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Original Research Article

An Integrated Fault Tree Analysis and Bayesian Network FTA-BN Framework for Predictive Maintenance of ICE-Powered Drilling Machines

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Abstract

The frequent breakdown of internal combustion engine (ICE)–powered drilling machines and other laboratory equipment in our higher institutions and field engineering environments is largely due to aging equipment, lack of spare parts, and absence of documentation for discontinued machines. These challenges reduce maintenance effectiveness and extend downtime. This study presents an integrated predictive maintenance framework that combines Fault Tree Analysis (FTA), Analytic Hierarchy Process (AHP), and Bayesian Network (BN) inference to address these issues. Unlike traditional FTA-based reliability approaches, the proposed framework supports dynamic updating of component failure probabilities using structured expert judgement and real-world diagnostic evidence. Expert assessments were weighted using AHP to construct unbiased prior failure probabilities mapped into a BN structure. Diagnostic field data—vibration, sound, and exhaust emissions—were collected to validate and update the model. Results show that carburetor faults, piston ring wear, and fuel line blockages are the dominant contributors to failure. Dynamic BN inference improved diagnostic accuracy, while the maintenance strategy derived from model outputs increased mean time between failures (MTBF) by approximately 25% and reduced unplanned downtime by about 30%. The proposed framework offers a practical, low-cost predictive maintenance solution for legacy equipment in resource-constrained environments.

Keywords: Petrol-powered rock drill; Diagnostic devices in rock drill; Maintenance; Failure rate.

1. Introduction

Internal combustion engine (ICE)–powered rock drilling machines are widely used in construction, mining, quarrying, and educational institutions. However, many higher institutions rely on outdated and undocumented machines that manufacturers no longer support. The lack of technical manuals, the absence of spare parts, and aging components result in frequent machine breakdowns and prolonged downtime. These issues pose challenges for both teaching and field operations.

The reliance on expert intuition and post-failure diagnostics results in prolonged downtimes and increased maintenance costs. Predictive maintenance frameworks adapted to such environments must rely on available manual measurement tools (tachometers, sound meters, vibration loggers, etc.) and logical-structural failure modeling. In this study, a combination of Fault Tree Analysis (FTA) and Bayesian Network (BN) inference was developed to support predictive diagnostics tools and decision-making for ICE-powered pneumatic drills in the absence of real-time sensor networks. In contrast, the pneumatic rock drill used in this study is rated at approximately 2 kW and features a 1-cylinder, 2-stroke design, as shown in Fig. 1.

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Figure 1. ICE-Powered Pneumatic Drilling Machine

