must be understood in order to do this. In addition, the technical aspects of the application should be examined to ensure that various technologies are properly hybridized. Table I provides an overview of the technical characteristics of the application.

TABLE I. APPLICATION OF MECHANICAL ENERGY STORAGE SYSTEMS

| Applications | Required time response | Reference duty cycle | ESS power (MW) | ESS AC voltage (kV) | Full power discharge duration |
|---|---|---|---|---|---|
| 3-hour load shift | 10 minutes | Scheduled 3 hours of discharge | 1-200 | 4.2-115 | 3 hours |
| 10-hour load shift | 10 minutes | Scheduled 10-hour discharge | 1-200 | 4.2-115 | 10 hours |
| Renewable time shift | 1 minute | Optimized by technology | 2-200 | 4.2-34.5 | 5-12 hours |
| Fluctuation suppression | 20 milliseconds | Continuous cycling | 2-50 | 4.2-34.5 | 10 seconds |
| Short-duration power quality | 20 milliseconds | Hot standby | 1-50 | 4.2-34.5 | 5 seconds |
| Long-duration power quality | 20 milliseconds | Hot standby | 1-50 | 4.2-34.5 | 4 hours |
| Frequency excursion suppression | 20 milliseconds | Hot standby | 10-500 | 4.2-750 | 15 minutes |

A second strategy for addressing the astronomically high cost of energy storage systems is to employ multifunctional storage system utilization. Using this method, a single energy storage device is managed to perform many tasks. The energy storage system's cost-effectiveness is increased, and its considerable slack period is decreased. The development of suitable control techniques is necessary for the deployment of energy storage for multifunctional use [21]. Additionally, the multifunctional operation of an energy storage system depends heavily on the selection of appropriate storage technology. While certain storage systems, like PHS and CAES, are energy-based and can give power over an extended period of time, others, like FES and SMESS, are power-based and can deliver high-impulse.

### *B. Integrity Management of Electrical Energy Assets*

Circuit breakers, which are crucial for safeguarding power systems against short circuits and overcurrent's, are mainly prone to mechanical issues. Wear, arcing-related burning, inadequate pressure, and incorrect opening/closing are examples of contact problems. Mechanism failures include shaft seizing, component deformation, and stiff operation. Additional mechanical problems include connecting rod fracture or distortion, spring fatigue, decreased force, and bolt loosening.

Electrical malfunctions, such as broken control circuit components, connection issues, or absent control signals[22], can potentially jeopardise functioning. Insufficient supply voltage that hinders opening, coil breaking, and turn-to-turn short circuits are examples of shunt-release faults. Stuck mechanisms or insufficient tripping force can cause undervoltage release devices to malfunction. Some of the fault detection techniques are described as follows:

#### *1) Voiceprint Analysis*

It involves recording of sounds when closing/opening with special recording equipment. The time-frequency representation of these signals is done by the S-transform, which produces amplitude matrices. Singular Value Decomposition (SVD) identifies the important features that are used to train the ML algorithms such as Support Vector Machines (SVM) to classify faults [23]. Essentially, this method detects mechanical flaws by identifying loose parts, pushing rod jamming, and iron core jamming.

They benefit from low-complexity, dependable technology that is simple to install in substations. SVM works well for nonlinear problems with limited sample sizes.

### 2) Vibration Analysis

Vibration analysis is a technique that uses strategically placed equipment to monitor vibration sources released at key operating points in order to identify mechanical flaws. It pinpoints the working mechanism's shortcomings as well as new ones that might prevent it from opening properly. The study involves preprocessing the signals, extracting features, and classifying faults using time-frequency techniques such as the Wavelet Transform and Short-Time Fourier Transform . This method classifies extracted characteristics for defect diagnosis using ML techniques including CNNs, SVMs, and multi-layer classifiers.

Applications include identifying contact defects, energy storage spring problems, bolt loosening, mechanism convulsions, and spring fatigue.

