

Article

AI-Driven Maintenance Optimisation for Natural Gas Liquid Pumps in the Oil and Gas Industry: A Digital Tool Approach

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Abstract: Natural Gas Liquid (NGL) pumps are critical assets in oil and gas operations, where unplanned failures can result in substantial production losses. Traditional maintenance approaches, often based on static schedules and expert judgement, are inadequate for optimising both availability and cost. This study proposes a novel Artificial Intelligence (AI)-based methodology and digital tool for optimising NGL pump maintenance using limited historical data and real-time sensor inputs. The approach combines dynamic reliability modelling, component condition assessment, and diagnostic logic within a unified framework. Component-specific maintenance intervals were computed using mean time between failures (MTBFs) estimation and remaining useful life (RUL) prediction based on vibration and leakage data, while fuzzy logic- and rule-based algorithms were employed for condition evaluation and failure diagnoses. The tool was implemented using Microsoft Excel Version 2406 and validated through a case study on pump G221 in a Saudi Aramco facility. The results show that the optimised maintenance routine reduced the total cost by approximately 80% compared to conventional individual scheduling, primarily by consolidating maintenance activities and reducing downtime. Additionally, a structured validation questionnaire completed by 15 industry professionals confirmed the methodology's technical accuracy, practical usability, and relevance to industrial needs. Over 90% of the experts strongly agreed on the tool's value in supporting AI-driven maintenance decision-making. The findings demonstrate that the proposed solution offers a practical, cost-effective, and scalable framework for the predictive maintenance of rotating equipment, especially in environments with limited sensory and operational data. It contributes both methodological innovation and validated industrial applicability to the field of maintenance optimisation.



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Keywords: NGL pumps; predictive maintenance; maintenance optimisation; AI-based diagnostics; remaining useful life (RUL); MTBFs estimation; fuzzy logic; rule-based system; oil and gas industry; digital tool validation

1. Introduction

Natural Gas Liquid (NGL) pumps are critical in the oil and gas industry, particularly in driving NGL fractionation processes. The failure of these pumps can lead to significant operational disruptions if uninterrupted production is halted across a full 24 h period [1]. Given the high stakes involved, ensuring the reliability and availability of NGL pumps is significant. Traditional maintenance practices, often reliant on manual methods and expert opinions, lack the structured frameworks to optimise pump uptime effectively. This limitation stresses the urgent need to develop innovative methods to predict and prevent equipment failures more accurately.

A substantial amount of research has been conducted on maintenance optimisation, covering various approaches to enhancing equipment reliability and maintenance efficiency [2–5]. Studies have explored methods including Failure Modes and Effects Analysis (FMEA) [6]; Reliability, Availability, and Maintainability (RAM) analysis [7]; as well as condition assessments combined with data analytics techniques [8]. These contributions have provided structured frameworks that guide maintenance decisions and improve industry asset performance. More recently, data-driven techniques have gained attention for enhancing maintenance decision-making. Methods such as predictive maintenance based on data analytics and digital twin technology have been introduced, enabling real-time condition monitoring and proactive maintenance planning [9–13]. Furthermore, various statistical and machine learning approaches have been applied to identify faults early and improve maintenance scheduling accuracy, resulting in better reliability and reduced operational costs [14–17]. These data-driven strategies offer advantages over traditional maintenance methods, especially for managing complex systems with limited or uncertain data availability [18–22].

A range of studies have been conducted across general industrial applications to evaluate the effectiveness of predictive models in maintenance planning. Using machine learning integrated with building information modelling, Cheng et al. [19] developed a predictive maintenance framework for mechanical, electrical, and plumbing (MEP) systems. Falamarzi et al. [23] applied artificial neural networks (ANNs) and support vector regression (SVR) for predicting tram track gauge deviations, though their model lacked a comprehensive performance analysis. Similarly, Susto et al. [24] and Susto and Beghi [25] proposed predictive systems for epitaxy processes, employing ridge regression and support vector machines (SVMs) but without a comparative evaluation or uncertainty quantification. Mathew et al. [26] implemented a support vector regression kernel to estimate the remaining useful life (RUL) for turbofan engines, whereas Amruthnath and Gupta [17] used unsupervised learning methods for early fault detection in industrial assets. Despite their technical strengths, these studies did not clearly define the operational contexts or validate models across varied working conditions.

Although these general models illustrate the utility of predictive techniques, they are typically not tailored to the specific operational requirements of rotating machinery, such as pumps and compressors, which often operate under different load profiles, environmental conditions, and maintenance constraints.

To address this limitation, a body of research has specifically focused on rotating equipment [27]. Janssens et al. [28] used a CNN with thermal imaging data to detect anomalies in machinery, though the absence of an equipment-specific context limited the study's practical relevance. Sampaio et al. [29] developed an ANN model for motor failure prediction but without a robust model comparison or a sensitivity analysis. Bekar et al. [30] designed an intelligent predictive method for motors, and Praveenkumar et al. [31] used support vector machines to diagnose gearbox faults. Similarly, Prytz et al. [21] applied random forest models to predict compressor failures using historical vehicle data. While these methods showed promise, many lacked depth in their performance validation and scalability.

For more complex rotating systems, Durbhaka and Selvaraj [32] analysed vibration signals in wind turbines using several classifiers, including k-NN, SVMs, and k-means clustering. Yet, the study's focus on a single data source constrained its generalisability. Su and Huang [33] and Butte [34] applied AI-based approaches to detect faults in exhaust fans. Their findings highlighted the importance of combining physical parameters and extended datasets to improve accuracy. Abu-Samah et al. [25] introduced a hybrid model using

Bayesian networks and multi-gene genetic programming to monitor pump conditions. However, they did not compare their approach against other modelling techniques.

Despite these contributions, current AI-based maintenance models show several limitations that are particularly critical in the context of NGL pump operations. Most existing models focus primarily on failure prediction, often without supporting comprehensive maintenance routines that consider equipment availability and maintenance costs [28–30,33]. In addition, many models rely on large, high-quality datasets for training, yet in practical applications such as NGL pumps, both historical and real-time data are often limited in quantity and resolution, which poses challenges for their implementation [23,33,35]. Although some studies cover diagnostics or prediction [36–40], few offer integrated solutions that address both dimensions within a single framework [21,31]. Furthermore, cost and downtime considerations are not typically incorporated into these models despite their importance in industrial maintenance decision-making. Lastly, while many existing approaches target rotating machinery, none are specifically tailored to the unique characteristics and constraints of NGL pumps.

To address these challenges, this study proposes a practical, Artificial Intelligence (AI)-supported digital tool specifically designed for the maintenance optimisation of NGL reflux pumps in the oil and gas sector. Unlike existing predictive models, the tool utilises historical failure records and real-time sensor inputs to evaluate component conditions, estimate reliability, and generate optimised maintenance plans over a 10-year operational horizon. In addition to producing maintenance schedules, the tool also incorporates diagnostic functionality and provides actionable recommendations to improve equipment availability while controlling maintenance costs. A simplified schematic of the proposed framework is shown in Figure 1.

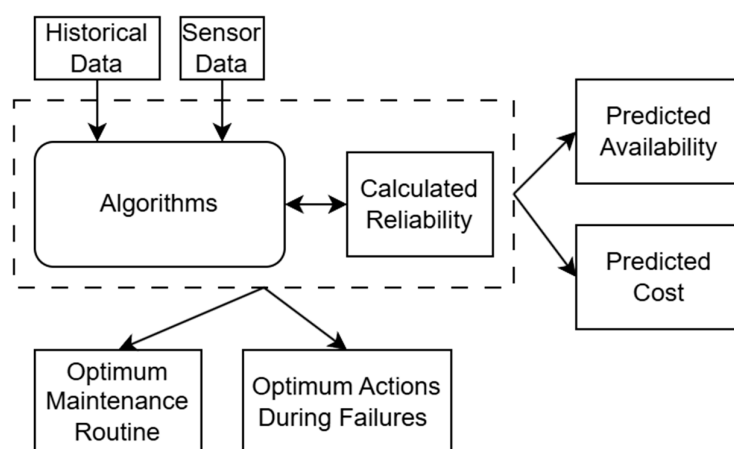


Figure 1. A schematic representation of the proposed AI-supported maintenance optimisation model for NGL pumps.

