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A Novel Energy Efficiency Based Predictive Maintenance optimization and Failure Prognosis for Centrifugal Gas Compressor

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Research Article

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Predictive maintenance (PdM), Energy efficiency (EE), Fault Prognosis (FP), Condition Monitoring (CM)

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A B S T R A C T

Unplanned shutdowns of centrifugal compressors (CC) in both onshore and offshore gas facilities pose significant operational and economic challenges, often resulting in losses of millions of dollars in production, maintenance, and energy costs. Similarly, undetected equipment degradation and operation under faulty conditions lead to excessive energy consumption and energy inefficiencies. To overcome this, the gas industry needs a robust maintenance strategy to increase energy efficiency and reduce unplanned shutdown. However, existing predictive maintenance models are limited to conventional maintenance indicators such as vibration, oil analysis, thermography, and remaining useful life (RUL) to address the critical and mechanical failures without addressing the failures due to thermodynamic and energy efficiency degradation. This study proposed a novel framework that uses sustainability indicators such as energy efficiency (EEI), and energy performance (EnPI) to develop a predictive hybrid machine learning (ML) model to optimise maintenance, sustainable operations, forecast future health performance, and novel remaining energy efficiency life (REEL) for CC. The results indicate that the remaining energy efficiency life (REEL) was forecast 1000 operating hours in advance, providing prognostic information for maintenance scheduling. Similarly, the energy efficiency indicator (EEI) detected degradation at 0.91% and 0.87% for low-pressure (LP) and high-pressure (HP) CC, respectively, while the prognostic model forecasted compressor failure at 7256 operating hours to optimise maintenance, prevent unplanned shutdowns, improve reliability, and minimise energy losses. Finally, the results obtained from the Receiver operating characteristic (ROC) curve for the hybrid ML model, the training data set showed a high true positive rate of 0.96, and the test or validation data set showed a true positive rate of 0.97 indicating high performance. The outcome of this research opens up a new possibility for industries to reduce downtime across assets, increase sustainable performance and reliability, and cut maintenance and energy costs.

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Predictive maintenance (PdM), Energy efficiency (EE), Fault Prognosis (FP), Condition Monitoring (CM)

1. Introduction

The centrifugal gas compressor is the key asset and the largest energy consumer in both onshore and offshore gas facilities. A suitable maintenance strategy can improve energy efficiency, reduce operating costs, enhance reliability, and reduce unplanned CC shutdown [1]. The energy efficiency of CC gradually decreases with use, leading to higher energy consumption due to performance degradation [2]. Existing literature has investigated the role of maintenance in the energy efficiency of rotating machinery. Their findings showed that maintenance not only contributes to energy savings but also provides other benefits, such as increasing equipment life, ensuring reliable operations, and supporting fault diagnosis and prognosis [3]. Traditional maintenance strategies, such as Reactive Maintenance (RM), Preventive Maintenance (PM), Reliability-Centred Maintenance (RCM), and Condition-based Maintenance (CBM), mainly rely on compressor reliability and operational availability. These maintenance strategies fail to consider sustainability indicators such as energy efficiency, energy consumption, and environmental impacts associated with performance degradation. Therefore, maintenance optimisation and the selection of a suitable maintenance strategy is crucial for ensuring the energy-efficient and sustainable operation of industrial assets, specifically CC. [4]. Recent studies indicate that poor and inefficient maintenance strategies can minimise industrial productivity up to 20% of total production capability. Furthermore, the International Society of Automation (ISA) reports that unplanned downtime costs more than USD647 billion annually across all sectors [5]. Industries continuously track sustainable improvement, and energy efficiency has emerged as a necessary performance measure that assesses how effectively energy assets are converted into useful output while reducing energy consumption. Maintenance plays an important role in improving the energy efficiency of a gas turbine by minimising performance deviations and ensuring the turbine operates near its design conditions. With time, fouling, wear, erosion, and component degradation increase fuel consumption and decrease power output. The efficient maintenance strategy restores its performance and reduces energy losses [6]. Recent studies have shown that Predictive Maintenance (PdM) is more energy-efficient than the maintenance approaches currently used across various industrial sectors. Predictive Maintenance is used to optimise operations and Maintenance by leveraging real-time operational data analytics of industrial assets [7]. In PdM, a hybrid machine learning model is useful for fault prognosis, maintenance optimisation, and automatically collecting, distributing, and evaluating maintenance data. Managers are equipped to effectively plan and oversee energy-efficient maintenance using this integrated approach. Detecting maintenance problems, such as wear and fouling, is based on deviations in pressure, temperature, volume flow, and energy consumption in centrifugal compressors. These degradations show variations from the required operating range and are diagnostic of possible problems inside a compressor subcomponent [8]. Compressor maintenance problems result in lower energy performance and higher operational costs, particularly in many small- to medium-sized industries. Predictive maintenance is very important for early fault detection, and resolving these issues can result in considerable energy savings [9]. PdM is the best maintenance strategy for achieving energy performance goals because maintenance actions are scheduled based on proper thresholds and real, monitored conditions of centrifugal compressors. PdM is carried out when one or more indicators indicate that the compressor will fail or performance will deteriorate, and the indicator value exceeds a threshold. The energy efficiency indicator (EEI) and energy performance indicator (EnPI) are the two important indicators to track a compressor's health and determine whether its energy performance is decreasing [10,11]. According to the literature, existing research has mostly addressed critical failures of centrifugal compressors, with minimal attention to failures due to energy performance degradation. Moreover, existing maintenance models lack consideration of energy efficiency and energy performance degradation in maintenance decisions, serving as a substitute for the currently used conventional maintenance indicators to optimise energy performance, reduce downtime, and minimise energy costs for the compressor. Existing maintenance strategies, such as reactive and preventive

maintenance, face critical limitations, including costly downtime, increased risk of asset degradation, high repair costs, unexpected failures, and unnecessary preventive maintenance costs. Predictive maintenance surpasses reactive and preventive maintenance strategies by predicting the precise maintenance time. This precision minimises energy waste when a centrifugal compressor is running with faults or performance degradation. Furthermore, existing predictive maintenance models are also limited to conventional maintenance indicators, such as reliability, vibration, oil analysis, thermography, and remaining useful life, for performance monitoring and critical failure analysis of centrifugal compressors. Several predictive maintenance methods have been suggested in the literature they are limited to predicting the remaining useful life (RUL) of compressors without considering sustainability indicators and to forecasting the remaining energy-efficient life (REEL) of compressors. According to this study, there is no framework for integrating energy efficiency metrics, such as energy efficiency indicators (EEI) and energy performance indicators (EnPIs), to trigger maintenance actions, forecast REEL, and assess future energy health performance when compressors consume excessive energy due to performance degradation. The main objective of this study is to detect CC failures promptly, REEL, and optimise maintenance decisions using a PdM model that incorporates energy efficiency as a key health indicator, with a hybrid machine learning tool.

2. Literature Review

This section provides a detailed review of literature on predictive maintenance for energy efficiency and existing approaches as covered in section 2.1., and Section 2.2 presents Prognostics approaches for centrifugal compressors. Finally, section 2.3 describes the summary of literature.

2.1 Predictive Maintenance for Energy Efficiency

In Petrochemical industry, timely maintenance decisions and the scheduling of an appropriate maintenance strategy for rotating equipment will save energy, reduce total life-cycle costs, and reduce the environmental footprint. Various maintenance strategies are used in the existing literature, such as Reliability-centred maintenance (RCM), corrective maintenance (CM), opportunity-based maintenance (OBM), inspection-based maintenance (IBM), time-based maintenance (TBM), condition-based maintenance (CBM), and predictive maintenance (PdM) are shown in Figure 1 [12]. Compared with PdM these traditional maintenance strategies considered less energy-efficient because they allow time-dependent performance degradation to persist throughout the CC operating cycle. Similarly, these maintenance except PdM strategies do not address fouling seals and bearing wear, which can degrade and increase power requirements, reducing compressor efficiency [12]. PdM strategy integrates sensor technology, Artificial Intelligence and Machine learning, diagnostic and prognostic, and digital twin models to detect early signs of failure and forecast remaining useful life (RUL). Consequently, energy consumption can be reduced while maintaining reliability and availability, and minimising the risk of failure. Therefore, PdM has been found to be the best maintenance strategy when compared to other maintenance strategies for achieving energy performance considerations [13]. The two primary phases of the PdM process are equipment condition analysis and energy monitoring. The first phase is energy monitoring, where information is gathered on equipment conditions related to energy performance. Figure 2 shows further classification of the comprehensive equipment energy monitoring into diagnostics and prognostics for PdM model [14].

