A Novel Prognostics and Health Management Framework to Extract System Health Requirements in the Oil and Gas Industry

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ABSTRACT

The paramountcy of Prognostics and Health Management (PHM) within the oil and gas sector is instrumental in ensuring safety, reliability, and economic efficiency by optimizing system availability. However, a prevalent industrial challenge is the lack of a comprehensive identification of health management requirements from actual operational situations. This study introduces an innovative Prognostics and Health Management Framework (PHMF), encompassing a methodical procedure to discern health management necessities systematically. The PHMF consolidates structured causal factors, foundational elements of functional failure, and the antecedents of unplanned downtime, which collectively inform the PHM strategy.

This framework offers an integrated view of multiple dimensions of system health, facilitating accurate portrayal and proactive monitoring. It particularly underscores a reverse engineering approach to scrutinize the root causes of system failures and unexpected operational halts. To validate the practicality and efficacy of the PHMF, it has been applied to a real-world scenario: a lubrication oil system within a gas turbine equipment, thereby elucidating the specific PHM strategy prerequisites.

1. INTRODUCTION

Prognostics and Health Management (PHM) encapsulates diagnosing and forestalling system failure while appraising component reliability and residual service life (Shin & Jun, 2015). Zio (2016) delineates PHM as a research and application domain dedicated to detecting component degradation, diagnosing faults, forecasting failure timelines, and proactively orchestrating their mitigation. PHM transcends condition-based maintenance, focusing on prognostic methodologies to steward equipment health (Vrignat et al., 2022). According to Biggio and Kastanis (2020), PHM aims to furnish a comprehensive machinery health assessment. Hu et al. (2022) characterize PHM as a pivotal technology for sustaining reliable, efficient, cost-effective, and safe operational systems.

Furthermore, Vrignat et al. (2022) highlight its critical role in effective maintenance policy formulation. We interpret PHM as a condition-based monitoring paradigm aggregating multifaceted parameters influencing system health, thus offering a cohesive snapshot of its condition and forecasting abilities, as data permits, to preempt potential malfunctions. The prevailing challenge is articulating health management strategies and systematically deriving health management requisites from pragmatic operation scenarios (Hu et al., 2022). The primary inquiry of this study is the comprehensive identification of health management requisites informed by practical operation scenarios.

Reliability constitutes an item's competency to fulfill required functions under specified environmental and operational parameters for a designated timeframe (Hoffmann Souza et al., 2020). We use reliability theory and analytical tools to appraise system reliability via historical failure data, such as failure rates. Reliability growth, a crucial industry Key Performance Indicator (KPI), gauges system reliability enhancement and necessitates further inquiry upon stagnation. Reliability management promotes the minimization of functional failures and unscheduled downtime by implementing measures across assets, personnel, and processes.

Moreover, risk-based process safety persists as a formidable challenge in process industries. With a historical precedent spanning decades, digitalization augments process safety management across a system's lifecycle (Lee et al., 2019). Standardized terminologies and ontologies could foster a unified framework conducive to sharing digitalization benefits. Industry 4.0 heralds an integration and optimization era, exploiting contemporary technologies and modeling techniques to bolster process safety (Melesse et al., 2020).

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Subsequently, Asset Performance Management (APM) prioritizes asset reliability, availability, and maintainability while balancing cost, safety, and environmental impacts. One key performance metric in APM is downtime, where targeting problematic assets can lead to significant annual cost savings. Nonetheless, enduring risks are linked to material degradation, subpar execution of reliability management, variations in operating conditions, maintenance protocols, asset upgrades, and operational shifts. State-of-the-art practices have underscored the efficacy of Reliability Centered Maintenance (RCM) in devising asset maintenance strategies (Pliego Marugán et al., 2019). Developed initially in the aero industry in the early 1960s, RCM has become a prevalent methodology in asset management within the oil and gas sector (Nithin et al., 2021). Although widely adopted for its effectiveness, RCM is not without its drawbacks; it is often labor-intensive, qualitative, and reliant on subjective judgment regarding the prioritization of equipment.

Similarly, the industry harnesses diverse methodologies to garner insights into asset health, viewing it through discipline-specific KPIs and monitoring various critical items. Decision-making is informed by leading and lagging KPIs that provide data on system health. Traditional condition-based maintenance (CBM) is also utilized, employing predictive analytics to monitor specific equipment failure modes. Moreover, adhering to best reliability, operations, and maintenance practices can enhance overall performance and system health. Despite these efforts, there remains a need to refine decision-making by acquiring more comprehensive, real-time data on vital health parameters, including reliability issues, causal factors of failures, and their interrelated effects leading to unplanned downtime. Commonly, industry KPIs are lagging, reflecting past performance, such as system availability rates. Leading KPIs, while indicative of future performance, tend to be reported with less frequency—monthly or quarterly, at best. While helpful, CBM techniques, like vibration diagnostics or efficiency assessments, do not provide a complete picture, as they may overlook factors such as spare parts availability that can significantly extend downtime, an indicator of poor system health.

Burgeoning data availability, computational advancements, and methodological innovation increasingly drive reliability and physical asset management. Modern modeling frameworks typically integrate aspects of physics-based analysis, machine learning, and statistical learning (Yucesan et al., 2021). In this context, reliability risk-based approaches leverage data to shape maintenance strategies, placing big data and computing capabilities at the forefront, surpassing traditional human capacities. Nevertheless, challenges persist concerning the vast volumes of data and associated quality concerns, ranging from collection and storage to utilization (Campbell & Jardine, 2010). This paper addresses such challenges by proposing a Prognostics and Health Management (PHM) framework designed to systematically collect and harness data pertinent to health management requirements.

The ubiquity of system data, encompassing process and operational details, as well as historical maintenance records, has opened new avenues for advanced analytics, including predictive failure modeling. The nexus of system reliability and health status is critical for informed decision-making within corporations, especially as novel technologies like the Industrial Internet of Things (IIoT), cyber-physical systems, blockchain, and data mining are being deployed to bolster equipment uptime. Examining data in the realm of reliability is fundamental to empowering artificial intelligence-driven tools. Thus, maintenance-related challenges can be surmounted through increased digitalization and the resultant surge in data and insights. Digitalization, encapsulated in the Industry 4.0 movement, is transforming decision-making processes in industrial settings. Nonetheless, the deployment of data analytics has often proceeded without a rigorous, quantitative evaluation of the cost-benefit equation or a methodical approach to sensor deployment and data extraction (Para et al., 2019). With an emphasis on refining production processes, there is ample scope for advancement (Filz et al., 2021).