2. Method

This study adopts a structured methodology for developing and validating a digital maintenance optimisation tool tailored to NGL reflux pumps. The methodological framework, summarised in Figure 2, consists of four main stages: dynamic optimisation model development, risk-based prioritisation using FMEA, integrated maintenance routine optimisation, and tool development and validation.

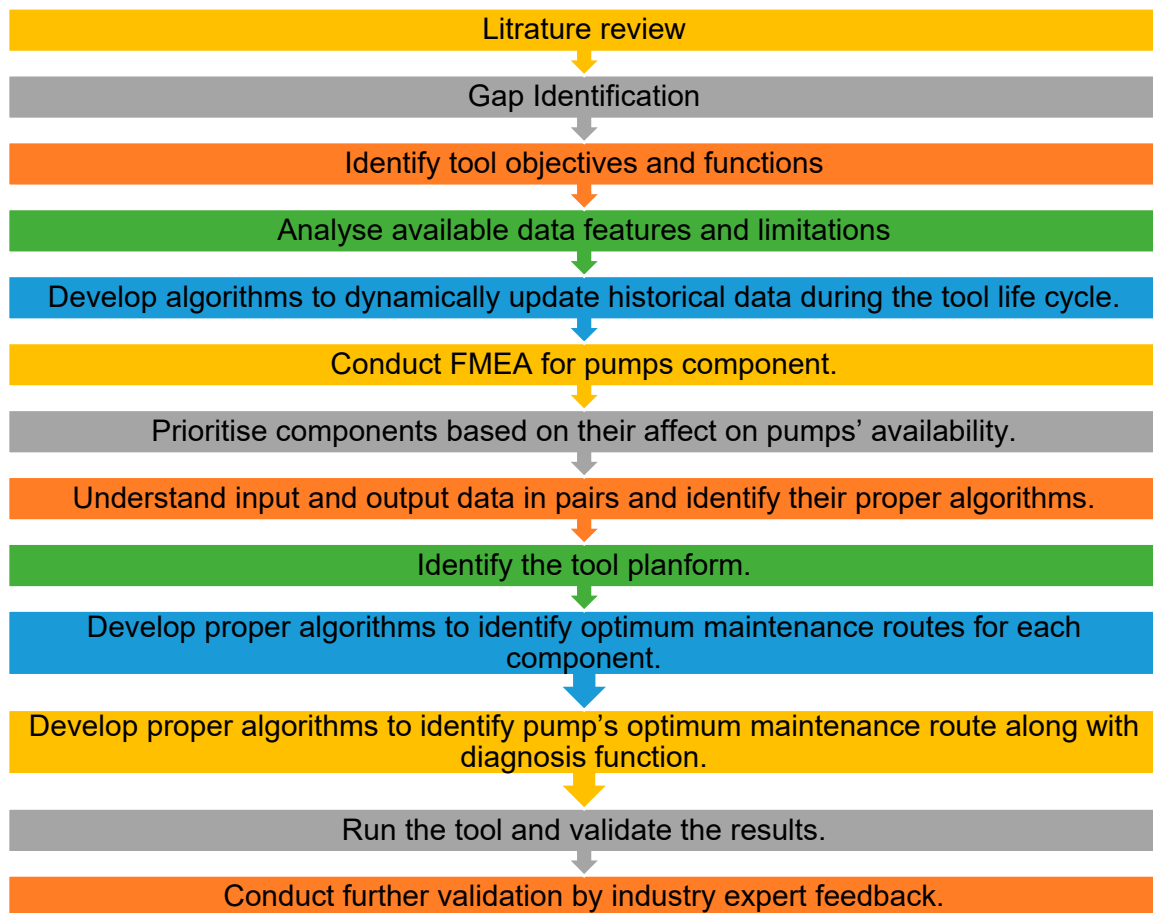


Figure 2. Flow chart of the framework and tool development.

2.1. Dynamic Optimisation of Maintenance Intervals

The first stage involves the development of a dynamic optimisation model that updates the Original Equipment Manufacturer (OEM)-recommended maintenance schedule based on actual operational conditions. This model incorporates both real-time sensor data and historical failure records to estimate the current mean time between failures (MTBFs) of individual pump components. Based on this analysis, the maintenance intervals are dynamically adjusted to better reflect the actual degradation behaviour of the system. This adaptive approach helps minimise unnecessary maintenance actions and avoids unexpected failures. A visual representation of this dynamic optimisation process is shown in Figure 3.

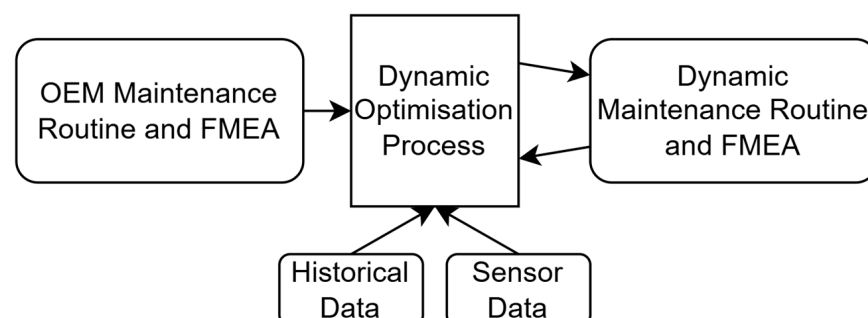


Figure 3. Dynamic optimisation flow diagram.

2.2. Risk-Based Prioritisation Using FMEA

Following the dynamic adjustment of component-specific maintenance intervals, an FMEA was developed to prioritise pump components according to their risk levels. Each component was evaluated based on its probability of failure, impact severity, and detection likelihood. The risk priority number (RPN) was then calculated to rank components by criticality. This ranking informs the maintenance planning by identifying which components require closer monitoring and more frequent interventions.

2.3. Integrated Maintenance Optimisation Logic

An optimum maintenance strategy for NGL pumps must satisfy three primary criteria. It should ensure optimum availability while maintaining reliability that meets operational requirements. In addition, it should minimise the total maintenance cost, accounting for both direct service activities and the associated operational losses during downtime. Furthermore, the strategy should be capable of reducing the occurrence of unplanned failures by supporting accurate diagnostics and appropriate maintenance actions when failures do occur. These criteria form the basis for the integrated optimisation logic presented in this section.

After establishing risk-based maintenance intervals, a system-level optimisation process was applied. The objective was to coordinate and integrate individual component schedules into a unified maintenance strategy that maximises availability and reduces the total cost. Simply applying each component's dynamic schedule independently does not guarantee overall optimisation. Therefore, this stage involved aligning maintenance activities during common downtime windows, where feasible. This integrated scheduling approach reduces the number of shutdowns and avoids redundant tasks. This approach is illustrated conceptually in Figure 4, where maintenance activities across different components are overlapped within shared downtime windows to maximise system availability and minimise operational disruption.