### 3) Coil Current Analysis

Analysis of coil current, which examines the trip and closure coils' current signature, provides an additional non-intrusive method for evaluating the operation and identifying problems with high-voltage circuit breakers. Electrical properties and mechanical movement are reflected in current waveforms; abnormalities point to defects. Current machine learning techniques that analyze contact travel waveforms and coil current. Benefits include ease of installation and computational efficiency with inexpensive microprocessors for embedded monitoring.

## C. Integrity Management of Electronic and Control Systems Assets

A SCADA system is made up of a network of connected hardware and software components. A SCADA system's general hardware design is seen in Fig. 3. A communication infrastructure connects one or more control centers with field devices, including PLCs, RTUs, and Intelligent Electronic Devices (IEDs), to form an architecture.

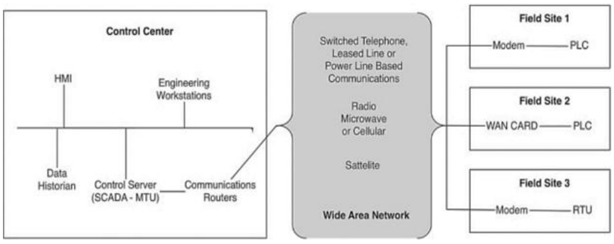


Fig. 3. Generic hardware architecture of a SCADA system.

Field devices deliver data to an RTU, which sends it to the control center after converting it into digital data. The RTU then manages alarms and gets digital commands from the center. To operate valves, solenoids, and other actuators, a PLC is a type of digital computer that uses user-written software to track sensors and make decisions [24]. An MTU is a component of a control center that commands RTUs, collects data from them, stores and processes data, and displays information to human operators to aid in decision-making. From a control center, human operators use Human–Machine Interface (HMI) screens to monitor and manage the system.

Cybersecurity issues in SCADA systems are further exacerbated by legacy problems. Because they operate continuously, some existing SCADA systems have not been updated or redesigned for decades. Because of this, patching and updating the SCADA software and the hosting operating system on a regular basis becomes challenging, if not impossible. The time-sensitive nature of SCADA systems and the absence of a test environment make patching them challenging; doing so might result in the introduction of new vulnerabilities or the system's eventual failure. The cybersecurity of SCADA systems is significantly impacted by the human element. The development process, intricate software design, and human supervision are aspects of SCADA systems that make the human element even more important. Ongoing vigilance regarding human factors helps prevent human errors that may lead to unintended attacks and to intended internal and external social engineering attacks.

# IV. Data-Driven and AI-Based Asset Integrity Frameworks

Data-driven prognostics is introduced into asset integrity management, encompassing both statistical and ML techniques for fault prediction and health evaluation. It also emphasizes sophisticated condition monitoring, IoT-based sensor networks, and important signal processing methods applied to use reliable asset monitoring and early fault detection.

## A. Data-driven Approaches (Statistical and ML)

The statistical and machine learning methods can broadly define the data-driven prognostics in asset integrity management. Statistical prognostics contain the parametric models that make assumptions about the probability distributions (Weibull or exponential) and provide estimates of failure behavior and useful life remaining, and non-parametric models that follow a data-driven estimation approach without any specific distributional constraints and provide increased flexibility in complex degradation behavior. On the other hand, machine learning strategies use a substantial amount of operational and sensor data to identify faults and forecast asset health. These are the supervised learning techniques (e.g., SVM, Random Forest, neural networks) in classification and regression, unsupervised learning techniques (e.g., clustering and PCA) in anomaly detection and pattern discovery, and deep learning models (e.g., CNN, LSTM) that can extract hierarchical features of high-dimensional time-series data in advanced prognostics and predictive maintenance. Data-driven (DD) prognostics, as seen in Fig. 4, consists of two main methods: statistical and machine learning (ML), which employ collected data to statistically and probabilistically generate prognostic information, including estimates, forecasts, and judgements [25]. Parametric and nonparametric techniques are examples of statistical approaches; supervised and unsupervised classification, clustering, regression, and ranking are examples of ML techniques.