In this vein, PHM within the oil and gas industry is instrumental in ensuring safety and maximizing economic returns by maintaining optimal uptime and system reliability. PHM is pivotal in bolstering reliability across engineered systems, becoming a cornerstone in reliability enhancement (Nor et al., 2021). Notably, operational element degradation in manufacturing systems is inevitable due to fatigue and wear, leading to failures absent maintenance interventions (Levitin et al., 2021). Concurrently, an operator's capacity to rectify incipient issues to forestall functional failures and unplanned downtime hinges on their understanding and data about the system's health. Operators can circumvent process safety incidents and the ramifications of system failure and unavailability. Unanticipated downtime resulting from failures equates to substantial production losses and significant revenue depletion. Proactively monitoring asset conditions and human and process factors can refine decisions to mitigate critical failures and curtail unplanned downtime. Hence, a comprehensive and holistic health monitoring system can underpin operational and maintenance decision-making strategies.

Amidst declining oil prices and the reduced costs associated with deploying renewable energy resources, stringent cost control within capital and operational expenditures has become increasingly imperative, aligning with industry trends. Thus, advancing comprehensive PHM systems is critical, enabling cost savings by curtailing downtime and enhancing asset reliability. Furthermore, an all-encompassing PHM facilitates the progression of the digital twin (DT) paradigm, which optimizes asset management across various dimensions, yielding multifaceted benefits (Poddar, 2018).

While integrating artificial intelligence into PHM is a nascent trend in the oil and gas sector, certain implementations have already demonstrated tangible benefits (Koroteev & Tekic, 2021). Concurrent with the advent of Industry 4.0, the oil and gas industry is progressively embracing digital technologies to boost productivity, augment efficiency, and ensure safety, all while striving to reduce capital and operational costs, mitigate health and environmental risks, and manage asset life cycle variability (Wanasinghe et al., 2020).

Numerous challenges impede PHM's comprehensive implementation and utilization in practical settings (Zio, 2022). Current research in PHM spans various domains, including inspection and maintenance strategies (Mancuso et al., 2021), maintenance decision-making (GAO et al., 2021), manufacturing performance (Li et al., 2022), autonomous maintenance (Khan et al., 2020), data-driven prognostics (Manjurul Islam et al., 2021), generic frameworks (Booyse et al., 2020), fault diagnostics (Soualhi et al., 2020), lifespan prediction (Yang et al., 2021), and strategic decision-making (Choo et al., 2016; Bougacha et al., 2020). Nevertheless, these studies often tackle isolated disciplines—electrical, instrumentation, mechanical, and process—without a holistic understanding of "health" or considering the full spectrum of practical causal factors of failures and downtime as integral to PHM. Moreover, due to constraints on data accessibility, many limit the scope of PHM to the usage of real-time sensor data for prognostics. This narrow focus can result in gaps in health knowledge and omit critical monitoring of known causal factors, leading to failures and downtime.

Despite these limitations, the predictability of failures can improve with a more robust representation of actual health status, even identifying suboptimal systems before overt failures manifest. This predictability can be achieved by deriving features from correlated parameters. Thus, advancing a practical PHM approach is critical to minimize oil and gas industry downtime and costs. This research aims to pinpoint the requisites for a health management strategy and to comprehensively capture health management parameters from real-world industrial operations while embracing the ongoing digital transformation and the proliferation of data.

The article is organized as follows: Section 2 delves into the proposed Prognostics and Health Management Framework (PHMF), which serves as the foundation for determining the components of PHM. Section 3 outlines the methodology and procedural steps. Section 4 illustrates a case study that delineates the PHM strategy for a lubrication oil system on a gas turbine. Finally, Section 5 concludes the study with conclusions and recommends future research.

2. PROPOSED PROGNOSTICS AND HEALTH MANAGEMENT FRAMEWORK (PHMF)

This research proposes a methodology to systematically extract PHM requirements from operational scenarios in the real world, specifically targeting the root causes of failures and unscheduled downtimes, alongside considerations for system performance and efficiency. The aim is to equip practitioners with the means to identify and judiciously determine PHM needs effectively. Monitoring relevant elements is crucial to accurately reflect system health and address potential failures and unscheduled downtimes. The PHMF, depicted in Figure 1, is designed to fulfill these requirements. It is structured into twelve pillars that are in harmony with lean manufacturing and management principles, covering a broad spectrum of system, process, and human factors. The categorization into twelve distinct pillars provides an extensive perspective on possible causes of failures and downtime. It allows for specialized attention and engagement of various focus groups and professionals interested in each area. Moreover, it enables leadership personnel to segment the PHM into different pillars for more targeted diagnostics and corrective actions.

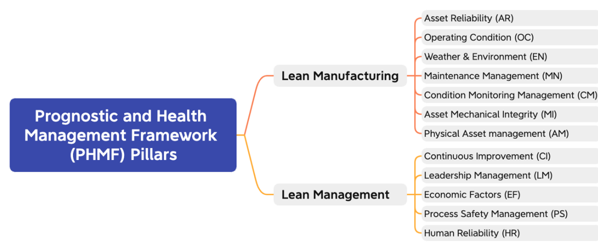

Figure 1: Proposed Prognostic and Health Management Framework (PHMF) Pillars

The PHMF we propose underpins identifying critical elements for inclusion in a PHM strategy, forming the foundational construct for understanding health-related concerns. The framework scrutinizes twelve critical pillars: asset reliability, operational conditions, weather, and environmental influences, maintenance and condition monitoring, asset mechanical integrity, physical asset management, continuous improvement, leadership, economic considerations, process safety, and human reliability. These pillars are integral to distilling parameters crucial for health monitoring, which are pivotal to constructing a health index within a quantitative framework. The twelve PHMF pillars delineate the determinants of a system's health status from the PHM perspective as either robust or compromised. For each pillar, a specific set of parameters is meticulously selected to reflect the system's health status practically, aiding in formulating strategies for efficient failure prevention and resource allocation. Moreover, as these parameters are data-driven, addressing the digitization challenges via PHMF in the industry will facilitate data gathering and enhance the effective deployment of PHM applications.

To explore the issue qualitatively, we conducted a thorough literature review and gathered insights from practitioners using interviews and a questionnaire. These instruments were developed with industry best practices and standards in mind for each PHMF pillar. An Expert Matter Ranking Framework was utilized to ascertain the applicability of the pillars as root causes of system failures and unplanned downtime, as depicted in Figure 2. The consensus among experts was high, affirming the relevance of the pillars within the framework. We surveyed twelve oil and gas industry specialists from Oman, soliciting their views on whether these twelve pillars constitute a comprehensive framework for PHM and whether they serve as direct or indirect causal factors for failures and downtime. Their assessments ranked on a scale from 1 to 10, yielded an average rating exceeding 7.45, reinforcing that the pillars contribute to failures and downtime.

