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Integrating Life Cycle Cost Analysis into Pipeline Asset Integrity Management: A Comprehensive Approach in Decision Support Systems

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Abstract: Pipelines serve as the foundation of the global oil and gas industry and play an essential role in transporting hydrocarbons over long distances. Ensuring the continuous and dependable operation of these pipelines is vital not only for meeting global energy needs but also for protecting the environment and the communities through which they pass. This paper emphasizes the importance of proactively managing the integrity of pipeline assets to prevent catastrophic incidents resulting from pipeline failures. Traditionally, the management of pipeline assets has been reactive, addressing problems only when they manifest as failures. Although this reactive approach can offer short-term fixes, it often leads to operational inefficiencies, increased expenses, unexpected downtime, and safety compromises. Aging pipeline infrastructure compounds these challenges, underscoring the need for a forward-looking strategy focused on the entire lifecycle of pipelines. To tackle these issues and revolutionize asset integrity management practices, life cycle cost analysis-based decision support systems (DSSs) have emerged as an innovative solution. An LCCA-based DSS integrates advanced data analytics, risk assessment techniques, and optimization algorithms to facilitate proactive decision-making that accounts for the full pipeline lifecycle. Thereby, construction, operation, maintenance, and decommissioning costs are considered. This review article delves into the historical context and the crucial role of managing pipeline asset integrity while highlighting the drawbacks of conventional asset management methods. It introduces LCCA-based DSS as a transformative approach that bridges the gap between asset integrity management and comprehensive financial considerations. By shedding light on the potential advantages and practical implications of an LCCA-based DSS, this review advances pipeline management practices. Ultimately, the adoption of an LCCA-based DSS holds the promise of enhancing safety, environmental protection, and economic efficiency in the energy sector, ensuring a sustainable and dependable future for pipeline infrastructure.

Keywords: pipeline, life cycle cost analysis, decision support system, asset management.

将生命周期成本分析集成到管道资产完整性管理中：决策支持系统的综合方法

摘要：管道是全球石油和天然气工业的基础，在长距离运输碳氢化合物方面发挥着至关重要的作用。确保这些管道的持续可靠运行不仅对于满足全球能源需求至关重要，而且对于保护管道所经过的环境和社区也至关重要。本文强调主动管理管道资产完整性以防止管道故障导致灾难性事件的重要性。传统上，管道资产的管理是被动的，仅在问题表现为故障时才解决。尽管这种反应性方法可以提供短期修复，但它通常会导致运营效率低下、费用增加、

意外停机和安全问题。老化的管道基础设施加剧了这些挑战，强调需要制定专注于管道整个生命周期的前瞻性战略。为了解决这些问题并彻底改变资产完整性管理实践，基于生命周期成本分析的决策支持系统(决策支持系统)作为一种创新解决方案应运而生。基于 LCCA 的决策支持系统集成了先进的数据分析、风险评估技术和优化算法，以促进考虑整个管道生命周期的主动决策。因此，需要考虑建设、运营、维护和退役成本。这篇评论文章深入探讨了管理管道资产完整性的历史背景和关键作用，同时强调了传统资产管理方法的缺点。它引入了基于 LCCA 的决策支持系统作为一种变革性方法，弥合了资产完整性管理和综合财务考虑之间的差距。通过揭示基于 LCCA 的决策支持系统的潜在优势和实际影响，本次审查推进了管道管理实践。最终，采用基于 LCCA 的决策支持系统有望提高能源行业的安全性、环境保护和经济效益，确保管道基础设施的可持续和可靠的未来。

关键词：管道、生命周期成本分析、决策支持系统、资产管理。

1. Introduction

Pipelines play a crucial role in the oil and gas industry, facilitating the transportation of large quantities of hydrocarbons over significant distances and connecting production centers with distribution networks [1]. Ensuring smooth and reliable operation of these pipelines is essential for maintaining energy security and meeting global demand for oil and gas [2]. However, assuring the integrity of pipeline assets is a complex challenge that requires a proactive and systematic approach [3]. The significance of managing pipeline asset integrity lies in its ability to prevent catastrophic incidents resulting from pipeline failures [4]. Such incidents can have severe consequences, including environmental contamination, loss of life, property damage, and significant financial losses. Therefore, effective asset integrity management is essential not only for protecting infrastructure but also for safeguarding the well-being of communities and preserving the environment.

In the pipeline industry, traditional methods of asset management have typically been reactive, addressing repairs and replacements only when failures occur or problems become evident [5]. While this reactive approach can address immediate issues, it often leads to inefficiencies, increased operational costs, and unexpected downtime. Furthermore, it can pose safety risks because decisions are made based on immediate needs rather than a comprehensive understanding of the asset's entire life cycle. The aging of pipeline infrastructure adds to the challenges of traditional asset management [6]. As many pipelines have been in operation for several decades, they have become more vulnerable to corrosion, mechanical stresses, and other forms of degradation [6]. Effectively managing these aging pipelines requires a forward-looking strategy that considers the long-term financial implications and the

impact of decisions on the entire life cycle of the pipeline [7].

To address these challenges and enhance asset integrity management practices, a ground-breaking solution called life cycle cost analysis-based decision support systems (DSSs) has emerged. An LCCA-based DSS integrates advanced data analytics, risk assessment methodologies, and optimization algorithms to facilitate proactive decision-making that considers the complete life cycle of a pipeline [8]. By considering factors such as construction, operation, maintenance, and eventual decommissioning costs, an LCCA-based DSS provides a comprehensive understanding of the financial implications linked to various asset integrity strategies. The LCCA-based DSS approach empowers asset managers and engineers to make well-informed decisions that prioritize long-term sustainability and cost-effectiveness [8]. By harnessing data-driven insights, pipeline operators can strategically plan maintenance and replacement activities, thereby minimizing downtime, lowering operational costs, and prolonging the lifespan of their assets. Furthermore, an LCCA-based DSS encourages the adoption of proactive measures to prevent failures, resulting in heightened safety, environmental protection, and overall operational efficiency.

This review article delves into the historical context and importance of managing the integrity of pipeline assets, emphasizing its critical role in ensuring the dependable functioning of oil and gas infrastructure. This study discusses the difficulties faced by traditional approaches to asset management, underscoring their limitations in addressing the intricate requirements of pipeline operations. Consequently, it introduces the idea of decision support systems based on life cycle cost analysis as a transformative method that bridges the gap between asset integrity management and comprehensive financial considerations. By shedding

light on the potential benefits and practical implications of an LCCA-based DSS, this review aims to facilitate progress in pipeline management practices, ultimately leading to increased safety, sustainability, and economic efficiency in the energy sector.