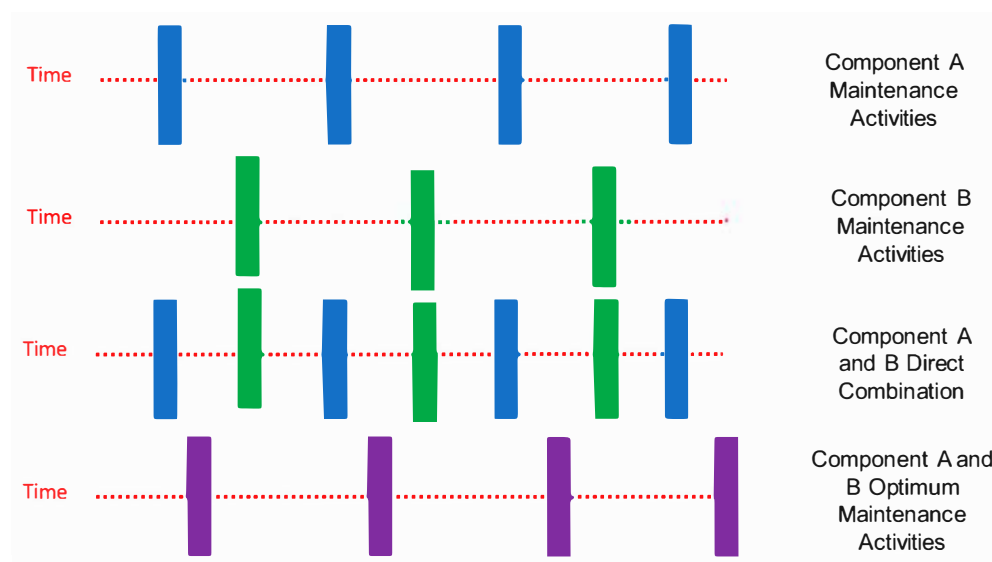


Figure 4. Overlaying activities concept.

The optimisation procedure employs an iterative process to identify combinations of component frequencies that satisfy user-defined reliability thresholds. An optimisation factor is computed for each combination, reflecting both the cost and operational impact. The combination yielding the lowest optimisation factor is selected. The total cost is calculated as the product of maintenance cost and operational loss cost associated with each maintenance plan. This process is summarised in Figure 5.

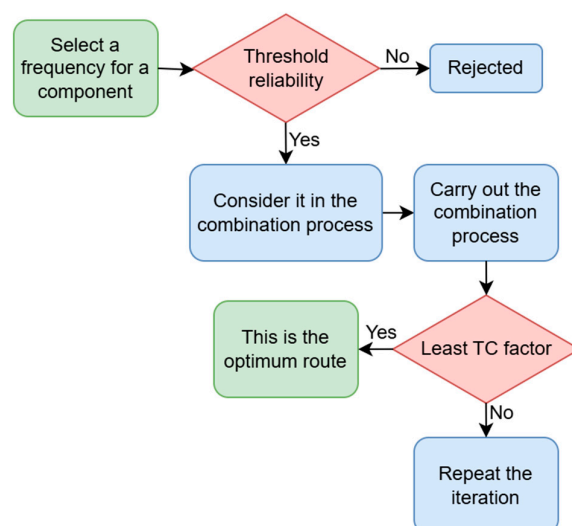


Figure 5. Optimisation logic flow diagram.

2.4. Handling Unplanned Failures

In addition to scheduled maintenance, the tool also supports optimising responses to unplanned failures. The tool interprets real-time sensor signals using embedded diagnostic logic to identify failure symptoms and generate appropriate maintenance actions. A structured database is incorporated into the system, mapping symptoms to possible causes and recommended interventions. This enables rapid decision-making during unexpected events and supports more accurate fault isolation.

2.5. Tool Development and Validation

The final stage of the methodology involved developing and validating the digital tool. The prototype was implemented using Microsoft Excel Version 2406 as the development platform. Data input included historical failure records, sensor readings, failure symptoms, and corresponding maintenance recommendations. The tool executes iterative calculations to determine optimal maintenance schedules and diagnoses.

Validation was performed in two stages. First, the tool was tested using operational data from Saudi Aramco’s single pump unit (G221) to verify its accuracy and practicality in a real-world setting. The pump unit is compliant with API 610/ISO 13709 [41]. Its specifications are shown in Table 1. Second, oil and gas maintenance experts were consulted to review the tool’s logic, usability, and applicability. Their feedback informed further model refinement and ensured its alignment with industry practices.

Table 1. G221 pump unit components and their specifications.

Pump Components		Specification Data
Pump Inboard Bearing (PIB)	Manufacturer	Byron Jackson® (Woodland, CA, USA)
Pump Outboard Bearing (POB)	Type–size	DSJH-10X14X20L
Motor Inboard Bearing (MIB)	Pump type	Horizontal
Motor Outboard Bearing (MOB)	Capacity	4715 usgpm
Inboard Mechanical Seal (IMS)	Rated speed	1770 rpm
Outboard Mechanical Seal (OMS)	Maximum allowable speed	1800 rpm
Coupling	Total weight	4873 lbs

Although the tool was validated using operational data from a single NGL pump unit (G221), the underlying algorithmic structure and diagnostic logic were intention-

ally designed to be adaptable to other rotating equipment types exhibiting similar degradation modes.

3. Digital Tool Development

This section outlines the development of a digital tool designed to support the maintenance optimisation for NGL pumps. The tool functions as a digital twin by simulating pump performance and predicting future maintenance needs using both historical and real-time data. Its primary aim is to operationalise the proposed methodology, validate its feasibility, and deliver actionable insights for improving pump availability and reducing maintenance costs.

3.1. Functional Design of the Digital Tool

The tool was built to address the limitations identified in Section 1 directly. It performs six essential functions: (1) optimising maintenance routines by balancing availability and cost, (2) identifying critical components through FMEA-based risk prioritisation, (3) assessing component condition based on sensor inputs, (4) predicting the remaining useful life (RUL), (5) reducing downtime via diagnostic support and recovery recommendations, and (6) acting as a digital twin to simulate maintenance scenarios and evaluate their impact on pump performance.

3.2. Data Structure: Inputs and Outputs

The tool is structured around two categories of data: input and output. The input data include both historical records and real-time sensor data, which serve as the basis for algorithmic calculations. The historical data consist of failure and replacement records, particularly for bearings, mechanical seals, and couplings. The real-time data include monthly vibration readings and mechanical seal leakage pressures. These inputs are processed to generate outputs such as MTBFs, RUL estimates, component condition assessments, maintenance diagnostics, and ultimately an optimised maintenance routine.

Figure 6 illustrates the hierarchical relationship between output functions, while Table 2 summarises each output and its corresponding inputs.

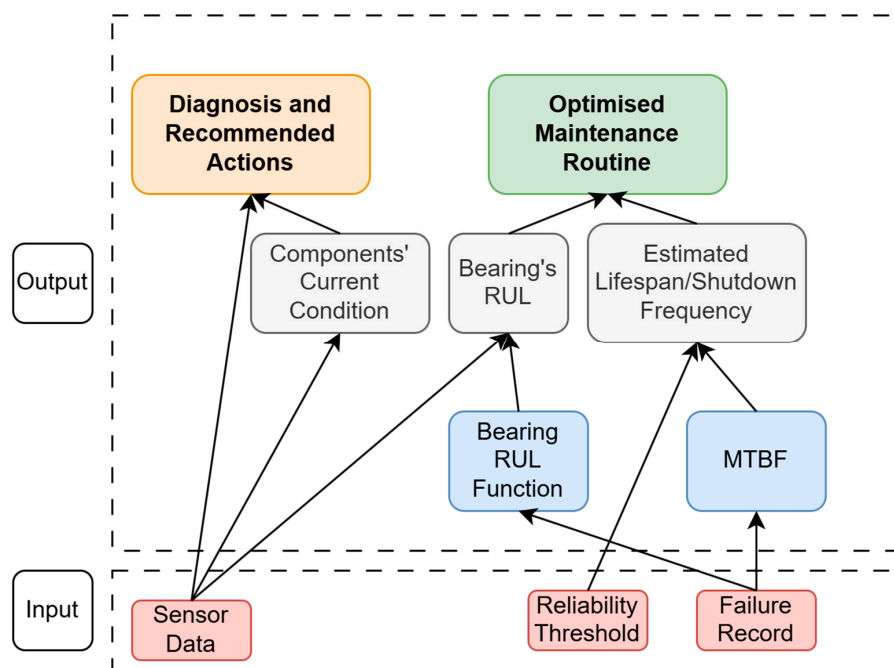


Figure 6. The tool's output map.

Table 2. Output summary.

