Uniosun Journal of Engineering and Environmental Sciences (UJEES), Vol. 8 No. 2, Sept., 2026
DOI: 10.64980/ujees.v8i2.013 **Raheem et al.**
Published: September 30, 2026

PREDICTIVE MAINTENANCE STRATEGIES IN PROCESS PLANT EQUIPMENT: A REVIEW OF TECHNIQUES AND APPLICABILITY TO PETROCHEMICAL OPERATIONS IN NIGERIA

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Abstract
Predictive maintenance (PdM) has become an important approach for improving equipment reliability and reducing unplanned downtime in process industries. However, many PdM studies focus on highly instrumented industrial environments and give limited attention to the infrastructure, skills, logistics and organisational conditions required for successful adoption in developing economies. This study combines a structured review of published literature with a qualitative case study of a Polypropylene Production Unit (PPU) in Nigeria to examine the technical capabilities and practical requirements for PdM adoption. Five major PdM techniques were examined: vibration analysis, infrared thermography, oil and lubricant analysis, ultrasonic and acoustic-emission methods, and artificial intelligence/machine-learning-based predictive models. The literature was synthesised based on fault-detection capabilities, data and infrastructure requirements, workforce skills, cost considerations and implementation challenges. The case study shows that the PPU combines preventive and corrective maintenance with routine "Look, Listen and Feel" (LLF) inspections, process instrumentation, and targeted use of vibration analysis, thermography, oil analysis, ultrasonic inspection and borescope examination. However, these activities are mainly initiated by observed abnormalities, maintenance requirements or engineering recommendations rather than through an integrated predictive analytics framework. The findings indicate that effective PdM adoption in such environments is better approached as a progressive process than as an immediate transition to fully connected, AI-driven monitoring. The paper therefore proposes a phased approach to PdM adoption that begins with reliable condition data and targeted monitoring, followed by systematic data integration and trend analysis, before progressing to online monitoring and advanced predictive models where sufficient data and infrastructure exist.

Keywords
predictive maintenance; condition monitoring; process industry; developing economies; infrastructure constraints

1. INTRODUCTION

Unplanned equipment failure remains a major concern in process and manufacturing industries because equipment breakdowns can interrupt production, increase maintenance costs and reduce overall operational efficiency. In Nigerian industries, persistent low equipment availability and productivity have been associated with weaknesses in maintenance practices, organisational support and maintenance management [1]. A case study of a Nigerian manufacturing plant showed that downtime can have substantial operational consequences, with 95% of recorded downtime and 92% of equipment failures attributed to manpower and method-related problems [2]. In process plants, the consequences of equipment failure can extend beyond the affected unit because interconnected equipment and production operations may also be disrupted [3]. These challenges highlight the importance of maintenance approaches because it can detect developing equipment degradation early and support timely maintenance decisions [4].

Maintenance practice has evolved from primarily reactive approaches into preventive and predictive modes of operation [5]. Restoration of equipment after a failure is usually carried out by means of reactive maintenance and can be appropriate for assets whose failure has limited operational consequences. Preventive maintenance, in contrast, uses predetermined time or usage intervals for inspection, servicing or component replacement. Although unexpected breakdowns can be reduced using this approach, it does not account for the actual condition of an individual component. Predictive maintenance (PdM) addresses this limitation by using condition-related information to identify developing faults and determine when maintenance intervention is required [5,6,7,8]. Depending on the equipment and failure mechanism, this information may come from vibration, temperature, lubricant condition, process parameters or other measurable indicators of equipment health.

Despite the rapid development of PdM and Industry 4.0 technologies, their implementation across all industrial settings is not uniformly straightforward. Most of the previous literatures on advanced predictive maintenance assumes access to reliable instrumentation, digital data infrastructure, technical expertise and established maintenance systems. These assumptions can be difficult to replicate in developing-economy manufacturing environments. A systematic literature review conducted by Peter et al. [9] examined 200 publications on PdM 4.0 in manufacturing industries published between 2016 and 2022, and found that only 2% originated from developing countries, with 7% concerning Africa specifically. The authors identified the limited research on PdM4 itself as a potential hindrance for PdM 4.0 development and adoption in African manufacturing industries [9]. This limited evidence base makes it difficult to determine whether technology-intensive approaches developed in well-resourced industrial settings can be transferred directly to plants operating under different technical and organisational conditions. A comprehensive review by Azeta et al. [10], with contributions from Nigerian-based researchers, examined the application of artificial intelligence and robotics in predictive maintenance and highlighted both the opportunities and the infrastructural and skills-related barriers relevant to African manufacturing contexts, a direction echoed by an early assessment of AI-based predictive maintenance readiness within Nigerian manufacturing industries [11].

The challenges extend beyond the availability of equipment for monitoring the maintenance of assets. Several factors including infrastructure, technical skills, financial resources, data availability and organizational readiness were identified as important barriers from studies examining predictive-maintenance adoption [9, 10, 11, 12]. Relevant challenges are also identified in the Nigerian engineering workforce including Gaps in technical, problem-solving, research and development, and management skills [13]. Although the study was not specifically focused on predictive maintenance, these findings highlight the importance of practical and analytical engineering capability when introducing more data-intensive maintenance practices. These findings established a long-standing, trend in Nigeria's industry where less than one percent of surveyed personnel understood the principles of effective preventive maintenance, with reactive, breakdown-driven maintenance dominating practice at the time of the study [14]. The experience of the Nigerian petrochemical industry mirrors general industrial difficulties specifically issues with maintenance within the conventional Nigeria refining sector. In the country's conventional refining sector, prolonged maintenance problems and other operational constraints have historically contributed to low refinery capacity utilisation [15], a pattern also evident in the petrochemical sector's performance [16] and in construction and operational challenges documented across the refining industry over more than five decades [17]. These experiences demonstrate why maintenance strategy, equipment reliability and the wider operating environment need to be considered together when assessing advanced maintenance approaches in Nigeria.