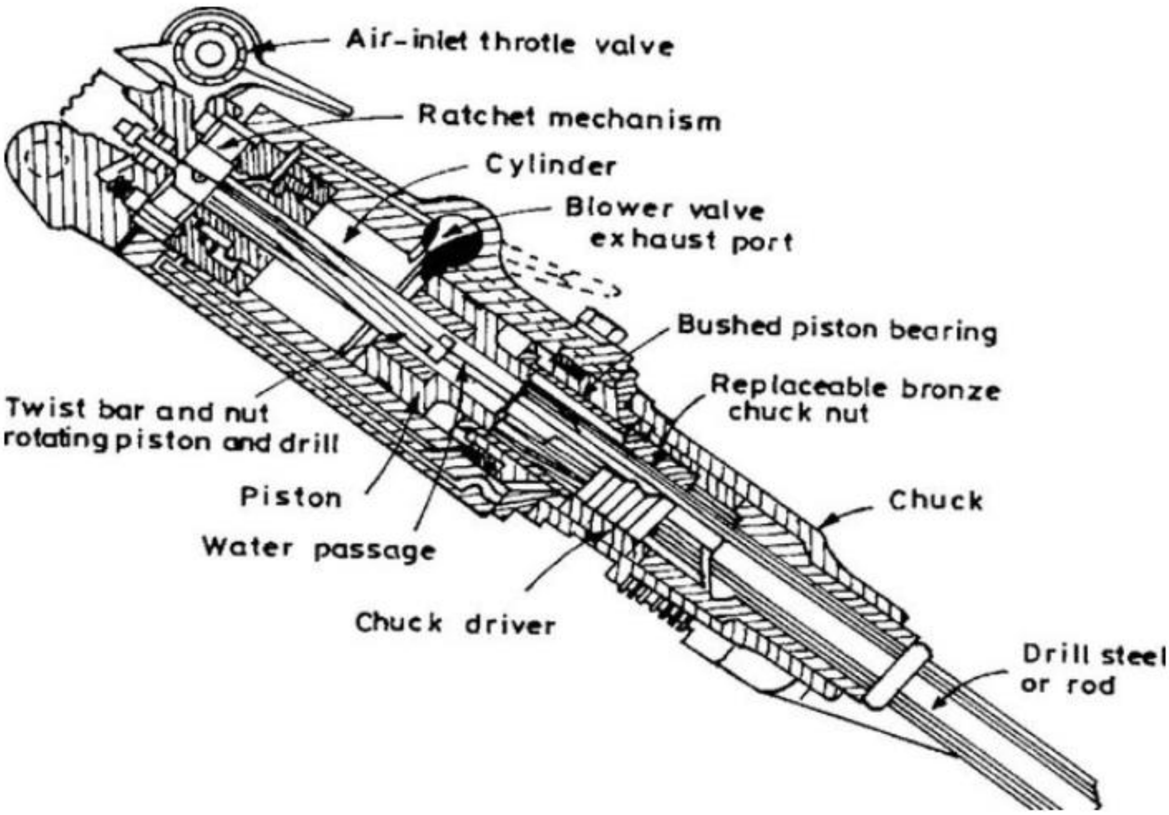

Figure 2. Pneumatic Jack Hammer [1] (this figure changed)

Prognostics and Health Management (PHM) systems traditionally rely on Condition-Based Monitoring (CBM) and embedded sensor feedback. [2]. However, as [3] notes, PHM strategies must be adapted to account for limited instrumentation environments, especially in older or manually operated machinery. Components that exhibit progressive deterioration—such as pistons, valves, and pneumatic hammers—can still be monitored using periodic assessments. [2] Introduced the 5S methodology for PHM design: (1) sensing, (2) signal processing, (3) state detection, (4) prognostics, and (5) decision support. While phases one and two are sensor-dependent, the remaining stages can still be implemented using structured knowledge from experts and historical logs (see Tables 1-4). This makes FTA-BN modeling particularly viable in systems without embedded sensors. Fault Tree Analysis is a top-down deductive failure analysis method that systematically traces potential failure modes back to their root causes. [4] (Fig. 3).

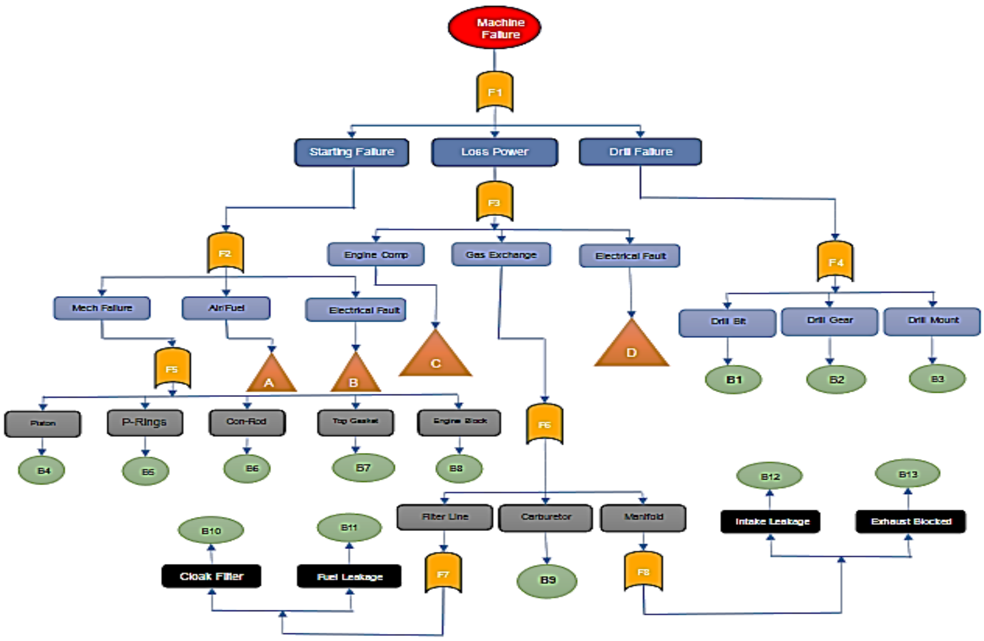

Figure 3. Schematic of Fault Tree Analysis (FTA)