Output	Description	Related Input
MTBFs	Components' mean time between failures	Failures Record (history)
Bearing RUL Function	The function relates the vibration reading with the bearings' RUL	Failures Record (history)
Estimated Lifespan/Shutdown Frequency	This is the estimated replacement time for each component	MTBFs, Reliability Threshold
Bearing RUL	The estimated bearings' RUL based on the current vibration reading	Bearing RUL Function, Sensor Data
Components' Current Condition	The current health condition of components based on the sensor data	Sensor Data
Diagnosis and Recommended Actions	Failures diagnosis and recommended actions to reduce pumps' downtime	Current Components' Condition, Sensor Data
Optimised Maintenance Routine	The optimum maintenance routine in terms of pumps' availability and cost	Estimated Lifespan/Shutdown Frequency, Bearings' RUL

3.3. AI Algorithm Determination for Processing Inputs

Each tool function is associated with one or more processing algorithms to generate a reliable output. The selection of algorithms is based on the characteristics of available data, the statistical behaviour of pump components, and the relationships between inputs and the required outputs.

3.3.1. Input Data Sources and Limitations

The tool uses historical failure records and real-time sensor data. Table 3 presents an overview of the features and limitations of these datasets. The historical failure records include each component's year of failure and replacement. These records are available starting from 2011. On average, each component has experienced only two to three failure incidents, making the dataset small in size and limited in statistical richness. Historical sensor data are also sparse and consist mostly of bearing vibration measurements taken before and after replacements. Regular condition-monitoring data for healthy operating states are not available.

Table 3. Input data features and limitations.

Input Data	Features	Limitations
Components' Failure Record	Accurate Used easily to calculate MTBFs Single dimensional	Very limited size
Sensors' Historical Data	Shows certain patterns Single dimensional	Very limited size
Real-Time Sensor Data	Accurate Detailed to support diagnosis Single dimensional	Limited databases

The real-time sensor data include monthly checks of bearing vibration and mechanical seal leakage. Bearing conditions are assessed using portable vibration analysers, while leakage is monitored by observing pressure on a dedicated gauge. Due to database storage constraints, only abnormal readings and failure-related data are recorded and stored.

3.3.2. Algorithm Allocation by Function

Each tool function is supported by a specific algorithm selected according to the type and quality of data available. Figure 7 outlines the main processing modules and their associated computational methods.

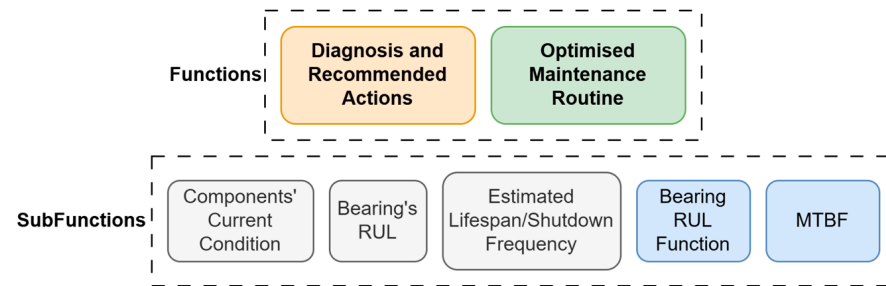


Figure 7. Functional mapping of the tool and algorithm allocation.

- MTBFs Estimation

The MTBFs for each component was calculated using historical failure records. The tool continuously updates the MTBFs value as new failure data become available. The calculation follows a deterministic approach, applying the following equation:

$$\text{MTBFs (years)} = \text{Total operational time (years)} / \text{Number of recorded failures}$$

- Bearing RUL Estimation

Although the historical data do not directly link the bearing condition and the RUL, the degradation behaviour of bearings is well established. Previous studies [34] have demonstrated empirical correlations between the RUL and vibration levels. One such relationship is given by Equation (1).

$$\text{RUL} = \frac{1}{V^n} \quad (1)$$

where V represents the current bearing vibration (in/sec), and n is a constant derived experimentally, which is influenced by the initial condition of the bearing and is suitable for the bearings used in NGL pumps, given their size, load, and operating speed.

When this equation is applied to bearings with known lifespans and documented initial vibration levels, a linear relationship is observed between the n value and the initial vibration reading at the replacement time. This linear pattern is used by the tool to estimate n from the initial vibration reading. The tool then applies Equation (1) along with the current real-time vibration measurement to estimate the RUL of the bearing.

Figure 8 presents this linear relationship as observed in pump G221. The linear regression model is updated continuously as new data become available.

- Component Lifespan Calculation

The tool uses historical failure data to estimate the operational lifespan of each component. Based on these estimates, it determines suitable shutdown intervals for scheduled replacements. This estimation process follows the exponential reliability model, where the reliability function is expressed as follows:

$$\text{Reliability} = e^{-t/\text{MTBF}} \quad (2)$$

From this, the expected lifespan corresponding to a specific reliability threshold is calculated as follows:

$$Lifespan = -MTBF \times \ln(\text{Reliability threshold}) \quad (3)$$

This method allows users to define an acceptable minimum reliability level, which the tool uses to determine replacement frequencies. The calculation is carried out using a deterministic algorithm.

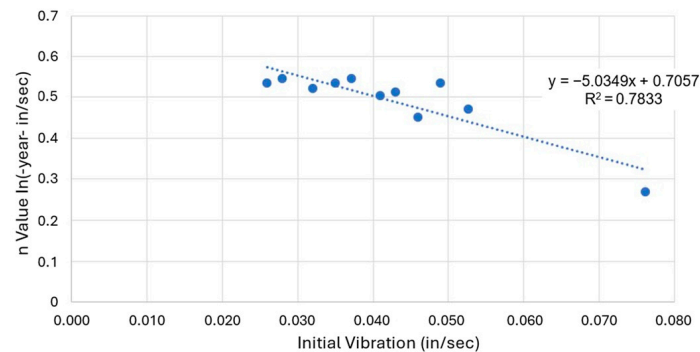


Figure 8. Linear relationship between parameter n and initial vibration levels. Dotted line represents the linear regression fitting.

- Component Condition Assessment

The tool assesses the condition of key components using real-time sensor data. For bearing evaluation, the ISO 20816 standard [42] is applied using a rule-based algorithm with defined alarm and fault thresholds set at 0.08 in/sec and 0.17 in/sec, respectively.

For mechanical seals, there are no explicitly defined leakage limits in either API 682 or Saudi Aramco Safety Standards [43]. Instead, these standards define overlapping pressure ranges for normal (0–7.5 psiG), alarming (5–10 psiG), and faulty (10–20 psiG) operating states. To interpret these ranges, the tool uses a fuzzy logic algorithm with triangular and trapezoidal membership functions. Figure 9 illustrates the membership structure.

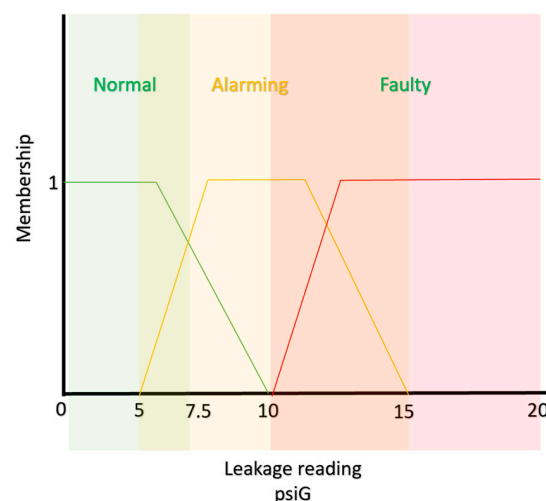


Figure 9. Fuzzy membership functions. Fuzzy sets: normal, alarming, faulty.

The fuzzy logic system classifies mechanical seal conditions into three sets: normal, alarming, and faulty. Each set is defined by a specific membership function. The normal condition is represented by a triangular function, which assigns a membership value of one when the leakage pressure is less than or equal to 5 psiG. This value decreases linearly between 5 and 10 psiG, reaching zero beyond 10 psiG. The selection of 10 psiG as the upper bound ensures a smooth transition between the condition states.