Additionally, for process industries, the choice of predictive-maintenance technique is not necessarily a question of which technology provides the highest diagnostic capability [18]. Different techniques including vibration monitoring, infrared thermography, oil analysis, ultrasonic inspection and AI/ML-based approaches differ considerably in their requirements for instrumentation, data, specialist skills, infrastructure and maintenance planning [19,20]. Consequently, a technique that performs well under highly instrumented conditions may not necessarily be the most practical starting point for a plant where data history, specialist personnel or supporting infrastructure are limited [21]. Therefore, the assessment of PdM not only relates to technology performance, but also to the circumstances under which it will work long-term [19].

Despite the growing literature on predictive maintenance, there remains limited evidence on how major PdM techniques can be practically adopted in process plants where infrastructure, technical skills, data availability, spare-parts logistics and organisational capacity may affect implementation. Existing studies have largely focused on individual technologies or highly developed industrial settings, with less attention given to how these requirements interact under the operating conditions of developing economies such as Nigeria. This present study addresses this gap by examining five major PdM techniques and their practical requirements, while using a Polypropylene Production Unit (PPU) in Nigeria to provide an operational perspective on existing maintenance and condition-monitoring practices. The findings were used to develop a practical, phased approach for strengthening PdM capability in process plants operating under similar conditions. This study bridges the gap between the technical requirements of major PdM techniques with the operational

realities such as infrastructure, workforce, logistics, cost and organisational conditions that influence their practical adoption.

2. METHODOLOGY

The methodology adopted in this study combines a targeted narrative review of the literature with an operational case study of predictive-maintenance practices in a Nigerian polypropylene production facility. The literature review provides the basis for examining major predictive-maintenance techniques and the conditions affecting their adoption, while the case study provides an operational context for assessing their practical applicability. The review design, literature selection process and basis of the case study are described in the following subsections.

2.1 Review Design and Literature Search

This study adopts a targeted narrative literature-review approach to examine predictive-maintenance techniques, their implementation requirements and the barriers affecting their adoption in developing-economy process industries. A narrative approach is suitable for bringing together evidence from different study designs and application areas to provide a contextual understanding of a research problem [22] The review therefore focused not only on the technical capabilities of PdM techniques but also on the practical conditions required for their implementation and their relevance to the operational case study presented in Section 5. Literature was identified through targeted searches of Google Scholar, ScienceDirect, IEEE Xplore, MDPI, PubMed/PMC and Semantic Scholar. The searches used combinations of terms including "predictive maintenance", "predictive maintenance 4.0", "condition monitoring", "condition-based maintenance", "vibration analysis", "infrared thermography", "oil analysis", "ultrasonic", "acoustic emission", "machine learning maintenance", "Industry 4.0 adoption barriers", "process industry", "petrochemical", "refinery", "Nigeria" and "Africa". Reference lists of relevant review papers were also examined to identify additional studies that were directly relevant to the review.

2.2 Eligibility and Selection Criteria

The identified literature was considered for inclusion based on its relevance to the scope of the study. Sources were eligible when they addressed at least one of the five PdM technique areas examined in Section 3, the adoption barriers discussed in Section 4, or the Nigerian and wider African industrial-maintenance context considered in Section 5. Both primary research and review articles were included. Recent literature, particularly from the preceding five to ten years, was emphasised, while earlier studies were retained where they provided established foundations for the techniques reviewed. Credible institutional or industry sources were also considered where they provided relevant contextual or supporting information.Sources that were unrelated to industrial maintenance or condition monitoring, lacked sufficient technical information, or could not be verified through a publisher record, DOI or recognised academic indexing service were excluded. These criteria were used to maintain relevance and consistency in the selection of literature used in the review.

2.3 Screening, Verification and Case Study Basis

Following the eligibility assessment, the identified literature was screened initially by title and abstract, after which potentially relevant studies were assessed in full text. Candidate references were subsequently checked against publisher records, DOI information or recognised academic indexing services to confirm their bibliographic details and relevance [22]. Reference lists of relevant studies were also examined during this process to identify additional publications that met the selection criteria [23]. The literature review was complemented by an operational case study of a Polypropylene Production Unit (PPU) in Nigeria. The case study draws on the professional experience of one of the authors as plant personnel at the facility, supported by general process information from plant operating documentation. The case study examines existing maintenance and condition-monitoring practices and provides an operational basis for considering the practical applicability of the PdM techniques reviewed. In accordance with confidentiality requirements, proprietary process parameters, detailed equipment specifications, failure rates, downtime and maintenance-cost data are not reported.

3. PREDICTIVE MAINTENANCE TECHNIQUES

Predictive maintenance uses condition and performance information from operating equipment to identify developing faults and support maintenance decisions before functional failure occurs. Since equipment degradation can occur in different forms, no single monitoring technique is sufficient for all equipment or fault conditions. The choice of technique therefore depends on the type of equipment, the nature of the fault, monitoring requirements and available infrastructure. This study considers five major areas: vibration analysis, thermographic and infrared monitoring, oil and lubricant analysis, ultrasonic and acoustic-emission

methods, and artificial intelligence/machine-learning-based predictive models**.** The relationship between these techniques and their role within a predictive-maintenance framework is illustrated in Figure 1.

