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Interpreting Maintenance Decisions in Age Replacement Models with LIME

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ABSTRACT

Proper maintenance of non-repairable systems is essential for ensuring uptime, minimising cost inefficiencies, and meeting performance targets. This study presents a hybridised framework that combines analytical age-replacement models, Monte Carlo simulation, and explainable machine learning (XAI) for improved maintenance decision-making. Empirical inter-failure-time data from a 20-kilowatt radio transmitter system were analysed using EasyFit, which identified the Birnbaum-Saunders distribution as the best-fit for modelling the system's failure rate. The optimal preventive replacement threshold was computed at $\tau = 113$ hours, with a minimum expected maintenance cost of 122.93 Naira, outperforming baseline models. To overcome the limitations of discrete analytical models, we simulated 10,000 maintenance events using Monte Carlo simulation, enabling the modelling of continuous operational metrics such as uptime, downtime, repair probability (RP) and maintainability index (MI). Classification targets, including Reliability, Availability, and Maintainability, were interpreted using the Local Interpretable Model-Agnostic Explanations (LIME) technique. LIME analysis revealed that inter-failure time (t) and reliability ($R(t)) \leq 0.75$ were the strongest negative contributors to low-reliability classification, while RP > 0.69 and MI > 0.69 had the highest positive contributions in maintainability predictions. The findings demonstrate that integrating analytical modelling with XAI offers both theoretical consistency and operational transparency, bridging the gap between optimisation and explainability. This integration enables data-driven, interpretable, and auditable maintenance recommendations suitable for high-reliability systems.

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1. INTRODUCTION

There is growing demand for the adoption of condition-based maintenance for industrial equipment rather than fixed-interval maintenance, to improve timeliness and prevent untimely failure. Non-repairable equipment is equipment in which its component, or the entire system, is replaced during maintenance action at failure. Examples of these types of equipment include electronic systems such as stabilisers, refrigerators, transmitters, and photocopy machines, among others. Non-repairable equipment is characterised by the failure-time distribution, such as the cumulative distribution function or the cumulative hazard function, of its time to failure.

Recent advancements in machine learning have introduced data-driven approaches to maintenance optimisation, especially within predictive and preventive maintenance frameworks. Models utilising condition-based monitoring, failure pattern recognition, and survival analysis (Badihi et al., 2022; Deep et al., 2023) have enhanced the accuracy of replacement decisions. However, these models often suffer from a lack of interpretability, particularly when black-box algorithms such as neural networks or ensemble methods are employed. To bridge the gap between accuracy and explainability, interpretability techniques such as Local Interpretable Model-agnostic Explanations (LIME) (Wang, 2024) have gained increased attention. LIME provides post-hoc explanations for complex machine learning models by locally approximating their behaviour with interpretable surrogates. While LIME has been widely adopted in healthcare (Eke & Shuib, 2024), finance (Munkhdalai et al., 2019), and fault detection (Mey & Neufeld, 2022), its application in maintenance decision-making, especially within age replacement models, is emerging. A few recent studies have explored explainable AI in reliability engineering (Ramezani et al., 2023). However, these approaches primarily focus on condition-based models rather than age-based replacement frameworks. This study differentiates itself by integrating LIME into age-replacement decision models, enabling the visualisation and interpretation of the factors driving maintenance timing decisions.

2. RELATED WORK

Maintenance refers to all technical and administrative actions taken to keep or restore a system to its functional state (Bahrami-G et al., 2000; Bagshaw & George, 2015). Beyond cost-efficiency, effective maintenance reduces the probability of catastrophic failure (Marais & Saleh, 2009) and requires planning that balances expected benefits and potential consequences (Zio, 2009). On the other hand, poor maintenance leads to defective products, customer dissatisfaction, lost production, cost inefficiencies, and facility unavailability (Lavy et al., 2010). In age-replacement policies, a unit is replaced at failure or preventively at a fixed time (Wang & Pham, 2006; Tam et al., 2007), with extensions to periodic replacement for interacting two-unit systems (Lai & Chen, 2006). Preventive maintenance policies remain among the most studied in the literature (Das & Sarmah, 2010). Subsequent developments include expected cost-rate models (Zhao et al., 2017), applications of optimal replacement (Jiang, 2018), a general replacement model combining age and random replacements (Nakagawa et al., 2018), and a survey of age replacement with minimal repair (Waziri & Yusuf, 2020). Comparative approaches target minimum expected cost and maximum availability (Udoh et al., 2020), with preventive replacement policies for non-repairable systems delivering optimal replacement times and minimum cost (Udoh et al., 2021; Udoh et al., 2022); as well as adaptation (Udoh et al., 2024). Recent work also contrasts analytical with intelligent policies on real-time data, with intelligent models outperforming analytical baselines (Ekpenyong & Udoh, 2024).