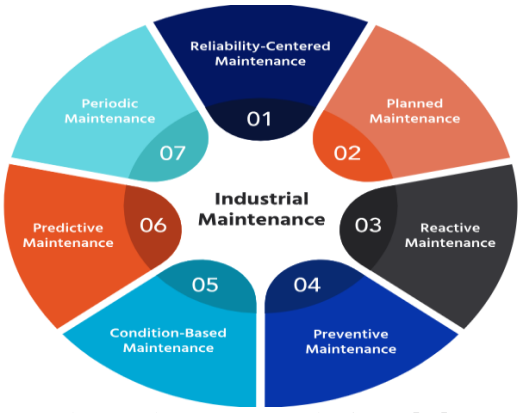


Fig. 1. Maintenance strategies for CC [12]

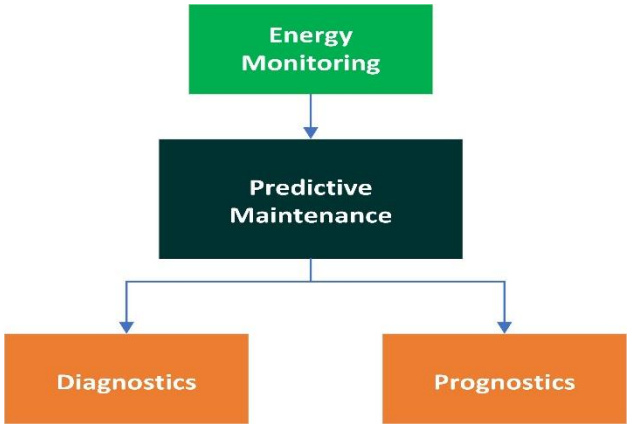


Fig. 2. Energy Monitoring for PdM model

Predicting anomalies and faults in rotating machinery is part of diagnostics. Its objectives regarding energy performance are to identify energy faults, detect energy deterioration, and determine their causes. The goal is to raise the alarm when energy consumption is excessively driven by degradation of the energy performance indicator (EnPI) and the energy efficiency indicator (EEI), as indicated by their exceeding the threshold. The prognostics stage follows diagnostics, in other words, diagnostic skills always accompany prognostics. The main goal of prognostics is to forecast future deterioration, specifically when equipment may fail [15]. Energy consumption is a critical concern for rotating machinery in the natural gas industry, particularly for centrifugal gas compressors, which consume excessive energy as they continue to operate despite degradation during periods of varying supply and demand. Additionally, energy performance is a well-known concept with several names, including energy intensity, specific energy consumption, and energy conservation. Defining energy efficiency can be complicated; it means using less energy to generate the same useful products or services, or producing more products or services with the same amount of energy [16]. Efficient maintenance strategies can prevent compressor failures and predict higher energy consumption. In the predictive maintenance of centrifugal gas compressors, maintenance costs and reliability are the key performance indicators (KPI) for conventional maintenance strategies. Sustainability indicators, such as excessive energy consumption and emissions caused by performance degradation, are not considered by these key performance indicators (KPIs) [17]. Various predictive maintenance approaches exist to improve the performance of centrifugal compressors. These techniques may be separated into two groups: AI-based and model-based, as described in Physics-based models are structured methods that integrate data collection and failure analysis to study, assess, and identify failure processes, thereby enabling the forecast of remaining useful life (RUL) and the detection of effective maintenance and faults at an early stage. Physics-based model is confined to specific and associated with high progress cost, and a low prediction accuracy under adverse operating conditions [18]. However, knowledge-

based models include fuzzy logic models and rule-based expert systems. Knowledge-based models can vary in efficiency, which is mostly dependent on expert knowledge within a particular sector [19,20]. Data-driven models have gained prominence in the field of centrifugal compressor fault detection in recent years, thanks to their ability to detect and predict various faults and anomalies using historical data. Among these models, the hybrid ML model is a very effective and powerful ML tool for efficiently detecting anomalies or faults in compressors [21]. Time series models are often used to forecast the exact time of maintenance, mean time between failure (MTBF), and failure rates per interval. These models use analysis techniques from both time and frequency domains [22]. Regression models are useful for predicting equipment failures and suggesting maintenance tasks. Logistic regression classifiers utilise multivariate feature data to label scenarios as healthy or faulty [23,24]. Decision trees (DT) are strong in dealing with anomalies and missing data, making them ideal for classification or regression jobs in maintenance prediction, even with large data sets [25]. ANNs have been extensively studied for predicting failure risk, lifetime expectancy, and optimal maintenance tasks [26,27]. SVMs are well known for their ability to converge to effective solutions while also improving failure prediction and maintenance scheduling [28]. The primary purpose of PdM is to maximise reliability, optimise energy use, and minimise costs. Various other existing predictive maintenance approaches for improving centrifugal compressor performance are summarised by this study from existing literature as shown in Figure 3.

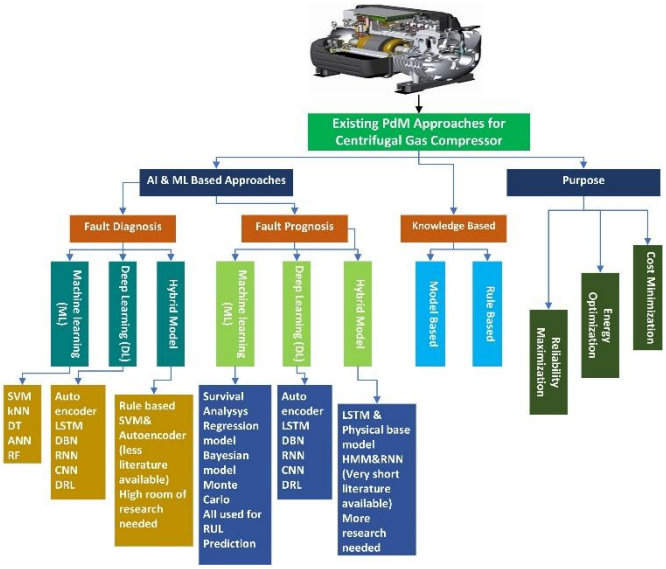


Fig. 3. Summary of existing PdM Approaches for CC

2.2 Fault Prognostics approaches for CC

Prognostics have historically calculated the remaining usable life (RUL), or the time until failure or breakdown. To anticipate RUL, many prognostic models have been developed, including experience-based, model-based, and data-driven prognostics. However, traditional RUL tends to ignore energy degradation; it may not be able to estimate equipment maintenance time when energy deterioration is considered. Furthermore, RUL is often a single condition represented by a single indicator, and energy performance activity may not always be precisely proportional to failure. As such, traditional RUL may not be appropriate for forecasting decline in energy performance [29,30]. Compressor performance-monitoring methods were primarily focused on identifying significant faults until around a decade ago. Lately, studies have focused on adding prognostic capabilities to monitoring systems by integrating time-evolution features, thereby improving understanding of a compressor's health. As explained by [31], prognostics seeks to forecast the continuous deterioration of the machine or its working components, in contrast to conventional reliability-based techniques, which use event record distributions of identical units to estimate features such as mean-time-to-failure. Prognostics, in short, depends on diagnostic outputs, and its accuracy depends on how well the diagnosis model is trained & tested. The Performance degradation and failure of the compressor can be identified, as shown in Figure 4, allowing documentation of the compressor's degradation history. The prognostic model relies heavily on collected data as input [31]. However, several prognostic models have been proposed in the literature, such as Experience-based, model-based, and data-driven models, used only to predict the remaining useful life (RUL) of compressors without considering energy efficiency degradation to predict REEL.