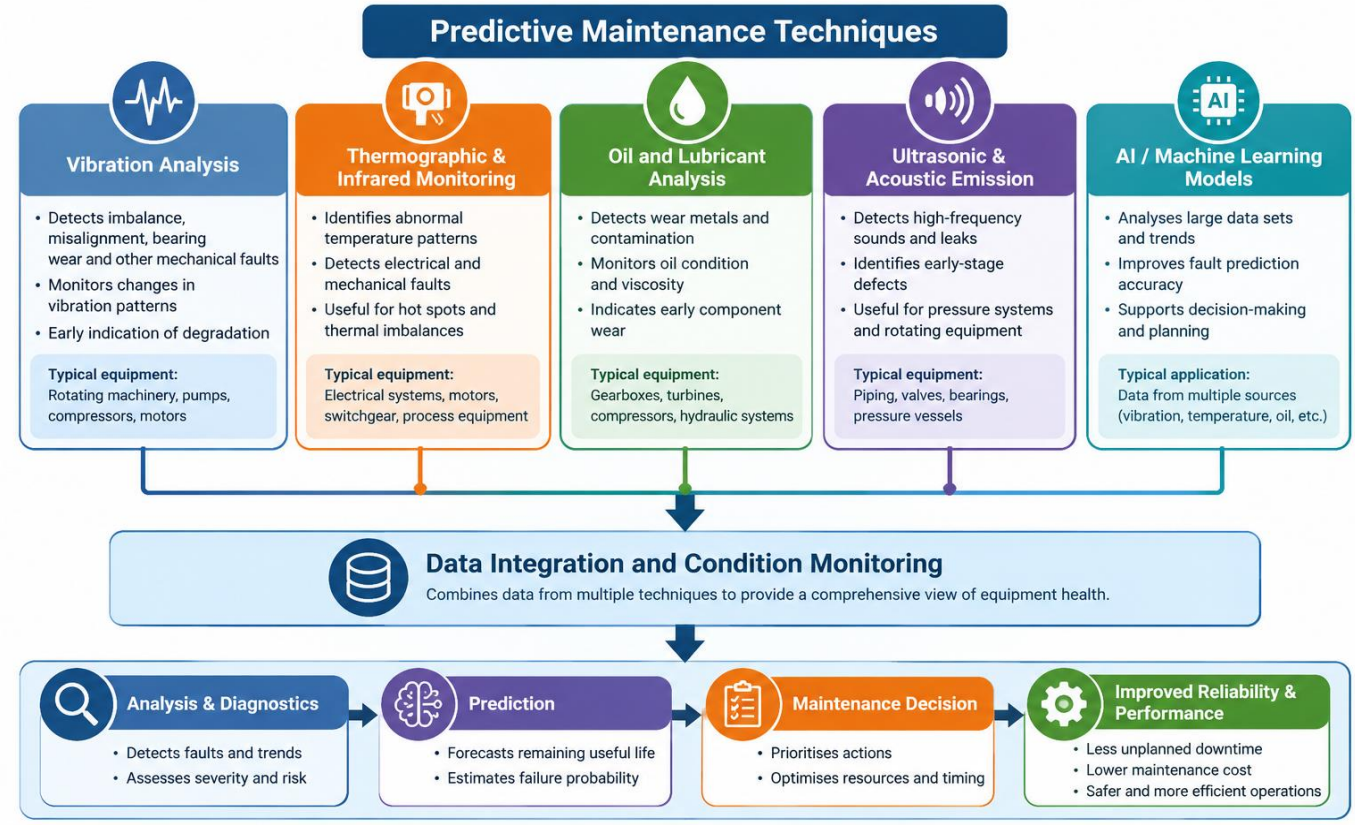


Figure 1: Predictive maintenance framework showing major condition-monitoring and predictive techniques (authors' synthesis).

3.1 Vibration Analysis and Condition Monitoring

Vibration analysis is one of the most established condition-monitoring methods for rotating equipment [24]. Changes in a machine's vibration behaviour can provide early indications of faults such as imbalance, misalignment, bearing deterioration and gear damage. Additionally, to monitor these changes, vibration measurements are commonly obtained using accelerometers, either through periodic portable measurements or permanently installed sensors for continuous monitoring of critical equipment [6]. The collected signals can then be analysed in the time and frequency domains to identify deviations from normal operating behaviour. Fast Fourier Transform (FFT) analysis is widely used to identify characteristic frequency components associated with mechanical faults [24,25]. For rolling-element bearings, envelope analysis can provide further information by highlighting repetitive impact features associated with localised defects that may be difficult to distinguish in the raw vibration signal [26]. Beyond these conventional signal-processing methods, vibration data can also be combined with statistical and machine-learning techniques to support automated fault detection and diagnosis [6]. The effectiveness of such approaches however, depends on the quality of the data, operating conditions and the availability of representative fault patterns. Consequently, vibration monitoring is particularly useful in process plants with substantial rotating equipment, especially when the resulting information is systematically analysed and incorporated into maintenance decisions.

3.2 Thermographic and Infrared Monitoring

Infrared Thermography (IRT) is a useful non-contact technique for detecting irregular surface temperature patterns that might signal growing equipment problems. Thermal imaging can help technicians identify problems in electrical systems, including poor electrical connections, load imbalance and inadequate insulation, before failure occurs [27]. IRT's ability to perform diagnostics on live electrical system and equipment means that the inspection can be conducted as required without having to shut down a component or physical contact [27]. Beyond regular inspection, the application of IRT can be further enhanced through the use of machine learning and automated image processing techniques. Venegas et al. [28] developed a system that used thermal images and machine learning to identify abnormal conditions in industrial equipment and reported a classification accuracy of 94% for the system evaluated. This result demonstrates the potential for combining thermographic inspection with automated analysis, although the reported performance relates to the specific equipment, dataset and experimental conditions of that study rather than to

IRT generally but shows how machine learning integrated into IRT can be a promising technique for condition monitoring of devices for which abnormal thermal behaviour correlates with degradation [28].