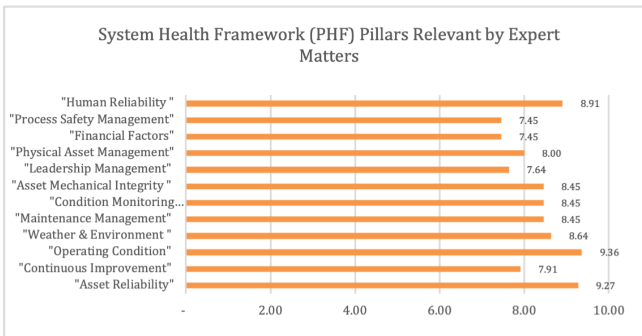

Figure 2: System Health Framework Pillars Relevant by Expert Matter

Therefore, the methodology recommended in section 3 for applying the PHMF entails an in-depth examination of system functions and health. It adopts a qualitative approach to pinpoint PHM requirements, facilitating the identification of potential systemic root causes of functional failures. Moreover, the PHMF methodologically reveals potential root causes of unplanned downtime while considering the economic and sustainability dimensions of system health as dictated by the system's design. The parameters identified through this methodology enable a deeper engagement with data collection, enhancing data quality, processing, and storage. This refined approach to data handling is essential for the subsequent development of reliable health indices.

The forthcoming subsections elucidate the twelve pillars that constitute the PHMF, detailing each pillar's definition, potential elements, associated limitations, data collection methodologies, and justifications for their inclusion. A data set must be identified for every pillar and its corresponding elements, which is targeted for monitoring and considered an integral part of the PHM input. Thus, for a given system j, a data set for a pillar at a specific time t, denoted as $U_{Pillar}^{j}(t)$ is compiled. This set consists of several parameters $x_n^{jT}(t)$ each tagged with a number T representing the specific asset or piece of equipment to which it pertains. Formally, this relationship is denoted as:

$$x_n^{jT}(t) \in U_{Pillar}^{j}(t) \tag{1}$$

Indeed, while this article delineates the scope of data collection within the PHMF, it is worth noting that data processing can encompass various types, such as numerical, discrete, continuous, categorical, or ordinal data. Moreover, methodologies for dataset usage, including sampling criteria, treatment of missing data, outlier detection, cluster analysis, and data standardization and normalization techniques, need to be systematically delineated. Although our current focus is on eliciting practical inputs for health management requirements, there is an undeniable impetus to expand future research to incorporate discussions on data propagation between systems, the identification of systems susceptible to failure without exhibiting explicit malfunctions, the determination of opportune timeframes for intervention, and the development of corrective strategies.

These parameters are vital for establishing an end-to-end process that elucidates the specifications for health management design. Moreover, these involve the comprehensive extraction and filtration of health management requirements derived from practical operational scenarios, ensuring a robust framework for health management within the industry.

2.1. Asset Reliability Pillar

Asset reliability serves as a pivotal decision-making criterion in industry, grounded in ISO 14224's definition of reliability: the capacity of an asset to perform as required, without failure, for a designated time frame under specified conditions, which is intrinsically tied to equipment or system failure events (ISO - ISO 14224:2006). Levitin et al. (2021) emphasized that reliability analysis, particularly of standby systems and their preemptive replacements, is a focal point of industry research efforts. This pillar integrates failure data as a core element of health management, empowering practitioners to comprehend system failure rates and initiate preventative designs for defects. Moreover, reliability growth is a critical KPI within the industry, gauging system reliability and signaling the need for in-depth analysis.

This pillar encompasses two primary elements: operational equipment and system reliabilities, offering insights from a reliability engineering perspective. These elements are predicated upon the failure rate, from which reliability is inferred probabilistically. Operational system reliability captures system redundancy, considering serial and parallel configurations in system reliability calculations. The oil and gas industry's data quality and collection practices substantiate this pillar's inclusion in PHM strategy development. Recognizing these elements provides a lens through which to assess reliability growth, determining whether it signifies a healthy or unhealthy system state.

2.2. Operating Condition Pillar

The operating condition pillar is focused on the state of process operating parameters, which can be either healthy, operating within the design envelope, or unhealthy, deviating from established design limits. This aspect of operational health is a critical requirement in PHM, and it has been prominently featured in numerous pivotal studies. Research by Al-Anzi et al. (2022), Liu et al. (2020), and Aizpurua et al. (2019) has incorporated the tracking of process parameters within the PHM framework. The root causes of deviations from healthy operating conditions are typically associated with identified failure modes connected to functional failures.

Proactive monitoring of these parameters and the early detection of abnormalities are crucial to preventing failures and addressing issues before they result in functional failure. This pillar thus underpins the broader scope of practical health management requirements within PHM. Data collection in this domain predominantly utilizes real-time sensors, though manual inputs, such as gauge readings, are still relevant for specific failure mode detections. In oil and gas facilities, commonly monitored process elements include pressure, temperature, flow, valve positions, equipment status, electrical parameters, system fault alarms, gas chromatograph readings, and oil specification parameters. This data is primarily numerical and continuous, captured through real-time sensor technology.

2.3. Weather & Environment Pillar

The weather and environment pillar examines environmental factors influencing system operations or contributing to specific functional failure modes. This pillar is significant not only for its role in understanding how weather conditions can affect asset performance but also for its impact on emissions that deviate from design parameters. Such factors are integral to providing a complete picture of a system's health. Moreover, this pillar addresses the crucial aspect of environmental greenhouse gas emissions, recognizing their relevance in assessing overall system health. Incorporating these environmental parameters into health management requirements is vital for accurately depicting system health and responding proactively to adverse conditions.

The data encompassed by this pillar might include real-time weather parameters, weather forecasts, and emission measurements pertinent to the system. Data points include ambient temperature, humidity, precipitation, wind speed, and UV index. Additionally, real-time sensors may monitor gases like NO_x, SO_x, CO_2, and H_2S for emission management. These measurements are typically continuous numerical values collected through real-time sensor networks.

2.4. Maintenance Management Pillar

System health is significantly influenced by its maintenance status, including the chosen maintenance philosophy or strategy, which is pivotal in restoring system reliability and functionality. Maintenance activities are the efforts to return a system to its functioning state. Maintenance management is a priority in the industry due to its impact on business performance and its significant share of the budget. Monitoring the efficacy of maintenance practices is an integral component of holistic health management.