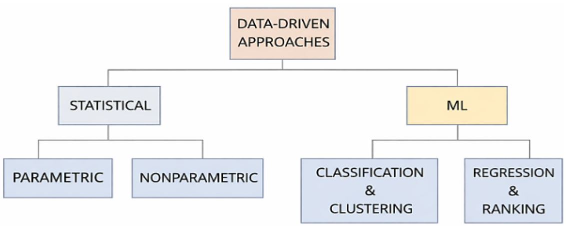


Fig. 4. Data-driven approaches.

### B. *Advanced Condition Monitoring and Health Assessment Techniques*

The process of keeping an eye on the state of equipment and activities is known as condition monitoring. The main goals of condition monitoring are to reduce possible hazards, improve plant accessibility, and avoid unplanned failures. This help in finding problems even before serious mechanical or component breakdowns take place. Examples are the oil and gas pipeline degradation and hidden leakages in the valves and pressure vessels, among others, which may have dire consequences, including bombings and fires.

The significance of diagnostic methods comes predominant in protecting maintaining structural integrity while improving operating performance. The concept of IRT is that it is based on the physics of thermodynamics. Thermal radiations can be emitted by objects, man-made, or natural due to their temperature. This radiation that may as well be observed in the human eye cannot see the infrared spectrum by nature [26]. Nevertheless, special infrared cameras that are fitted with advanced sensors and optics are in a position to turn this invisible radiation into images referred to as thermograms.

The key principle of the success of IRT is emissivity, which is one of the fundamental characteristics, quantifying the capacity of a surface to radiate heat. These differences in emissivity of materials affect the thermal distributions as detected in thermograms, which allows professionals to determine areas of concern [27]. Having knowledge of the concepts of emissivity and how it impacts temperature measurements, practitioners would be able to identify the true anomalies and the ones brought about by emissivity, so the diagnostic assessment could be conducted correctly. The importance of IRT in developing diagnostics is supported by its broad scope of application, each of which deals with essential components of the structural health and energy efficiency.

### C. *Sensor Networks and IoT-Enabled Asset Monitoring*

The WSN of industrial applications, a number of hard requirements should be fulfilled. As an illustration, proper network topologies, techniques, and algorithms should be developed to guarantee quality communication and system stability in monitoring and controlling a certain process [28][29][30][31]. Moreover, the implementations in the industry should make sure that data is reliable at all times, as the environmental conditions may be challenging. Although it is difficult to suggest the universal approach to developing WSNs to be used in industries, such a solution takes into consideration some of the most common resource constraints of this field, such as power, durability, processing power, and storage.

The key features of the sensor network are as follows:

#### 1) *Scalability*

It demonstrates how a sensor network may expand by adding additional nodes that collect data without noticeably increasing the network's overall effectiveness. Additionally, the network must be able to function effectively as the number of sensors rises without sacrificing data transfer speeds and processing power. Applications with wide coverage, such smart city infrastructure or environmental monitoring of large geographic areas, require this functionality.

#### 2) *Energy efficiency*

It's another crucial aspect of sensor networks. It is difficult to maintain a consistent power source or replace batteries since many of the sensor nodes are located in difficult-to-reach places. To increase the length of time that these networks can function, the sensor nodes have been made to use the least amount of power possible. Energy-efficient data transmission is optimized, and low-power communication techniques are widely employed. Frequently employed energy-saving strategies include duty cycling, which alternates between active and sleep states using sensors.

#### 3) *Reliability*

It ensures reliable and constant data collection and transmission, even under difficult circumstances. Reliability is necessary for applications like industrial process control and healthcare monitoring where data integrity is crucial. Sensor networks must be resilient to external factors that might deteriorate data quality, such as interference and node failures. Implementing error-checking methods and multiple data transfer paths usually improve it.