3.3 Oil and Lubricant Analysis

Oil analysis provides information on both lubricant condition and the condition of the machine in which it operates. Wear particles, contamination and changes in lubricant properties can be identified using oil analysis, providing evidence of developing problems in components such as bearings, gears and other lubricated surfaces [29]. It is particularly useful where mechanical deterioration produces changes in the lubricant before the equipment reaches a severe failure condition. Ahmadi and Mollazade [30] demonstrated the use of repeated oil sampling and analysis for monitoring machine condition and informing maintenance decisions, showing how oil-condition information from repeated oil sampling, alongside operating data, is used for the specification of maintenance actions. Oil analysis is commonly performed through periodic sampling and laboratory examination, although online and in-line sensing technologies are increasingly being developed for parameters such as wear debris, moisture and lubricant properties [31,32]. These approaches can provide more frequent information on equipment condition, but their value depends on appropriate sensor selection, sampling practice and interpretation of the resulting data. Oil analysis therefore provides a useful complement to vibration monitoring rather than a replacement for it. While vibration data provide information about the mechanical response of rotating equipment, lubricant analysis can provide additional evidence of wear and contamination within lubricated components [33]. Using the two methods together can therefore provide a broader picture of equipment condition, particularly for critical rotating machinery [34, 29]

3.4 Ultrasonic and Acoustic Emission Methods

Ultrasonic and acoustic-emission techniques are used to detect high-frequency signals generated by phenomena such as friction, impacts, leakage and material deformation [35]. It is commonly used in industrial maintenance for applications such as compressed-air and steam-leak detection, while contact-based ultrasonic or acoustic-emission measurements can monitor the progression of conditions in the development stages of wear in bearings and other mechanical equipment [36]. Their higher-frequency response can make them useful for detecting some localised or early-stage defects which may not be obvious from conventional vibration measurement [37]. Air-coupled and piezoelectric ultrasonic sensors were compared by Rezaei et al. [38] in a test carried out on rotating equipment with an accelerometer for bearing-fault detection under different shaft speeds and loads. Their results showed that acoustic features responded to changes in operating condition and fault severity with performance correlating to size of the fault, location of fault, and the signal-processing method applied [38]. This highlights that ultrasonic monitoring should be viewed as a complementary technique rather than a universal replacement for vibration analysis. Acoustic-emission signals can also be processed using advanced signal-analysis methods as observed by Gao et al. [39] who applied empirical wavelet transform and correlated kurtosis to bearing acoustic-emission signals and demonstrated effective identification of fault-related frequency information even with significant background noise [39]. This technique provides an additional diagnostic option for selected equipment and failure modes and when to deploy it in process plant environments depends on the form of defect, background process noise, optimal sensor positions and whether relevant signals can be distinguished from normal operational processes.

3.5 Artificial Intelligence/Machine-Learning-Based Predictive Models

Unlike the techniques discussed above, artificial intelligence and machine learning are not sensing methods rather they provide an analytical layer that use vibration, temperature, lubricant, process and other equipment data to identify abnormal conditions, classify fault states or predict a future condition. A systematic review by Carvalho et al. [8] shows the wide range of machine-learning methods applied to predictive maintenance, including supervised approaches such as support vector machines, random forests [40] and artificial neural networks, as well as unsupervised methods for detecting abnormal operating patterns. Additionally, the choice of machine-learning method depends on the features being analysed, the nature of the data and the problem being addressed [8]. Despite these challenges, the use of machine learning in condition monitoring has expanded alongside the availability of industrial sensor data. Phan et al. [41] found that research in this area is concentrated around established machine-learning approaches, while techniques such as reinforcement learning and transfer learning remain less represented. The study also identified growing interest in hybrid approaches that combine different learning methods [41]. Khan et al. [42] identified technical capability and economic considerations as important factors influencing predictive-maintenance adoption in SMEs, in addition to the choice of technology. Furthermore, due to limited availability of labelled failure data in an industrial predictive maintenance scenario, real equipment failures are relatively rare, even though routine operations usually involve vast amounts of operational data. Hakami [43] addressed this problem using synthetic data generation with a generative adversarial network, combined with temporal feature extraction using long short-term memory networks. The study demonstrates how machine-learning techniques can be used to address data scarcity and class imbalance, but also shows that such approaches still require sufficient

real equipment data to train the models effectively [43]. For process plants, effective AI/ML-based PdM therefore depends not only on a certain type of algorithms but it also requires reliable sensor data, historical maintenance records, appropriate data storage and the technical capability to develop, validate and maintain the models [8,41,43]. Table 1 summarises the main characteristics and implementation requirements of the reviewed PdM techniques.

Table 1: Comparative Summary of Predictive Maintenance Techniques

Technique	**Typical Applications**	**Primary Condition Information**	**Relative Cost**	**Data/Infrastructure Requirement**	**Typical Detection Threshold**
Vibration analysis	Pumps, compressors, turbines, gearboxes, motors	Imbalance, misalignment, bearing and gear deterioration	Medium–High	Accelerometers, vibration analyser/software, trained personnel [6,24,26]	Early-to-moderate stage; effective once measurable defect frequencies emerge (e.g., developing bearing or gear wear)
Infrared thermography	Electrical equipment, motors and selected process equipment	Abnormal temperature patterns, overheating, thermal imbalance	Medium	Handheld or fixed IR camera, appropriate thermal baselines [27,28]	Moderate stage; detects once a measurable thermal anomaly relative to baseline has developed
Oil and lubricant analysis	Gearboxes, compressors, hydraulic systems and other lubricated equipment	Wear debris, contamination and lubricant degradation	Low–Medium	Sampling points, laboratory analysis or suitable online sensors [29,30]	Early stage; wear particles and contamination can appear in the lubricant before mechanical symptoms become detectable
Ultrasonic/acoustic emission	Leak detection, bearings and selected mechanical components	High-frequency emissions associated with leakage, friction or localised defects	Low–Medium	Ultrasonic/AE sensors, portable instruments, trained personnel [38,39]	Very early stage for slow-speed or lubrication-related bearing defects; can register before comparable signs appear in a conventional vibration spectrum
AI/ML-based models	Cross-cutting application to equipment and process data	Anomaly detection, fault classification and predictive assessment	Medium–High	Historical condition/failure data, data infrastructure, computing and modelling capability [8,41,43]	Variable; depends on model training data quality and the maturity of historical failure records

Note: Relative cost refers to the overall cost of implementing and operating each technique, including monitoring equipment, installation, data acquisition and analysis requirements. Low indicates relatively limited investment and operating requirements, Medium indicates moderate investment and operating requirements, while High indicates substantial investment, infrastructure or specialist resources compared with the other techniques considered.