The alarming condition is modelled using a trapezoidal membership function. It begins with a membership value of zero for leakage pressures at or below 5 psiG, then increases linearly from 5 to 7.5 psiG. The function maintains a value of one between 7.5 and 12.5 psiG and decreases linearly from 12.5 to 15 psiG, returning to zero beyond 15 psiG.

The faulty condition is also defined using a trapezoidal function. It starts with a membership value of zero for leakage pressures at or below 12.5 psiG, increases linearly up to 15 psiG, and maintains a membership value of one for any pressure equal to or greater than 15 psiG.

A defuzzification process is used to derive a single output value from the fuzzy sets. This involves calculating a weighted average based on representative midpoints for each fuzzy set—3.75, 10, and 17.5 psiG, respectively. The defuzzification formula is shown in Equation (4):

$$Crisp = \frac{(Normal\ Membership \times 3.75 + Alarming\ Membership \times 10 + Faulty\ Membership \times 17.5)}{Normal\ Membership + Alarming\ Membership + Faulty\ Membership} \quad (4)$$

Based on the resulting crisp value, the condition is classified into one of three discrete states: values less than or equal to 5 indicate a normal condition; values between 5 and 12.5 indicate an alarming condition; and values above 12.5 are classified as faulty.

- Diagnostic Functions and Maintenance Recommendations

This function is designed to reduce downtime by diagnosing faults and recommending actions for bearing and mechanical seal replacements. Coupling replacements are excluded, as their procedures are typically straightforward and do not require AI-based decision-making.

For bearing diagnostics, the tool uses vibration frequency and bearing clearance data to identify possible failure causes and propose corrective actions. A rule-based algorithm based on if–then logic is employed to guide this analysis. The decision structure is presented in Figure 10.

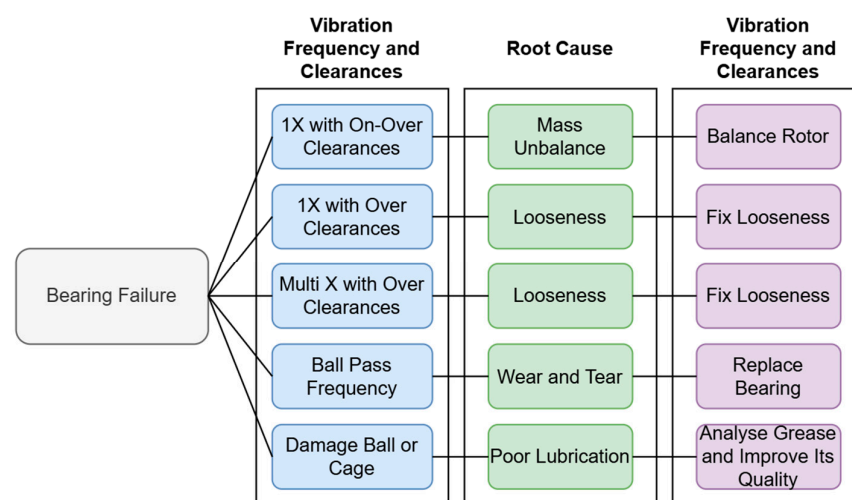


Figure 10. Logic tree for failure causes and recommended actions for bearings.

In the case of mechanical seals, the diagnostic process is informed by measurements such as casing concentricity and squareness, along with visual inspections of seal flashing lines. These inputs help identify causes of failure and support the recommendation of appropriate maintenance actions. Like the bearing module, the seal diagnosis function uses a rule-based if–then algorithm to process input data and determine the output. The diagnostic framework is summarised in Figure 11.

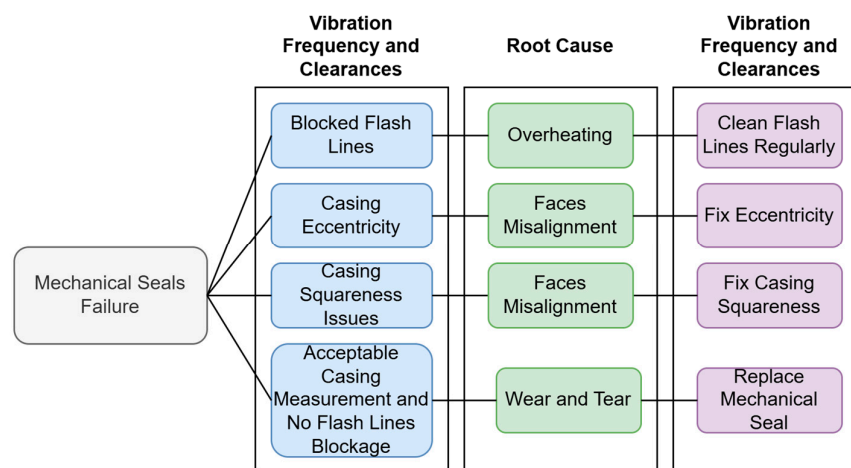


Figure 11. Logic tree for failure causes and recommended actions for mechanical seals [39].

- Maintenance Schedule Optimisation

This function represents a core element of the tool and is responsible for optimising maintenance strategies based on the estimated lifespan of each component and predefined reliability thresholds. The tool considers three major components—bearings, mechanical seals, and couplings—each with its own replacement frequency derived from lifespan calculations.

Two types of maintenance schedules are evaluated. The first is the Optimal Replacement Frequency approach, which treats each component independently and determines its most effective replacement interval to maximise its lifespan. The second is the Unified Maintenance Schedule, in which the tool identifies the component with the shortest lifespan and aligns the replacement of other components with this timeframe. This approach seeks to consolidate maintenance actions within shared downtime periods, thereby reducing the total number of shutdowns and minimising cumulative disruption. This concept is illustrated in Figure 6.

The tool performs a cost analysis for both strategies, incorporating both the direct maintenance costs and the indirect operational losses associated with downtime. The total routine cost is calculated using the following equation:

$$\text{Total routine cost} = \text{Total maintenance cost} + (\text{Total shutdown days} \times \text{Daily operational cost}) \quad (5)$$

Users are required to input values such as the shutdown duration for each component, maintenance costs, and daily operational losses due to unavailability. A simple if-then algorithm is then used to compare all options and select the maintenance routine that yields the lowest total cost. This schedule is applied to optimise maintenance planning over a 10-year period extending to the year 2034.

3.4. Development Platform and Validation

The tool was implemented using Microsoft Excel. It uses built-in functions and logical operations to analyse data and produce recommendations. The tool was validated through two procedures: a case application using data from pump G221 and expert reviews by oil and gas industry engineers to assess its usability and practical relevance.

4. Case Study Results and Discussion

The proposed methodology and the developed tool were tested using data from NGL Pump G221. This section presents the case study's outcome and discusses the results'

technical validity. The analysis focuses on generating the optimised maintenance plan and the accuracy of the computed reliability metrics.

4.1. MTBFs of Components

The computed MTBFs for the pump's bearings shows close agreement with the OEM's five-year estimated lifetime. Specifically, the inboard bearing recorded an MTBFs of 6.5 years, while the outboard bearings showed an MTBFs of 4.3 years. These values are compared with OEM estimates in Figure 12.