### D. *Data Acquisition, Signal Processing Methods*

Data acquisition refers to the process of collecting and storing monitoring data from sensors installed on the equipment being observed. It is the first phase in equipment prognostics that provides basic condition monitoring data to the procedures that follow. A data collection system consists of sensors, data transmission devices, and data storage devices. Numerous sensors are employed to capture different types of monitoring data that might indicate the machinery's deteriorating process [32][33]. Sensors that are often utilised include accelerometers, sound emission sensors, infrared thermometers, and current sensor.

Therefore, Some Signal Processing Methods, which are described as:

#### 1) *Envelope Analysis*

This method can identify bearing problems on the inside as well as the outside. Furthermore, it is capable of anticipating and identifying fretting corrosion and bearing assembly deterioration early on. The approach relies on a time-domain signal that requires additional signal processing methods for processing.

#### 2) *Statistical Analysis*

In commercial wind turbine systems, the statistical analysis techniques are well-established. The required statistical features, including mean value, variance, crest factor, root-mean-square value, skewness, and kurtosis, are calculated using the base values maintained in the wind turbine's healthy condition. Despite providing precise information about the problem location or mode, this approach can only show that a fault has occurred.

#### 3) *Fast Fourier Transform (FFT)*

In digital systems, Fourier analysis is arguably the most widely used frequency analysis method. A particular defect is indicated by changes in certain harmonic components of the frequency spectrum [34]. While frequency analysis for stationary signals may be performed using the conventional FFT, it is unable to show how the frequency spectra of a nonstationary source vary over time.

#### 4) *Synchronous Sampling*

In order to generate nonstationary vibration and electrical impulses, a wind turbine typically rotates at different speeds.

After converting the nonstationary signal characteristics to constant values using a number of synchronous sampling methods, the conventional FFT may be applied.

*5) Short-Term Fourier Transform (STFT)*

The variable speed wind turbine system's rotor unbalance, blade structural degradation, gearbox tooth flaws, and open and short circuit faults are all detected using the short-term Fourier transform.

## V. LITERATURE REVIEW

The literature reviewed highlights AI-based, data-integrated, and lifecycle-based asset integrity management models, which are more reliable, more proactive, with decision support and visualization, as shown in Table II, but have a problem with scalability, data quality, and real-life applicability.

Coronel, Barán and Gardel et al. (2025) Highlight the most widely used data mining methods, including convolutional neural networks, support vector machines, random forests, expert systems, and proportional hazard models. Additionally, to examining five asset types—mechanical, electromechanical, electrical, electronic, and computer assets, the assessment suggests four-level levels of asset complexity. Alongside the continuous use of conventional methods, such as rule-based and model-based techniques and shallow ML, highlight the increasing use of DL [35].

Jones et al. (2025) improve the dependability, security, and economy of offshore oil and gas pipeline asset management, look at the latest developments in AI-driven asset management. The first step involves utilizing citational network analysis to map current studies on AI applications in oil and gas pipeline management. Eight major theme clusters were found, each of which highlighted a particular field of study and potential avenues for future investigation. A structured AI-based asset integrity management system is suggested for oil and gas infrastructure, including pipelines, based on these findings. It takes into account real-world implementation issues such system integration, data dependability, and geographical limitations [36].

Abubakar et al. (2024) highlight how crucial it is to oversee pipeline assets' integrity proactively in order to avoid disastrous events brought on by pipeline breaches. Pipeline asset management has always been reactive, taking care of issues only after they became failures. This reactive strategy frequently results in operational inefficiencies even if it might provide temporary solutions, increased expenses, unexpected downtime, and safety compromises. Aging pipeline infrastructure compounds these difficulties, highlighting the necessity of an ambitious plan centred on pipelines' full lifespan [37].

Jin, Kim and Abu-Siada et al. (2023) examine the core goal of asset management, which is to strike a balance between system dependability and cost. Regular condition monitoring, fault diagnosis, and general health evaluation are necessary to maintain the dependability of power transformers. Asset managers can also plan capital investments by calculating the power transformers' remaining life. The integrity team may determine the best maintenance plan for each transformer in the network by examining the techniques utilised for power transformer asset management [38].