4. ADOPTION BARRIERS, COST-BENEFIT, AND IMPLEMENTATION FRAMEWORKS

Although the PdM techniques discussed in the previous section can provide useful information on equipment condition and developing faults, their successful application depends on the conditions under which they are implemented. In process plants, these conditions include the availability of suitable infrastructure and instrumentation, technical skills, reliable data, spare-parts supply and organisational support. Additionally, the cost of monitoring systems and the expected benefits also influence decisions on where and how PdM should be introduced. This section therefore examines the main barriers to PdM adoption and the practical

considerations that influence its implementation in process industries, particularly in developing-economy settings.

4.1 Infrastructure and Instrumentation Constraints

Successful predictive maintenance depends on several factors, including the availability of reliable condition data, effective means of transferring, storing the resulting information and suitable sensing infrastructure [44,45]. The infrastructure requirement is not limited to only installing individual sensors but also include power system, communication networks, data storage and suitable interfaces with existing control or maintenance systems [44]. Additionally, where these supporting infrastructure is not extensive, poor data collection or difficulties in integrating information from different sources can undermine the benefits of PdM programme [44,46]. Furthermore, the cost and availability of dedicated condition monitoring equipment also pose challenges to implementing PdM as online vibration monitoring, oil-condition sensors, and other dedicated devices often require specialised installation setup and technical support thus increasing both upfront costs and long-term maintenance expenses [7]. Khan et al. [42] identified data availability, cost, PdM management, and skilled personnel as the barriers to PdM adoption in SMEs. However, for modern large-scale process plants, the major challenge is often not a lack of instrumentation, as modern facilities already have extensive sensors, alarms, and process-control systems. The challenge is ensuring that the data generated by these systems are consistently captured, integrated, and made available for condition assessment and maintenance decision-making [44]. This distinction is important because where data from instruments are poorly collected or does not converge into a centralized and cohesive form then the instrumentation itself has no power to facilitate PdM.

4.2 Workforce and Technical Capacity Gaps

The effectiveness of condition monitoring depends not only on the availability of sensors and data but also on the ability of maintenance personnel to interpret the information correctly [42]. Vibration spectra, thermal images, lubricant results and ultrasonic signals can all contain information about equipment condition, but distinguishing a developing fault from normal variation requires appropriate technical knowledge [47]. The challenge becomes broader when we attempt to employ machine learning approaches, since their implementation requires skills in data preparation, model development, validation and interpretation in addition to conventional maintenance expertise [47]. Moreover, experience from some developing manufacturing also suggests that workforce capability is closely connected to the wider organisational conditions for PdM adoption. Peter et al. [48], using interviews with industry experts and survey data from Tanzanian manufacturing organisations, found that factors including equipment-data utilisation, resource availability, organisational culture, perceived benefits, strategic decision-making and perceived risk were significantly associated with PdM 4.0 adoption. A systematic review of PdM 4.0 in Tanzanian manufacturing similarly identified the poor level of implementation in the sector and identified the need for human capacity building alongside improvements in digital infrastructure and implementation frameworks [9]. A comparable pattern has been reported within Nigeria specifically: Okokpujie et al. [49] examined maintainability and reliability challenges facing Nigerian manufacturing under Industry 4.0 and identified inadequate technical skills, infrastructural deficits and organisational readiness as principal barriers to improved maintenance practice. This reinforces the fact that acquiring monitoring equipment alone is not sufficient and unlikely to establish a sustainable PdM programme. Personnel must be able to interpret condition data, connect abnormal trends with equipment behaviour and translate the findings into appropriate maintenance actions. Additionally, for AI/ML-based systems, this capability extends further to data management and model oversight [42]. The practical challenge is therefore not simply only a shortage of technical skills, but the need to develop a maintenance workforce capable of combining equipment knowledge with the increasingly data-driven methods used to support maintenance decisions.

4.3 Spare-Parts Logistics and Supply Chain Limitations

Detecting a developing equipment fault does not by itself prevent equipment downtime. The maintenance team must also be able to respond within the available planning window, which depends partly on the availability of the required spare, replacement component or specialist service. The supply duration can therefore reduce the effectiveness of Condition Monitoring, particularly for critical equipment where continued operation depends on the timely replacement of a failed component. This issue is relevant to the Nigerian refining context, where supply-chain constraints have historically contributed to operational disruption. Ogbuigwe [15], citing an analysis of Nigeria's refining sector, reported that supply-chain issues accounted for 53% of unplanned refinery shutdowns, compared with 47% attributed to equipment failure. Although this finding relates specifically to the historical performance of Nigeria's state-owned refineries and should not be generalised to all process plants, it illustrates the extent to which equipment availability can be influenced by factors beyond the physical condition of the equipment itself [15]. The relationship between maintenance planning and spare-parts availability is also recognised in the maintenance and inventory literature. Scarf et al. [50] demonstrated the close relationship between maintenance planning and spare-parts availability, particularly where component demand and replenishment times are uncertain. In process plants,

reliability-based maintenance approaches emphasise equipment criticality when determining maintenance priorities and spare-parts requirements [20], a link also demonstrated in reliability-centred maintenance models developed specifically for refinery electrical systems, where criticality-based fault prioritisation is used to guide both maintenance and spares planning [51]. For PdM, detecting a developing fault should therefore trigger not only a maintenance assessment but also a decision on whether the required spare should be inspected, reserved or ordered [50]. Condition monitoring therefore provides the greatest operational value when it is linked to maintenance planning and the plant's spare-parts strategy