FTA was built using logical relationships between observed failures and their potential causes. Nodes include basic Events such as spark plug wear, valve clearance deviation, carburetor blockage; Intermediate events include combustion inefficiency, excessive vibration, low torque, while top events are engine not starting, drill not rotating, compressor underperforming, among others. Note that event gates (AND, OR) were used to reflect the dependency logic. The FTA was refined using failure logs and expert feedback from operators and technicians. [5]. FTA structures failure events from top-level symptoms (e.g., engine not starting) down to basic causes (e.g., clogged carburetor, broken valve) [6]. It enables intuitive visualization of fault propagation.

A Bayesian Network is a data structure that represents the dependencies among random variables. [7]. They are ensemble methods for which the simple building block is a regressor. [8] Or a classification tree. This approach combines many simple “building block” models to obtain a single and potentially potent model, as reported by Soltani et al. [9]. Bayesian Network extends this by allowing probabilistic inference under uncertainty. As highlighted in [3], a critical component’s failure probability can be dynamically updated as new observations become available. Adaptations of Preventive Maintenance in the absence of sensors occur in resource-limited contexts. Preventive maintenance adaptations include manual data collection (vibration, engine rotational speed (RPM), sound level, etc.); subjective scoring systems (expert evaluations of symptoms); empirical measurements using portable devices and FTA-BN hybrid modeling to infer unseen states. These align with suggestions by [2] and the empirical methods in the literature [5]. In general, machine learning has been applied to a reasonable number of mechatronics systems to improve performance. [10]. However, you rarely find the application of machine learning on ICE-drilling machines due to their limited sensory capabilities. This work is based on practical field evaluations and fault observations in two quarry sites (Kuje and Wasa), Abuja, Nigeria, supported by a structured experimental methodology and references to global PHM literature, including works by [2], [3], and the Repair procedure. This research was centered on the performance evaluation of an internal combustion engine-powered pneumatic rock drilling machine using fault tree analysis techniques to develop a detailed cause-to-effect failure and a Bayesian Network for prediction. Objectives are the evaluation of failure modes of the components of the petrol-powered internal combustion engine with a pneumatic rock drilling machine; Determination of rotation speed, sound level, and vibration rate in blast hole drilling using a petrol-powered internal combustion engine with a pneumatic rock drill. The proposed approach is specifically designed for obsolete drilling equipment, enabling informed maintenance decisions in the absence of automated monitoring tools.

Predictive maintenance research has explored various approaches, including statistical reliability models, sensor-based diagnostics, and AI-driven prognostics. FTA is widely used to identify causal pathways in mechanical systems, including ICE-driven machinery. However, FTA is limited by its static probability structure [6].

Bayesian Networks (BN) address this limitation by enabling dynamic updating of failure probabilities using Bayes' theorem—studies such as Soltanali et al. [9] have demonstrated the value of BN in complex automotive systems. Research published by [11] confirms the ability of BN to enhance reliable decision-making. Additionally, the study highlights the effectiveness of hybrid probabilistic models.

Despite these contributions, gaps remain in:

- The application of FTA-BN to ICE-powered pneumatic drilling machines.
- The integration of AHP-weighted expert judgement in Bayesian priors.
- Predictive maintenance approaches tailored for aging equipment with limited sensor data.

This study addresses these gaps and demonstrates how probabilistic modeling can be effectively implemented for aging, undocumented drilling machines.

2. Methodology

The machine studied is a petrol-powered ICE drilling system with a two-stroke engine, air compressor, and pneumatic drill. Field measurements were collected from operational sites in Wasa Village and Kuje, FCT, Nigeria.

2.1 Data Acquisition Without Sensors

The diagnostic devices were used to obtain relevant data instead of continuous data streaming. A digital tachometer of model 99960-2 was used to obtain the RPM of the drill, measured manually at regular intervals, according to the procedures outlined by Bilim et al. [12]. The Sound Level Meter (Extech) [13] was used to measure sound emission, recorded according to the procedures stated by [14]. The Vibrometer Logger [15] was used to measure the periodic vibration as captured at key engine-pneumatic interfaces [16].