Shekargoftar et al. (2022) propose a pipeline operation and maintenance management system (POMMS) by employing building information modeling (BIM), geographic information system (GIS), augmented reality (AR), and combining several project data sources using cloud databases and application programming interfaces (API). This system's more lifelike 3D visualizations can help in decision-making, enhanced integration of construction, inspection and geographic data, as well as effective data retrieval. To verify the suggested system's effectiveness, it is used on a real project [39].

Johannes et al. (2021) determine measurable maturity dimensions for intelligent maintenance of built assets. Four embedded case studies in corporate facilities management organizations are utilized to gather data from various sources using a research methodology based on two opposing scenarios. A maturity framework that has been validated through expert consultation was developed by coding data from many cross-case analyses. Both behavioral (like culture) and technical (like tracking and tracing) aspects are included in the suggested smart maintenance maturity paradigm [40].

TABLE II. OVERVIEW OF DATA-DRIVEN AND INTELLIGENT ASSET INTEGRITY MANAGEMENT STUDIES

| Authors (Year) | Focus Area | Approaches | Limitations | Objectives | Future Work |
|---|---|---|---|---|---|
| Barán & Gardel et al., (2025) | Data-driven asset integrity management | Data mining, ML (SVM, RF), DL (CNN, Autoencoder), rule-based models; asset complexity classification | Limited real-time validation; data dependency; scalability challenges | Review and classify algorithms and asset complexity levels | Hybrid models; explainable AI; real-time deployment |
| Jones et al., (2025) | AI-based offshore pipeline asset integrity | Citation network analysis; AI-driven integrity framework; thematic clustering | Regional constraints; data reliability; system integration issues | Develop structured AI-based asset integrity system | Field-scale validation; digital twins; adaptive AI systems |
| Abubakar et al., (2024) | Pipeline asset integrity and lifecycle management | Decision Support Systems (DSS); Life Cycle Cost Analysis (LCCA) | Requires accurate long-term data; high modeling complexity | Shift from reactive to proactive integrity management | AI-integrated DSS; uncertainty modeling; real-time analytics |
| Kim & Abu-Siada et al., (2023) | Power transformer asset management | Condition monitoring; fault diagnosis; health index; remaining life estimation | Transformer-specific focus; limited cross-asset applicability | Balance reliability and cost through informed maintenance | AI-based prognosis; digital asset management platforms |
| Shekargoftar et al., (2022) | Management of pipeline operations and maintenance | BIM–GIS–AR integration; cloud database; API-based data fusion | High implementation cost; technical complexity | Improve O&M decision-making using 3D visualization | Scalability studies; AI-enabled inspection analytics |

| | | | | | |
|---|---|---|---|---|---|
| Johannes et al., (2021) | Smart maintenance maturity of built assets | Case studies; maturity framework; technological & behavioral dimensions | Qualitative bias; limited generalization | Develop and validate a smart maintenance maturity model | Quantitative metrics; automation readiness assessment |

## VI. Conclusion and Future Work

Asset management structures of industrial facilities with particular emphasis on energy assets working in hazardous situations. It identified the shift of reactive and time-based maintenance to lifecycle-oriented and data-driven AIM plans made possible through advanced sensing, IIoT architecture, and intelligent analytics. Mechanical, electrical and electronic control system assets were categorized systematically, and integrity issues that are unique to each category were analyzed. The review showed that statistical, ML, and DL models are useful in condition monitoring, fault diagnosis, and prognostics, which in turn contribute to safety, reliability, and cost effectiveness. Nevertheless, the effective implementation of smart AIM frameworks is limited by the problem of data quality, scalability of the system, security vulnerabilities, and challenges in implementing it in real-time, especially in old systems. In general, the results highlight that AI-based, integrated, and lifecycle-based asset integrity management is vital to attaining resilient, sustainable and economically viable operation of the contemporary industrial energy systems.