4.4 Cost-Benefit and ROI Considerations

The economic justification for predictive maintenance depends on more than the cost of monitoring equipment. A comprehensive assessment would need to consider the expected reduction in failures and downtime alongside the costs of sensors, data infrastructure, software, specialist analysis, training and ongoing maintenance of the monitoring system. The relationship between maintenance decisions and spare-parts requirements further means that the economic assessment should account for both the probability and consequence of equipment failure, rather than treating monitoring as an isolated investment [42],[50]. This becomes more challenging where historical maintenance and failure records are unavailable. Additionally, accurate predictions cannot be made if no reliable data is available on failure rates, times between failures, downtime duration, repair costs and equipment priority. Khan et al. [42] identified financial considerations as an important aspect of PdM adoption, while the broader predictive-maintenance literature also points to the importance of data availability in evaluating and implementing PdM systems [8,42]. Consequently, a conventional ROI calculation based on assumptions from another plant or operating environment may not accurately represent the economics of implementation in a different process plant. Therefore, economic assessment of PdM should be linked to the specific operating reality of the plant. Several factors including equipment criticality, failure consequences, existing monitoring capability, spare-parts availability and the cost of maintenance interventions influence whether additional monitoring provides sufficient value to justify its implementation. Overall, rather than assuming that every critical asset requires the same level of monitoring, a practical framework would identify where additional condition-monitoring capability is most likely to reduce maintenance risk or avoid significant production losses. This provides a basis for comparing the cost of different PdM options with their expected operational benefit.

4.5 Organisational and Change-Management Barriers

A shift from predominantly time-based or reactive maintenanceto condition-based maintenance is not just a technological challenge. It also requires changes in how maintenance information is interpreted, communicated and acted upon. Karuppiah et al. [12] identified several organisational barriers to sustainable predictive maintenance, including limited management commitment, the lack of performance-standardization systems, poor coordination between technologies and departments, and lack of awareness about the benefits of condition-based maintenance and resistance to organisational change. The study also emphasised that these barriers are interconnected rather than independent [12]. This is an important consideration in the successful implementation of PdM, since having monitoring capability alone does not guarantee that the resulting information will improve maintenance decisions. A plant may have suitable sensors and technically competent personnel, but will remain limited if the information generated by the monitoring system is not incorporated into maintenance planning and operational decisions. For example, an abnormal vibration trend might tell us about an emerging pump problem, but the value of this information does solely depend on whether maintenance personnel can assess the finding, obtain the required spare, plan the intervention and coordinate the work with production. PdM therefore needs to become an integral part of the existing maintenance and operational system rather than as a stand-alone monitoring activity [44]. The barriers discussed in Sections 4.1–4.5 varies and do not affect every monitoring technique to the same extent. Route-based vibration monitoring, periodic thermography, oil analysis and ultrasonic inspection require minimal initial additional infrastructure, compare to continuous online monitoring and AI/ML-based systems which require greater investment in sensing, data management, analytical capability and organisational coordination. Table 2 presents a qualitative synthesis of these relative exposures based on the characteristics of each technique and the barriers discussed in this section.

Table 2: Qualitative assessment of condition-monitoring techniques against the adoption barriers identified in this review

Technique	Infrastructure / Power	Workforce / Skills	Spare-Parts Logistics	Cost-Benefit Uncertainty	Organisational Change
Vibration analysis (route-based)	Low	Medium	Medium	Medium	Medium
Vibration analysis (continuous online)	High	Medium–High	Medium	Medium	Medium
Infrared	Low	Low–	Low	Low	Low

thermography (periodic survey)		Medium			
Oil and lubricant analysis	Low	Low–Medium	Low–Medium	Low	Low
Ultrasonic / acoustic emission	Low	Low–Medium	Low–Medium	Low	Low
AI/ML-based predictive models	High	High	Medium	High	High

Note: Ratings represent a qualitative synthesis of the infrastructure, skills, data, maintenance-planning and organisational requirements discussed in Sections 3 and 4. Low indicates limited additional requirements beyond existing maintenance practices; Medium indicates a moderate need for additional resources, technical skills, data management or organisational support; and High indicates substantial requirements for infrastructure, specialist skills, data availability, system integration or organisational change. The ratings are comparative assessments and are not empirical scores or numerical measurements of adoption difficulty.

5. OPERATIONAL CONTEXT AND MAINTENANCE PRACTICES IN A NIGERIAN POLYPROPYLENE PRODUCTION FACILITY

The application of predictive maintenance in process industries depends on the existing equipment, maintenance practices, condition-monitoring activities and availability of operational data. This section presents the operational context of a Polypropylene Production Unit (PPU) in Nigeria and examines the maintenance and condition-monitoring practices observed during commissioning and plant operation. The study considers the types of equipment monitored, the condition indicators available to maintenance personnel and how maintenance decisions are currently made. It also identifies the existing practices that can support a gradual transition towards a more integrated predictive-maintenance approach.

5.1 Operational Context

The Polypropylene Unit (PPU) considered in this study is a continuous process facility consisting of two operating trains, Train A and Train B. The unit contains different rotating and static equipment supporting the polymerization process, material handling and associated process functions. Equipment encountered during the study includes pumps, compressors, reactors, extruders, gearboxes, motors, conveying systems, blending silos, pelletising equipment, heat-transfer equipment, valves, lubrication systems and sealing systems. The extrusion section also includes specialised equipment such as extruder barrels, die plates, screen-pack changers, screw conveyors and pelletising-water systems.