These measurements were performed at multiple operational sites, including Kuje Area Council and Wasa Village, as described in [5]. Two-stroke internal combustion engines are mechanically complex systems whose performance relies heavily on precise thermo-fluid analysis and structural integrity capable of withstanding thermal loads, vibrations, and induced stresses during operation. In cases where legacy machines lack historical reliability data or repair manuals, a maintenance log must be developed based on expert input. This log serves as a foundation for maintenance actions and conducting further reliability assessments. In this study, a Multi-Criteria Decision Analysis (MCDA) approach was employed using Saaty's Analytic Hierarchy Process (AHP) (Appendix) [17], as adapted for multi-stakeholder environments in the framework reported by [5].

2.2 Maintenance Strategies in Low-Infrastructure Environments

Maintainability represents the intrinsic quality of an item, indicating its ability to be either preserved in its current state or restored to a predefined condition when maintenance actions are undertaken. [18].

$$m(t) = \int_0^t f_r(x)dx \tag{1}$$

Where $m(t)$ Is the maintainability function, t Is time and $f_r(t)$ Is the repair time probability density function? Other crucial metrics in maintenance are:

Availability (A): Availability is a crucial metric that indicates the proportion of time the pneumatic drill is available for use, considering both its operational time and downtime for corrective maintenance. Availability can be calculated using this formula. [18].

$$A = (MTBF)/(MTBF + MTTR) \tag{2}$$

Here, MTBF (Mean Time Between Failures) represents the average time the drill operates without encountering a failure, while MTTR (Mean Time to Repair) is the average time it takes to restore the drill after a failure (James et al, 2023).

Failure Rate (λ): The failure rate measures the rate at which failures occur within the internal combustion engine-powered pneumatic drill. It can be calculated as [18]:

$$\lambda = 1/MTBF \tag{3}$$

$$R(t) = 1 - F(t) = 1 - \int_0^t f(x)dx \tag{4}$$

where $R(t)$Is the reliability at time t? $F(t)$Is the cumulative failure distribution function and $f(x)$Is the failure probability density function. Maintenance strategies have evolved from reactive (RM) and preventive (PM) to CBM and PHM. [3]. In low-infrastructure regions, the transition from PM to PHM must bypass the dependency on advanced monitoring. The studies by Sumit [4] and Knezevic et al. [19] provide an applied case study demonstrating how FTA and BN. [7] Can model component failure logic and interdependencies using expert ratings, maintenance records, and periodic device measurements.

2.3 Bayesian Network.

The FTA structure was transformed into a Bayesian Network (see Fig. 4), with conditional probability tables (CPTs) derived from field data and expert scoring, Tables 1 and 2. CPTs were initialized using subjective expert ratings (Saaty's scale) (Appendix) [17] and later updated through field validation. The inference queries allowed for predicting the most probable cause given a fault, estimating failure probabilities under partial observations, and sensitivity analysis to identify critical components.

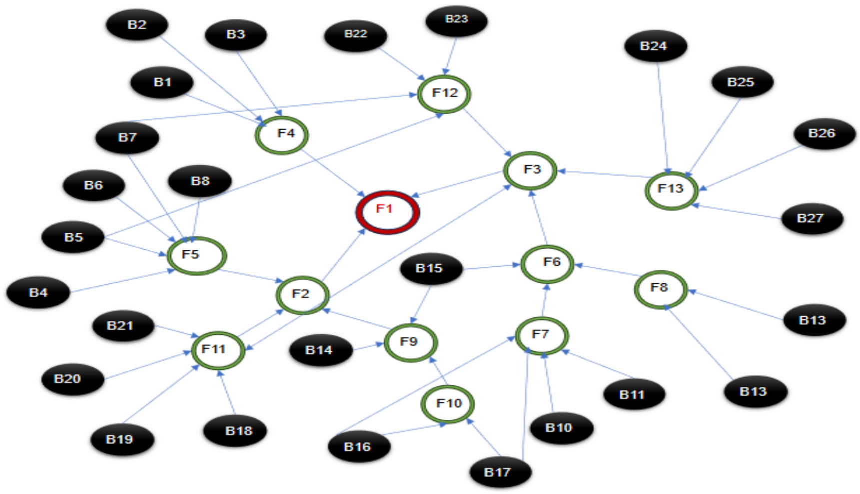

Figure 4. Bayesian Network Model of ICE-Pneumatic Drilling Machine Failure

2.4 Failure Mode Evaluation

Failure mode analysis focused on combustion system degradation (misfires, air-fuel mixing errors), pneumatic inefficiencies (pressure drop, leakages), and mechanical misalignments (rotational friction, shaft imbalance). The ratings and probability computations followed the methodology of the weighted analytic hierarchy process in [5]. Key indicators such as vibration amplitude (>2.5 g) and sound pressure (>90 dB) were identified as thresholds for alert generation.