Nithin et al. (2021) advocated integrating probabilistic and statistical analysis with reliability-centered maintenance methodology to furnish quantitative, cost-effective asset maintenance solutions and failure predictions over time. Consequently, health management informs maintenance decision-making, such as condition-based maintenance, which is prevalent for estimating the useful life of assets. This pillar includes elements such as maintenance compliance, the status of work orders pending materials or awaiting shutdown, workforce effectiveness and utilization rates, the proportion of jobs completed on time, job closures, rework instances, the balance between planned and unplanned work, maintenance quality control, and mean time to repair.

Industry best practices leverage computerized maintenance management systems (CMMS) to administer and archive data, which can serve as input for PHM. These parameters are indispensable for depicting the comprehensive health of maintenance management practices. Ineffective maintenance management can lead to system failure and downtime, directly or indirectly, and is a justified component of the PHMF. A PHM framework that encapsulates maintenance management elements is considered thorough and provides valuable insights for more informed decision-making.

2.5. Condition Monitoring Management Pillar

Condition Monitoring Management is an integral part of a condition-based maintenance strategy, which focuses on ongoing equipment and system health assessment to inform maintenance actions. Hanachi et al. (2018) highlighted the importance of asset health monitoring as a cornerstone of condition-based maintenance, where the prognostic framework for predicting the remaining useful life is crucial for health monitoring, diagnostics, and prognostics of an asset.

This pillar encompasses various data derived from condition monitoring or predictive maintenance techniques, including but not limited to vibration analysis, lubricant testing, ultrasound assessments, thermographic inspections, performance monitoring, and efficiency evaluations. Additionally, front-line maintenance, often called operator rounds, leverages human observational capacity to identify failure signs preemptively. Effective implementation of these rounds can avert functional failures and minimize downtime.

Incorporating these condition monitoring tools as part of PHM input is essential for accurately reflecting the actual health status of a system. Any abnormalities these tools detect indicate potential system health issues that necessitate preventive actions to avert failures and downtime. Data acquisition from these tools can be conducted manually or via automated sensors, and their analysis plays a critical role in maintenance decision-making processes.

2.6. Asset Mechanical Integrity Pillar

Asset mechanical integrity is a critical aspect of system health that significantly influences downtime and can potentially affect safety and environmental compliance. A comprehensive system health assessment necessarily includes an evaluation of an asset's mechanical integrity. Under industry standards, mechanical integrity programs cover the asset's entire lifespan, from design to life extension and eventual decommissioning. A thorough understanding of mechanical integrity is essential for making timely decisions on repairing or replacing assets, thereby ensuring system reliability.

Mechanical integrity primarily pertains to pressure vessels, piping systems, heat exchangers, storage tanks, and pressure relief devices. Processes integral to mechanical integrity include risk-based inspections, fitness-for-service assessments, identification of damage mechanisms, and integrity operating windows, all aimed at ensuring adherence to relevant industrial standards. Yingchao et al. (2019) have focused on condition-based maintenance and the Remaining Useful Life (RUL) prediction to minimize unexpected downtime and maintain quality. Lyu et al. (2020) addressed PHM related to RUL estimates, a crucial aspect for assuring system safety and reliability, suggesting that RUL can be projected by analyzing past impacts and representing the system's historical degradation events in localized segments.

In the realm of mechanical integrity, being in a healthy state is synonymous with maintaining reliability and preventing unplanned downtimes. This PHMF pillar considers elements such as RUL estimations, regular non-destructive testing data, and compliance with inspection schedules. Actioning the recommendations from mechanical integrity inspections is vital and should be diligently monitored to influence system health positively. Compliance with these recommendations is, therefore, a requisite for PHM. Corrosion control is also a critical factor within this pillar, as it is imperative for maximizing RUL and averting failures. Parameters like integrity operating windows (IOW) conditions, cathodic protection status, and compliance with corrosion inhibitor injections are essential components that should be monitored as part of PHM.

2.7. Physical Asset Management Pillar

Physical Asset Management (PAM) is recognized for its substantial contributions to business value across various aspects. Regarded as one of the rapidly evolving engineering disciplines, PAM involves a complex interplay of activities and disciplines focused on planning and controlling the lifecycle of physical assets (al Marzooqi et al., 2019). With historical roots, the contemporary understanding of PAM pertains to the professional practices aimed at the stewardship of physical assets (Alhazmi, 2018). Reliability management, a component of maintenance excellence, is encapsulated within asset management, enhancing system dependability and predictability (Campbell & Jardine, 2010). Alhazmi (2018) developed a theoretical framework to deepen the understanding of PAM practices, drawing on established standards and guidelines. This framework showed that the logic underpinning the management of physical asset lifecycles is consistent across various PAM standards and guidelines.

PAM is also inextricably linked with risk management. For instance, Syed & Lawryshyn (2020) introduced a decision-making approach incorporating risk-informed perspectives within PAM, encompassing cost-benefit analyses and risk evaluation. Lu et al. (2020) pointed to the lack of efficient strategies and all-encompassing approaches to asset management, highlighting the need for a system that can monitor, detect, document, and correlate operational and maintenance issues effectively.

While many elements of PAM have been addressed in other pillars of the PHMF, there are still critical components to be considered, including document control, spare parts/ inventory management, and competency issues related to asset-related training. The data relevant to this pillar are predominantly digital and accessible, mainly when industry best practices are in place. It encompasses data related to human resources and document control systems. Such data is pivotal for monitoring conditions that may adversely affect systems, processes, and people, and it is integral to maintaining a holistic perspective on asset management within an organization.

2.8. Continuous Improvement Pillar

Continuous Improvement (CI) practices in manufacturing represent a dynamic, quality-centric approach. The American Society for Quality (ASQ) describes CI as "the ongoing improvement of products, services, or processes through incremental and breakthrough improvements." This concept aligns with the pursuit of operational excellence and reliability enhancement within manufacturing systems. Therefore, adopting CI practices involves a proactive stance on enhancing operations and entails compliance with CI protocols to mitigate failures and downtimes indirectly. Such compliance contributes to a healthier, more resilient system. Within this pillar, relevant elements include tracking the number of CI-recommended tasks over a specific period and monitoring task completion, especially the number of tasks overdue. Ensuring the timely closure of CI tasks is a testament to a commitment to system improvement and reliability, reinforcing the overall health and performance of the system.

2.9. Leadership Management Pillar

The leadership management pillar underscores the significance of leadership in day-to-day operations, which is crucial for ensuring system reliability and making successful decisions. Effective leadership that proactively prevents functional failures curtails losses and maximizes system utilization, uptime, and safety. Leadership issues may underlie functional failures, necessitating research to evaluate their impact on system health. Identifying leadership-related parameters within this pillar is the first step in this process.