2. Overview of Existing Research on Pipeline Asset Integrity Management

Over the course of time, extensive investigations have been conducted in the area of pipeline asset integrity management. These inquiries have been motivated by the urgent requirement to uphold the safety and reliability of essential oil and gas infrastructure. Scholars, engineers, and industry specialists have committed their efforts to developing a variety of approaches, methodologies, and tools to address the challenges presented by pipeline aging, environmental conditions, and operational stresses. Existing research in this field spans a wide array of topics, including risk assessment, inspection methodologies, corrosion prevention, failure analysis, and maintenance strategies. Pipeline integrity is the pipeline's ability to safely convey petroleum products without jeopardizing the environment, personnel, or overall business operations [9]. This involves ensuring the pipeline's structural soundness, absence of leaks or corrosion, and adherence to specified parameters to uphold the safety and reliability of the transportation process. To maintain pipeline integrity, a comprehensive scope of processes and activities, known as pipeline integrity management (PIM), is executed. PIM is devised to preserve the integrity of pipelines throughout their entire lifespan and ensure compliance with relevant industry codes and regulations [10]. By effectively enacting PIM, the chances of pipeline failures due to various types of damage mechanisms can be minimized. The typical PIM process consists of the following core components: inspection, monitoring, and testing activities; evaluation of pipeline integrity, implementation of measures to mitigate risks, intervention and repair procedures, risk assessment, and strategic planning [9].

3. Pipeline Integrity Management for Oil and Gas Industries

Integrity management is vital to an organization not only to extend the asset life cycle but also to prevent accidents, spills, plant shutdown, and loss of income and production [20]. Pipeline integrity management provides an integrated framework for successful pipeline asset management, which assists in pipeline operation and maintenance. Control procedures (preventive maintenance), monitoring techniques (predictive maintenance), and data entry comprise PIM.

PIM offers numerous advantages, such as enhancing the expertise of pipeline operators and improving the

integrity of pipelines. It provides benefits by enabling managers, risk assessment experts, and engineers to analyze and evaluate data obtained from different surveys, thereby increasing the data shared throughout the organization [21]. The goal of PIM is to ensure the normal operation of pipelines with minimum risk rates and environmental impact while also maintaining cost-effectiveness [22], [23]. Pipeline integrity management has been the subject of numerous studies, but none of them have particularly looked at the costs involved in setting up a system to achieve those benefits. Therefore, the goal of this study is to close this gap. The research that has already been conducted in the oil and gas industry is listed chronologically in the paragraph that follows. It is critical to emphasize that this strategy has two goals: to determine and select a cost-effective maintenance approach and to identify and evaluate the costs associated with adopting a pipeline integrity management system.

Techniques for preventing, detecting, and controlling oil spills in European oil pipelines were investigated by Martins in 1998. The primary causes of oil leaks were determined by the study to be mechanical failure, operational failure, corrosion, natural hazards, and third-party activities. The adoption of a PIM system was successful in minimizing spills. To prevent spills, the paper emphasizes the significance of meticulous design, construction, inspection, and control procedures in addition to effective operation. The need for pipeline monitoring as a tool for pipeline system maintenance was also emphasized. Data from the Conservation of Clean Air and Water in Europe (CONCAWE) were examined during the first 25 years to evaluate the efficacy of a pipeline integrity monitoring system. The results show that less than 0.0002% of the transported volume was spilled, indicating a very low level of spills. These findings demonstrated a considerable decrease in spillage rates [24]. Nam et al. [25] focused on evaluating the potential of risk-based models for selecting pipeline inspection and monitoring procedures. Variables such as corrosion, outside interference, material and construction flaws, acts of God, and human and operational errors were identified as factors influencing pipeline failures. Risk-based model, specifically the analytical hierarchy process (AHP), was applied to Indian oil and gas pipelines. Consequence analysis was used to determine the severity of failure, whereas probability analysis calculated the cost impact of each risk factor and its cumulative effect on failure. The model helped reduce subjectivity in inspection technique selection, prioritize pipeline segments requiring inspection and maintenance, and secure funding and guidance support for optimal inspection and maintenance strategies. Consequently, there was a reduction in the operational expenses of the pipelines [25]. Pipeline integrity management encompasses a wide array of activities, including control strategies,

monitoring, ensuring reliability and availability, and complying with legal regulations. This study emphasizes the importance of pipeline integrity management in guaranteeing smooth operation and long-term viability of pipelines [26]. Moreover, [23] introduced a decision analysis framework for effectively handling the risk associated with crude oil pipeline systems. The developed model employed structured expert judgment and the AHP to evaluate the frequency and consequences of failures in various segments of a crude oil pipeline. The AHP approach was used to determine the relative likelihood of failure criteria for low-probability mechanisms, whereas expert opinions were used to estimate the failure frequency of identified mechanisms. The findings of the case study underscored the significant impact of pipeline placement on its integrity and revealed variations in the projected cost of failure among different pipeline segments.

Furthermore, the research indicated that over half of pipeline failures result from third-party causes, primarily due to acts of sabotage and mechanical damage occurring in proximity to the pipeline's route. As a result, the researchers advised installing a surveillance system along the pipeline's right of way (ROW) to increase the pipeline's integrity [23]. Burlini and Araruna [27] used Bayesian network modeling to suggest a strategy for improving pipeline integrity in a study on decision-making on pipeline maintenance. According to the study, the primary causes of pipeline failure include corrosion (27%), mechanical failures (5%), third-party damages (24%), operator errors (10%), and natural disasters (5%). The study also examined three different maintenance approaches: preventive (planned inspections, repairs, and overhauls), corrective (no scheduled maintenance; repairs are conducted as problems occur), and predictive (maintenance depending on the state of the system at the time). It was advised to employ a Bayesian network model because of its adaptability and probabilistic character. According to research on managing oil spills along the Nigerian coast [28], the Niger Delta region has experienced frequent oil spills because of operations related to oil exploration and extraction. These oil disasters are primarily attributed to operator error, sabotage, and corrosion of oil pipes and storage tanks. The devastating effects of such spills, including human mortality and environmental damage, are further highlighted. The proposal suggests that to solve this issue, the oil and gas industry, governmental organizations, academic institutions, and research facilities should work together to create efficient management plans designed to lessen the likelihood of oil leaks. In [29], it was found that site data and historical data were used to assess third-party damage, which is a significant cause of pipeline failures. The data analysis revealed a failure rate of approximately 0.35 per kilometer per year, which is

higher than that of other pipeline systems worldwide. In Nigeria, pipeline failures result in fatalities at rates ranging from 0.04 to 0.38 per kilometer per year. The operator of the pipeline system investigated in this study incurs an average annual loss of approximately \$100 million due to these failures. While not factored into the analysis, supplementary costs such as remuneration, fines, environmental remediation, and legal expenses contribute to the total expenditures. The study emphasized the need to enhance the integrity of the pipes to reduce failures and associated costs. It also highlighted the importance of exercising caution in identifying internal and external corrosion, drill holes, and cracks in the pipeline walls. Based on the observed pattern of failure frequencies, this study suggests adjusting the intervals between inspection and surveillance activities. In particular, intensified surveillance is recommended, especially in the Niger Delta region [29].