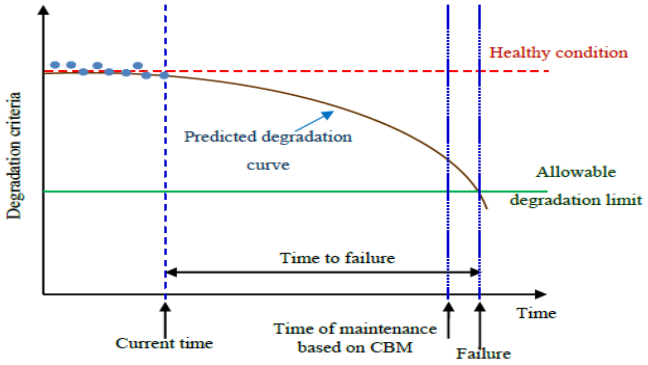


Fig. 4. Performance degradation and failure prediction for CC [31]

Data-driven prognostics enables the detection of trends or patterns that indicate emerging anomalies or faults, and it predicts when they will reach a certain threshold [32]. These techniques make use of information from previously trained data. Neural networks (NN), fuzzy logic (FL), regression analysis (RA), Bayesian algorithms, and support vector machines (SVM) are some of the approaches that may be used to analyse a system's real-time health. Data-driven approaches are more precise than experience-based prognostics because they rely on known system behaviours without requiring a specific physical model [33]. However, they need a monitoring system and training time. In the field of PdM for compressor diagnostics, prognostics, and RUL prediction, several "shallow" ML methods precede more complex ones. These include ANN, DT, SVM, and k-NN, illustrated in Table 1 [34,35.36,37]. Several survey articles have been published throughout the years, covering various areas of fault detection and prognosis in Predictive Maintenance (PdM).

Table 1: Limitations and advantages of ML approaches

Approaches	Advantages	Limitations	Applications
ANN	1. High accuracy in prediction & classification 2. Excellent performance for complex and non-linear problems	1. Several weight parameters need to be trained. 2. High computer skills required. 3. Overfitting problems	1. Fault diagnosis and prognosis of compressors & turbines 2. Fault diagnosis and prognosis of Bearings 3. RUL prediction for rotating machinery
DT	1. Simple in learning 2. Non-parametric	1. Less accurate 2. Overfitting issues	1. Fault diagnosis and prognosis of compressors & turbines 2. Fault diagnosis and prognosis of Bearings 3. RUL prediction for rotating machinery

SVM	1. Ability of handle unstructured and semi-structured data 2. Efficient to handle high dimensional data. 3. Efficient to deal with overfitting issue	1. No probability of classification 2. No criteria for assessing the kernel function. 3. Less efficiently deal large data	1. Fault diagnosis and prognosis of compressors & turbines 2. Fault diagnosis and prognosis of Bearings 3. RUL prediction for rotating machinery
kNN	1.Parameters required to tune. 2. Very simple to execute. 3. No Training process	1. K should be determined before 2. Constraint of dimension	1. Fault diagnosis and prognosis of compressors & turbines 2. RUL prediction of rotating machinery

According to the literature, these approaches primarily focus on estimating the remaining useful life (RUL) of equipment such as wind turbines, gas turbines, bearings, rotating equipment, and electronic devices [38,39,40]. However, there is a limitation and gap available in existing research for prediction of the remaining energy-efficient life of equipment, particularly in compressors. While traditional indicators have been used to estimate RUL using single AI models, they are not using hybrid ML model to anticipate compressor energy performance. In line with the traditional prognostic methodologies previously described, we suggest that an energy performance-based prognostics model employs a predictive technique to forecast future performance and energy consumption trends for centrifugal compressors. This study will forecast energy usage, evaluate the remaining energy-efficient life (REEL) of the compressor, and recommend optimal maintenance schedules. Additionally, the proposed prognostic method assists in minimise energy waste and unscheduled downtime using hybrid ML model.

2.3 Summary of the literature

Energy efficiency in industrial systems is then studied, stressing the importance of energy saving, optimisation, and cutting operating costs and environmental impacts. Relevant scientific literature and important research activities related to this study are reviewed, with a focus on maintenance strategies such as IBM, TBM, CM, PM, CBM, and PdM. The literature indicates that PdM is the most energy-efficient strategy. Furthermore, the EEI and EnPI formulation and its integration into PdM have been widely discussed. Latest research trends in fault diagnosis and prognosis methods, including model-based, rule-based, and experience-based approaches, are explored. Data-driven methods, particularly AI-based specifically hybrid ML model, are praised for their effectiveness in handling nonlinearity and the complexity of dynamic systems. The review emphasises the significance of energy performance in compressor operation and its impact on overall energy consumption and industrial sustainability.

3. Proposed Methodology

This section explains the proposed methodology, in which a supervised ML algorithm with the highest accuracy was selected via a trial-and-error approach, using GB, DT, and kNN as base classifiers. An ensemble approach was developed, combining predictions from base algorithms to build a hybrid ML model using the stacking method to address underfitting and overfitting. A hybrid ML model using EEI and EnPI indicators enables final users to continuously monitor CC degradation to track energy efficiency, forecast failure, and prognose remaining energy efficiency life (REEL) and PdM mitigation actions to avoid unplanned downtime. A proposed hybrid ML model was developed in Orange Data Mining Software version 3.34, an open-source AI and ML platform. Orange software is a robust open-source data mining and machine learning tool that provides a user-friendly platform for visual programming, analysis, and various machine learning algorithms in a single workflow. Orange leverages common Python open-source libraries for scientific computing, such as numpy, scipy, and scikit-learn. In this study a two-stage Low Pressure (LP), and High Pressure (HP) Centrifugal Compressor (CC) will be selected as the proof-of-concept for the proposed hybrid machine learning model. The flowchart outlining the suggested methodology for this study is presented in Figure 5. First, a comprehensive literature review was conducted to identify methods, limitations, challenges, and the research gap. Then, real time data for various performance parameters such as energy consumption, shaft speed, Inlet and outlet pressures, discharge temperature, Power Consumption, volume flow, and polytropic head etc, were collected over one year at one-hour intervals. Data analysis in this study was conducted using the orange software, including widgets for data preprocessing, visualization, and feature selection, with a focus on REEL, Failure, and Energy Efficiency. The model was trained on 70% of the data and tested and validated on 30%, and performance was predicted accordingly. After, a supervised ML algorithm with the highest accuracy was selected via a trial-and-error approach, using GB, DT, and kNN as base classifiers to develop a hybrid ML model that uses the predictions from base single classifiers to forecast REEL and predict failure and future health performance, track energy efficiency, and optimise maintenance decisions for CC.

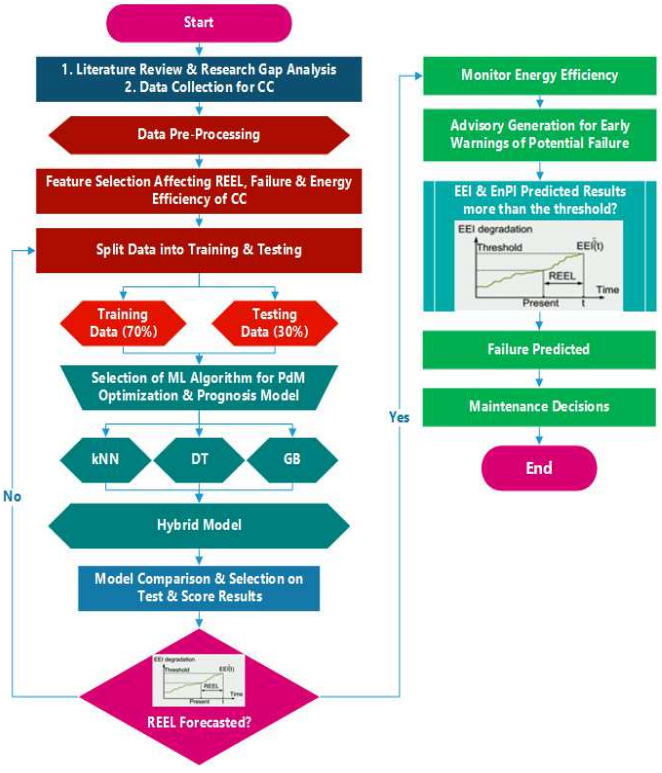


Fig. 5. Methodology flowchart.