This study posits that leaders with a strong influence can contribute to system health by providing clear direction and making decisions that mitigate the impact of failures and downtime. Thus, understanding the role of leadership is vital for gaining insights into its effects on the system. A challenge lies in capturing relevant data. For instance, the absence of an operations supervisor during a shift or a maintenance supervisor during a shutdown might indicate an unhealthy operational condition. Engaged leadership is associated with healthier operational states, reliability, and safety.

This research suggests that leadership involvement is a fundamental aspect that should be considered as part of PHM input. The positive impact of effective leadership is reflected in operational performance and business resilience. Additionally, enhancing a culture of reliability requires leadership backing to fortify system reliability. Leadership compliance with actions intended to cultivate such a culture and the closure of related tasks can lead to heightened operational excellence. Leadership endeavors and actions toward cultural enhancement should be incorporated within this pillar despite the challenges in collecting consistent data. Integrating such information into the management indicators system is feasible and can offer a comprehensive perspective on leadership's impact on system health.

2.10. Economic Factors Pillar

The economic factors pillar emphasizes the financial aspects of system health. For a system to be deemed healthy, it must not only perform effectively but also do so in an economically sustainable manner over the asset's lifecycle. Economic efficiency and operational costs incurred throughout the asset's life are crucial in practical health management.

This pillar involves monitoring system-related costs and integrating these financial parameters into PHM requirements. Such monitoring helps shape strategic decision-making, especially when costs approach predefined limits. The elements under consideration within this pillar typically include the value of production loss, maintenance expenses, and utility costs such as fuel and electricity. The data related to these elements can be obtained through sensor or meter readings and by calculating the downtime cost associated with the unit's output product. These inputs are integral components of operation and maintenance budgeting, and they are consistently tracked throughout the asset's lifecycle, providing a comprehensive view of the system's economic health.

2.11. Process Safety Management Pillar

Process safety is the rigorous management of operating systems and processes handling hazardous materials, grounded in sound design and operating procedures, as outlined by the Centre for Chemical Process Safety (CCPS) (AIChE, n.d.). Monitoring and measuring the efficacy of process safety management (PSM) elements is essential for maintaining system integrity.

While certain PSM elements are accounted for within other pillars of the PHMF, additional elements critical to preventing functional failures, minimizing downtime, and upholding safety need to be integrated. Within this pillar, particular attention is given to five key aspects of PSM that should be factored into PHM: process hazard analysis, work permit systems, pre-startup safety reviews, management of change protocols, and internal and external audits.

Capturing data for these aspects poses challenges; nonetheless, their inclusion in the PHM strategy renders it more comprehensive. Emphasis on the digitization of such data is paramount. The availability and proper management of this data facilitate monitoring these elements and initiating actions in response to nonconformities or deviations, which represent unhealthy conditions within the process safety framework. Incorporating PSM into PHM ensures a proactive stance towards maintaining safety and operational integrity.

2.12. Human Reliability Pillar

Human reliability is critical in PHM, as human error is a known cause of failures and downtime. Effective incident prevention involves management recognition of potential human error and its potential consequences in daily operations (Hunszu et al., 2004). A PHM framework that does not measure human reliability falls short of being comprehensive.

Monitoring human reliability is complex; however, there are several techniques for its assessment, such as the Human Error Assessment and Reduction Technique (HEART) developed by Kirwan, B. (1994). The first step in incorporating human reliability into PHM is identifying individual tasks that affect system operation. Subsequently, the human error probability associated with these tasks can be estimated, considering the specific conditions and environment at the execution time.

Operator tasks, such as opening manual valves, adjusting settings on human-machine interface (HMI) panels, or manually initiating standby equipment, are prime examples of activities heavily influenced by the human element in system operations. The performance data for these tasks is significantly impacted by individual competencies and the context in which they are performed.

Integrating the human reliability aspect into the PHM framework is crucial for comprehensive system health management. It acknowledges that human actions are critical to the system's operational integrity. Including such data in PHM allows for the monitoring and analysis of human performance, thereby providing a more complete understanding of system health and enabling the development of strategies to mitigate risks associated with human error. This holistic approach ensures that the PHM framework considers technical and mechanical data and encompasses the variability and potential fallibility inherent in human interaction with the system.

3. METHODOLOGY

The methodology for thoroughly determining a system's health management requirements within real-world operational contexts involves utilizing the PHMF. This approach hinges on grasping the system's critical functions. Detailed in Figure 3 is an end-to-end procedural flowchart designed to guide users through this process.

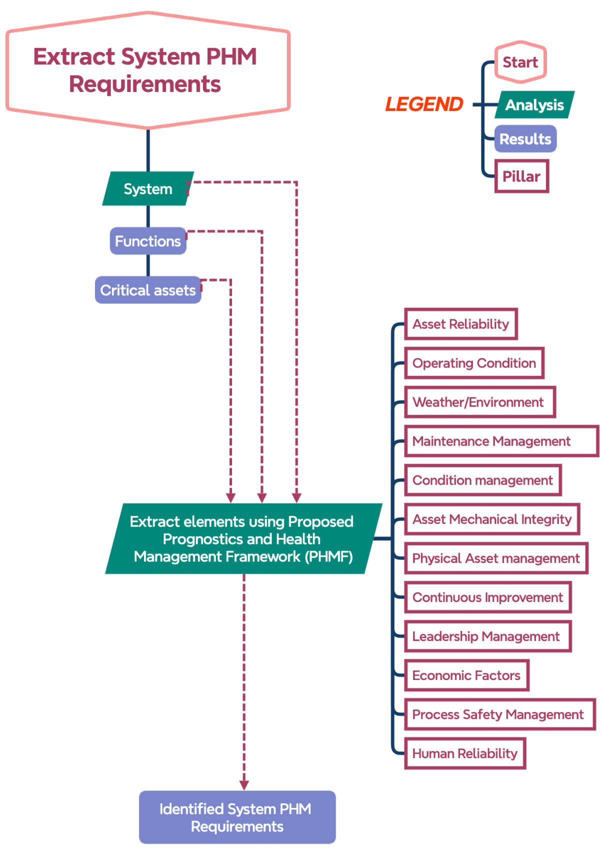

Figure 3: Methodology Procedure Workflow

We pinpoint functions tied to various critical equipment and components to map out the health management requirements of manufacturing processing systems. The process unfolds in three main stages:

1) **System Function Identification:** The operational flow is segmented into subsystems directly affecting the final product. During this initial phase, numerous functions within each system are identified. This step is pivotal as it involves an in-depth examination of system failures and failure modes, necessitating a thorough comprehension of each system's function. Understanding the function is crucial as it lays the foundation for discerning potential points of failure and planning for effective health management.
2) **Critical Equipment and Component Identification:** The PHM strategy should be refined by focusing on functional failure modes specific to vital equipment and components. This targeted approach considers the repercussions these failures have on the system's overall reliability and the occurrence of unscheduled downtime. Identifying which equipment and components are critical ensures that the PHM strategy is effective and efficient, directing attention and resources to areas with the most significant impact on operational continuity and system health.
3) **PHMF Pillars Analysis:** The process involves scrutinizing each PHFM pillar to identify relevant elements and determine the parameters that will be monitored for health management requirements. This detailed analysis helps pinpoint the specific data points critical for understanding and maintaining the system's health.