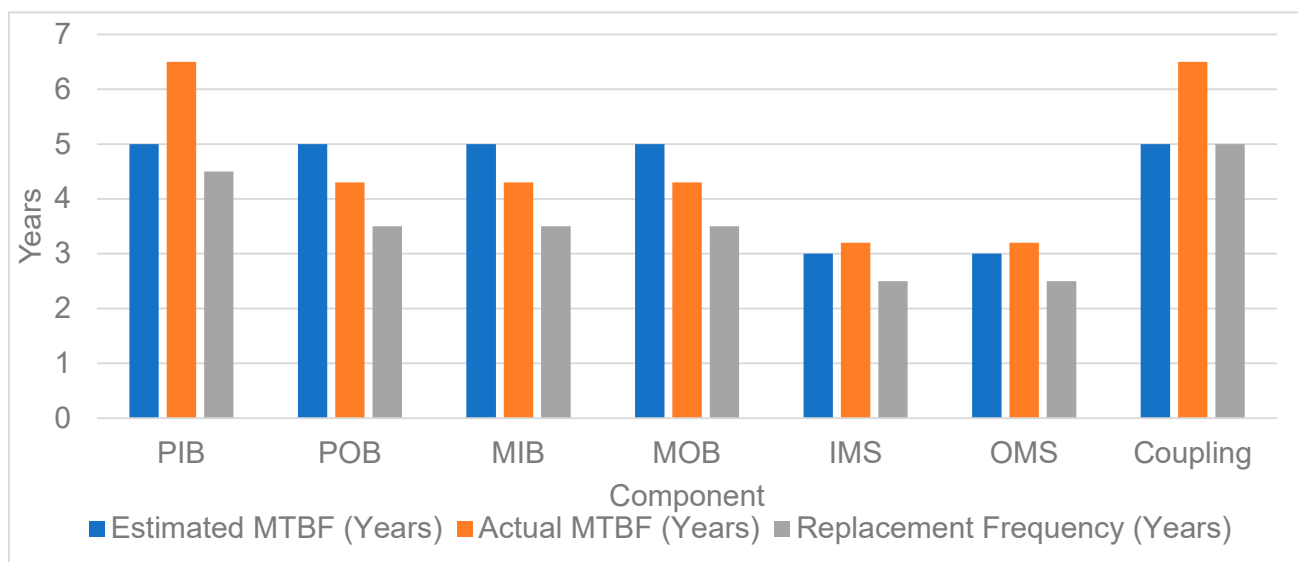


Figure 12. Components' MTBFs comparisons and replacement frequencies—replacement frequencies are shown to be shorter than MTBFs values.

The slight variation in bearing MTBFs values may be attributed to differences in lubrication management and installation accuracy. Each bearing operates with its own oil reservoir, making lubrication levels and prioritisation critical to operational life. Additionally, factors such as alignment precision and clearance tolerances during installation contribute significantly to overall bearing reliability.

For the mechanical seals, the tool estimated an MTBFs of 3.2 years, which closely aligns with both API 682 and OEM expectations of approximately three years. The minor deviation may be explained by the high purity of process conditions maintained at the Saudi Aramco NGL facility.

Although the coupling does not have a specified OEM service life, the estimated MTBFs of 6.5 years is considered acceptable compared to values reported in the literature, which suggest an average lifespan of approximately five years [44]. These findings indicate that the historical input data are consistent and technically adequate for generating reliable MTBFs estimates.

4.2. Optimised Component Replacement Frequencies

This part of the case study evaluates the relationship between reliability thresholds and optimised component replacement intervals. A reliability threshold of 60% was applied to the analysis. The resulting replacement frequencies were determined based on optimising component lifespan while maintaining an acceptable probability of failure.

In the oil and gas industry, unplanned downtime generally incurs higher costs than scheduled component replacement. Therefore, selecting an appropriate reliability threshold is essential to reduce unexpected outages while maintaining cost-effectiveness. Although

a 60% reliability implies a 40% probability of failure within the replacement interval, the historical records confirm that no components have failed within the predicted replacement times. This outcome validates the practical suitability of the selected reliability threshold.

Moreover, the historical failure data display limited variation, reinforcing the use of MTBFs as a dependable estimate for lifespan calculation. This provides additional confidence that the computed replacement frequencies, which are intentionally shorter than the MTBFs, are both realistic and conservative. Figure 12 illustrates the comparison between the calculated MTBFs values and the replacement frequencies generated by the tool.

4.3. Component Condition

The tool assessed the condition of the pump's major components—bearings, mechanical seals, and coupling—using current sensor data and corresponding evaluation algorithms.

4.3.1. Bearings

The analysis provides two key outputs: the current condition of each bearing and its estimated RUL. All the bearings are within acceptable condition limits, as confirmed by vibration readings that comply with ISO and Saudi Aramco standards. Due to the limited historical dataset, a rule-based algorithm was applied instead of machine learning models.

RUL estimations were generated using the current vibration values and Equation (1), which incorporates the parameter “ n ”. This parameter has a documented correlation with bearing vibration and can potentially be predicted using regression-based machine learning if sufficient data become available. In this study, a linear relationship was observed between initial vibration readings and “ n ”, yielding an R^2 value of 0.78 (as shown in Figure 8), which supports the use of this approach.

Although the maintenance plan calls for all the bearings to be replaced in 2024, the tool recommends extending the service life of three bearings until 2026. These bearings were replaced in 2023 and have operated for only one year; however, statistical and reliability calculations suggest scheduling their replacement during the planned shutdown in 2024. In contrast, the outboard (OB) bearing, replaced in 2022, shows a shorter RUL and does not qualify for the extension.

4.3.2. Mechanical Seals

The inboard (I) and outboard (O) mechanical seals (MSs) were assessed based on leakage readings. Although the seals are typically replaced on a schedule due to their unpredictable failure behaviour, the tool offers real-time condition insights to prevent unexpected failures. Fuzzy logic was applied to evaluate their condition, as the thresholds are less clearly defined than for bearings.

The results show that the IB mechanical seal remains in normal condition, with a current leakage of 2 psiG. This aligns with the historical data, which show an initial leakage in the 0–1 psiG range and average lifespans of approximately four years. The current IB seal was installed in 2023 and remains within expected parameters.

The OB seal, however, is flagged as alarming, with a leakage of 8 psiG. This is not yet considered faulty, as the leakage pipe's safety valve is set to release at 15 psiG. The trend is consistent with the statistically estimated lifespan. Historical records indicate that the OB seal's service life has declined from five years to three years over recent replacements, which may warrant a further inspection of the sealing system.

4.3.3. Coupling

The coupling condition remains acceptable according to the visual inspection data. It was replaced in 2023 and has only one year of service, which is consistent with its expected service life.

4.4. Maintenance Optimisation

The results shown in Table 4 demonstrate that the optimised maintenance routine (Route 2) is significantly more cost-effective than the traditional approach (Route 1), in which each component is maintained independently based on its individual estimated lifespan and condition. Although Route 1 reflects a component-level optimisation approach, it does not consolidate maintenance activities into shared downtime windows. Consequently, this approach results in substantially higher total costs—up to six times greater than Route 2. The elevated cost arises primarily from operational losses due to frequent pump downtimes, which far exceed the cost of component replacement in the oil and gas sector.

Table 4. Optimised route cost-effectiveness comparison (Unit: USD).

	Route 1	Route 2
Pump IB Bearing	1,507,364	1250
Pump OB Bearing	2,261,046	2500
Motor IB Bearing	2,261,046	2500
Motor OB Bearing	2,261,046	2500
IB Mechanical Seal	3,023,763	10,000
OB Mechanical Seal	3,023,763	10,000
Coupling	1,508,267	2000
Total	1,584,6293	2,530,750
Route 1/Route 2	6.26	

In contrast, Route 2 consolidates component replacements into common shutdown periods. This reduces the total downtime by approximately 80% and leads to an overall cost reduction of the same magnitude. Notably, Route 2 includes more frequent component replacements than Route 1, but this trade-off is economically favourable due to the dominance of downtime costs. The result reflects the conservative assumption that cost savings are driven largely by uptime optimisation, rather than spare part conservation. Figure 13 highlights the increase in the number of component replacements when comparing Route 1 and Route 2 over a ten-year period.