3.1 Hybrid ML Model Performance Assessment

The accuracy and effectiveness of a proposed hybrid ML model for detecting anomalies in the raw data for centrifugal compressors are evaluated using Confusion performance metrics. It assesses the model's capacity to generate accurate predictions or classifications on data not used during training. The performance of the supervised classification model for anomaly detection was evaluated using various performance metrics, including the confusion matrix shown in Figure 6, as well as

Recall, ROC, F1 score, and AUC. The equations used for the performance evaluation of the model are given as follows:

$$\text{TPR} = \frac{TP}{\text{Actual Positive}} = \frac{TP}{TP+FN} \quad (1)$$

$$\text{FNR} = \frac{FN}{\text{Actual Positive}} = \frac{FN}{TP+FN} \quad (2)$$

$$\text{TNR} = \frac{TN}{\text{Actual Negative}} = \frac{TN}{TN+FP} \quad (3)$$

$$\text{FPR} = \frac{FP}{\text{Actual Negative}} = \frac{FP}{TN+FP} \quad (4)$$

Where:

TPR= True Positive Rate

FNR= False Negative Rate

TNR= True Negative Rate

FPR= False Positive Rate

3.2 Energy performance model

Energy performance is a well-known concept with several names, including energy intensity, specific energy consumption, energy conservation, and energy efficiency. Defining energy efficiency may be complicated, it frequently means employing small amounts of energy to generate the same useful product or services or producing more output or services with the same amount of energy. Additionally, governing equations and mathematical formulations of EnPI and EEI are given below [3,15,17]. The EnPI is a ratio of energy consumption per unit output, but it is also known as specific energy consumption.

$$EnPI = \frac{Energy\ consumption}{Out\ put} \quad (5)$$

EEI and EnPI are energy consumption labels, lower the EEI & EnPI value more energy efficiently the compressor is due to less energy utilized to attain a specific level of performance. While EEI is obtained by following equations [3,15,17].

$$EEI = \frac{Actual\ Energy\ required\ for\ gas\ compression}{Energy\ supplied} \quad (6)$$

4. Results and Discussion

In this study, an ML hybrid model was developed to predict anomalies, REEL, and CC failure. Sustainability indicators, namely EEI and EnPI, were utilised to assess and monitor Energy Efficiency for CC using a supervised classification model. In the proposed model, the meta classifier integrates the outputs of the base classifiers GB, kNN, and DT to generate final predictions, thereby improving the hybrid model's performance and accuracy. Furthermore, findings are ordered into six sections. Section 4.1 presented the Classification Model for Anomaly Detection of LP CC, and high pressure (HP) CC. Section 4.2 Discusses the Classification Model for Anomaly Detection of HP CC, while Section 4.3 Development of EE based Predictive Maintenance optimization and Failure Prognosis for CC, and Section 4.4 Evaluate Performance of proposed hybrid ML model. Lastly, Section 4.5 discuss Model validation for current study and data acquired from another offshore CC.

4.1 Classification Model for Anomaly Detection of LP CC

The development of a classification model to efficiently detect healthy conditions and anomaly detection of low-pressure (LP) compressors for both the actual and predicted output. The timely detection of abnormal operating conditions is necessary to prevent compressor failure, ensure energy efficiency and optimise the reliability of the predictive model. Confusion metrics provide a detailed understanding of the proposed ML model's performance, including GB, kNN, DT, and Hybrid models, by determining correct and incorrect predictions, as shown in Tables 2 and 3 for the training data set. 3 for testing or a validated data set. The performance efficiency of the model comprises true positives (TP), indicating correct anomalies and energy inefficient conditions, false positives (FP) representing healthy and energy efficient behaviour incorrectly as anomalies, true negatives (TN), presenting correctly identified healthy and energy efficient conditions, and false negatives (FN), indicating anomalies and energy inefficient conditions that were incorrectly classified as healthy conditions.

Table.2 Confusion metric results for GB, kNN, DT vs Hybrid ML model for LP CC training data set

Confusion matrix for Gradient Boosting (showing sum of probabilities)

		Predicted: Anomaly & Energy Inefficient	Predicted: Healthy & Energy Efficient	Σ
Actual	Anomaly & Energy Inefficient	1611.7	332.3	1,944
	Healthy & Energy Efficient	332.6	3561.4	3,894
	Σ	1,944	3,894	5,838

Confusion matrix for kNN (showing sum of probabilities)

		Predicted: Anomaly & Energy Inefficient	Predicted: Healthy & Energy Efficient	Σ
Actual	Anomaly & Energy Inefficient	1614.2	329.8	1,944
	Healthy & Energy Efficient	256.4	3637.6	3,894
	Σ	1,871	3,967	5,838

Confusion matrix for Tree (showing sum of probabilities)

		Predicted: Anomaly & Energy Inefficient	Predicted: Healthy & Energy Efficient	Σ
Actual	Anomaly & Energy Inefficient	1710.2	233.8	1,944
	Healthy & Energy Efficient	233.8	3660.2	3,894
	Σ	1,944	3,894	5,838

Confusion matrix for Hybrid model (showing sum of probabilities)

		Predicted: Anomaly & Energy Inefficient	Predicted: Healthy & Energy Efficient	Σ
Actual	Anomaly & Energy Inefficient	1745.8	198.2	1,944
	Healthy & Energy Efficient	220.9	3673.1	3,894
	Σ	1,967	3,871	5,838

Table.3 Confusion metric results for GB, kNN, DT vs Hybrid ML model for LP CC Testing or validation data set

Confusion matrix for Gradient Boosting (showing sum of probabilities)

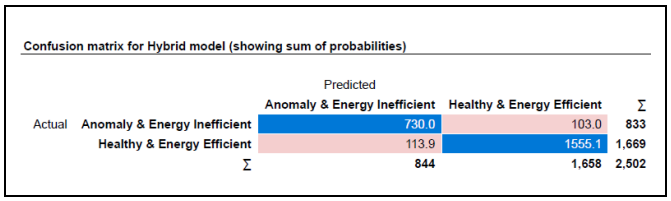
		Predicted: Anomaly & Energy Inefficient	Predicted: Healthy & Energy Efficient	Σ
Actual	Anomaly & Energy Inefficient	675.9	157.1	833
	Healthy & Energy Efficient	156.4	1512.6	1,669
	Σ	832	1,670	2,502

Confusion matrix for kNN (showing sum of probabilities)

		Predicted: Anomaly & Energy Inefficient	Predicted: Healthy & Energy Efficient	Σ
Actual	Anomaly & Energy Inefficient	683.2	149.8	833
	Healthy & Energy Efficient	133.8	1535.2	1,669
	Σ	817	1,685	2,502

Confusion matrix for Tree (showing sum of probabilities)

		Predicted: Anomaly & Energy Inefficient	Predicted: Healthy & Energy Efficient	Σ
Actual	Anomaly & Energy Inefficient	702.8	130.2	833
	Healthy & Energy Efficient	137.1	1531.9	1,669
	Σ	840	1,662	2,502

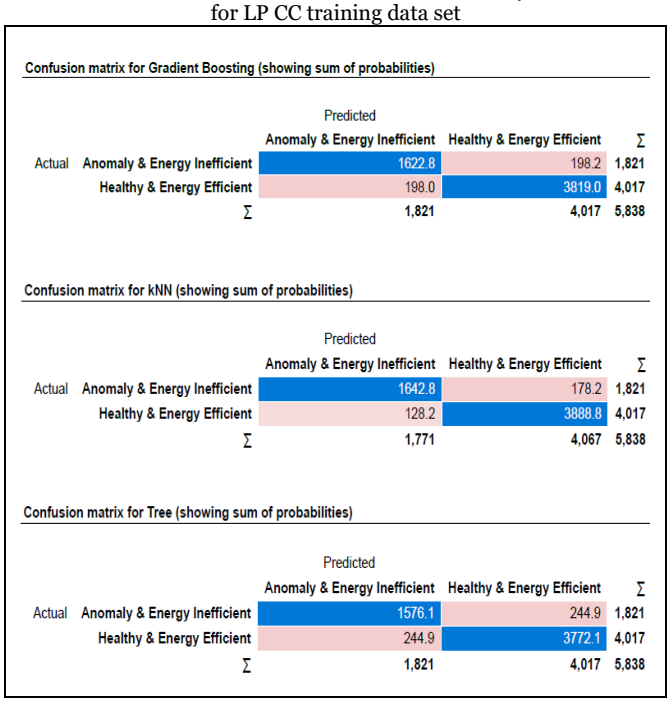


From the predictions, it is observed that the hybrid machine learning model is more efficient at detecting anomalies and maintaining healthy performance for the LP compressor than the single ML models GB, kNN, and DT. For the unseen test/validation data set, the hybrid ML model predicted 730 anomaly and energy-inefficient data instances true positive (TP), and 1555.1 healthy, energy-efficient true negative (TN). Additionally, 103 healthy and energy-efficient data instances predicted False Positive (FP), and 113.9 data instances for anomaly- and energy-inefficient data instances as False Negative (FN).