Integrity management plays a crucial role in organizations, serving to prolong the lifespan of assets and prevent accidents, spills, plant shutdowns, and loss of income and production. It offers an integrated framework for effective pipeline asset management and facilitates the maintenance of pipeline integrity. The key components of pipeline integrity management include control procedures for preventive maintenance, monitoring techniques for predictive maintenance, and data management. The primary benefits of implementing pipeline integrity management are as follows:

- Enhancing the integrity and safety of pipelines.
- Updating pipeline information by comparing and analyzing data from previous years, enabling operators to stay current with best practices, regulatory compliance, and optimal maintenance approaches.
- Identifying and analyzing existing and potential threats to pipelines.

Overall, the existing research on pipeline asset integrity management demonstrates a diverse and dynamic landscape of studies aimed at tackling the industry's multifaceted challenges. As pipelines continue to play a crucial role in the global energy supply chain, ongoing research efforts are vital for advancing the field, implementing best practices, and ensuring the safe and sustainable operation of pipeline infrastructure.

4. Evaluation of Pipeline Asset Maintenance Strategies

Effective management of pipeline asset integrity plays a crucial role in the oil and gas industry. Extensive research has been dedicated to assessing different strategies for managing assets to improve pipeline operations' safety, reliability, and cost-effectiveness. In this review of existing literature, we delve into the essential findings and insights from

studies that have explored various asset management strategies, their applications, and their impact on pipeline integrity. The selection of maintenance techniques and approaches is primarily influenced by the potential costs and safety implications associated with system failures [11]. As highlighted by [12], the ability to extend the remaining lifespan of equipment depends on the frequency of technical inspections and the effectiveness of repair measures. The objective of maintenance, as defined by [11], is to achieve uninterrupted system operation and prolong the equipment's lifespan. Furthermore, these maintenance procedures can improve the overall condition of the equipment. Hence, maintenance encompasses the tasks performed to sustain the functionality of equipment and systems for the duration specified in their design life [11]. An effective maintenance strategy, according to [13], is the most important component of systematic solutions for pipeline integrity and safety. To prevent operational failures, several measures are crucial. To improve pipeline system reliability and avoid or minimize system failure, some policies have been established. Oil and gas pipeline reliability is decreasing, and environmental risks are created by ineffective maintenance [4]. Alawode and Ogunleye [14] presented a set of recommendations aimed at improving the safety and integrity of pipelines. They suggested that outdated pipelines be completely overhauled, regular integrity checks be performed, inspections be improved, surveillance be increased, aerial and satellite monitoring of pipeline installations be implemented, and an immediate response to oil spills be implemented [14]. This will significantly help lower pipeline failures. Preventive maintenance, corrective maintenance, and predictive maintenance are the three types of maintenance strategies that may be used.

5. Life Cycle Costing

The three pillars of sustainability are economic, social, and environmental. To evaluate an asset holistically in terms of sustainability, its entire life cycle must be considered. This section investigates life cycle costing as a component of sustainability assessment [15].

LCC can be defined as a method for determining the economic value of design project decisions. LCC is essentially a cost from gate to grave. It includes all investment, operational, maintenance, and disposal costs. Life cycle cost (LCC) analysis is a technique for calculating total ownership costs [91]. To account for all expenses associated with the life cycle cost, the LCC assessment model is introduced in Equation (1):

$$LCC_e = CAP_e + C_{INST} + \sum_{t=l_o+l_e}^{l_o+l_e} \frac{C_o(t)+C_M(t)+C_R(t)}{(1+r)^t} \dots \quad (1)$$

LCC_e represents the overall cost throughout the entire life cycle of a program aimed at extending the lifespan of a system. CAP_e signifies the initial financial

investment needed for this extension program. C_{INST} accounts for the expenses related to installing new hardware or software upgrades required for the extension. Meanwhile, $C_I(t)$ and $C_R(t)$ indicate the costs associated with maintaining capital expenditure (CapManEx) and risk expenditure (RiskEx) in year t of the extended operational life, respectively.

In the area of life extension strategies, it is essential to acknowledge that implementing additional safety measures and enhancing process and hazard control methods necessitates a financial investment to align the asset with established standards and regulatory mandates. To determine the capital needed for the creation and procurement of safety and process control measures, we can apply the equation originally proposed by [16]:

$$CAP_e = \sum_{i=1}^m n_i c_i, \dots \dots \dots \quad (2)$$

where m denotes the number of different types of these devices, n_i (where $i = 1, 2, \dots, m$) signifies the number of devices of type i installed in the system, and c_i represents the cost per unit of a device of type i .

Installation cost encompasses labor expenses (labor cost) denoted as (C_{INST}^l), the cost associated with asset downtime (C_{INST}^d) and logistics-related expenditures (C_{INST}^L). Consequently, the total installation cost, denoted as C_{INST} , is calculated by summing these three cost components as described below:

$$C_{INST} = C_{INST}^l + C_{INST}^d + C_{INST}^L \quad (3)$$

The costs related to extending the lifespan of pipeline oil and gas assets include expenses such as barge rental, procurement of spare parts and essential supplies, and crew transportation. Labor costs and expenses incurred due to asset downtime during the installation for extending the lifespan can be determined using Equations (4) and (5), respectively.

$$C_{INST}^l = l_{RT/d} \times M d_{INST} \dots \dots \dots \quad (4)$$

$$C_{INST}^d = C_{PL} \times d_{INST}, \quad (5)$$

$l_{RT/d}$ denotes the daily labor rate, $M d_{INST}$ signifies the overall number of man-days needed for life extension installation, C_{PL} stands for the daily cost of production loss, and d_{INST} represents the anticipated duration in days for the life extension installation to be completed. To compute the daily cost of production loss, C_{PL} , we use the formula outlined in ISO 15663-1 (2000):

$$C_{PL} = P_{RT/d} \times C_p \times (1 - A_o) \dots \dots \quad (6)$$

$P_{RT/d}$ stands for the daily oil production rate in barrels (BOPD), C_p represents the monetary worth of a production unit, and A_o denotes the typical operational asset availability. This is expressed as the proportion of time the system is operational within a specific time frame.