The recommended methodology should be applied comprehensively to a system, considering any changes throughout the system's life cycle. Implementing the PHMF and following this procedure aids in thoroughly extracting health management design requirements based on actual operational scenarios. Monitoring the designated parameters can swiftly address the critical causal factors that may lead to unplanned downtime and functional failures, thereby bolstering system reliability.

This end-to-end and holistic procedure accurately represents the system's health, ensuring that no known issues concerning assets, processes, or personnel are overlooked. Furthermore, this method facilitates digital transformation and promotes data availability for applying PHM in the oil and gas industry. It paves the way for enhanced diagnostic and predictive capabilities within the framework of proactive health management.

The PHMF's pillars encapsulate the key domains necessary to maintain and enhance system health from a reliability management perspective. While many studies in PHM have traditionally concentrated on operating conditions and condition monitoring of equipment or systems, they have often not fully addressed the breadth of factors that the additional pillars represent. These other pillars provide a more holistic view of a system's health and offer avenues for improving practical operations within the oil and gas industry. The framework can significantly contribute to operational excellence and system integrity by incorporating these comprehensive elements.

The methodology presented has drawbacks; it demands considerable time and effort, relies on quantitative assessments such as the health index method, and necessitates a digital transformation framework for effective data collection, storage, and analysis. Additionally, it involves a degree of human judgment in its execution.

Future research should focus on refining the procedure to enhance efficiency, especially regarding parameter criticality and independence, and incorporating risk assessments for each parameter. PHMF provides a systematic approach to identifying parameters encompassing all known failure modes and causes of unplanned downtime. That could enable the execution of comprehensive analytics integral to the PHM strategy.

This study also catalyzes advancing digital transformation initiatives, reinforcing the need for system reliability and exploring additional data capture methodologies for the extensive future application of PHM in big data.

4. CASE STUDY

This case study examines a lube oil system in a gas turbine generator unit, which serves as a supportive system fulfilling multiple functions. The aim is to demonstrate the efficacy and practical application of the proposed PHMF in determining health management needs from a real-world operational standpoint within the context of the lube oil system. The process began with articulating the system's function: "*supply oil with a correct pressure and temperature to the gas turbine bearings and the driven equipment for lubrication and cooling.*"

A typical lube oil system layout for a gas turbine, as depicted in Figure 4, consists of an oil tank that stores the system's oil, along with pumps and pressure regulators. A piping network facilitates the transportation of the lubricating oil to the requisite components of the turbine generator. A filtration system is in place to ensure the delivered oil meets quality standards. The system's temperature is regulated via a heater, temperature control valves, and heat exchangers equipped with electrical air fans to maintain optimal operating conditions.

The second step in applying PHMF to the lube oil system involves identifying critical equipment tags. These tags represent components whose failure could lead to system functional failure and unplanned downtime. The failure modes analysis in this case study has pinpointed 42 critical tags that significantly influence the system's functionality and, hence, warrant particular attention. The identified tags include one cooler, one control valve, twelve transmitters, four motor fans, seven motor pumps, and seventeen piping components. Table 1, which is not visible in this format, presumably lists these tags and their detailed descriptions.

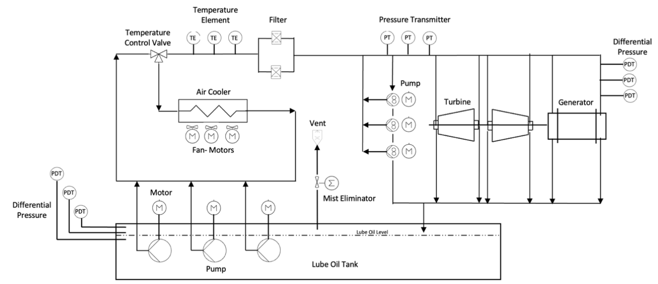

Figure 4: A Typical Lube Oil System in Turbine Generator

Tag Number (T)	Equipment Short Description
110-LO-01	PIPE (LUBE OIL)
510-LO-01	PIPE (LUBE OIL)
130-LO-01	PIPE (LUBE OIL)
150-LO-01	PIPE (LUBE OIL)
E-04	LUBE OIL COOLER, AIR-COOLED
534-LOD-01	PIPE LUBE OIL)
110-LO-01	PIPE (LUBE OIL)
110-REG-05	PIPE (LUBE OIL)
510-LO-01	PIPE (LUBE OIL)
534-LOD-01	PIPE (LUBE OIL)
130-LO-01	PIPE (LUBE OIL)
130-LOD-01	PIPE (LUBE OIL DRAIN)
110-REG-05	PIPE (LUBE OIL)
150-LO-01	PIPE (LUBE OIL)
130-LO-01	PIPE (LUBE OIL)
130-LOD-01	PIPE (LUBE OIL DRAIN)
150-LO-01	PIPE (LUBE OIL)
510-LO-01	PIPE (LUBE OIL)
TV-779	LO TEMP CONTRL VALVE
KM-05	MOTOR, FAN 1, LUBE OIL MIST
KM-06	MOTOR, LUBE OIL COOLER FAN 1
KM-07	MOTOR, LUBE OIL COOLER FAN 2
KM-08	MOTOR, LUBE OIL COOLER FAN 3
PM-01	MOTOR, PUMP, PURIFICATION UNIT
PM-02	MOTOR, PUMP 1, MAIN LUBE OIL
PM-03	MOTOR, PUMP 2, MAIN LUBE OIL
PM-04	MOTOR, PUMP 3, MAIN LUBE OIL
PM-05	MOTOR, SCAVENGER PUMP
PM-06	MOTOR, SCAVENGER PUMP
PM-07	MOTOR, SCAVENGER PUMP
PDT-777B	PDT PRESSUREIN LO TANK
PDT-777C	PDT PRESSUREIN LO TANK
TE-778A	TEMP ELEM L.O. TEMPERATURE
TE-778C	TEMP ELEM L.O. TEMPERATURE
PT-786C	PRESS TRANS LO PRESSURE
TE-778B	TEMP ELEM L.O. TEMPERATURE
PT-786A	PRESS TRANS LO PRESSURE
PT-786B	PRESS TRANS LO PRESSURE
PDT-777A	PDT PRESSUREIN LO TANK
PDT-752A	PDT DIFF.PRESSURE BEARING 2
PDT-752B	PDT DIFF.PRESSURE BEARING 2
PDT-752C	PDT DIFF.PRESSURE BEARING 2