Practical implementations have combined scheduling and rule-based prognostics for limited, repairable, multi-component aircraft systems (de Pater & Mitici, 2021). Examples include: network-reliability-driven protection allocation (Cao et al., 2022); predictive-driven inspection/replacement for

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aging systems with real-time degradation limits (Wang et al., 2023); reliability-based optimisation for complex mechanically repairable machines with imperfect maintenance for improved availability and cost (Zhang et al., 2023); joint cost-distribution approaches comparing age replacement and inspection (Eddouh et al., 2023); component-level joint preventive maintenance for resilience and cost reduction (Fu & Zhu, 2023); state-dependent dynamic regulation of maintenance methods (He & Gao, 2023); optimal mitigation with sensitivity analysis for long-term costs (Zheng et al., 2023); and refinery-scale simulation/assessment for downtime cut and spinning equipment sustenance (Hosseinzadeh et al., 2023).

Despite advances in optimising age replacement and predictive maintenance, most models emphasise operational efficiency and cost minimisation while offering limited interpretability of decisions. Many rely on black-box algorithms or analytical approximations without explanatory interfaces, obscuring how inputs or preventive actions drive replacement recommendations. This study addresses that gap by integrating LIME into age-based replacement models, providing transparent, data-driven explanations for each maintenance decision.

3. MATERIALS AND METHODS

Fig. 1 presents the workflow for interpreting maintenance decisions in non-repairable systems, with an emphasis on maintainability modelling and explanation. The pipeline begins with an empirical maintenance log radio transmitter, 2020–2023. An analytical failure model is then fitted using the Birnbaum-Saunders distribution to capture the non-linear behaviour of inter-failure times and guide realistic event generation. Dataset assembly integrates inter-failure time (*t*), preventive/servicing downtime (*Dpr*), failure replacement downtime (*Dfr*), repair probability (RP), uptime, downtime, and maintainability index (MI). From these features, maintainability metrics are derived and used as inputs to a random forest (RF) classifier to predict the target classes (Reliability, Availability, Maintainability). RF was chosen because this classifier handles nonlinearities and higher-order interactions among the input features, requires minimal feature scaling, and is robust to outliers.

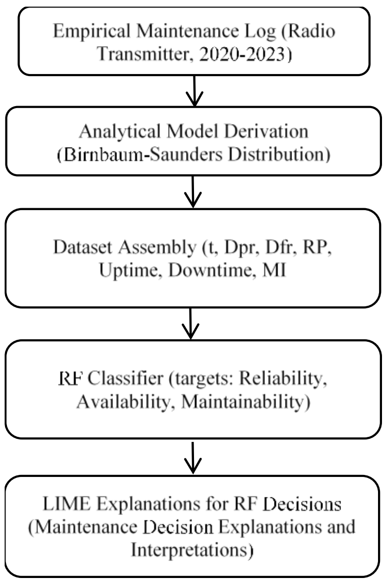

Fig. 1. Proposed workflow for interpreting maintenance decisions

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Relative to common alternatives (e.g., logistic/SVM for linear margins, boosting/GBMs for more aggressive fitting, or deep networks for large datasets), RF offers a strong accuracy–variance trade-off with lower overfitting risk, straightforward cross-validation (including out-of-bag error), class-imbalance options (class weights/resampling), and diagnostics that pair naturally with LIME for local explanations. Finally, LIME provides instance-level explanations of RF decisions, ensuring transparent maintenance recommendations.

3.1 Analytical Models

The relevant mathematical models and relations required for the formulation and implementation of maintenance decisions for a given non-repairable system are derived in this section. First, a table of notations and their meanings is presented. Second, a set of age-based replacement models, which are optimised with respect to maintenance replacement time (Table 2) is presented. Third, the limiting availability index for measuring the total uptime of the system is presented.

3.1.1 Mathematical Notations and Definitions

To support the analytical derivation of the reliability and availability models, a set of notations is adopted. These notations form the mathematical foundation for modelling age-based replacement strategies and interpreting failure-related behaviours under the Birnbaum-Saunders distribution. Table 1 summarises the key parameters and their associated meanings as used throughout the formulation of the preventive replacement models.