The maintenance costs in year t , $CM(t)$, are estimated by Equation (7):

$$C_M(t) = [C_{RM} \times M d_{RM}] + [C_{CM} \times M d_{CM}(t)] + [C_{PM} \times M d_{PM}], \dots \dots \quad (7)$$

where C_{RM} , C_{CM} , and C_{PM} correspond to the expenses associated with executing RM, CM, and PM tasks per

person-day, and Md_{RM} , Md_{CM} , and M_{dPM} indicate the cumulative person-days necessary for performing RM, CM, and PM activities, Md_{RM} and M_{dPM} are influenced by the number of RM and PM tasks planned for each year and the number of maintenance personnel needed for each task. The value of $Md_{CM(t)}$ can be determined on the basis of the anticipated number of asset failures in year t , denoted as $n_f(t)$. If we use $\lambda(.)$ to denote the hazard rate function for asset failure time, the anticipated count of asset failures between year t and year $t+1$ during the extended life phase can be computed as follows:

$$n_f(t) = \int_t^{t+1} \lambda(t)dt \dots\dots (8)$$

For instance, in the case of a two-parameter Weibull distribution failure model characterized by shape parameter β and scale parameter η , the anticipated count of asset failures in year t can be expressed as follows:

$$n_f(t) = \int_t^{t+1} (\beta/\eta)(t/\eta)^{\beta-1} = [(t+1)^\beta - t^\beta]/\eta^\beta, t = l_0, \dots, l_0 + l_e - 1 \dots\dots\dots (9)$$

Let X1, X2, and X3 represent the proportions of man-days dedicated to inspection, repair, and logistics activities, such that X1 + X2 + X3 equals 1. Then,

$$C_M(t) = [X_1 \times C_{RM}^L + X_2 \times C_{RM}^R + X_3 \times C_{RM}^L] \times Md_{RM} + [C_{CM}^L + C_{CM}^d + C_{CM}^{fab}] \times Md_{CM} + \dots (10)$$

$[X_1 \times C_{PM}^L + X_2 \times C_{PM}^R + X_3 \times C_{PM}^L] \times Md_{PM}$, where C_{RM}^L , C_{RM}^R , and C_{RM}^L correspond to the inspection cost, repair cost, and logistic expenses related to RM activities. C_{RM}^L , C_{CM}^d , and C_{CM}^{fab} correspond to the labor costs, downtime expenses, and fabrication expenditures associated with CM activities. C_{PM}^L , C_{PM}^R , and C_{PM}^L correspond to inspection, repair, and logistic expenses related to PM activities.

6. Life-Cycle Costing (LCC) in the Oil and Gas Industry

Using all costs incurred throughout the course of an asset's life cycle, from initial investment, ongoing maintenance, and operating costs to salvage and resale value, life-cycle costing (LCC) is a crucial economic analysis for determining the total cost of asset ownership. The US Department of Defense (DoD) created the LCC concept in the early 1960s to improve the efficiency of federal procurement activities [17], [18]. Since then, it has been used in several projects spanning numerous industries, such as transportation, energy, manufacturing, and healthcare. This section provides a quick review of LCC studies relevant to the oil and gas sector. Smith and Celant [19] used the LCC approach to compare the net present value (NPV) of various materials for downhole tubing and then chose the best option. During the conceptual stage of the Ekofisk redevelopment project in the Norwegian North Sea, [20] used LCC analysis to arrive at an ideal blend of materials and equipment. Paula et al. [21] used the LCC approach to compare various generations of such

equipment and looked into effective approaches to enhance the design of subsea manifolds. To enhance the decision-making process for facility management, including inspection and maintenance work executions in the refinery industry, [22] created an activity-based LCC methodology. To assess and contrast the costs related to the installation of new offshore structures, [23] provided a structural breakdown of cost (SBC) and created an LCC technique. Using data from SAP, the model was used in a case study involving a water injection pump (Systems, Applications, and Products in Data Processing). Kayrbekova and Markeset [24] developed an activity-based LCC and applied it to a case study in an offshore Arctic setting. Results from the case study showed that activity-based LCC, as opposed to the conventional LCC method, which solely deals with cash flows, is capable of handling expenses and cash flows.

To analyze potential offshore process alternatives at the conceptual design stage while accounting for risk expenditures, [25] presented a new LCC technique. According to the study, LCC might be a crucial factor in choosing the optimum liquefaction process for floating LNG production plants. An LCC approach was developed by [26] to assist in the selection of appropriate production technologies for heavy oil well construction projects. LCC analysis was used by [27] to analyze waste control initiatives throughout the exploration phase of offshore oil and gas projects. To comply with the current regulatory framework, this study aimed to assist Brazilian enterprises engaged in oil and gas exploration in including the LCC approach into waste management decision-making. A novel LCC approach was created by [28] to assess how much of an earthquake force decrease could reduce the price of base-isolated large LNG tanks. An integrated bottom-up LCC method was created by [29] to assist objective decision-making by encouraging oilfield service suppliers to be transparent about costs. This method was employed to suggest a practical way to create a closed-loop rotary steering service for an oilfield service provider. Therefore, LCC holds great importance in the oil and gas sector as it serves as a tool that extends beyond conventional financial assessments. Through its comprehensive evaluation of an asset's entire lifecycle, from the initial planning and construction phases to its operational use and eventual decommissioning, LCC facilitates well-informed decision-making. This approach aids in efficiently allocating resources, improving risk management practices, and guaranteeing adherence to environmental and regulatory requirements. Considering the complex and uncertain nature of the industry, LCC empowers stakeholders to make informed financial choices that contribute to the promotion of operations that are not only sustainable but also profitable.

7. Life Cycle Cost Analysis and Its Significance for Pipeline Infrastructure

Effective management of pipeline infrastructure has become a top priority for industries that depend on efficient transportation of liquids, gases, and chemicals [30]. In this context, the concept of life cycle cost analysis (LCCA) has gained significant recognition as a crucial tool for making well-informed decisions and developing strong asset management strategies. LCCA entails a thorough assessment of all expenses incurred throughout the entire lifespan of a pipeline asset, covering its initial design, construction, operational phase, maintenance activities, and eventual decommissioning [31]. This review explores the critical significance of LCCA in the field of pipeline infrastructure and its implications for optimizing resource allocation and ensuring long-term economic sustainability. Pipeline networks play a central role in various sectors, including oil and gas, water distribution, and petrochemicals. By incorporating LCCA, organizations can consider both the immediate and long-term costs associated with their pipeline assets [32]. Traditional approaches often focus solely on upfront construction costs, neglecting the ongoing operational and maintenance expenses that accumulate over time. Conversely, LCCA takes a holistic view, empowering stakeholders to make well-considered choices by systematically comparing different designs, materials, and maintenance strategies. By considering variables such as material longevity, maintenance frequency, and potential costs linked to operational downtime, LCCA empowers decision-makers to pinpoint the most economically efficient solutions in line with the anticipated lifecycle of the asset. A

prominent advantage of LCCA is its ability to foster a proactive approach to asset management [33]. Instead of merely responding to issues as they arise, organizations can anticipate future expenditures and allocate resources judiciously. This forward-looking perspective is particularly essential for pipeline assets, which often have lifespans spanning decades and are susceptible to various environmental, operational, and regulatory changes. LCCA assists in identifying optimal maintenance schedules, facilitating timely interventions that extend the asset's useful life and mitigate the risks associated with unforeseen failures [34]. Furthermore, it aids in striking a balance between initial expenses and long-term benefits, ensuring that investments in high-quality materials and construction methods yield substantial returns over the asset's operational lifetime.