3. Results and Discussion

Field measurements revealed key insights into the operational stress and degradation patterns of ICE-powered pneumatic drills. The obtained sound Levels under high-load conditions consistently exceeded 90 dB at peak combustion intervals. The rock drill has a minimum of 59.8 dB and a threshold value of 117 dB, as stated by the rock drill manufacturer [1]. Excessive sound was linked to incomplete combustion and valve misalignment, as well as the abrasion resistance of the rock, as the drill bits release impact energy to perforate the rock to create blast holes. The measurement results of sound generated by the rock drill with internal combustion engines showed that the sound level recorded near the operator's ear is over 90 dB(A) and is dependent on the engine power, type of rocks, and depth of the blast holes. The result from a 2-kW rock drill was similar to a grass trimmer of about 1.6 kW, which generated sound at a level of about 95 dB(A) as reported by [14]. Sound levels of over 90 dB can cause loss of hearing to the drill operator. The drill operator requires periodic hearing tests, the use of ear muffs, and regulated hours of operation to avoid damage to the hearing organs.

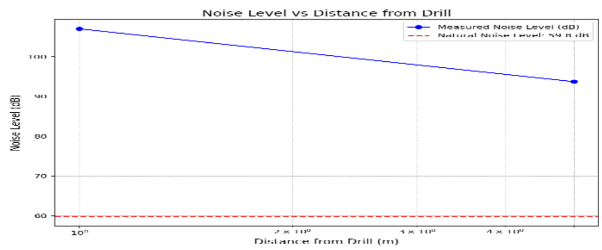

Figure 5. Noise Level Measurement

The vibration was observed to be in three directions, namely X, Y, and Z axes. The magnitudes of vibration of pneumatic rock drill as recorded during drilling of blast holes by the accelerometer were recorded to range from +22 to -20 m/s^2, with irregular and erratic peaks and valleys between 4 to 10 seconds during active perforation of blast holes (see Figure 4). Similarly, during the period of crawler hydraulic rock drill operation to perforate rocks for blast holes, the vibrations obtained were in the range of +10 to -5 m/s^2(see Figure 5). The pneumatic rock drill without an internal combustion engine had a vibration level of 9.3 m/s^2, in all three axes of vibration [1]. The Y-18 rock drill may have inbuilt attenuation to reduce the intensity of vibration waves. The vibration values in this study slightly differ from the vibration levels recorded by Clemm et al [16]. They obtained the vibration mean of all the measurements was 28.5 m/s^2. The differences can be attributed to vibration measurements in the individual *X*, *Y*, and *Z* axes from the tool-attached accelerometers. Their approach was necessary to achieve the objective of vibration reduction in small hand-held rock drills.

In comparison, the approach in this study is to determine the comfort of the drill operator during the perforation of blast holes using a 2-kW rock drill. Again, for the prediction of the rock drill's maintenance status.

Periodic measurements indicated a steady increase in vibration amplitudes with operational hours. Rock drills nearing critical failure thresholds showed values above 28.0 m/s^2, confirming correlations with loose engine mounts and piston wear.

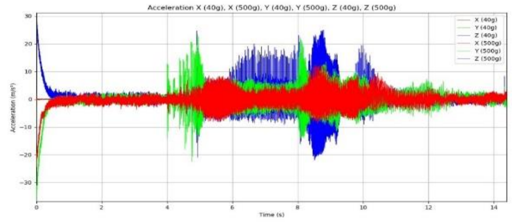

Figure 6. Vibration Level Wasa Village, Apo Road, Abuja. Lat 08.88142600, Log 07.46728960 ± 9m @ 238.7-degree

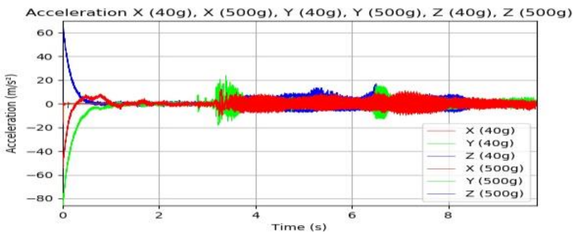

Figure 7. Kuje Road Construction, Abuja Lat 08.94648360, Log 07.26159340 ± 6m @ 108.6-degree