Table 1: Lube Oil System Tags and Types Description

The third step involves thoroughly evaluating the pillars outlined by PHMF to determine specific elements critical to health management. In this case study, a comprehensive analysis yielded 275 parameters pertinent to the lube oil system's health management. Table 2 shows the elements and the conditions signifying healthy operation for each parameter. This data provides crucial insights into the appropriate measures to be taken in the event of deviations from these healthy conditions.

The following in-depth examination and application of the PHMF's pillars focus on the health management requirements for a lube oil system in a gas turbine unit. This meticulous process has led to the identification of critical parameters:

In the *Asset Reliability (AR) pillar*, the 42 critical tags identified must be monitored for failure rates to assess reliability. The goal is to track reliability growth, which, for these tags, translates to 42 sub-parameters. Additionally, overall system reliability is considered concerning its foundational components, accounting for series and parallel relationships, adding one more parameter from this pillar. Any unhealthy condition detected among these parameters necessitates investigative action.

Within the *Continuous Improvement (CI) pillar*, it is necessary to monitor approved CI tasks. Two parameters emerge the quantity of recommended tasks as a leading indicator and the number of overdue tasks, which reflect compliance. Unhealthy conditions in this area require a task force to address compliance gaps and establish preventive measures.

The *Operating Condition (OC) pillar* encompasses multiple elements. Existing sensors provide real-time pressure and temperature data, with nine pressure transmitters and three temperature transmitters in play. A temperature control valve (TCV) is critical and must be included. Motor fans and pumps are monitored for their operational status, and the electrical parameters of all motors are tracked. Faulty alarms across all critical transmitters and motor parameters sensors lead to 46 additional tags to be monitored. Any deviation from prescribed limits signals a need for troubleshooting and corrective actions.

For the *Weather and Environment (EN)* pillar, weather conditions affecting the lube oil system's performance, especially those involving an air cooler and TCV, are significant. At the same time, forecast and current weather data are applicable and valuable for proactive measures since the lube oil system does not generate emissions. Manual adjustments to the TCV may be necessary under adverse weather conditions. Environmental parameters relating to emissions are non-applicable.

In the *Maintenance Management (MN) pillar*, preventive and corrective maintenance activities are crucial. Maintenance compliance, work order status, workforce effectiveness, job completion rates, maintenance quality alerts, and mean time to repair are all vital parameters. Unhealthy readings in these areas prompt a deeper look into improving maintenance practices.

The *Condition Monitoring (CM) pillar* considers various techniques relevant to the lube oil system. Mineral oil conditions, daily operator rounds, vibration monitoring for rotating equipment, and motor performance efficiency must be under surveillance. Actions taken in response to alerts from these parameters aim to preempt failures or unplanned events.

The *Asset Mechanical Integrity (MI) pillar* involves risk-based inspection analyses of critical piping and equipment. Compliance with non-destructive testing (NDT) inspections, Remaining Useful Life (RUL) estimations, and adherence to post-inspection recommendations form part of the integrity checks. Corrosion control is also a factor, though due to its nature, the lube oil system excludes chemical injections or cathodic protections.

For the *Leadership Management (LS) pillar*, the presence of an operational supervisor during shifts is considered a parameter, with leadership engagement and reliability culture actions extending beyond the lube oil system to the broader station or plant level.

The *Physical Asset Management (AM)* pillar comprises documentation control, spare parts inventory monitoring for critical components, and tracking of operator and technician competencies related to the lube oil system, all critical for maintaining the system's PHM.

Within the *Economic Factors (EF) pillar*, monitoring operational expenses related to the lube oil system, which encompasses maintenance and electricity costs for operating the motors, is crucial. Should costs exceed expected thresholds, an investigation should be initiated to identify and implement improvements.

For the *Process Safety Management (PS) pillar*, maintaining adherence to PS practices within the lube oil system is fundamental. Parameters that inform the health management strategy include compliance with work permits, effective Management of Change (MOC) processes, and the implementation of audit recommendations. These parameters are instrumental in proactively remedying conditions that may compromise health and safety, thereby preempting failures and potential incidents.

Lastly, in the *Human Reliability (HR) pillar,* tasks that require manual intervention, such as changing or swapping oil filters, are particularly prone to human error, which can cause functional failures or even a unit trip. It is essential to provide clear communication and oversight to those performing the tasks and to monitor the execution closely to minimize risk. Incorporating the likelihood of human error for these tasks into the health management strategy, especially if scheduled during a specific shift, is a proactive measure to alert the system to potential issues.

The analysis of this case study reveals that the extraction of health management requirements is thorough, encompassing a wide range of aspects and conditions. This comprehensive scope accurately portrays system health, particularly in identifying unhealthy conditions. Such a detailed understanding facilitates timely interventions—akin to seizing an opportune window—to preclude failures and enhance overall system reliability.