Table 1. List of notations and their meanings

Parameter	Meaning
$S(t)$	The probability that a machine continues to operate successfully without failure throughout a specified time interval.
t	The specific time at which the machine experiences failure
$f(t)$	The probability density function that describes the likelihood of the machine failing precisely at time t.
$\lambda(t)$	The instantaneous rate of failure at time t, given that the machine has survived up to that point.
$\eta(t)$	The total count of failures that occur within one complete operating or maintenance cycle of the machine.
$E[\eta(t)]$	The average or mean number of failures anticipated to occur within the time interval from 0 to t.
τ	The particular time at which maintenance action or replacement minimises total expected cost or maximizes system performance.
π	The likelihood that a certain number of failures will occur within the time interval from 0 to t.
$E[\eta(\tau)]$	The average number of failures predicted to occur up to the chosen optimal time τ.
$F(\tau)$	The probability that the machine will have failed at least once before or by time τ.
C_{pr}	The overall expenditure incurred when a machine is deliberately replaced or maintained before failure occurs.
C_{fr}	The total expenses resulting from corrective actions taken after the machine fails within the time interval up to time τ.
$E[\varphi(\tau)]$	The average cost anticipated for one complete maintenance cycle when preventive replacement is carried out at the specified time τ.
$\Lambda(\tau)$	The accumulated measure of the risk of failure from the start of operation up to time, τ.
$f(\tau)$	The probability density function that describes the likelihood that the machine will fail exactly at a particular time τ
$C(\tau)$	A function that gives the total number of maintenance actions, both preventive and corrective, carried out from the start of operation up to time τ.
${\tau^*}_f$	The specific time at which preventive replacement should be performed to minimize total expected cost or maximize reliability is determined using the probability or frequency of failures.
${\tau^*}_h$	The time τ at which preventive replacement is most cost-effective, identified using the machine's hazard (failure replacement downtime) function as the decision criterion.
$A(\tau)$	The probability that the machine is operational and capable of performing its intended function at time τ
D_{pr}	The mean duration during which the machine is unavailable due to scheduled preventive maintenance or replacement activities.

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Parameter	Meaning
D_τ	The anticipated total period the machine is not operational due to maintenance or failure repairs up to the specified time, τ
$E(U_\tau)$	The expected total time within the interval (0, τ] during which the machine remains in working condition and performs its intended function.
$E(D_\tau)$	The average amount of time the machine is predicted to be non-operational due to maintenance activities or failures up to the specified time, τ
α	The parameter that controls the skewness and spreads of the Birnbaum–Saunders distribution is known as the shape parameter.
β	Scale parameter of Birnbaum Saunders distribution function
Y_n	A normal random variable representing crack on materials due to repeated application of load
W_n	Y_n with dominant cracks due to the application of load
n	Dominant cracks due to the application of load
Q	An integer-valued non-negative (discrete) random variable for the smallest number of cycles at which W_n exceeds a critical value ω
ω	A critical value for W_n
μ	Mean of Y_n - a normal random variable
σ	Standard deviation of Y_n - a normal random variable
T	A continuous non-negative Birnbaum Saunders random variable
∅	A standardised value of the normal random variable, Y_n
X	A special normal random variable with $\mu = 0$ and $\sigma = \frac{\alpha^2}{4}$
$R'(t)$	1-*R(t)* = F(t) where F(t) is the cumulative failure distribution function

3.1.2 Preventive Replacement Models

The primary goal of the analytical framework is to identify the optimal interval for carrying out preventive replacement maintenance while minimising the total expected replacement cost per unit time. To achieve this, four replacement models proposed by Udoh et al. (2022) are examined and modified for application to the radio transmitter case study.

3.1.3 Age-Based Preventive Replacement Models

Let E[φ(τ)] be the sum of the anticipated cost for each maintenance interval of preventive replacement carried out at time τ. It is expressed by Bahrami-G et al. (2000) as:

$$E[\varphi(\tau)] = \frac{sum\ of\ expected\ cost}{time\ of\ replacement} = \frac{C_{pr}+C_{fr}E\{\eta(\tau)]}{\tau} \tag{1}$$

In Eq. (1), the term $E[\eta(\tau)]$ represents the probability that failure occurs before time τ. In this expression, C_{fr} denotes the total cost incurred during failure replacement, C_{pr} represents the total cost of preventive replacement maintenance, and τ is the designated time of replacement. The expected cost per cycle time for replacing a system component within the period (0,t] can be expressed as: $E[\eta(\tau)] = \sum_{n=0}^{\infty} \eta \times G(\eta) = 0 \times [1 - F(\tau)] + 1 \times F(\tau)\, E[\eta(\tau)] = F(\tau)$. Note that F(τ) is the probability that the machine will have failed at least once before or by time τ. The total count of failures that happen in the time interval (0,t] is denoted as $\eta(x)$, and is treated as a discrete random variable. It has a probability distribution function is defined as: $P[\eta(x) = n] = G(n); n = 0,1,2, \dots$ and its expected value is given by: $E[\eta(x)] = \sum_{N(t)=0}^{N(t)=n} \eta(x) \times G[\eta(x)]$.