The adoption of LCCA represents a transformative shift in the management of pipeline infrastructure. By embracing LCCA, industries can make well-informed decisions, optimize resource allocation, and enhance the economic sustainability of their pipeline assets. As technology continues to advance and considerations around sustainability gain prominence, the application of LCCA is poised to become even more significant, guiding the evolution of pipeline design, operation, and maintenance practices toward a more resilient and economically effective future. LCCA for pipeline integrity management involves evaluating the total cost of owning, operating, maintaining, and decommissioning a pipeline asset over its entire life cycle [35]. The components of LCCA for pipeline integrity management include the following:

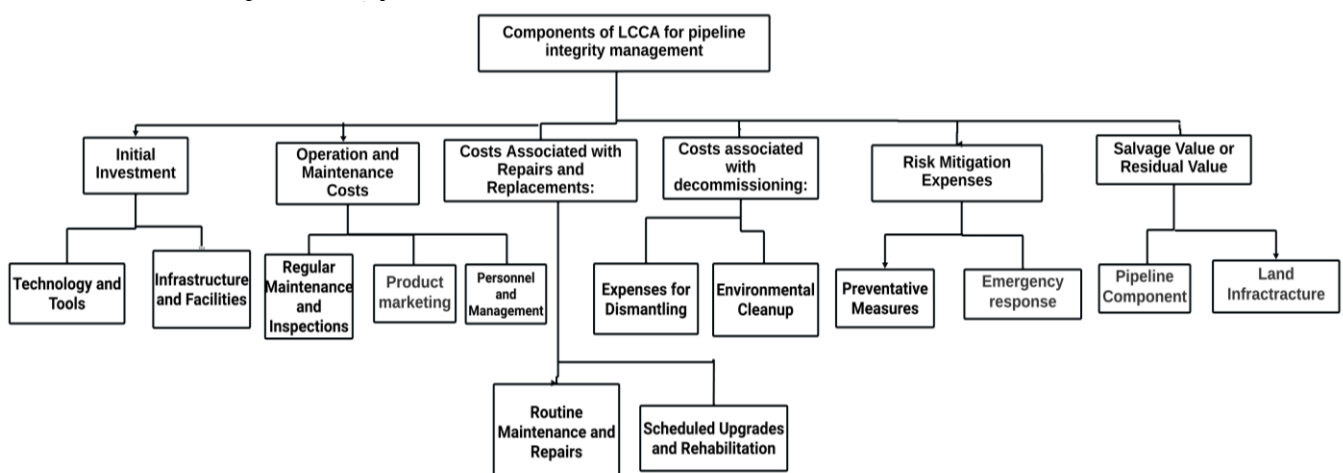


Fig. 1 Components of LCCA for pipeline integrity (The authors)

8. Decision Support Systems (DSSs) for Pipeline Asset Integrity

In the current intricate and swiftly changing landscape of business, the art of effective decision-making is a pivotal factor in determining an organization's success, involving navigating complex processing and deciphering substantial volumes of data,

extracting valuable insights, and aiding decision-makers in selecting the most suitable courses of action [36]. With the advent of artificial intelligence and machine learning, DSSs have evolved beyond their role as mere data processing tools, now encompassing predictive and prescriptive capabilities that render them indispensable for enterprises aiming to maintain a

competitive edge [37].

8.1. Role of DSSs in Asset Integrity Management

Ensuring the integrity of assets is a paramount concern for sectors involving critical infrastructure, such as energy, oil and gas, and manufacturing. The preservation and monitoring of these assets are imperative to ensure smooth operations, safety, and compliance with regulatory standards. Within this context, DSSs have emerged as pivotal tools for enhancing asset integrity management practices [38], thereby issuing alerts to stakeholders about potential concerns well before they escalate. By incorporating predictive analytics, DSSs empower decision-makers to proactively address impending risks, ultimately preventing costly disruptions and ensuring uninterrupted operations. In this context, this paper delves into the intricate role that DSSs play in reshaping practices related to asset integrity management, fostering a more reliable, secure, and

efficient operational landscape for industries dependent on critical infrastructure.

8.2. Components of an Effective DSS for Enhanced Decision-Making

According to [39], DSSs have transformed into vital instruments that enable organizations to arrive at informed choices within the intricate realm of today’s business environment. A holistic DSS encompasses multiple pivotal elements that, when integrated, elevate the decision-making process. This study explores the fundamental constituents of a proficient DSS and its functions in facilitating strategic judgments across various fields.

The significance of this aspect lies in its role as the bedrock for subsequent analytical processes, ensuring the accuracy and reliability of insights derived from the DSS. Table 1 presents some recent studies on the adoption of LCCA in asset management.

Table 1 Previous studies on asset integrity management and LCCA (The authors)

Ref.	Objectives	Methods	Findings
[40]	Evaluating whether offshore wind energy is cost-effective in Southeast Asia	Life cycle analysis for cost-benefit analysis	It is expensive now but could become competitive with onshore renewables, such as solar, through tech innovation.
[41]	Evaluating how energy island concepts can help small urban communities with battery storage	A new model to analyze the costs and benefits of battery systems in small communities	Adding external factors improves battery system economics.
[42]	Creating a tool to analyze sustainable food waste management at airports	Combining life-cycle assessment and cost-benefit analysis to examine food waste at Hong Kong Airport	On-site incineration is the best choice, saving money and energy and benefiting the environment. The tool works globally.
[9]	Understanding asset integrity challenges and creating a holistic approach for asset value	Reviewing AIM, exploring dimensions, and assessing asset performance	Sustainable value management is key to asset balance, stakeholder pressure reduction, and integrity improvement.
[43]	Combining economics with LCCA decision-making	Merging LCCA methods with cost accounting and economic risk models	Considering both economics and the environment in design decisions
[44]	Addressing issues in analyzing the costs and benefits of structures such as offshore platforms, bridges, and nuclear installations using stochastic modeling	Using excerpts from past conference papers and a preliminary study to explore challenges in modeling, user costs, and repair strategies in cost–benefit analysis	User costs, especially in bridge maintenance, can far exceed repair expenses, sometimes by more than ten times.
[45]	Creating models for offshore platform decisions, considering uncertainties, and comparing with NPV	Considering uncertainty factors in RO models such as price, maintenance, and structure	NPV can underestimate platform costs. RO allows flexibility in maintenance and decisions based on future data.