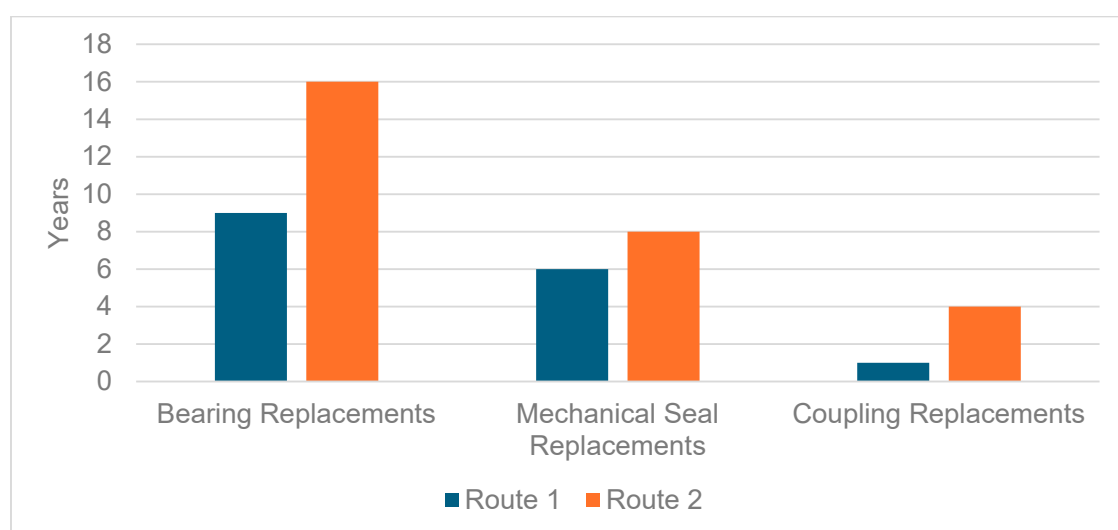


Figure 13. Route 1 and Route 2 comparison in terms of component replacements over 10 years.

The optimised schedule produced by Route 2 provides replacement dates for each component from 2024 to 2034. This long-range forecast supports maintenance planning and spare part availability. Although cost inputs such as replacement costs and daily operational losses are user-defined, the values used in this case study reflect actual NGL plant figures and are consistent with the published literature.

4.5. Diagnosis and Recommended Actions

While no actual replacements of bearings or mechanical seals occurred at the time of testing, the diagnostic and recommendation functions of the tool were validated using representative dummy datasets. These test scenarios confirmed that the tool performs as expected in identifying fault causes and recommending corrective actions. Figure 14 illustrates example outputs for bearing and mechanical seal diagnostics, respectively.

Bearing Diagnosis and Replacement Actions				Mechanical Seal Diagnosis and Replacement Actions		
Please Insert Vibration Frequency	1X		Failure Cause	How is Flashing Line's Condition?	Normal	Failure Cause
Please Insert Outer Race Clearance	−1	Normal	Mass Imbalance	How is the Casting Concentricity?	Accepted	Damaged Casing
Please Insert Inner Race Clearance	2	Normal		How is the Casting Squareness?	Unacceptable	
Please Insert Balls Clearance	1	Normal		Recommended Actions 1 Disconnect Flashing Lines 2 Put On the Fixing Plates 3 Gently Pull Out the Seal and Pull In the New One 4 Fix Casing		
Please Insert Axial Floating Clearance	3	Normal				
Recommended Actions 1 Isolate the Pump 2 Open Bearing Cover 3 Pull the Bearing Using Pulling Tool 4 Mark Bearing Face and Back 5 Ensure Correct Bearing is Available, Consider Face and Back Then Side the Bearing In 6 Check All Clearances 7 Balance Rotor						

Figure 14. Diagnostic output for bearings and mechanical seals in the case study.

4.6. Comparison with Existing Studies

To further evaluate the distinctiveness and practical value of the proposed methodology, this section presents a comparative analysis against recent predictive maintenance approaches reported in the literature.

Most recent advances focus on specific aspects, such as a single component or failure prediction, and lack integrated decision support [45]. Kumar et al. [46] proposed a digital twin approach with domain adaptation to identify bearing defects. Although the method effectively handles data scarcity and adapts simulated knowledge to real systems, it remains focused on a single failure type and does not assist with maintenance execution. By comparison, our approach supports multi-component diagnostics.

Mohammed [47] developed a data-driven model using multiple linear regression to predict failures in seawater pumps. In contrast, our method not only predicts potential failures but also diagnoses fault causes and translates predictions into cost-driven, actionable maintenance schedules. Similarly, Souza et al. [48] utilised CNNs to detect faults in offshore centrifugal pumps. While the model achieved a high classification accuracy, it offered no guidance for maintenance planning and did not address how to manage operational downtime. Our method improves upon this by directly linking diagnostic results to optimised maintenance interventions, including the consolidation of shutdowns and the prioritisation of tasks based on their cost and risk. In addition, Upasane et al. [49] developed a type-2, fuzzy-based, explainable AI system to improve transparency in predictive models. The emphasis on interpretability is valuable, particularly for user trust. However, their method does not incorporate any cost modelling or multi-component planning.

Our method maintains model interpretability while extending functionality to include coordinated task scheduling and cost-effective intervention strategies.

In summary, most recent studies stop short of translating prediction into specific, cost-informed actions. Our framework closes this gap by linking prediction, diagnosis, and scheduling within a single, unified maintenance tool that delivers operational benefits under constrained data conditions.

5. Validation Questionnaire Results and Discussion

Following the technical testing of the developed tool, a validation questionnaire was distributed to a selected group of 15 industry experts. The objective of this survey was to evaluate the methodology and the practical performance of the tool from an industrial perspective. This section presents the expert feedback and provides a discussion of the validation results.

The questionnaire consisted of 10 questions, each targeting a specific aspect of the tool's value and robustness. Topics included the business relevance of such a predictive maintenance system, the validity of underlying assumptions, the ease of implementation, and the effectiveness of the diagnostic functionalities. The responses were captured using a four-point Likert scale: "Strongly Agree", "Agree", "Neutral" (indicating partial familiarity with the topic), and "Disagree". This design was deliberately selected to avoid a true neutral midpoint, thereby encouraging respondents to make a clear evaluative choice. Such forced-choice formats are particularly effective when collecting expert feedback on prototype tools, as they reduce the central tendency bias and yield more actionable results.

The expert panel comprised 15 professionals from major industrial organisations in the Middle East region, as summarised in Table 5. Their areas of expertise ranged from engineering to management and technical operations, with most of the respondents being affiliated with either Saudi Aramco or SABIC. The distribution of their expertise is shown below.

Table 5. Subject matter experts' details.

Number of Experts	Expertise Field	Employer
5	Maintenance engineers	Saudi Aramco
4	Maintenance engineers	SABIC
3	Maintenance Managers	Saudi Aramco
3	Maintenance Technicians	Saudi Aramco

5.1. The Need for an AI Tool to Optimise NGL Pump Maintenance

- **Question 1: There is a business need to deploy AI for NGL pump maintenance optimisation instead of manual optimisation.**

The experts' responses to this question were highly consistent. Fourteen out of fifteen participants selected "Strongly Agree", indicating a clear and unanimous recognition of the value and necessity of AI-based maintenance optimisation in the NGL pump context. One respondent selected "Neutral", which was interpreted as reflecting limited familiarity with AI technologies, rather than disagreement with the concept.

This strong consensus aligns with the current gap in the literature, where existing approaches primarily focus on predictive modelling or fault detection in isolation, with little emphasis on integrated, AI-supported decision tools tailored to the scheduling and operational realities of NGL systems. The expert feedback, therefore, reinforces both the relevance and the timeliness of the proposed tool.

5.2. Assumption Technical Validation

- **Question 2: The assumptions regarding bearing conditions are accurate.**

All the subject matter experts strongly agreed that the assumptions used to assess bearing conditions based on vibration measurements are technically valid. This consensus aligns with the clearly defined thresholds provided in the ISO and Saudi Aramco standards.