Note that $G[\eta(x)]$ is the failure distribution function of η(x) occurring within the time period (0, t]. It is assumed that each time interval is sufficiently small, making the likelihood of more than one failure within the same interval insignificant. Consequently, the probability of two or more failures occurring is considerably smaller than that of a single failure. Hence, $P[\eta(x) = 2] < P[\eta(x) = 1]$; $P[\eta(x) = 3] < P[\eta(x) = 2]$, etc. Implying that $P[\eta(t) = 1] > P[\eta(t) = 2] > \cdots$. For preventive replacement carried out at time, τ. The expected number of failures within the period (0, τ], designated by $E[\eta(\tau)]$ can be approximated as: $G(1) = P[\eta(t) = 1] \approx F(\tau)$ and $G(0) = P[\eta(t) = 0 \approx 1 - F(\tau)]$.

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The models summarised in Table 2 were obtained using this formalism. For instance, Model 1 is obtained by substituting F(τ) into Eq. (1). Model 2 was introduced by Cassady et al. (2001), while Models 3 and 4 were developed by Udoh et al. (2022). By applying the minimisation condition (taking the partial derivative of each model with respect to τ and setting it equal to zero), the corresponding algebraic expressions for the optimal preventive replacement times are obtained. These expressions, along with their respective cost models, are summarised in Table 2.

Table 2. Expected cost and optimal replacement time models

	Model 1	Model 2	Model 3	Model 4
Cost	$E[\varphi(\tau)] = \frac{C_{pr} + C_{fr}F(\tau)]}{\tau}$	$E[\varphi(\tau)] = \frac{C_{pr} + C_{fr}\Lambda(\tau)]}{\tau}$	$E[\varphi(T)] = \frac{C_r F(T) + C_p F^{/}(T)}{\tau}$	$E[\varphi(T)] = \frac{C_r \Lambda(T) + C_p \Lambda^{/}(T)}{\tau}$
Optimal replacement time	$\tau^*{}_f = \frac{\frac{C_{pr}}{C_{fr}} + F(\tau)}{f(t)}$	$\tau^*{}_h = \frac{\frac{C_{pr}}{C_{fr}} + \Lambda(\tau)}{h(t)}$	$\tau^*{}_f = \frac{F(\tau)}{f(t)} + \frac{c_p}{(c_r - c_p)f(T)}$	$\tau^*{}_h = \frac{\Lambda(\tau)}{\lambda(t)} + \frac{c_p}{(c_r - c_p)h(T)}$

3.1.4 Limiting Availability

The availability of a system, which is the probability that the system will function as required during a particular period, is given in Eq. (2).

$$A(\tau^*) = \frac{E(U_\tau)}{E(U_\tau)+E(D_\tau)} = \frac{=\int_0^{\tau^*} R(t)dt}{=\int_0^{\tau^*} R(t)dt + \left(D_{pr}F(\tau^*)+D_{fr}S(\tau^*)\right)}, \tag{2}$$

where $D_{fr} = \frac{\sum_{i=1}^{n} D_i}{n}$ and $D_{pr} = \frac{\sum_{j=1}^{m} D_i}{m}$.

3.2 Adapting the Replacement Models for the Maintenance of Radio Transmitter Systems

The operational and cost parameters, namely, inter-failure time, cost of failure and preventive maintenance (servicing), failure and servicing downtimes covering the period 2020 – 2023 were obtained from the maintenance logbook of Radio Nigeria Atlantic FM 104.5 Uyo (Table 3). The collected data begin at the start of operation of the transmitter at 0 hours to the date of the first replacement (repair) to subsequent ones with their associated cost values in Nigerian Naira (₦). Inter-failure rates (in hours) were obtained by subtracting successive replacement/servicing dates in days for the respective days of the month including Sundays, multiplied by 24 hours of operation.

The costs of replacement were referred to as the cost of failure maintenance and the costs of servicing were referred to as the cost of servicing and were recorded in real time. The replacement downtimes of the machine are the total times consisting of failure downtimes and servicing downtimes taken for the machine to be replaced or maintained before resuming operations after failure.

Table 3. Raw data showing operational and cost parameters of a 20-kilowatt Solid-State Electronic Radio Transmitter System

Date	Operation Type	Inter-failure Time (h)	Cost of Servicing or Replacement (₦)		Servicing Downtime Time (h)	Replacement Downtime Time (h)
28-08-2020	-	-	-	-	-	-
28-01-2021	Replacement	3,864	-	4,000	-	4
05-02-2021	Replacement	168	-	3,000	-	3
21-02-2021	Replacement	384	-	10,000	-	4
26-02-2021	Servicing	120	3,000	-	4	-
07-03-2021	Replacement	216	-	25,000	-	4
29-03-2021	Replacement	528	-	10,000	-	3
10-05-2021	Replacement	1008	-	15,000	-	3