The pneumatic rock drill speed was determined to range from 340 to 480 rpm, which depends on the mechanical properties of the rock. Again, the Y-18 rock drill was stated to have a drill steel rotation speed of 2500 rpm by the manufacturer. The rpm obtained in this study is similar to the 451-681 rpm by Bilim et al [12]. RPM fluctuation was observed to be attributed to irregularities when there was reduced air compressor efficiency and identified as an early indicator of carburetor clogging. It must be stressed that drill bit rpm contributes to the rate of penetration into rock, ceramic, or metal to create holes.

Failure Probabilities were determined using a Bayesian Network, comprising field data and an expert reasoning Table 1. The results indicate that components such as the carburetor, piston rings, and ignition coil have the highest failure probabilities, which aligns with the operational challenges reported by drill operators in the field. For instance, the carburetor has a failure probability of 0.862 for non-starting conditions and 0.805 for power-loss conditions. This is consistent with studies by [20], who identified the carburetor as a critical failure point due to its role in regulating the air-fuel mixture. The high failure probability is attributed to clogging, wear, and improper maintenance, which can lead to inefficient combustion and engine failure. The piston rings have a failure probability of 0.726 for non-starting conditions and 0.810 for power-loss conditions. This aligns with findings by [21], who reported that piston rings are prone to wear and tear due to high thermal and mechanical stresses. The failure of piston rings can lead to loss of compression, reduced engine power, and increased emissions. The ignition coil has a failure probability of 0.608 for non-starting conditions and 0.583 for power-loss conditions. This is consistent with studies by [22], who emphasized the importance of regular inspection and replacement of ignition components to prevent engine failure.

Table 1. Average expert rating with weighted AHP and probabilities (Non-Starting-Engine)

Component / Score	Repair Avg	Maintenance Avg	Service Avg	AI Avg	Final AHP Score	Probability of Failure
Spark Plug	6.6	7.0	6.0	6.2	6.45	64.5%
Drill Bit	5.6	6.0	5.4	5.8	5.7	57.0%
Motor	7.0	7.6	6.8	7.2	7.15	71.5%
Air Compressor	6.4	6.6	5.6	6.0	6.15	61.5%
Pneumatic Hose	5.8	6.2	5.2	5.6	5.7	57.0%
Ignition Coil	6.8	6.4	5.8	6.0	6.25	62.5%
Piston	7.2	7.0	6.6	6.8	6.9	69.0%
Piston Ring	7.4	7.6	7.6	7.6	7.55	75.5%
Cylinder Head Gasket	6.8	7.2	6.2	6.6	6.7	67.0%
Connecting Rod	6.0	5.8	5.6	5.4	5.7	57.0%
Engine Block	5.6	5.2	5.4	5.0	5.3	53.0%
Crankshaft	6.2	6.0	5.8	5.6	5.9	59.0%
Valve Timing	6.6	6.4	6.0	6.2	6.3	63.0%
Lubrication	5.8	5.4	5.2	5.4	5.45	54.5%
Bearing	7.2	7.0	6.4	6.8	6.85	68.5%
Intake/Exhaust	5.2	5.4	4.8	5.0	5.1	51.0%
Combustion Chamber	7.4	7.2	6.6	7.0	7.05	70.5%
Cylinder Valve Damage	6.4	6.8	6.0	6.6	6.45	64.5%

Table 2. Expert Rating and Failure Probability: Power-Loss and Misfiring Engine

Component	Repair Avg	Maint Avg	Serv Avg	AI Avg	Final AHP Score	Probability of Failure
Carburetor	8.8	8.8	8.6	9	8.76	86.2%
Piston Rings	8.2	8.4	8.2	8.4	8.29	81.0%
Spark Plug	6.8	6.6	6.8	6.8	6.75	63.9%
Ignition Coil	6.2	6.4	6.2	6.2	6.25	58.3%
Air Filter	5.2	5.4	5.2	5	5.18	46.4%
Burnt Top Gasket	6.2	6.4	6.2	6.4	6.29	58.8%
Crankshaft Bearings	6.8	6.6	6.8	6.6	6.7	63.3%
Fuel Pipe and Filter	8.2	8.4	8.2	8.4	8.29	81.0%
Oil Seal	6.8	6.6	6.8	6.6	6.7	63.3%
Exhaust Manifold	5.8	5.6	5.8	5.8	5.73	52.6%
Intake Manifold	7.2	7.4	7.2	7.4	7.29	69.9%
Top Cylinder Valve	6.2	6.4	6.2	6.4	6.29	58.8%