Future investigations need to be aimed at scalable, real-time AIM architectures incorporating edge-cloud intelligence, digital twins, and explainable AI. It is imperative to focus on designs that are conscious of cybersecurity, standardized data models and field-level validation to facilitate well-structured deployment of intelligent asset integrity systems in the various industrial facilities.

## References


[1] L. Rojas, Á. Peña, and J. Garcia, "AI-Driven Predictive Maintenance in Mining: A Systematic Literature Review on Fault Detection, Digital Twins, and Intelligent Asset Management," *Appl. Sci.*, vol. 15, no. 6, 2025, doi: 10.3390/app15063337.

[2] Y. Patel, "A Reputation-Resilient Seller Ranking Mechanism for Online Marketplaces," *Newark J. Human-Centric AI Robot. Interact.*, vol. 4, pp. 374–393, 2024.

[3] P. R. Marapatla, "Digital Innovation In Nonprofit Brand Transformation: A Technology-First Approach," *J. Int. Cris. RISK Commun. Res.*, vol. 8, 2025.

[4] A. K. R. Seella, "Data-Driven Prediction of Advertising Digital Campaign Effectiveness Using Artificial Intelligence," in *2026 14th International Symposium on Digital Forensics and Security (ISDFS)*, IEEE, Mar. 2026, pp. 1–6. doi: 10.1109/ISDFS69419.2026.11459096.

[5] M. Ayomoh and B. Ongwae, "A Systematic Review of Asset Integrity and Process Safety Management Sustainability for Onshore Petrochemical Installations," *Sustainability*, vol. 17, no. 1, p. 286, Jan. 2025, doi: 10.3390/su17010286.

[6] R. Patel, "Optimizing Oil and Gas Pipeline Monitoring with AI Machine Learning Based Predictive Framework," in *2025 International Conference on Smart & Sustainable Technology (INCSST)*, IEEE, Jul. 2025, pp. 1–6. doi: 10.1109/INCSST64791.2025.11210432.

[7] A. Alkhard, "Leveraging Digital Asset Management and Meta-Data Integration for Enhanced Asset Management," *Constr. Econ. Build.*, vol. 24, no. 3, Jun. 2024, doi: 10.5130/AJCEB.v24i3.8741.

[8] B. Adebisi, E. Aigbedion, O. B. Ayorinde, and E. C. Onukwulu, "A conceptual model for predictive asset integrity management using data analytics to enhance maintenance and reliability in oil \& gas operations," *Int. J. Multidiscip. Res. Growth Eval.*, vol. 2, no. 1, pp. 534–554, 2021.

[9] R. Patel and P. B Patel, "The Role of Simulation & Engineering Software in Optimizing Mechanical System Performance," *Tech. Int. J. Eng. Res.*, vol. 11, no. 6, pp. 991–996, 2024, doi: 10.56975/tijer.v11i6.158468.

[10] E. O. Nwulu, T. Y. Elete, O. V. Erhueh, O. A. Akano, and A. T. Aderamo, "Integrative project and asset management strategies to maximize gas production: A review of best practices," *World J. Adv. Sci. Technol.*, vol. 2, no. 2, pp. 18–33, 2022.

[11] A. H. Gomaa, "Optimizing Asset Integrity for Critical Manufacturing Systems Using Advanced Proactive Maintenance Strategies," *Int. J. Emerg. Sci. Eng.*, vol. 13, no. 4, pp. 21–33, Mar. 2025, doi: 10.35940/ijese.B2026.13040325.

[12] S. Chatterjee, "Risk Management in Advanced Persistent Threats (APTs) for Critical Infrastructure in the Utility Industry," *Int. J. Multidiscip. Res.*, vol. 3, no. 4, Aug. 2021, doi: 10.36948/ijfmr.2021.v03i04.34396.

[13] E. Vandenberg, "Asset management and risk based process safety management approaches to the energy trilemma," *Aust. Energy Prod. J.*, vol. 64, no. 2, pp. S289--S293, 2024.