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Date	Operation Type	Inter-failure Time (h)	Cost of Servicing or Replacement (₦)		Servicing Downtime Time (h)	Replacement Downtime Time (h)
02-06-2021	Replacement	1272	-	20,000	-	6
29-08-2021	Replacement	2112		10,000		-
04-09-2021	Servicing	144	4,000	-	2	-
23-09-2021	Replacement	456		8,000	-	4
03-11-2021	Replacement	984	-	8,000	-	4
27-12-2021	Replacement	1320	-	4,000	-	5
18-03-2022	Replacement	1968	-	11,200	-	4
12-04-2022	Replacement	840	-	5,000	-	2
03-05-2022	Replacement	500	-	1,000	-	5
25-05-2022	Replacement	528	-	10,000	-	3
27-06-2022	Replacement	792		15,000	-	2.5
21-08-2022	Replacement	1320	-	20,000	-	4
28-08-2022	Servicing	168	2,000	-	3	-
15-11-2022	Replacement	1896	-	4,000	-	5
28-11-2022	Servicing	300	-	11,200	-	4
10-12-2022	Replacement	312	-	5,000	-	5
07-01-2023	Replacement	672	-	15,000	-	6
19-01-2023	Replacement	288	-	20,000	-	7
21-02-2023	Replacement	792	-	5,000	-	1
09-04-2023	Replacement	1128	-	15,000	-	5
18-04-2023	Replacement	216	-	3,000	-	4
19-05-2023	Replacement	744	-	20,000	-	3
05-06-2023	Replacement	414	-	30,000	-	5
10-06-2023	Replacement	120	-	20,000	-	4

3.2.1 Choice of Appropriate Failure Distribution Function

The radio transmitter is a complex electronic device whose major components are integrated circuits, diodes and fuses, which are replaced after each failure. Therefore, the transmitter is a non-repairable system. It fails suddenly but at a non-constant rate. The experimental data for this work consists of the failure times of a 20-kilowatt solid-state electronic transmitter, whose distribution was shown to follow the Birnbaum-Saunders (fatigue failure) distribution with shape and scale parameters: $\alpha = 0.95748 \; and \; \beta = 557.37$ respectively using the Chi-square goodness-of-fit tests with the aid of EasyFit (5.6) software.

EasyFit is a statistical analysis software used for goodness-of-fit tests to select the best-fit probability distribution (ranking them in order of best-fit), and providing visualisation and estimation of parameters of the identified probability distributions for a sample of data. The Birnbaum-Saunders model was ranked number 2 in terms of best-fit among several failure distributions. It was adjudged to be the best-fit model among other distributions for the sample data because the failure distribution which ranked first (General Pareto distribution) is asymmetrical and the bounds of its random variable are dependent on the shape parameter, making it inappropriate to model the failure distribution.

3.2.2 Failure and Cumulative Failure Distributions of Two-Parameter Birnbaum-Saunders Distribution

Let T be a continuous non-negative random variable denoting the time to failure of the system with a distribution function, $F(t)$. Then, $F(t) = P(T \leq t) = \emptyset\left(\emptyset\left(\frac{\mu\sqrt{t}}{\sigma} - \frac{\omega}{\sigma\sqrt{t}}\right)\right)$. Let $\alpha = \frac{\sigma}{\sqrt{\mu\omega}} \; and \; \beta = \frac{\omega}{\mu}$; then,

$$F(t; \alpha, \beta) = \emptyset\left(\frac{1}{\alpha}\left[\sqrt{\frac{t}{\beta}} - \sqrt{\frac{\beta}{t}}\right]\right) \quad (3)$$

Eq. (3) is the two-parameter Birnbaum-Saunders failure cumulative distribution function with shape parameter α and scale parameter β and the probability density function of T is given in (4) as;

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$$f(t;\alpha,\beta) = \frac{1}{2\sqrt{2\pi}\alpha\beta}\left[\left(\frac{t}{\beta}\right)^{\frac{1}{2}} + \left(\frac{\beta}{t}\right)^{\frac{3}{2}}\right] exp\left[-\frac{1}{2\alpha^2}\left(\frac{t}{\beta} + \frac{\beta}{t} - 2\right)\right]; t > 0; \alpha,\beta > 0 \quad (4)$$

3.2.3 Parameter Estimation of the Birnbaum-Saunders Distribution

The parameters of the distribution ($\hat{\alpha}$ and $\hat{\beta}$) were obtained using the Easyfit software as: α =0.95748 and β =557.37.

3.2.4 Reliability Function of Birnbaum-Saunders Distribution

Let $S(t)$ represent the reliability function associated with the Birnbaum–Saunders distribution. It is expressed as:

$$S(t) = 1 - F(t) = P(T > t); t > 0 = 1 - \int_0^t f(u)du = \int_t^\infty f(u)du$$

Thus, $S(t)$ denotes the probability that a machine continues to operate successfully without failure throughout a specified time interval (0, t]; equivalently, it represents the probability that the item survives up to time t and remains operational.