Pillar	Dataset	Element	Parameters	Healthy Criteria
Asset Reliability (AR)	U_{AR}^{1}	Operational Asset Reliability	$x_1^{1T}(t)$ 42 tags	Positive reliability growth, no new failures
		Operational System Reliability	$x_2^{1}(t)$	Positive reliability growth
Continuous Improvement (CI)	U_{CI}^{1}	number of tasks recommended	$x_3^{1}(t)$	A target number of tasks to be recommended archived
		number of tasks overdue	$x_4^{1}(t)$	NO recommended task is overdue
Operating Condition (OC)	U_{OC}^{1}	Pressure Transmitter reading	$x_5^{1T}(t)$ 9 tags	Within accepted limits
		Temperature Transmitter reading	$x_6^{1T}(t)$ 3 tags	Within accepted limits
		Control Valve Position Reading	$x_7^{1T}(t)$ 1 tag	Within accepted limits
		Equipment Status (Auto)	$x_8^{1T}(t)$ 11 tags	Must be Auto
		Standby/Out of service	$x_9^{1T}(t)$11 tags	No out of service
		Electrical Current	$x_{10}^{1T}(t)$11 tags	Within accepted limits
		Electrical Voltage	$x_{11}^{1T}(t)$11 tags	Within accepted limits
		Electrical Frequency	$x_{12}^{1T}(t)$11 tags	Within accepted limits
		System Faulty detection alarm	$x_{13}^{1T}(t)$ 46 tags	No alarm
Weather & Environment (EN)	U_{EN}^{1}	Weather Temp	$x_{14}^{1}(t)$	Within accepted limits
		Weather Humidity	$x_{15}^{1}(t)$	Within accepted limits
		Weather Rain perception	$x_{16}^{1}(t)$	Within accepted limits
		Weather Wind speed	$x_{17}^{1}(t)$	Within accepted limits
		Weather Wind Direction	$x_{18}^{1}(t)$	Within accepted limits
		Weather UV index	$x_{19}^{1}(t)$	Within accepted limits
		Forecasting Temp	$x_{20}^{1}(t)$	Within accepted limits
		Forecasting Humidity	$x_{21}^{1}(t)$	Within accepted limits
		Forecasting Rain	$x_{22}^{1}(t)$	Within accepted limits
		Forecasting Wind speed	$x_{23}^{1}(t)$	Within accepted limits
		Forecasting Wind Direction	$x_{24}^{1}(t)$	Within accepted limits
		Forecasting Weather UV index	$x_{25}^{1}(t)$	Within accepted limits
Maintenance management (MN)	U_{MN}^{1}	PM Compliance %	$x_{26}^{1}(t)$	Within accepted limits
		WO Waiting for the materials %	$x_{27}^{1}(t)$	0% (or end user target)
		WO Waiting for Shutdown	$x_{28}^{1}(t)$	0% (or end user target)
		Manpower Effectiveness %	$x_{29}^{1}(t)$	Within accepted limits
		WO completed on time %	$x_{30}^{1}(t)$	100% (or end user target)
		WO Closure %	$x_{31}^{1}(t)$	100% (or end user target)
		Rework WO %	$x_{32}^{1}(t)$	0% (or end user target)
		% Of planned Work (CM/PM)	$x_{33}^{1}(t)$	Within accepted limits
		Quality Control -Alarms	$x_{34}^{1}(t)$	No alarm
		MTTR (Mean Time to Repair)	$x_{35}^{1}(t)$	Within accepted limits
Condition Monitoring (CM)	U_{CM}^{1}	FLM Compliance	$x_{36}^{1}(t)$	100% compliance (or end-user target)
		FLM Alert	$x_{37}^{1}(t)$	No alert
		Vibration Alert	$x_{38}^{1T}(t)$ 11 tags	No alert
		Lube oil condition Alert	$x_{39}^{1T}(t)$ 1 tag	No alert
		Performance Alert	$x_{40}^{1T}(t)$ 7 tags	No alert
		Efficiency Alert	$x_{41}^{1T}(t)$ 4 tags	No alert
Asset Mechanical Integrity (MI)	U_{MI}^{1}	Useful Remaining life (URL) Alert	$x_{42}^{1T}(t)$ 18 tags	No alert
		NDT inspection Alert	$x_{43}^{1T}(t)$ 18 tags	No alert
		Inspection compliance	$x_{44}^{1T}(t)$ 18 tags	100% compliance
		MI Recommendations compliance	$x_{45}^{1}(t)$	no overdue task
Leadership Management (LS)	U_{LS}^{1}	Supervisor existing	$x_{46}^{1}(t)$	no supervisor absence
		Leadership Engagement	$x_{47}^{1}(t)$	the target of Engagement sessions achieved
		Reliability Culture action	$x_{48}^{1}(t)$	No overdue action
Physical asset management (AM)	U_{AM}^{1}	Documents Control	$x_{49}^{1}(t)$	No missing Documents to the system (revision up to date)
		Spare parts Out of Stock	$x_{50}^{1}(t)$	No Inventory Out of Stock
		Training Competency	$x_{51}^{1}(t)$	no missing Competency with Individuals related to the system
Economic Factors (EF)	U_{EF}^{1}	Preventive Maintenance Cost	$x_{52}^{1}(t)$	within budget
		Corrective Maintenance Cost	$x_{53}^{1}(t)$	within budget
		Utility cost Electricity	$x_{54}^{1}(t)$	Limit of design consumption rate
Process Safety Management (PS)	U_{PS}^{1}	Work Permit Compliance	$x_{55}^{1}(t)$	100% compliance (or end-user target)
		Open Management of Change	$x_{56}^{1}(t)$	no overdue task
		MOC Compliance	$x_{57}^{1}(t)$	100% compliance (or end-user target)
		Compliance Audits Overdue	$x_{58}^{1}(t)$	no overdue task
Human Reliability (HR)	U_{HR}^{1}	Probability of Human Error for a task	$x_{59}^{1T}(t)$ 1 tag	The task does not require it to be done. However, the operator's mistake during the task must be carefully assisted once high alarm differential pressure appears to perform the task.
		The total extracted parameters for the health management strategy of the Lube oil system are 275 parameters.		

Table 2: Lube Oil System PHMF Elements

The analysis of this case study reveals that the extraction of health management requirements is thorough, encompassing a wide range of aspects and conditions. This comprehensive scope accurately portrays system health, particularly in identifying unhealthy conditions. Such a detailed understanding facilitates timely interventions—akin to seizing an opportune window—to preclude failures and enhance overall system reliability.

5. Conclusion

This study explored the extraction and refinement of health management requirements from operational scenarios. A novel framework, the Prognostics and Health Management Framework (PHMF), alongside a dedicated procedure, was proposed to pinpoint system health components for monitoring purposes. The PHMF, encompassing twelve distinct pillars and various elements, provides a customizable approach to PHM design, accurately reflecting a system's health.

Implementing the PHMF enhances the utility of Digital Twins (DTs) by supporting the collection of extensive data sets, leading to improved PHM applications and more significant value generation. The case study showcased the practicality of the PHMF and its associated procedure, proving its applicability and scalability in industrial settings and its efficacy in facilitating comprehensive root cause analysis for failures and unplanned downtime.

Future research could include the development of a system health index derived from the PHMF's data sets, integrating prognostics, crafting a prioritized decision matrix to hasten health restoration, and further industrial case studies to validate and refine the methodology.

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Nomenclature

j	Number of system
$U^{j}_{Pillar}(t)$	dataset of a pillar on a system
t	time
n	Number of parameters
$x^{j_T}_{n}(t)$	parameter (variable at time t)
T	tag number of asset

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