[14] D. Patel, "Explainable Risk Decision Systems Using Artificial Intelligence Models for Payment Fraud Identification with Mitigation," in *2026 14th International Symposium on Digital Forensics and Security (ISDFS)*, IEEE, Mar. 2026, pp. 01–06. doi: 10.1109/ISDFS69419.2026.11459006.

[15] M. K. Chinnathai and B. Alkan, "A digital life-cycle management framework for sustainable smart manufacturing in energy intensive industries," *J. Clean. Prod.*, vol. 419, p. 138259, 2023.

[16] S. K. Chintagunta, "The Role of Artificial Intelligence in Software Engineering: A Review of Frameworks, and Impact on the Software Development Life Cycle," *Int. J. Emerg. Res. Eng. Technol.*, vol. 6, no. 4, pp. 72–79, 2025, doi: 10.63282/3050-922X.IJERET-V6I4P109.

[17] U. A. Korat and A. Alimohammad, "A Reconfigurable Hardware Architecture for Principal Component Analysis," *Circuits, Syst. Signal Process.*, vol. 38, no. 5, pp. 2097–2113, 2019, doi: 10.1007/s00034-018-0953-y.

[18] R. M. Chandima Ratnayake and T. Markeset, "Asset integrity management for sustainable industrial operations: measuring the performance," *Int. J. Sustain. Eng.*, vol. 5, no. 2, pp. 145–158, Jun. 2012, doi: 10.1080/19397038.2011.581391.

[19] R. Patel and P. Patel, "A Survey on AI-Driven Autonomous Robots for Smart Manufacturing and Industrial Automation," *Tech. Int. J. Eng. Res.*, vol. 9, no. 2, pp. 46–55, 2022, doi: 10.56975/tijer.v9i2.158819.

[20] F. K. Tesfaye, A. M. Getaneh, and M. Birhan, "The management of sustainable energy sources in the mechanical sector," *Urban Resilien. Sustain.*, vol. 1, no. 2, pp. 138–145, 2023.

[21] K. M. R. Seetharaman, "Incorporating the Internet of Things (IoT) for Smart Cities: Applications, Challenges, and Emerging Trends," *Asian J. Comput. Sci. Eng.*, vol. 8, no. 1, March, pp. 8–14, 2023.

[22] S. Chatterjee, "Advanced Malware Detection in Operational Technology: Signature-Based Vs. Behaviour-Based Approaches," *ESP J. Eng. Technol. Adv.*, vol. 1, 2021, doi: 10.56472/25832646/JETA-V1I2P128.

[23] E. D. Fylladitakis, "Fault Identification and Predictive Maintenance Techniques for High-Voltage Equipment: A Review and Recent Advances," *J. Power Energy Eng.*, vol. 13, no. 07, pp. 1–39, 2025, doi: 10.4236/jpee.2025.137001.

[24] Y. Cherdantseva *et al.*, "A review of cyber security risk assessment methods for SCADA systems," *Comput. Secur.*, vol. 56, pp. 1–27, Feb. 2016, doi: 10.1016/j.cose.2015.09.009.

[25] S. Akhtar, M. Z. Bin Sujod, and S. S. H. Rizvi, "An Intelligent Data-Driven Approach for Electrical Energy Load Management Using Machine Learning Algorithms," *Energies*, vol. 15, no. 15, Aug. 2022, doi: 10.3390/en15155742.

[26] H. Kim, N. Lamichhane, C. Kim, and R. Shrestha, "Innovations in Building Diagnostics and Condition Monitoring: A Comprehensive Review of Infrared Thermography Applications," *Buildings*, vol. 13, no. 11, p. 2829, Nov. 2023, doi: 10.3390/buildings13112829.

[27] D. Goyal and B. S. Pabla, "The vibration monitoring methods and signal processing techniques for structural health monitoring: a review," *Arch. Comput. Methods Eng.*, vol. 23, no. 4, pp. 585–594,

2016.