The Bayesian Network identified the following components as the most critical (Figure 6 and Table 1). The most prone components to failure in the internal combustion engine of a petrol-powered rock drill were determined to be carburetors, piston rings, fuel pipe and filter, ignition coil, spark plug, crankshaft bearings, intake manifold, and top cylinder valve. These components accounted for over 70% of system failures, with the carburetor and piston rings being the most prone to wear. Similarly, in the rock drills, the most frequently defective components are the ratchet mechanism and pawl assembly (pawls, pawl spring, and pawl plunger), valve assembly (valve stem, valve guide, and valve stem), shank, chuck driver, and chuck, as well as O-ring seals. These components account for over 55% of rock drill system failure, for well well-lubricated rock drill and an experienced drill operator. The effect of poor operation and lack of lubrication can raise the failure rates of the rock drill components to 80%.

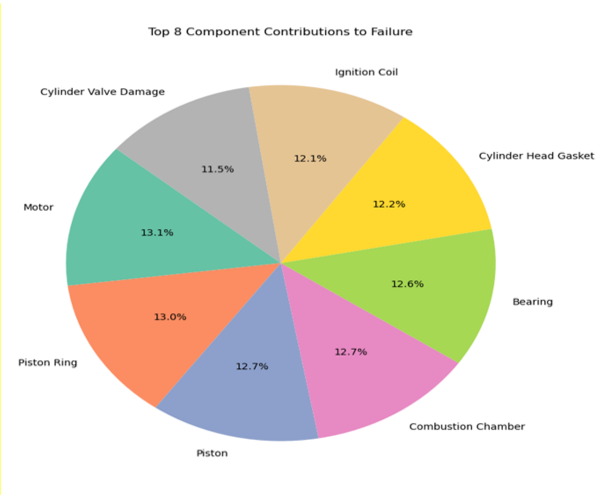

Figure 8. Top 8 critical components contributing to failure.

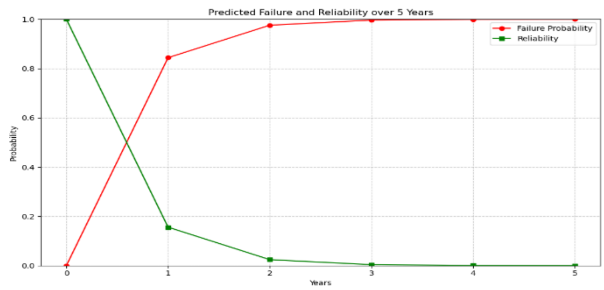

Figure 9. Five-Year Prediction

The study used Fault Tree Analysis (FTA) and Bayesian Network (BN) modeling to predict the reliability of the internal combustion engine (ICE)-powered pneumatic drilling machine over five years. The results indicated a significant decline in reliability, with the system retaining only ~10% reliability by Year 4 (Figure 7). A 30% improvement in component lifespan (like carburetor, piston rings) through preventive maintenance increased reliability to ~20% by Year 2, demonstrating the impact of targeted interventions. The Weibull distribution model highlighted the system's fragility due to low redundancy and high interdependency among components.

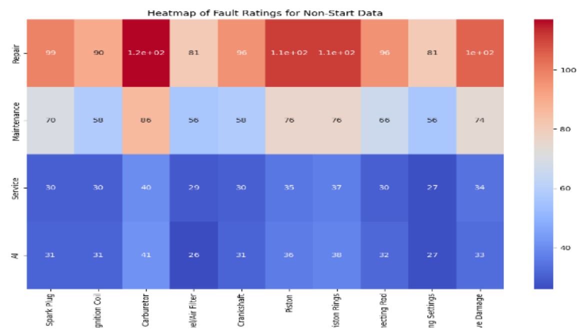

Figure 10. Cause of the Engine not starting

The heatmaps in (Figures 8 and 9) highlight the critical components that require immediate attention, such as the carburetor and piston rings, as well as for rock drills to focus on the ratchet assembly and shank. It also shows the magnitude of component reliability and failure frequency. The heat map visualized failure severity, with the carburetor, piston rings, and fuel system showing the highest risk (red zones). For example, piston rings scored 8.29/10 in failure likelihood (Table 2), and the air filter and exhaust manifold had lower but still significant risks (Pf = 0.464 and 0.526, respectively).