For the two-parameter Birnbaum–Saunders distribution**,** the reliability function is expressed as: $S(t) = 1 - F(t;\alpha,\beta)$. From (3): $S(t) = 1 - \emptyset\left\{\frac{1}{\alpha}\left(\sqrt{\frac{t}{\beta}} - \sqrt{\frac{\beta}{t}}\right)\right\}$. Due to the symmetry of the normal distribution, $S(t)$ can be written as;

$$S(t) = \emptyset\left\{\frac{1}{\alpha}\left(\sqrt{\frac{\beta}{t}} - \sqrt{\frac{t}{\beta}}\right)\right\} \quad (5)$$

3.2.5 The Hazard Function of Birnbaum-Sanders Distribution, λ(t)

The hazard function is the instantaneous probability that an item will fail in the interval (t,t+Δt) given that it is functioning at time t. It is given as the ratio of the density function and the reliability function in (6) as;

$$\lambda(t) = \frac{f(t)}{S(t)} \quad (6)$$

According to Tam et al. (2007), the density of the Birnbaum-Saunders failure distribution can be written in a different form as: $f(t) = \frac{\left(\sqrt{\frac{t}{\beta}} - \sqrt{\frac{\beta}{t}}\right)}{2\alpha t} \times \emptyset\left\{\frac{1}{\alpha}\left(\sqrt{\frac{t}{\beta}} - \sqrt{\frac{\beta}{t}}\right)\right\}$; $Z = \frac{1}{\alpha}\left(\sqrt{\frac{t}{\beta}} - \sqrt{\frac{\beta}{t}}\right)$ and $\emptyset(Z) = \frac{exp\left(-\frac{Z^2}{2}\right)}{\sqrt{2\pi}}$
Therefore, $S(t) = \emptyset(-Z)$. Hence,

$$\lambda(t) = \frac{\left(\sqrt{\frac{t}{\beta}} - \sqrt{\frac{\beta}{t}}\right)}{2\alpha t} \times \left(\frac{\emptyset(Z)}{\emptyset(-Z)}\right) \quad (7)$$

3.2.6 Cumulative Hazard Function of Birnbaum-Saunders distribution

By definition, $f(t) = \frac{d}{dt}F(t) = \frac{d}{dt}\left(1 - S(t)\right) = -S(t)$. Then, $\lambda(t) = \frac{R^{/}(t)}{S(t)} = -\frac{d}{dt}lnS(t)$.
t$\int \lambda(t)\, dt = -lnR(t) = \Lambda(t)$;

$$\Lambda(t) = -lnR(t) \quad (8)$$

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3.3 Simulation of Maintenance Events and Operational Metrics

To model the behaviour of non-repairable systems under various maintenance regimes, we simulated 10,000 maintenance events using the Birnbaum-Saunders distribution, parameterised with α = 0.95748 (shape) and β = 557.37 (scale). These parameters were derived from empirical fitting to observed operational data and reflect the system's ageing and failure behaviour. The inter-failure time t was simulated within the empirically observed bounds of [120, 3,864] hours, capturing the range of normal operation before failure or servicing. Dpr and Dfr were assigned under a strict mutual exclusivity constraint: for any event, Dpr>0 implies Dfr=0, and vice versa. This reflects real-world maintenance workflows, where either preventive servicing or corrective replacement is carried out, but not both simultaneously. Each simulated record includes derived uptime and downtime values based on the nature of the operation, enabling the computation of key operational metrics for performance assessment.

3.3.1 Symbolic Feature and Data Generation

To augment the real-world dataset and ensure broad coverage of maintenance scenarios, a symbolic data generation process was implemented using Monte Carlo simulation. By applying structured prompting techniques, Generative Pre-trained Transformer 4 (GPT-4) was guided to generate statistically realistic maintenance scenarios, as follows:

- Simulate inter-failure times (t) for 10,000 synthetic maintenance instances (data points) within the bounded range [120, 3,864] hours.
- Compute operational metrics using the Birnbaum-Saunders distribution with α = 0.95748 and β = 557.37, generating corresponding reliability $S(t)$ and availability $A(t)$.
- Randomly assign *Dpr* and *Dfr* values within realistic downtime ranges (2 – 4 hours for *Dpr*, 1 – 7 hours for *Dfr*), while maintaining mutual exclusivity.
- Derive complementary features such as Uptime, Downtime, MI, and RP from simulated inputs.