- **Question 3: The correlation used to estimate bearing RUL based on vibration readings is applicable and provides a fair estimation.**

Figure 15 presents the results of expert opinions regarding the Questions 3 to 8. All the maintenance engineers expressed strong agreement regarding the applicability of the correlation in Equation (1) for estimating the RUL. They confirmed the appropriateness of using vibration readings and supported the use of a linear relationship between the initial vibration and the coefficient n . The maintenance managers also agreed once the theoretical basis of the correlation was explained in line with the literature. However, some of the maintenance technicians selected “Neutral”, citing that the correlation is not explicitly recognised in Saudi Aramco’s current standards. Nevertheless, the overall feedback supports the validity and applicability of the correlation approach used in the tool.

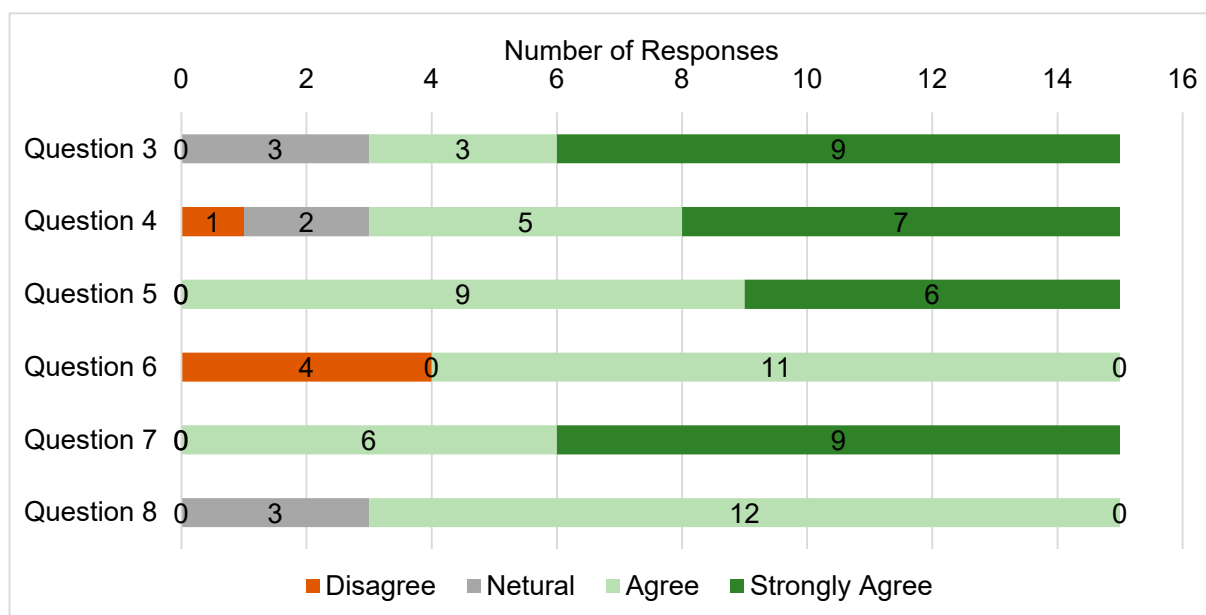


Figure 15. Questionnaire results for Questions 3 to 8.

- **Question 4: The adopted approach reflects mechanical seals’ condition accurately.**

Most of the experts (12 of 15) supported the use of fuzzy logic and the defined fuzzy sets for classifying mechanical seal conditions. The Saudi Aramco engineers and two of the maintenance managers strongly endorsed the approach. In contrast, the SABIC engineers agreed in principle but noted that their organisation does not apply fixed criteria for seal condition statuses, which affects their evaluation. One maintenance technician endorsed the approach based on consultation with engineers, while another chose “Neutral” due to limited familiarity with seal condition assessment. One maintenance manager expressed disagreement, citing a belief that seals should be replaced once leakage reaches 5 psiG—an approach inconsistent with current standards. Despite a range of perspectives, the majority of the experts validated the fuzzy logic methodology used in the tool.

5.3. Tool Practicality

- **Question 5: The proposed methodology helps reduce the total cost significantly.**

All the field experts—including the maintenance managers and the technicians—strongly agreed with the methodology of aligning component maintenance within shared shutdown periods. Many noted that this practice is informally adopted even in the absence of formal directives from engineers. The engineering staff also agreed with the principle, recognising its potential to reduce the overall maintenance costs through improved scheduling.

- **Question 6: The tool is simple and user-friendly.**

All the Saudi Aramco experts agreed that the tool is intuitive and easy to operate. However, the SABIC engineers provided a more critical assessment, suggesting that integration with the SAP maintenance system would enhance its usability. It is worth noting that, unlike SABIC, Saudi Aramco enforces strict IT policies that prohibit third-party software from directly interfacing with SAP, which influences perceptions of tool compatibility.

- **Question 7: The methodology and developed tool address the business need for using AI to optimise NGL pump maintenance.**

Both the Saudi Aramco and the SABIC maintenance engineers strongly agreed that the methodology and tool address the core business need for AI-driven maintenance optimisation. The field technicians also acknowledged the tool's practical contribution to improving NGL pump availability and reducing costs.

Collectively, the responses to Questions 1 through 7 provide a secondary validation of the tool's effectiveness and alignment with the operational goals. This complements the primary validation obtained through the technical testing of the tool.

5.4. Tool Diagnostic Functionality

- **Question 8: The tool provides useful diagnoses and recommended actions that reduce pump downtime.**

Both the Saudi Aramco and the SABIC engineers agreed that the tool delivers effective diagnostic insights and maintenance recommendations that help reduce reliance on manual inspection processes and contribute to shorter downtimes. This feedback confirms the technical soundness of the diagnostic module.

In contrast, the maintenance managers and the technicians selected "Neutral", primarily because they are not directly involved in diagnostic tasks for NGL pumps and thus could not fully assess this aspect of the tool's functionality.

6. Conclusions

This study introduced an AI-based methodology and digital tool specifically developed to optimise the maintenance of NGL pumps. Unlike conventional approaches that focus solely on failure prediction or isolated condition monitoring, the proposed framework integrates reliability-based scheduling, real-time condition assessment, and AI-driven diagnostics within a unified system. This comprehensive approach allows for the development of optimised maintenance routines that balance component longevity with the operational cost, even under limited data availability—a common constraint in industrial settings.

The significance of the work lies in its ability to reduce unplanned downtime and operational losses by aligning component maintenance within consolidated shutdown windows. In the case study involving pump G221, the optimised routine reduced the total cost by approximately 80% compared to conventional individual replacement scheduling. This improvement was primarily achieved by minimising downtime, which was reduced by a similar margin. Furthermore, while the number of replacements increased under

the optimised plan, the overall routine cost remained significantly lower due to reduced production losses.

The tool was validated through both technical application and structured expert feedback from 15 industry professionals. The survey results showed that over 90% of the experts strongly agreed with the need for such a tool and acknowledged its effectiveness in addressing key operational and diagnostic challenges.

While this study focuses on a single equipment type (NGL pumps), the proposed methodology is designed to be generalisable to other rotating assets, such as compressors and fans. Future work will involve extending the tool's application to a broader range of equipment under varied operational conditions.

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Nomenclature

AI	Artificial Intelligence
API	American Petroleum Institute
ANN	artificial neural network
CCW	Counter-Clockwise
CNN	Convolutional Neural Network
C-MAPSS	Commercial Modular Aero-Propulsion System Simulation
FMEA	Failure Modes and Effects Analysis
IMS	Inboard Mechanical Seal
ISO	International Organization for Standardization
LSTM	Long Short-Term Memory
MOB	Motor Outboard Bearing
MEP	mechanical, electrical, and plumbing
MIB	Motor Inboard Bearing
MTBF	mean time between failures
NGL	Natural Gas Liquid
OB	outboard
OEM	Original Equipment Manufacturer
OMS	Outboard Mechanical Seal
PIB	Pump Inboard Bearing
POB	Pump Outboard Bearing
RAM	Reliability, Availability, and Maintainability
RPN	risk priority number
RUL	remaining useful life
SAP	Systems, Applications, and Products (in Data Processing)
SVM	support vector machine

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AI-driven maintenance optimisation for natural gas liquid pumps in the oil and gas industry: a digital tool approach

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