8.3. Integration of LCCA into DSSs

Long-term financial considerations significantly impact decision-making [46]. Integrating LCCA into a DSS offers a holistic perspective on the financial implications of various options. LCCA evaluates the overall costs associated with an asset over its lifecycle, encompassing acquisition, operation, maintenance, and disposal [35]. By incorporating LCCA, decision-makers can make well-informed choices that strike a balance between immediate benefits and long-term costs. This integration enhances decision-making by providing a comprehensive understanding of the financial effects of different alternatives and facilitating prudent allocation of resources. A proficient DSS

comprises interrelated elements that collectively strengthen decision-making capabilities [47]. The seamless integration of data, foresight provided by risk evaluation and prediction models, optimization enabled by maintenance algorithms, and strategic insights offered by LCCA collectively equip decision-makers with a robust toolkit for navigating complexity, mitigating risks, and selecting options aligned with organizational objectives. As businesses grapple with evolving challenges, the effectiveness of these components ensures the continued significance of DSS as a foundation for sound decision-making. The concept of DSS is gaining momentum daily. Table 2 presents some recent findings based on literature.

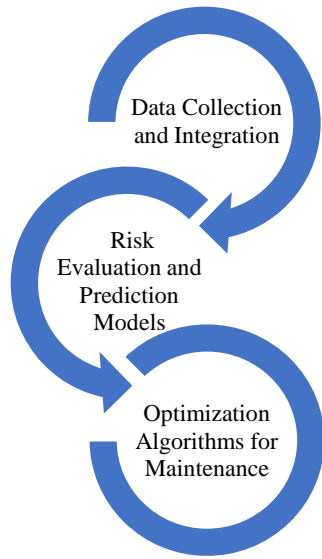


Fig. 2 Components of an effective DSS for enhanced decision-making (The authors)

Table 2 Previous studies on the application of DSSs in pipeline asset integrity management (The authors)

Pipeline management category		ML Task	Objectives	Input data	Pre-processing	Learning algorithm	Output	Ref.
Defect detection	Inspection MFL	Identifying anomalies, estimating their sizes, and predicting their depths	Automating assessment of magnetic scans for detection and characterization of pipeline anomalies	Magnetic scans of pipelines containing unique patterns associated with anomalies	Applying pattern-adapted wavelets to identify and assess anomaly sizes	Using artificial neural networks to forecast anomaly depths	Automated anomaly characterization and high accuracy and computational efficiency across various anomaly shapes	[48]
		Detecting defects, predicting their depth, and assessing their severity using MFL technology	Creating an intelligent system to predict oil and gas pipeline defects	Using MFL signals from pipeline inspections	Using the wavelet transform to spot defects and extract depth-related features	Implementing adaptive neuro-fuzzy inference systems, neural networks, and support vector machines	Enhanced defect detection, precisely forecasting its depth, and determining its severity; promising results in comparison with existing solutions	[49]
		Wavelet-based neural network for identifying defects in pipeline inspection data	Enhancing the safety evaluation of oil and gas pipelines by introducing an innovative MFL inspection device	MFL inspection signals gathered from the pipelines	Time-frequency analysis, filtering, and interpolation to prepare the data for analysis	Wavelet-based neural network	Combining neural networks, data fusion, and expert systems to enhance defect recognition capabilities	[50]
Ultrasonic test		WBF neural network to describe pipeline defects	Identifying defects in natural gas pipelines by using magnetic flux leakage	Magnetic flux leakage signals obtained from the pipeline assessments	Using Gaussian radial basis functions and Mexican hat wavelet frames	Multiresolution, hierarchical WBF neural network	3D defect profiles with customizable precision	[51]
		Neural network to analyze ultrasound echoes for pipe defect assessment	Creating a procedure to assess flaws in pipes that are not easily reached	Data comprising ultrasound wave signals reflecting pipe flaws	Applying the wavelet transform and choosing coefficients using a filtering method and genetic algorithm	Neural network classifier to evaluate the dimensions of defects	Precise measurements of the angular and axial extensions of the pipe flaws	[52]
		Classifying defects based on the A-scan data	Enhancing flaw detection in ultrasonic testing using machine learning	Noisy ultrasonic signals	Wavelet transform to reduce noise and improve the flaw location	Utilizing artificial neural networks	Defect localization and creating a tool for predicting the component service life	[53]
		Implementing a classification system using artificial neural networks	Creating two distinct feature extraction methods for categorizing ultrasonic NDE signals	Utilization of ultrasonic NDE signals obtained from weld inspection regions	Employing feature extraction techniques	Applying artificial neural networks	Superior performance of the clustered DWT approach	[54]

Continuation of Table 2

	Extraction and selection of features to enable automatic flaw classification.	Extracting and selecting features within a neural network	Ultrasonic test findings from steel welded joints	Using discrete Fourier, wavelet, and cosine transforms for feature extraction	Two distinct neural networks	Enhanced discrimination efficiency achieved by reducing the feature set from 2500 A-scan sample points	[55]
Eddy current testing	Using artificial neural networks (ANNs)	Assessing the structural integrity of critical metallic parts by estimating the defect parameters	Eddy current non-destructive testing data	Feature extraction employing additive Gaussian functions, nonlinear regression	An ANN is trained using features derived from synthetic data.	Estimation of the dimensional defect parameters in metallic components	[56]
	Developing a novel model for defect recognition	Ensuring the precise and swift identification of defects during eddy current NDT for in-service devices	Using eddy current (EC) signals	Implementing a two-stage differential structure	Multi-class support vector machine (SVM)	Developed improved particle swarm optimization (IPSO)-SVM model to enhance defect recognition	[57]
Leakage detection monitoring	Using a multi-layer perceptron neural network (MLPNN)	Creating a new approach for identifying leaks in hydrocarbon pipelines	Pipeline inlet pressure and outlet flow rates	Statistical methods, wavelet transformations, and a combination of both	The MLPNN classifier is employed.	92% accuracy in correctly identifying the location and severity of leaks with a minimal false alarm rate	[58]
	SVM algorithms are used to predict pipeline conditions.	Monitoring pipelines for damage, pressure, flow, and leaks using FBG sensors	FBG sensors monitoring pipe conditions	Preparing and cleaning the collected data	Using SVM for classification	SVM classifiers perform well in classifying the flow rate, pressure, and leak size.	[59]
	Training a system to detect leaks	Creating a system to detect leaks using multiple models and clustering	Data from an experiment using pressure and flow variables	Analyzing the data and using clustering	Use of multiple models and clustering for leak detection	Better leak detection results than those with a single model	[60]
	Developing a leak detection system using the rough set theory, SVM, and ABC algorithm	Enhancing accuracy and reducing false alarms in fuel pipeline leak detection	Data from the pipeline experiments	Using rough set theory to condense data and make rules; using SVM to check missed cases	SVM trained using ABC	Better leak detection than the PSO and EPSO methods	[61]
	SVM for detecting negative pressure waves (NPWs)	Identifying pipeline leaks using machine learning	1500 pressure curve samples, including 500 with NPWs	Framing NPW detection as a supervised learning challenge	SVM employed to create the detection algorithm	Enhanced NPW detection compared with wavelet-based approaches	[62]
	Creating a system that spots pipeline leaks	Finding pipeline leaks using groups of ANNs	Information about the pipeline properties	No details provided	Groups of ANNs	Good results in detecting pipeline leaks	[63]
	Extracting features and classifying data	Creating a method for monitoring pipeline leaks using software	Using measurements from the pipe's inlet and outlet	Changing the time domain features to a feature matrix	Applying the k-nearest neighbor and Bayesian classifiers	Detecting pipeline leaks and differentiating them from operational changes	[64]
	Identifying if there is a leak	Creating a system to detect pipeline leaks	Use of pressure and flow measurements	Handling noisy data and operational changes	Use of an ANN	Improved leak detection with fewer false alarms	[65]
	Combining a rough set and ANN for fault detection	Introducing a new method to detect pipeline faults	Real oil pipeline system data	Trimming pipeline system parameters using the rough set	Applying a three-layer ANN	Determined pipeline status, both stationary and non-stationary	[66]
	Classifying patterns using the wavelet packet transform and fuzzy SVM	Detecting small gas pipeline leaks to prevent harm	Acoustic signals from pipeline leaks	Simulating leak sounds and understanding their source	Fuzzy SVM for classification	Identified small gas pipeline leaks	[67]
	VM to identify issues by	Creating a system that can detect	Vibration data from a fiber-	Preparing the data using a method	SVM for classification	Spotting and pinpointing	[68]