4.2 Classification Model for Anomaly Detection of HP CC

A classification model was built to detect healthy and anomalous conditions in a High-pressure (HP) compressor, enabling tracking of energy efficiency for both actual and predicted outputs. Early detection of an abnormal operating state is necessary to prevent compressor failure, improve energy efficiency, and optimise the reliability of the predictive model. Confusion metrics assess and evaluate the performance of the proposed hybrid ML model, including GB, kNN, and DT. These metrics quantify the number of True and false predictions for both training and testing/validation, as shown in Tables 4 and 5, respectively. The assessment comprises true positives (TP), indicating correct anomalies and energy inefficient conditions, false positives (FP) representing healthy and energy efficient behaviour incorrectly as anomalies, true negatives (TN), presenting correctly identified healthy and energy efficient conditions, and false negatives (FN), indicating anomalies and energy inefficient conditions that were incorrectly classified as healthy conditions.

Table.4 Confusion metric results for GB, kNN, DT vs Hybrid ML model for LP CC training data set



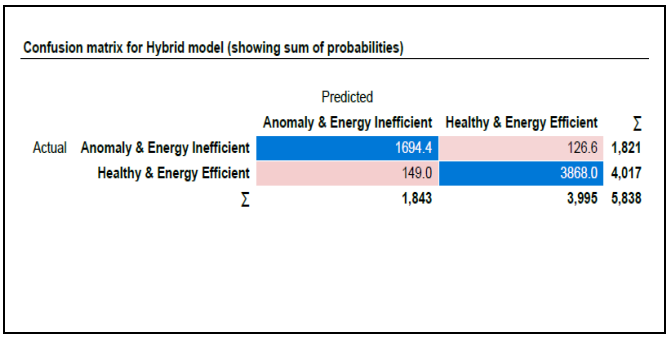
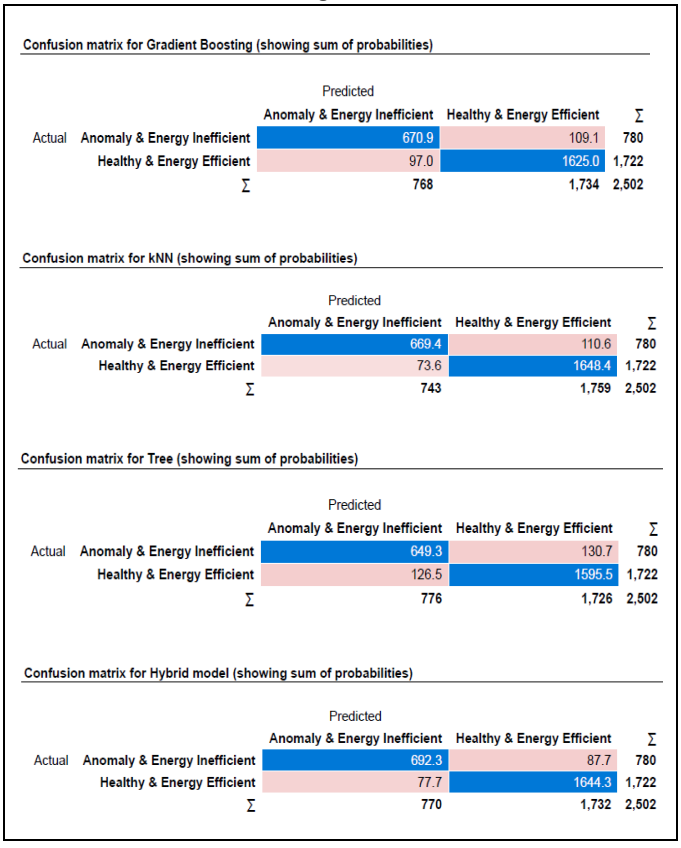


Table.5 Confusion metric results for GB, kNN, DT vs Hybrid ML model for HP CC Testing or validation data set



From the predictions, it is observed that the hybrid machine learning model is more efficient at detecting anomalies and maintaining healthy performance for the LP compressor than the single ML models GB, kNN, and DT. For the unseen test/validation data set, the hybrid ML model predicted 692.3 anomaly and energy-inefficient data instances true positive (TP), and 1644.3 healthy, energy-efficient true negative (TN). Additionally, 87.7 healthy and energy-efficient data instances predicted False Positive (FP), and 77.7 data instances for anomaly- and energy-inefficient data instances as False Negative (FN).

4.3 Development of EE based Predictive Maintenance optimization and Failure Prognosis for CC

A novel Energy Efficiency (EE)- based Predictive Maintenance optimisation and Failure Prognosis is developed to forecast the compressors' remaining energy efficiency life (REEL), failure based on EEI and EnPI degradations, and a hybrid ML model to increase reliability, sustainability, and prevent unplanned shutdowns for CC. This framework optimises maintenance decisions based on actual condition and energy performance, thereby minimising maintenance costs, increasing operational life, and improving the energy efficiency of CC. The EEI and EnPI degradations are used to establish a threshold based on the lower of EEI & EnPI, as less energy is required to attain a specific

output level, which is considered a healthy and energy-efficient operation. A high EEI & EnPI value is labelled as a failure threshold or an energy-inefficient operation, owing to maximum energy consumption in both LP & HP CC. Furthermore, when CC continues to operate with degradations consuming excessive energy until failure due to maximum energy consumption, to address these early warnings, timely maintenance decisions have been introduced to increase the EE of CC. Moreover, a novel concept of sustainable actions has been proposed, maintenance action should be triggered if EEI & EnPI ≥ EEIthreshold, if EEI ≤ EEIthreshold, no maintenance action is triggered. Tables 6 and 7 illustrate the degraded parameters vs established thresholds for failure detection, forecasting REEL, maintenance actions, and early warnings for LP and HP CC.

Table. 6: Performance parameters vs thresholds for failure detection, forecasting REEL, maintenance actions, and early warnings for LP CC

Performance parameters of LP CC	Thresholds		Maintenance action should be triggered if EEI & EnPI ≥ $EEI_{threshold}$ If EEI & EnPI ≤ $EEI_{threshold}$ no maintenance action triggered
	Healthy State	Early warnings for maintenance	Failure thresholds EEI and EnPI ≥ $EEI_{threshold}$
EnPI for Shaft Speed Sensor	0.50	0.57	0.61
EnPI for P_{suc} Sensor	3.2	3.6	3.8
EnPI P_{dis} Sensor	1.0	1.15	1.22
EnPI T_{dis} Sensor	33	39.80	42.75
EnPI Gas flow Sensor	0.70	0.80	0.85
EnPI H_{poly} Sensor	34	41	44.50
EnPI T_{ratio} Sensor	1300	1680	1840
EnPI P_{diff} Sensor	1.40	1.70	1.80
EEI for EE Sensor	0.78	0.91	0.96

Table. 7: Performance parameters vs thresholds for failure detection, forecasting REEL, maintenance actions, and early warnings for HP CC