[28] M. Majid *et al.*, "Applications of Wireless Sensor Networks and Internet of Things Frameworks in the Industry Revolution 4.0: A Systematic Literature Review," *Sensors*, vol. 22, no. 6, p. 2087, Mar. 2022, doi: 10.3390/s22062087.

[29] Y. Muni, ""Understanding The Evolution Of Internet Protocols: An In-Depth Review Of Ipv4 And Ipv6: A Comparative Review Of Transition Challenges And Solutions," *Int. J. Adv. Res. Comput. Sci.*, vol. 16, no. 4, pp. 109–117, Aug. 2025, doi: 10.26483/ijarcs.v16i4.7307.

[30] S. Dodda, N. Kamuni, P. Nutalapati, and J. R. Vummadi, "Intelligent Data Processing for IoT Real-Time Analytics and Predictive Modeling," in *2025 International Conference on Data Science and Its Applications (ICoDSA)*, IEEE, Jul. 2025, pp. 649–654. doi: 10.1109/ICoDSA67155.2025.11157424.

[31] S. Das, V. Challagulla, Dr.P.Balaramesh, D. A. M. A. Mohan, B. V. Jyothi, and S.Saravanan, "Deep Learning for Corrosion Monitoring Virtual Sensor and Predictive Modelling Approaches in Industrial Water Pipeline," *The Bioscan*, vol. 21, no. 1, pp. 35–45, Jan. 2026, doi: 10.63001/tbs.2026.v21.i01.pp35-45.

[32] Y. Lei, N. Li, L. Guo, N. Li, T. Yan, and J. Lin, "Machinery health prognostics: A systematic review from data acquisition to RUL prediction," *Mech. Syst. Signal Process.*, vol. 104, pp. 799–834, May 2018, doi: 10.1016/j.ymssp.2017.11.016.

[33] S. Achouche, U. B. Yalamanchi, and N. Raveendran, "Method, apparatus, and computer-readable medium for dynamic binding of tasks in a data exchange," 2021

[34] M. L. Hossain, A. Abu-Siada, and S. M. Muyeen, "Methods for Advanced Wind Turbine Condition Monitoring and Early Diagnosis: A Literature Review," *Energies*, vol. 11, no. 5, p. 1309, May 2018, doi: 10.3390/en11051309.

[35] E. Coronel, B. Barán, and P. Gardel, "A Survey on Data Mining for Data-Driven Industrial Assets Maintenance," *Technologies*, vol. 13, no. 2, p. 67, Feb. 2025, doi: 10.3390/technologies13020067.

[36] J. F. Jones *et al.*, "Application of artificial intelligence for asset integrity management of offshore oil and gas pipelines," *Life Cycle Reliab. Saf. Eng.*, vol. 14, no. 4, pp. 503–530, Dec. 2025, doi: 10.1007/s41872-025-00353-2.

[37] A. S. Abubakar, M. M. B. A. Wahab, N. Shafiq, K. U. Danyaro, and A. U. Adebanjo, "Integrating life cycle cost analysis into pipeline asset integrity management: A comprehensive approach in decision support systems," *J. Hunan Univ. Nat. Sci.*, vol. 51, no. 1, 2024.

[38] L. Jin, D. Kim, and A. Abu-Siada, "State-of-the-art review on asset management methodologies for oil-immersed power transformers," *Electr. Power Syst. Res.*, vol. 218, p. 109194, May 2023, doi: 10.1016/j.epsr.2023.109194.

[39] A. Shekargoftar, H. Taghaddos, A. Azodi, A. Nekouvaght Tak, and K. Ghorab, "An integrated framework for operation and maintenance of gas utility pipeline using BIM, GIS, and AR," *J. Perform. Constr. Facil.*, vol. 36, no. 3, p. 4022023, 2022.

[40] K. Johannes, J. Theodorus Voordijk, A. Marias Adriaanse, and G. Aranda-Mena, "Identifying maturity dimensions for smart maintenance management of constructed assets: A multiple case study," *J. Constr. Eng. Manag.*, vol. 147, no. 9, p. 5021007, 2021.

 