		analyzing vibration data from optical fibers	leaks in pipelines and provide early warnings using GA SVM	based sensor	called the energy pattern		pipeline issues, proven accurate in real-world tests	
	Detection of defects	Sorting sensor data to identify unusual conditions	Creating a pipeline monitoring system using special sensors to detect wall thinning	Use of raw sensor readings from special sensors	Processing data using DWT	SVM to classify the data	Identifying wall thinning by analyzing signal changes	[69]
		Applying pattern recognition to identify damage	Determining whether continuous monitoring with PZTs on steel pipes is feasible	Ultrasonic waves from PZTs and extracting 303 features using wavelet	Using wavelet techniques for feature extraction	Using adaptive boosting, modified adaptive boosting, and SVM	Average classification accuracies of 85%, 89%, and 94% for the three classifiers	[70]
		Classifying pipeline defects	Predicting pipeline defects in real time using long-range ultrasonic transducers	56 feature data points obtained from an experimental setup that simulates pipeline defects	Not specified	SVM	Real-time prediction and monitoring of pipeline defects	[71]
	Surveillance	Identifying patterns to recognize threats using two modes	Creating a system to spot threats near a gas pipeline using advanced technology	Real data from eight machine activity pairs	Adjusting the data for analysis	Not mentioned	Promising results for threat detection	[72]
Integrity and risk assessment	Defect depth and corrosion rate prediction	Use of regression for corrosion rate prediction	Predicting the corrosion rates in wet gas pipelines using machine learning	Gathering factors affecting corrosion as per corrosion engineers' guidelines	Improving input variables using gray relational analysis	Applying BP, GA and BP, and ANN	Creating a numerical corrosion rate prediction model using GA and BP ANN	[73]
		Employing an RBF neural network and ANFIS	Forecasting L245NB steel corrosion in the soil	Use of emerging corrosion test data	Creating models from the test data	RBF neural network and adaptive neural-fuzzy inference system (ANFIS)	The ANFIS model outperforms RBF for real-world data	[74]
		Classifying corrosion types based on specific data	Creating a model to predict corrosion types using electrochemical data and neural networks	Use of inhibitor levels, exposure time, and impedance data	Adjusting for inhibitor concentration variations	Employing the Levenberg–Marquardt algorithm with specific transfer functions	Accurately predicting corrosion types and rates ($R > 0.99$)	[75]
		ANN to predict corrosion	Creating a model to estimate corrosion rates in oil/gas equipment	pH, velocity, temperature, and CO ₂ pressure	Dividing data and selecting the best ANN structure	ANN	Predicted corrosion rate and checking accuracy with statistics	[76]
		Use of past pipeline data to predict future corrosion	Determining how corrosion damages pipelines and manage their safety	Data on old pipelines	Obtaining predictions using a subspace clustered neural network	Subspace clustered neural network with adjustments	Predicted corrosion and assessed pipeline safety	[77]
		Use of a data-driven approach to predict corrosion in old pipelines	Determining pipeline corrosion risk for safety and the environment	Collecting pipeline data and transforming them using PCA	Modifying the data with PCA	Various algorithms such as PSO, FFANN, GBM, RF, and DNN	PCA-transformed GBM is the most accurate for predicting corrosion.	[78]

8.4. Methods for Integrating LCCA into DSSs

8.4.1. Developing Cost Models for Various Pipeline Components

An essential approach to incorporate LCCA into DSS involves creating unique cost models for different pipeline components [79]. This entails defining expenses associated with the complete lifecycle of each element, including installation, upkeep, repairs, and

replacements. These cost models encompass elements such as material costs, labor charges, energy consumption, and disposal expenditures. By constructing comprehensive cost models, decision-makers can systematically assess the financial impact of various choices concerning pipeline components over time [80]. This method enhances decision-making by offering a clear overview of overall ownership costs, enabling stakeholders to choose options that strike a

balance between initial and long-term operational costs.

8.4.2. Incorporating Deterioration Models and Failure Probabilities

To increase the precision of LCCA within DSS, the integration of deterioration models and failure probabilities is pivotal. Pipeline components are susceptible to wear and tear, potentially leading to failures and associated costs [81]. By merging deterioration models grounded in historical data and industry norms with failure probabilities derived from probabilistic risk assessments, DSSs can anticipate when pipeline components might degrade or malfunction. This predictive capability empowers decision-makers to proactively plan maintenance and replacements, thus reducing unforeseen downtimes and mitigating the financial consequences of unscheduled repairs [82].

8.5. Case Studies Illustrating Effective LCCA Integration into DSSs

8.5.1. Oil and Gas Industry: Managing Pipelines

In the oil and gas sector, a leading pipeline management company successfully integrated LCCA into their DSS [81]. The company developed comprehensive financial models for different pipeline components, encompassing expenses from installation and maintenance to repairs and replacements. By merging historical data with real-time monitoring, the DSS accurately predicted component deterioration and the likelihood of failures [83]. This proactive approach allowed well-planned maintenance scheduling, reducing operational downtime, and avoiding costly emergency repairs. Through the LCCA integration, decision-makers could select strategies that balance initial costs with long-term operational efficiency, resulting in significant cost savings and improved pipeline integrity.

8.5.2. Transportation Infrastructure: Bridge Maintenance

Within the field of transportation infrastructure, a governmental agency responsible for bridge maintenance effectively incorporated LCCA into their DSS. They developed detailed financial models covering the complete lifecycle of bridge elements, including construction, regular maintenance, structural repairs, and eventual replacements. These models were combined with deterioration predictions derived from the bridge inspection data. By supplementing this with real-time data from sensors embedded in critical bridge areas, continuous monitoring was ensured [84]. Consequently, the agency could allocate resources optimally, minimize disruptions in traffic flow, optimize long-term maintenance costs, and extend the lifespan of bridges.