Performance parameters of HP CC	Thresholds		Maintenance action should be triggered if EEI & EnPI ≥ $EEI_{threshold}$ If EEI & EnPI ≤ $EEI_{threshold}$ no maintenance action triggered
	Healthy State	Early warnings for maintenance	Failure thresholds EEI and EnPI ≥ $EEI_{threshold}$
EnPI for Shaft Speed Sensor	0.80	0.91	0.95
EnPI for P_{suc} Sensor	1.6	1.89	2.09
EnPI P_{dis} Sensor	0.72	0.79	0.83
EnPI T_{dis} Sensor	33	39.80	42.75
EnPI Gas flow Sensor	1.78	1.90	1.98
EnPI H_{poly} Sensor	80	91	94
EnPI T_{ratio} Sensor	2500	3300	3600
EnPI P_{diff} Sensor	1.28	1.39	1.43
EEI for EE Sensor	0.78	0.91	0.92

4.3.1 Predictive Maintenance optimization and Failure Prognosis for LP CC

In this section, the results generated by the proposed novel model for analysing the degradation patterns and trends for EnPI and EEI sustainable indicators are presented. The model uses real-time data from various sensors, including energy consumption, shaft speed, Inlet and outlet pressures, discharge temperature, Power Consumption, volume flow, and polytropic head, to assess the operational conditions and energy efficiency of CC. However, by evaluating the degradation behaviour of these performance parameters, the hybrid ML model enables the prediction of current health conditions, forecasted REEL, identification of potential failures, and early warnings. These insights support the PdM strategy, optimise timely maintenance actions to increase energy efficiency and reliability, and reduce maintenance costs and unplanned downtime. The findings and predicted performance trends to track energy efficiency for PdM optimization and failure prognosis for performance parametrs of LP CC are illustrated in Figures 6, 7, and 8.

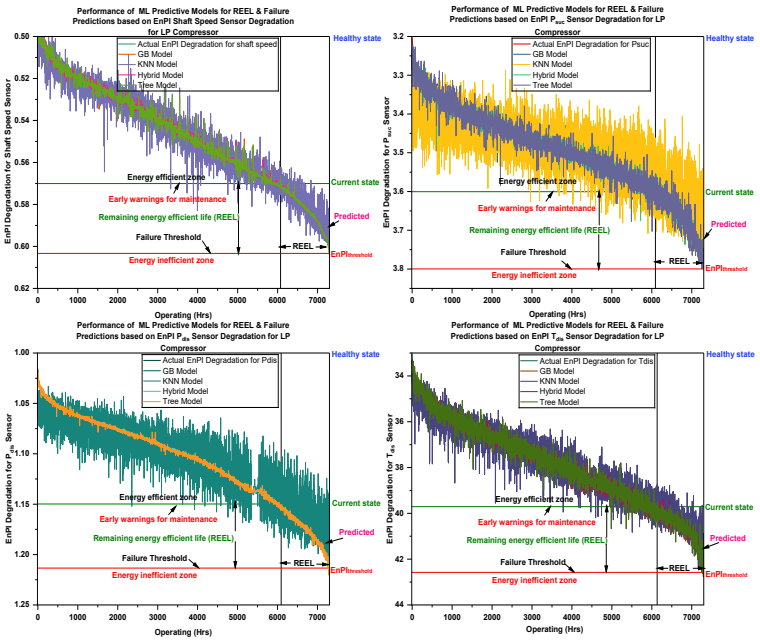


Fig 6: REEL & Failure Prediction using EnPI metrics for Speed, Psuc, Pdis, Tdis Sensors for LP CC

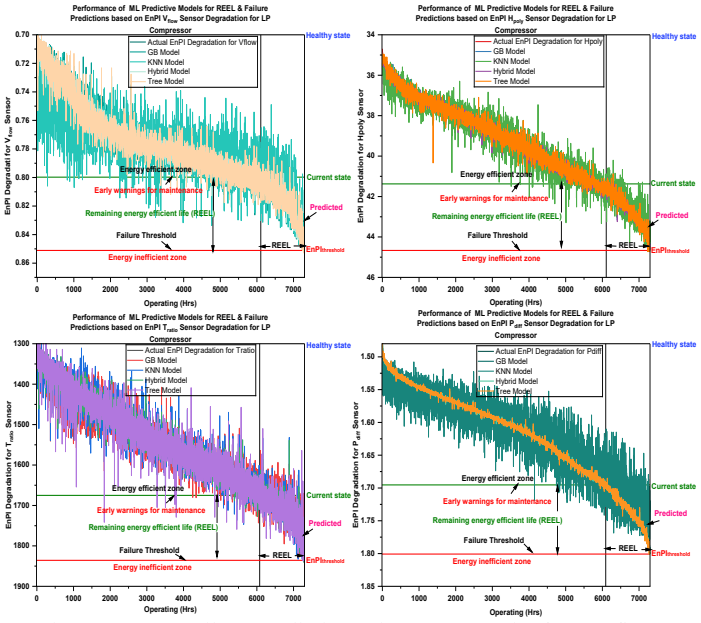


Fig 7: REEL & Failure Prediction using EnPI metrics for Gas flow, Hpoly, Tratio, Pdiff Sensors for LP

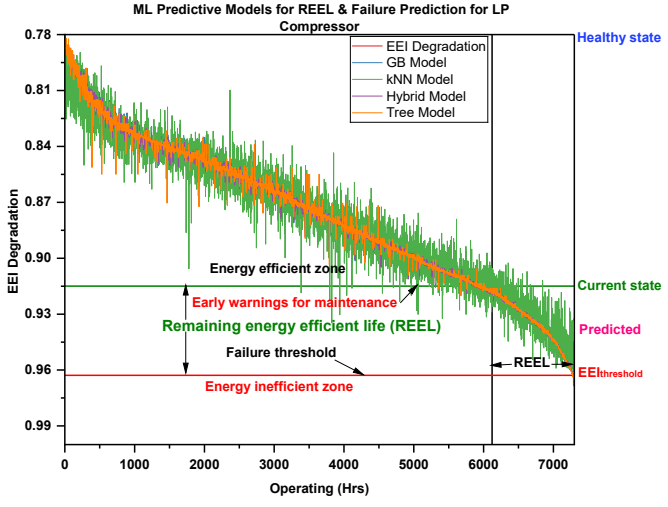


Fig 8: REEL & Failure Prediction using EEI metrics for LP CC

From the findings and the graphs of LP CC using EnPI and EEI sustainability indicators illustrated in Figures 6,7, and 8, the REEL value computed up to (1000 hrs) provides pertinent information to optimise the PdM maintenance schedule. Furthermore, from the results and graphs, it is clearly shown that when CC continues to operate with degradations consuming excessive energy, early warnings are needed to fix this issue and optimise energy efficiency for LP CC. From the findings the early warnings for EnPI metrics have been obtained at 0.57 kWh/rpm while considering energy consumption (EC) per load for shaft speed sensor, 3.6 kWh/kPa EC at suction pressure sensor, 1.15 kWh/kPa EC per discharge pressure sensor, 39.80 kWh/Co EC per discharge temperature sensor, 0.80 kWh/m3/h at EC per gas flow rate sensor, 41 kWh/kJ/kg for polytropic head sensor, 1680 kWh at EC per temperature ratio sensor, 1.70 kWh/kPa while considering energy consumption for pressure difference sensor, finally for EEI metric 0.91%. EEI and EnPI metrics monitor energy consumption and help identify CC degradation in a timely manner to inform maintenance decisions and bring it back from an energy-inefficient zone to an energy-efficient zone, optimising the energy performance and reliability of CC. These graphs can be useful for forecasting when a CC is likely to fail, and for triggering maintenance actions when EEI & EnPI ≥ EEI and EnPI thresholds. Furthermore, by evaluating trends and patterns in the REEL graphs, maintenance managers and engineers can make informed decisions on resource allocation, prioritising maintenance operations, and optimising LP CC energy efficiency to increase its reliability and productivity.

4.3.2 Predictive Maintenance optimization and Failure Prognosis for HP CC

The results obtained from the proposed novel model for analysing the degradation patterns and trends for EnPI and EEI sustainable indicators are presented. The model uses real-time data from various sensors, including energy consumption, shaft speed, Inlet and outlet pressures, discharge temperature, Power Consumption, volume flow, and polytropic head, to assess the operational conditions and energy efficiency of HP CC. However, by evaluating the degradation behaviour of these performance parameters, the hybrid ML model enables the prediction of current health conditions, forecasted REEL, identification of potential failures, and early warnings. These insights support the PdM strategy, optimise timely maintenance actions to increase energy efficiency and reliability, and reduce maintenance costs and unplanned downtime. The findings and predicted performance trends to track energy efficiency for PdM optimization and failure prognosis for performance parametrs of HP CC are illustrated in Figures 9, 10, and 11.