To enhance interpretability and facilitate explainability, each operational metric was also categorised into classes based on domain-informed thresholds. Specifically, Reliability was classified as Low ($R(t) <$ 0.80), Medium ($0.80 \leq R(t) < 0.95$), and High ($R(t) \geq 0.95$), following conventions in high-dependability systems such as aerospace and safety-critical domains (Rice et al., 2003). Availability was similarly binned using thresholds tailored to high-assurance systems: Low (< 0.90), Medium (0.90-0.98), and High (> 0.98), consistent with recommendations in ISO 14224 and industrial availability studies (Østebø et al., 2018). Maintainability was categorised using MI scores and MTTR-based indices: Low (MTTR > 5 hours), Medium (2 – 5 hours), and High (< 2 hours), reflecting maintainability standards for mission-critical infrastructure (Navas et al., 2020). These classification thresholds were selected to reflect realistic maintenance planning and to support explainable AI modelling of decision boundaries.

An extract of the simulated maintenance data is shown in Table 4, illustrating how Reliability, Availability, and Maintainability classes vary across operational conditions. To validate the representativeness of the simulated data, a statistical comparison with the original dataset was performed. Both datasets were confirmed to follow the Birnbaum-Saunders distribution (rank = 2, via chi-squared goodness-of-fit), with shared parameters α = 0.95748 and β = 557.37. The mean inter-failure time in the simulated data was 1,970.13 hours, closely matching the empirical mean, and the variance was 1,159,686.03, indicating high fidelity to the original distribution structure while offering scalability for training and interpretability analysis.

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Table 4. Extract of simulated maintenance data

Maint_Event	Operation_Type	t	Dpr	Dfr	Repair_Probability	Uptime	Downtime	Maintainability_Index	R(t)	A(t)	Reliability_Class	Availability_Class	Maintainability_Class
1	Replacement	1522.278	0	3.87	0.598682884	208.5008963	2.747281637	0.598682884	0.863033645	0.985313113	1	2	0
2	Servicing	3679.474	2.67	0	0.587670553	41.92643309	2.665824192	0.587670553	0.98860532	0.940352041	2	1	0
3	Replacement	2860.585	0	2.88	0.542391751	81.20347305	2.352307825	0.542391751	0.971612987	0.971607304	2	1	0
4	Replacement	2361.377	0	5.04	0.656402712	118.6906028	3.21453334	0.656402712	0.949736707	0.972922771	1	1	1
5	Replacement	704.1338	0	4.38	0.625233533	284.0151771	2.953248321	0.625233533	0.596646005	0.98840388	0	2	0
6	Replacement	704.0435	0	6.33	0.710631928	284.0155168	3.731401985	0.710631928	0.596593785	0.984685502	0	2	1
7	Replacement	337.465	0	2.16	0.496414307	236.830656	2.064219161	0.496414307	0.298206851	0.977849408	0	1	0
8	Servicing	3362.963	3.29	0	0.664660676	54.37155444	3.287735855	0.664660676	0.98383225	0.943400141	2	1	1
9	Replacement	2370.575	0	5.81	0.69017902	117.8895227	3.525897757	0.69017902	0.950269642	0.970271927	2	1	1
10	Replacement	2771.024	0	5.8	0.689465221	87.0655944	3.518973138	0.689465221	0.96857999	0.961531796	2	1	1
11	Replacement	197.0683	0	6.43	0.714523877	171.8239276	3.772147934	0.714523877	0.128099816	0.979906135	0	1	1
12	Servicing	3751.342	3.46	0	0.683115719	39.49819067	3.458067486	0.683115719	0.989470919	0.920007777	2	1	1
13	Servicing	3236.665	3.86	0	0.722334236	60.22764636	3.855620123	0.722334236	0.981392068	0.940391309	2	1	1
14	Replacement	914.9976	0	3.66	0.587600526	274.9381513	2.6653132	0.587600526	0.699520368	0.990127327	0	2	0
15	Replacement	800.7527	0	4.52	0.631797545	281.6985887	3.006418834	0.631797545	0.648207747	0.989384612	0	2	0
16	Replacement	806.6665	0	2.07	0.490343154	281.4434644	2.028159327	0.490343154	0.651103065	0.98753452	0	2	0
17	Replacement	1259.083	0	2.03	0.487924844	240.2699028	2.013915175	0.487924844	0.809170713	0.98901049	1	2	0
18	Replacement	2084.688	0	3.2	0.561441417	144.8051505	2.480253241	0.561441417	0.930538697	0.981146082	1	2	0
19	Replacement	1737.202	0	2.5	0.518891232	182.8198144	2.201614394	0.518891232	0.894761923	0.986757777	1	2	0
20	Replacement	1210.362	0	3.3	0.567257058	245.9179784	2.520422736	0.567257058	0.79682277	0.989911722	0	2	0
21	Replacement	2410.777	0	2.89	0.54266218	114.4382568	2.354086589	0.54266218	0.952530555	0.979600221	2	1	0
22	Replacement	642.265	0	2.14	0.495211401	283.3003912	2.05704005	0.495211401	0.558904214	0.991470309	0	2	0
23	Replacement	1213.79	0	6.55	0.718897819	245.5252737	3.818608293	0.718897819	0.797720065	0.985372557	0	2	1
24	Replacement	1491.659	0	2.04	0.488355398	212.2269092	2.016446263	0.488355398	0.857724221	0.988604496	1	2	0
25	Replacement	1827.526	0	5.68	0.684596782	172.441214	3.472164289	0.684596782	0.905642266	0.979887494	1	1	1
9989	Replacement	245.117	0	3.18	0.560424953	198.8373926	2.473287096	0.560424953	0.1888061	0.982482111	0	2	0
9990	Servicing	3174.433	3.9	0	0.72618125	63.31998886	3.897601659	0.72618125	0.980053136	0.942388098	2	1	1
9991	Replacement	1806.235	0	4.87	0.648855799	174.8597311	3.149156493	0.648855799	0.903191027	0.981959936	1	2	0
9992	Replacement	1337.298	0	5.8	0.689431576	230.9704876	3.518647137	0.689431576	0.827285659	0.983441546	1	2	1
9993	Replacement	1883.837	0	2.45	0.515266928	166.1343512	2.1790314	0.515266928	0.911810663	0.987172417	1	2	0
9994	Servicing	3185.355	2.99	0	0.629207764	62.76705447	2.985328452	0.629207764	0.980295115	0.954953853	2	1	0
9995	Replacement	586.5556	0	6.51	0.717349239	280.808958	3.802076995	0.717349239	0.521257727	0.98861369	0	2	1
9996	Servicing	3331.064	3.75	0	0.712804314	55.79919358	3.754077258	0.712804314	0.983248838	0.936183358	2	1	1
9997	Servicing	3480.273	2.09	0	0.50131208	49.40597357	2.093627914	0.50131208	0.985803995	0.958450204	2	1	0
9998	Servicing	3664.474	2.61	0	0.579586071	42.45057745	2.607396938	0.579586071	0.988415644	0.942493606	2	1	0
9999	Replacement	1608.195	0	4.22	0.616845234	198.1082337	2.886640013	0.616845234	0.876813304	0.985324587	1	2	0
10000	Replacement	932.9737	0	2.86	0.541207337	273.5693463	2.344529629	0.541207337	0.706776992	0.991292129	0	2	0