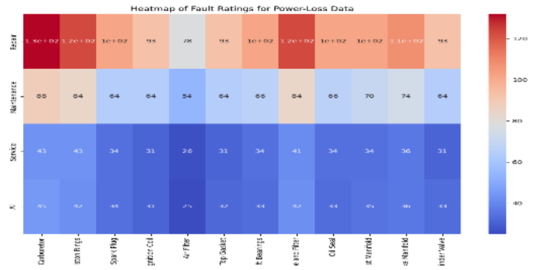

Figure 11. Heat Map for Engine Power Loss

The Fault Tree Analysis (Figure 4a) traced non-start conditions to three primary failure pathways. The FTA indicated that fuel system issues, such as a clogged carburetor, fuel leaks, had a probability of failure (PF) of 98.8%. Other results were ignition failures (e.g., faulty spark plug, ignition coil; Pf = 0.925) and mechanical faults (e.g., piston ring wear, cylinder valve damage; Pf = 0.892). The carburetor alone had an 86.2% probability of causing non-start events (Table 2), emphasizing its critical role, which correlates with reports by [21].

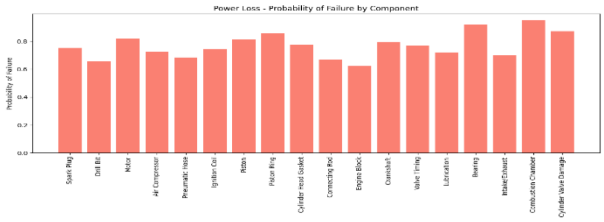

Figure 12. Probability of Engine Component Failure

The hybrid FTA-BN model provided a framework for identifying root causes and conditional dependencies. Expert-driven scoring proved to be effective in the absence of real-time sensors, and validation with site observations aligned strongly with the modeled probabilities. Comparative performance evaluations of drills over some period showed a reduction in unplanned failures, affirming the utility of predictive logic modeling in maintenance decision-making. This aligns with the literature findings of Baur et al. [3], who emphasize that even in sensor-limited contexts, structured PHM methodologies remain effective. The discussion also emphasizes the role of threshold-based diagnostics using vibration and sound signatures, as validated in similar PHM studies for machine tools. [3].

The petrol-powered rock drill performance was monitored during road construction activities. Observations showed that drills with periodic diagnostics had 25% longer MTBF and reduced maintenance lead times by 40%. Again, piston ring wear and spark plug carbon deposits were identified as leading causes of engine misfire. This triggered preventive replacement, avoiding unscheduled downtime. Similarly, maintenance logs indicated that predictive alerts helped shift workflows from reactive to proactive strategies. Operator feedback revealed better confidence in machine readiness and fault isolation.

4. Conclusions

The work presents predictive maintenance of internal combustion engine-2 kW-powered pneumatic rock drills using machine learning and fault tree analysis. The conclusions drawn were: The pneumatic rock drill had a sound level that exceeded 90 dB. The vibration rate obtained from the pneumatic rock drill ranges from +22 to -20 m/s^2, with irregular and erratic peaks and valleys. The drill steel rotation speed was determined to range from 340-480 rpm. The internal combustion engine part of the rock drill had 70% of the system failures. The component failure probabilities, such as the carburetor, were obtained as 0.862 for non-starting conditions and 0.805 for power loss conditions. Piston rings had failure probabilities of 0.726 for non-starting conditions and 0.810 for power loss conditions. In a pneumatic rock drill, the ratchet mechanism, pawl assembly, and valve assembly account for over 55% of system failures. However, when the lack of lubrication and poor skills of the rock drill operator are considered, the system failure rate of the rock drill increases to 80%. Fault tree analysis and Bayesian network predict a decline in reliability of less than 10% by year 4 and a 30% improvement in components of the rock drill system. The petrol-powered rock drill performance was monitored during road construction activities. Observations showed that drills with periodic diagnostics had 25% longer MTBF and reduced maintenance lead times by 40%.

Conflict of Interests

No conflict of interest has been expressed by the authors.

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