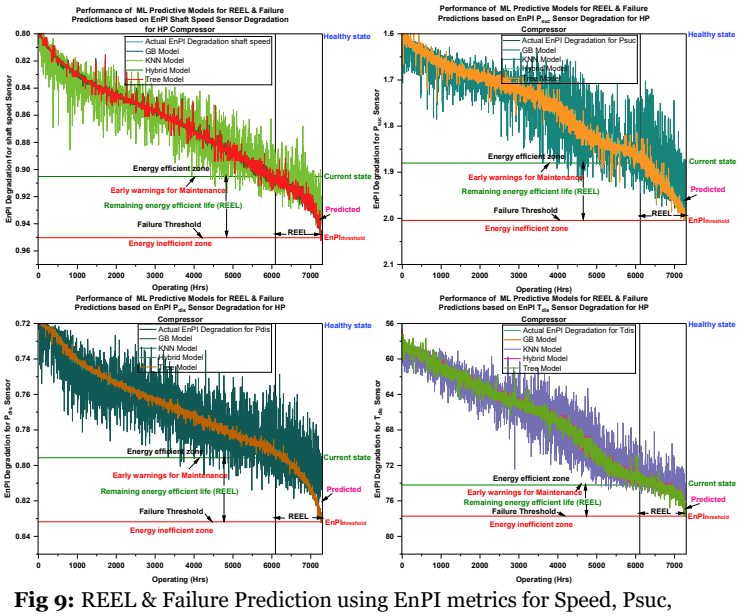


Fig 9: REEL & Failure Prediction using EnPI metrics for Speed, Psuc, Pdis, Tdis Sensors for HP CC

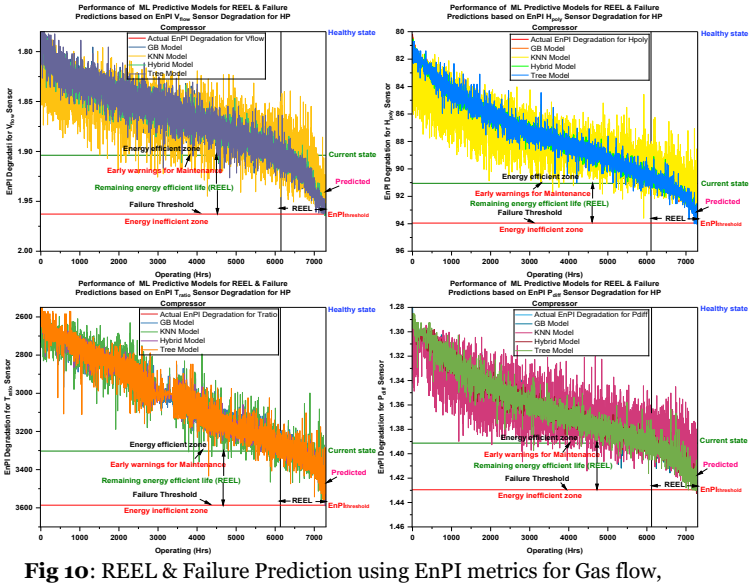


Fig 10: REEL & Failure Prediction using EnPI metrics for Gas flow, Hpoly, Tratio, Pdiff Sensors for HP CC

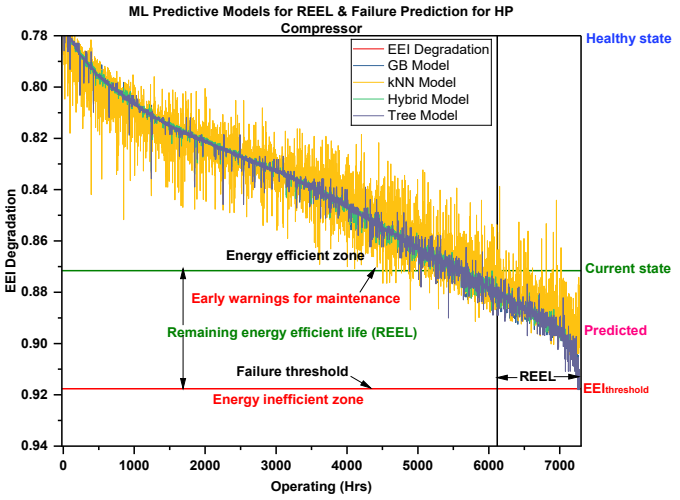


Fig 11: REEL & Failure Prediction using EEI metrics for HP CC

From the results using EnPI and EEI sustainability indicators illustrated in Figures 9 to 11, the REEL value computed up to (1000 hrs) provides pertinent information to optimise the PdM maintenance schedule. Furthermore, from the results and graphs, it is clearly shown that when CC continues to operate with degradations consuming excessive energy to fix this problem, early warnings have been proposed to optimise the energy performance of HP CC. From the findings the early warnings for EnPI metrics have been obtained at 0.91 kWh/rpm while considering energy consumption (EC) for shaft load sensor, 1.89 kWh/kPa EC for suction pressure sensor, 0.79 kWh/kPa EC for discharge pressure sensor, 39.80 kWh/Co EC for discharge temperature sensor, 1.90 kWh/m3/h at EC per gas flow rate sensor, 91 kWh/kJ/kg for polytropic head sensor, 3300 kWh at EC for temperature ratio sensor, 1.39 kWh/kPa while considering energy consumption per pressure difference sensor, finally for EEI metric 0.87%. EEI and EnPI metrics monitor energy consumption and help identify CC degradation in time to inform maintenance decisions and bring it back from an energy-inefficient zone to an energy-efficient zone, optimising energy efficiency and reliability. These graphs can be useful for forecasting when a CC is likely to fail, and for triggering maintenance actions when EEI & EnPI exceed their thresholds. Furthermore, by evaluating trends and patterns in the REEL graphs, maintenance managers and engineers can make informed decisions regarding resource allocation, prioritising maintenance operations, and optimising the energy performance of CC to increase its reliability and productivity.

4.4 Performance evaluation of proposed hybrid ML model

Receiver operating curve (ROC) assesses the accuracy and reliability of the proposed framework for novel energy efficiency based predictive maintenance optimization and failure prognosis model using hybrid ML model. Compared with the predictions of the hybrid ML model, the results for single classifiers GB, kNN, and DT show that the hybrid ML model outperforms. Receiver operating curve (ROC) is a graphical tool used to assess and present the prognostic performance of ML classifiers. It shows the relationship between true positive rate (sensitivity), and the false positive rate (1-specificity). Hybrid ML model with efficient failure detection capability is presented by an ROC curve that reaches the upper left corner of the plot, representing higher true positive rates, and lower false positive rates over varying threshold values. The ROC curves for the LP CC for both training and validation model are presented in Figures 12 and 13, while those for the HP CC are shown in Figures 14 and 15. The ROC curve shows that the proposed hybrid ML model outperforms the base classifiers GB, kNN, and DT in detecting failures, forecasting REEL, and identifying energy-efficiency degradation. For the training data, the hybrid model attained a high true positive rate (sensitivity) of 0.96 with a low false positive rate (1-specificity) of 0.1 for the LP CC. In contrast, the HP CC attained a sensitivity of 0.97 and a false-positive rate of 0.1. Similar performance was observed for the validation model, where the hybrid model achieved a sensitivity of 0.97 and a false-positive rate of 0.1 for the LP CC. For the HP CC validation model, the model achieved a sensitivity of 0.95 and a low false-positive rate of 0.1. These results demonstrated the hybrid ML model's efficient predictive capability, reliability, and performance.