The maintenance environment combines preventive, corrective and condition-monitoring activities. Daily Look, Listen and Feel (LLF) inspections provide an initial means of identifying abnormal conditions such as unusual noise, temperature changes, leakage, vibration and other visible changes in equipment behaviour. Where an abnormality is observed, further inspection or specialised condition-monitoring techniques are initiated. The PPU also has extensive instrumentation for monitoring operating conditions. Temperature, pressure and other process variables are continuously monitored through installed sensors and control systems, with alarms and protective trips for defined abnormal conditions. The control room therefore provides an important source of operational information when process trends indicate changes in equipment or system behaviour. However, the use of this information for maintenance prediction is not yet equivalent to a fully integrated AI- or data-driven PdM system. Maintenance decisions still rely substantially on field observations, scheduled maintenance, engineering judgement and targeted condition-monitoring investigations [52].

The two-train configuration also affects equipment criticality. Several process services have running and standby equipment, enabling the standby equipment to be placed in service when an operating unit develops a fault or requires maintenance. This reduces the immediate production consequence of failure for some pumps and similar equipment. However, it does not provide the same protection for equipment without equivalent standby capacity. An extruder trip, for example, can cause significant process interruption, while failure of certain larger compressors such as Off gas compressor may have wider consequences depending on the nature and severity of the fault. Equipment criticality therefore depends not only on the probability of failure but also on redundancy, production consequence, safe-operating requirements and restoration time. This provides a practical basis for directing condition-monitoring resources towards equipment where earlier fault detection is likely to provide the greatest benefit. Such criticality-based selection is consistent with reliability-based maintenance approaches for process plants [20].

5.2 Maintenance and Condition-Monitoring Practice

Maintenance Practice in the PPU combines scheduled preventive maintenance, corrective intervention and targeted condition monitoring. Planned maintenance schedules are used for rotating equipment, while daily

LLF inspections provide a routine means of identifying abnormal conditions. Corrective maintenance is carried out when equipment breakdown occurs or when inspections indicate that action is required while specialised condition-monitoring techniques are generally introduced when an abnormal condition is identified or when additional information is required to assess equipment condition. For rotating equipment vibration monitoring is considered one of the primary methods for condition monitoring [53]. In one observed scenario in this case study, an abnormal noise or change in equipment behaviour led to a vibration assessment of the equipment, which identified a bearing-related problem and was followed by maintenance intervention. This reflects the diagnostic role of vibration analysis in identifying developing faults in rotating machinery, as reported in previous studies[53,54,55].

Additionally, Oil analysis, thermography, and ultrasonic inspection are also applied similarly targeted for the purposes outlined above. There is already a sensor indicating temperature conditions, while thermographic inspections are undertaken when an abnormal thermal condition requires further investigation. Oil sampling and analysis have also been used during equipment-related activities, including lubricant flushing and cleanliness verification during pre-commissioning. The usage of ultrasonics and borescopes inspection will generally occur if other techniques provide too little information to judge the condition correctly [38]. For example, when a process line experienced suspected blockage or restricted passage in one of the reaction area, borescope inspection was used to examine the internal condition, consistent with established non-destructive testing practice for internal condition assessment [56].

The existing practice incorporates many aspects of condition-based maintenance. Therefore, the main limitation is not the absence of monitoring technology but the way the information is currently used. A primary driver for the current condition monitoring activities is an observed anomaly or a maintenance need or an engineering suggestion. A more systematic approach could combine historical condition-monitoring results, process data trends and maintenance records to identify degradation patterns earlier. This distinction is consistent with the broader condition-based maintenance framework described by Jardine et al. [24].

5.3 Maintenance Experience from Commissioning and Operation

The maintenance experience considered in this study extends from pre-commissioning, commissioning and to the operational life. The mechanical activities during pre-commissioning and commissioning includes mechanical assembly installation and verification, hydrostatic testing, asset-integrity checks, lubrication-system activities and lube-oil flushing. These activities provided opportunities to establish the initial mechanical condition of equipment and verify system readiness before start-up. During operation, maintenance activities involved both static and rotating equipment, including pump inspection and overhaul, alignment, mechanical-seal replacement, bearing replacement, troubleshooting, extrusion-equipment maintenance and inspection of heat-transfer equipment. These experiences show that equipment degradation does not occur through a single parameter but it depends of failure mechanism. The initial indication may be a change in noise, temperature, pressure, vibration, leakage, process performance or visual condition [57]

Additionally, several examples from PPU operation further support this finding, a deterioration observed in the heat-transfer performance of an interstage heat exchanger led to further inspection and cleaning after fouling was suspected. In another case, a significant drop in mechanical-seal pressure prompted investigation, which confirmed seal damage and required replacement. Bearing deterioration was also identified through abnormal operating indications and subsequent inspection after which the affected bearing was replaced.

These different cases demonstrate how equipment problems are currently identified through a combination of operator observations, process trends and targeted condition-monitoring activities rather than relying on a single monitoring technique [57]. Furthermore, they also highlight an opportunity for PdM practice by systematically recording these observations, inspection results and maintenance findings as equipment history, allowing developing faults to be identified earlier and maintenance decisions to be better informed [58]

5.4 Current State and Opportunity for Predictive Maintenance

The PPU maintenance environment observed in this case study combines preventive maintenance, corrective intervention, routine look-listen-feel (LLF) inspection and targeted condition monitoring. Process instrumentation provides continuous operating information, while vibration analysis, oil analysis, thermography and ultrasonic inspection are used when further investigation is required. These activities provide a useful foundation for PdM, but are not consistently organised around routine data trending and predictive analysis, consistent with the condition-based maintenance framework described by Jardine et al. [24]. In practice, condition-monitoring activities are often initiated by abnormal observations, maintenance recommendations or specific equipment concerns.

The main opportunity is therefore to make better use of the condition and maintenance information already generated by the plant. Vibration measurements, process trends, temperature and pressure data, inspection findings and maintenance records can be analysed together to identify changes in equipment condition over time, consistent with the value of maintained equipment histories for maintenance planning [58]. A gradual transition is more appropriate than installing continuous monitoring across all assets, with greater attention

given to equipment where failure could cause significant process disruption, such as extruders and selected large compressors, in line with criticality-based prioritisation approaches to maintenance planning [20,51]. The proposed pathway in Figure 2 therefore begins with reliable data collection and periodic monitoring, followed by selective online monitoring and, where sufficient data and infrastructure exist, AI/ML-based predictive models.