8.5.3. Manufacturing Sector: Equipment Asset Management

A manufacturing conglomerate successfully integrated LCCA into its DSS to proficiently manage equipment assets. The company developed intricate financial models for each type of equipment, incorporating acquisition, installation, operation, maintenance, and disposal costs. Real-time data from sensors on machinery were incorporated, providing current performance insights. Furthermore, the DSS employed historical patterns and failure probabilities to predict potential breakdowns [85]. This enabled proactive planning of maintenance and equipment replacements, thus mitigating unplanned downtime expenses. The incorporation of LCCA into DSSs has resulted in enhanced production efficiency, lowered maintenance expenses, and improved equipment lifecycle management. These case studies highlight the effective integration of LCCA into DSSs in diverse sectors, as shown in Fig. 3. By integrating precise financial models, anticipating wear and tear, and using real-time data, these entities realized substantial cost reductions, boosted operational dependability, and enhanced overall performance [85]. This integration serves as a model for making informed decisions and efficiently allocating resources throughout an asset's lifecycle.

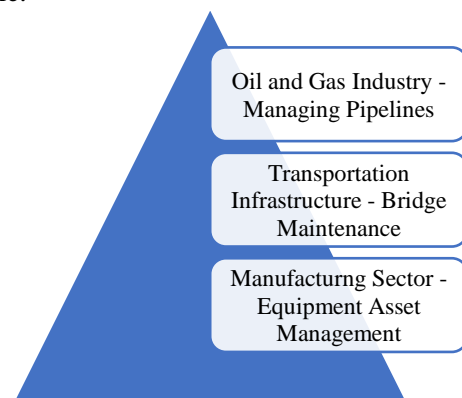


Fig. 3 Case studies illustrating effective LCCA integration into DSSs (The authors)

9. Challenges and Prospects for the Future of DSSs

9.1. Issues Surrounding Data Quality and Availability

In the domain of DSSs, persistent hurdles pertain to the caliber and accessibility of data, despite technological advancements. The efficacy of a DSS hinges on the accuracy, comprehensiveness, and reliability of the data it processes [86]. Inaccurate or incomplete data can lead to skewed insights and misguided decisions, potentially undermining the very essence of the system [87]. Furthermore, obtaining and integrating data from diverse sources presents challenges due to variations in data formats, standards, and ease of access. Addressing these obstacles requires

a focus on data governance, standardization, and the adoption of data validation techniques to ensure the dependability and uniformity of input data.

9.2. Complexity of Integrating LCCA into DSSs

Incorporating LCCA into DSSs introduces an additional layer of complexity to the decision-making process. Computing the comprehensive cost of an asset throughout its entire lifecycle involves considering various factors, such as procurement expenses, maintenance costs, operational efficiency, and potential risks. Ensuring the accuracy of these computations within the DSS structure requires advanced algorithms and robust data inputs [88]. Integrating LCCA necessitates a multidisciplinary approach, engaging specialists from disciplines such as finance, engineering, and data analysis to collaboratively develop comprehensive and precise models. Future directions should explore simplifying the integration of LCCA, potentially through standardized frameworks and tools designed to streamline the incorporation of lifecycle cost considerations into decision-making processes.

9.3. Ongoing Need for Updates and Recalibration

A consistent challenge in the operation of DSSs is the need for continuous updates and recalibration. As business landscapes, technologies, and regulations evolve, the fundamental data, models, and algorithms of DSS require periodic adjustments to remain applicable and effective [89]. Neglecting these updates can result in outdated information undermining the value of the DSS or even leading to misguided conclusions. Future developments in DSS creation should encompass mechanisms for automated updates and recalibration, guaranteeing that decision-makers can access the most current and precise information available. This could involve using machine learning methods to enable the DSS to autonomously adapt to shifting conditions.

9.4. Advancements in Predictive Analytics and Artificial Intelligence for Enhanced Decision Support

The future trajectory of DSSs holds considerable potential with rapid strides in predictive analytics and artificial intelligence (AI). These technologies enable DSSs to surpass retrospective analysis and offer proactive insights and recommendations. By harnessing historical data, machine learning algorithms can anticipate forthcoming trends, potential risks, and opportunities, equipping decision-makers to make informed decisions grounded in foresight [90]. Nevertheless, this advancement also introduces challenges, including the imperative for robust model validation and transparency in AI-driven decisions. As the integration of predictive analytics and AI deepens

within DSSs, upcoming directions should prioritize crafting intelligible AI models and addressing ethical considerations to ensure transparency, fairness, and accountability in decision-making processes [90]. Therefore, while DSSs have made substantial progress in assisting decision-makers, they also present challenges. Overcoming data quality concerns, streamlining LCCA integration, automating updates, and harnessing AI advancements are pivotal directions that can enhance the effectiveness and value of DSSs across a wide array of industries and decision contexts. Addressing these challenges will enable DSSs to continue evolving as indispensable tools for navigating the complexities of modern decision-making environments.

10. Conclusion

This article emphasizes the crucial need to integrate life cycle cost analysis into decision support systems for effective pipeline asset integrity management. Conventional methods often overlook the financial consequences of decision-making, necessitating a fresh perspective. This study introduces an innovative decision support system that combines advanced data analysis, risk assessment methods, and optimization algorithms. This convergence of disciplines empowers well-informed decision-making throughout various pipeline development stages, effectively merging financial considerations with asset integrity strategies. By bridging the field of pipeline asset integrity management and life cycle cost analysis, this study introduces a distinctive approach to enhance pipeline management. The resulting DSS can transform resource allocation practices for stakeholders, ensuring continued safe and reliable operation of oil and gas infrastructure. Furthermore, the incorporation of LCCA provides a comprehensive understanding of the financial implications of different asset integrity approaches, promoting economically sustainable management practices. The anticipated outcomes of this study are two-fold. First, the proposed decision support system grants stakeholders the ability to make informed decisions, harnessing technological advancements while accounting for financial variables. Second, the seamless integration of life cycle cost analysis into the decision-making process equips stakeholders with a comprehensive view of financial impacts, culminating in improved safety, reliability, and economic efficiency within pipeline operations. Fundamentally, this research bridges the gap between asset integrity management and life cycle cost analysis, presenting an inventive approach with broad implications for industry stakeholders, regulatory bodies, and asset management entities. Adopting this approach not only enhances safety and reliability but also fosters sustainable and financially prudent practices within the sphere of pipeline operations. This

incorporation underscores the research's value, paving a promising path toward enhanced pipeline management practices and, consequently, the enduring triumph of oil and gas infrastructure.

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