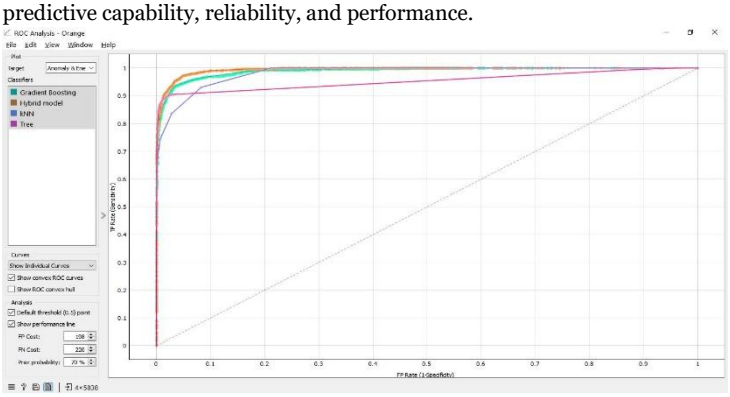


Fig 12: ROC based performance comparison of single ML model with Hybrid ML model for LP CC training model

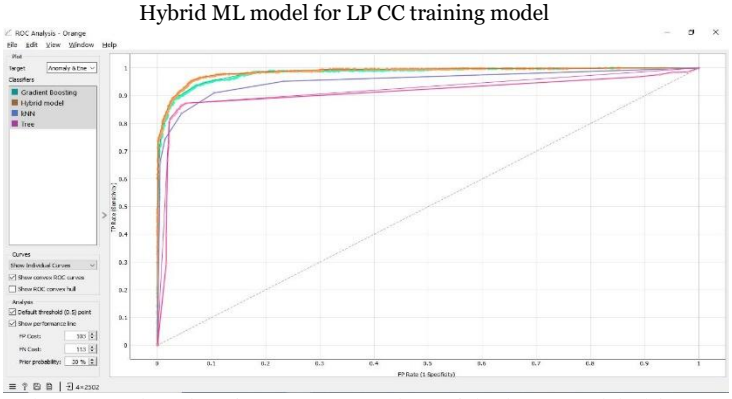


Fig **13**: ROC based performance comparison of single ML model with Hybrid ML model for LP CC validation model

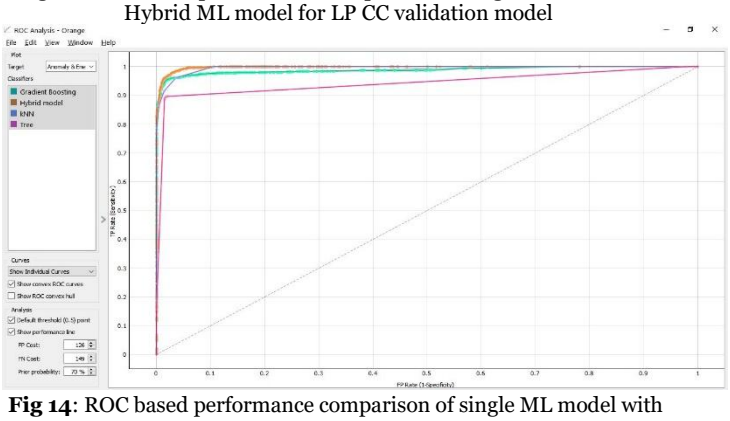


Fig 14: ROC based performance comparison of single ML model with Hybrid ML model for HP CC training model

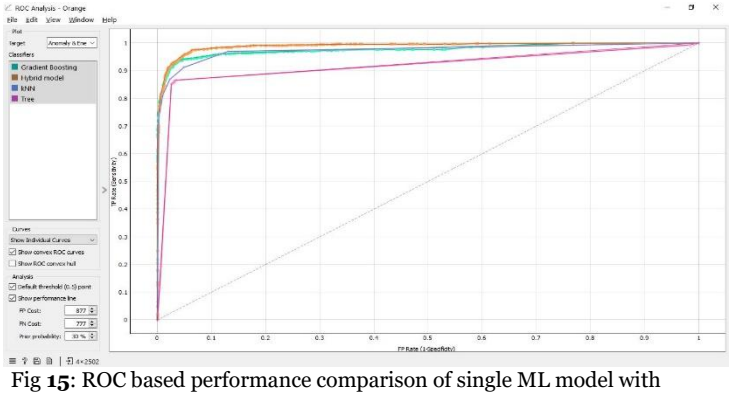


Fig **15**: ROC based performance comparison of single ML model with Hybrid ML model for HP CC validation model

4.5 Model Validation

The energy-efficiency-based predictive maintenance optimisation and failure prognosis using the hybrid ML model developed by the present study is validated using data acquired from another offshore centrifugal gas compressor. The validation model was developed using the EEI metric to assess energy consumption degradation patterns and trends in both the present and validated data, to predict REEL, failure, and early warnings for maintenance optimisation of the centrifugal compressor, as shown in Figure 16.

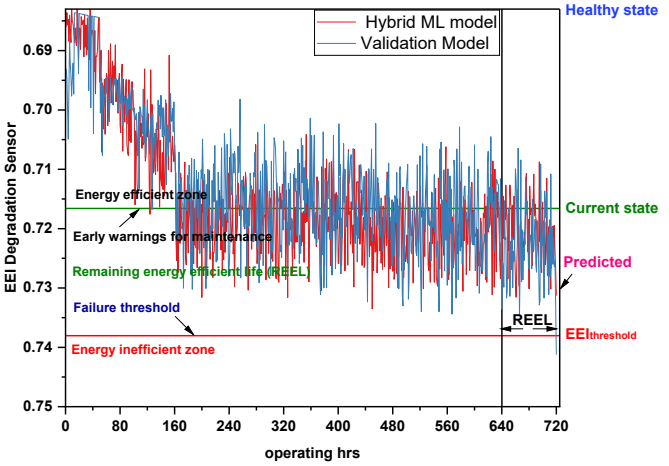


Fig 16: Comparison of Present and validation study model

According to the results obtained for one-month validation data using EEI sustainability indicators, illustrated in graphs (Figure 16), the REEL forecasted 80 hrs of operating hours in advance, and the failure predicted at 720 operating hours provides pertinent information for optimising the PdM maintenance schedule for the centrifugal compressor. Furthermore, the results and graphs clearly show that, when it continues to operate, degradations consume excessive energy. To address this problem, early warnings were proposed to optimise energy efficiency for validation. The findings provide early warning thresholds for the EEI metric, which is identified as 0.71%. These findings are very useful across industries, particularly in the oil and gas industry, to reduce unplanned asset downtime, improve sustainable performance and reliability, reduce maintenance and energy costs, and increase revenue.

5. Conclusion and Future Recommendations

This study proposed a novel framework that uses sustainability indicators such as energy efficiency (EEI) and energy performance (EnPI) to develop a predictive hybrid machine learning (ML) model to optimise maintenance, support sustainable operations, forecast future health performance, and estimate the remaining energy efficiency life (REEL) for CC. The results indicate that the remaining energy efficiency life (REEL) was forecast 1000 operating hours in advance, providing prognostic information for maintenance scheduling. Similarly, the energy efficiency indicator (EEI) detected degradation at 0.91% and 0.87% for low-pressure (LP) and high-pressure (HP) CC, respectively, while the prognostic model forecasted compressor failure at 7256 operating hours to optimise maintenance, prevent unplanned shutdowns, improve reliability, and minimise energy losses. Finally, the Receiver operating characteristic (ROC) curve for the hybrid ML model showed a high true positive rate of 0.96 in the training data set and 0.97 in the test or validation data set, indicating high performance. Compared with the predictions of the hybrid ML model, the results for the single classifiers GB, kNN, and DT show that the hybrid ML model outperforms them. The model developed in the present study was validated using other compressor data, forecasting REEL 80 hrs in advance, and the failure predicted at 720 operating hours provides pertinent information for optimising the PdM maintenance schedule for the validated centrifugal compressor. Additionally, the contribution of this study is not limited to a single centrifugal compressor but can be extended to other centrifugal compressors. The outcome of this research opens up a new possibility for industries to reduce downtime across assets, increase sustainable performance and reliability, and cut maintenance and energy costs.

For future recommendations, the current study can be extended to apply a sophisticated prescriptive maintenance model to optimise decision-making on which actions to take in response to maintenance predictions for the centrifugal gas compressors. Furthermore, future research can be conducted on energy-efficiency-based predictive maintenance using mechanical failure data for CC.

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Competing Interest Declaration: The authors declared that they have no competing Interests.

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