5.5 Future Trends and Study Limitations

Recent developments in PdM are increasingly focused on improving how equipment condition data are collected, processed and used for maintenance decisions. Connected sensors and industrial Internet of Things (IIoT) technologies support more continuous data collection, while edge computing enables faster processing of data closer to the equipment [7]. Digital twins and advanced artificial intelligence and machine-learning (AI/ML) models are also being explored for condition prediction and remaining-useful-life estimation [7,52]. However, the effective application of these technologies requires reliable data, adequate infrastructure and personnel with the skills to implement and maintain the systems. The PPU case study is based primarily on operational observations and maintenance experience rather than statistical analysis of plant reliability. Detailed failure rates, equipment downtime, maintenance expenditure, facility age and long-term maintenance history are not reported because of confidentiality and data-access restrictions. The findings are therefore intended to describe the existing maintenance and condition-monitoring environment and identify practical opportunities for PdM adoption, rather than provide a quantitative assessment of plant reliability or the financial performance of a PdM programme.

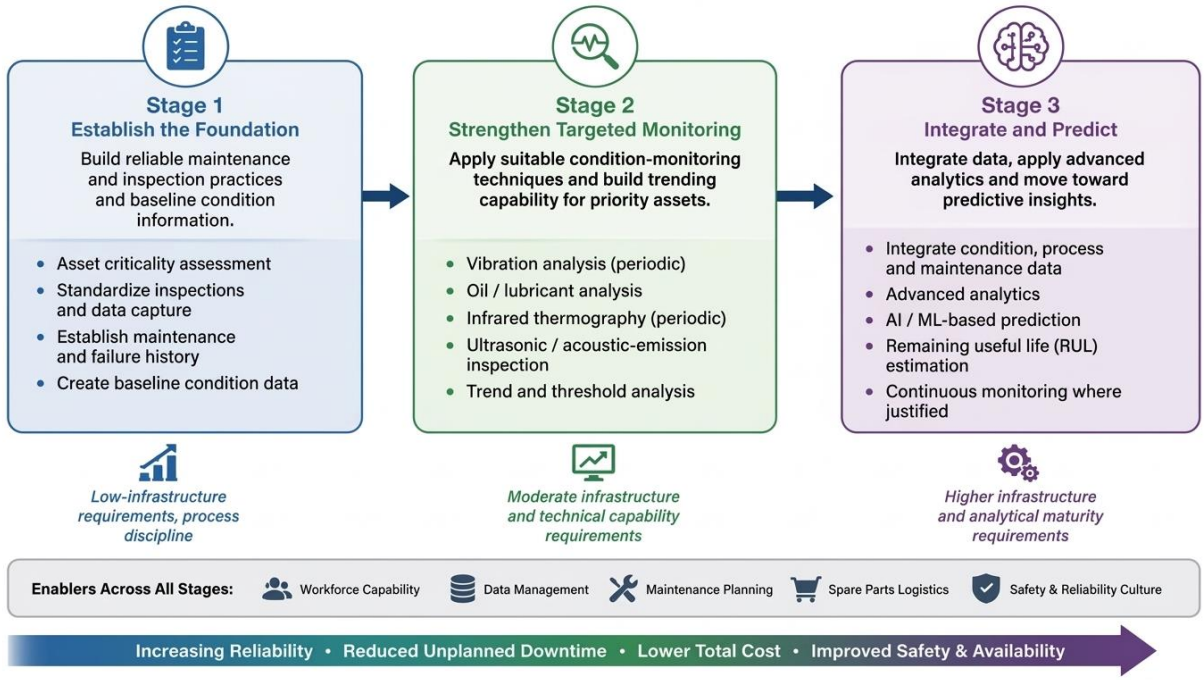


Figure 2: Recommended phased predictive-maintenance adoption pathway for infrastructure-constrained process plants (author synthesis).

6. CONCLUSIONS

This study examined predictive-maintenance (PdM) techniques in relation to the practical conditions that influence their adoption in process plants operating under infrastructure, skills, logistical and organisational constraints. The review shows that the suitability of a PdM approach depends not only on the capability of the monitoring technique but also on the type and criticality of the equipment, the availability and quality of condition data, and the plant's ability to act on detected degradation. PdM is therefore better considered as a maintenance strategy that develops according to the operational and technical capacity of the plant rather than as a single technology to be adopted as a complete system.

The PPU case study illustrates that a process plant can have a useful foundation for PdM through existing preventive and corrective maintenance practices, field inspections, process instrumentation and targeted condition monitoring. The main opportunity identified is to make better and more systematic use of the operational, inspection and maintenance information already generated by the plant. A gradual approach is therefore proposed, beginning with reliable equipment histories and condition data for critical assets, followed by improved periodic monitoring and trend analysis, and progressing to continuous monitoring and AI/ML-based prediction where sufficient data, infrastructure and technical capability are available. This

approach also recognises that monitoring requirements should reflect equipment criticality, since assets whose failure can interrupt production may require greater attention than equipment supported by effective standby arrangements.

The study is limited by the absence of detailed plant-level failure, downtime, maintenance-cost and long-term reliability data because of confidentiality and data-access restrictions. The findings should therefore be interpreted as a practical assessment of PdM applicability rather than a quantitative evaluation of plant reliability or economic performance. Future research should build on this work through longitudinal plant-level studies that relate condition indicators to maintenance interventions, equipment downtime and lifecycle cost. Such data would support the development of locally relevant cost-benefit models and provide a stronger basis for selecting monitoring strategies for different categories of process equipment.

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