3.3.2 Classification Target Distribution

To evaluate the representativeness of the generated dataset, we analysed the distribution of the data points or instances across the three classification targets: Reliability, Availability, and Maintainability. Each metric was categorised into domain-informed classes (Low, Medium, High), as described in Section 3.3.1. Figure 2 plots the resulting class frequencies. The Reliability distribution is moderately skewed, with the majority of events classified as High (≈51%), followed by Medium (≈36%) and a smaller proportion as Low (≈13%). This reflects real-world expectations in high-dependability systems, where components are generally engineered for extended reliable performance. For Availability, the distribution is skewed toward the High class (≈62%), indicating consistently high system readiness. The Low availability class constitutes the smallest share (≈9%), suggesting that only a small fraction of events exhibit suboptimal availability levels, aligning with design goals for critical infrastructure. Maintainability exhibits a relatively more balanced distribution, with the Medium class dominating (≈48%), followed by High (≈35%) and Low (≈17%). This distribution captures practical variations in repair complexity and intervention outcomes and offers sufficient variability for training interpretable predictive models.

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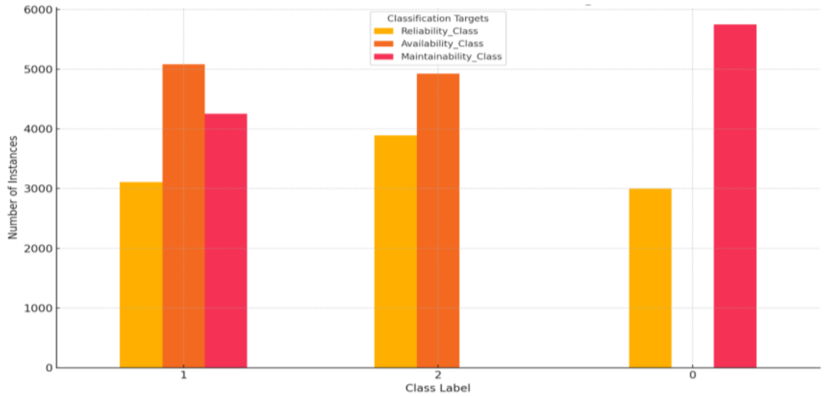

Fig. 2. Class distribution across classification targets

4. RESULTS AND DISCUSSION

This section presents the analytical results for the four preventive replacement models, summarising optimal probabilities, reliability/availability metrics, and expected costs, and discusses their implications alongside LIME-based explainability findings.

4.1 Analytical Results

Optimal probability functions in Eqs. (3), (4), (5) and (7), availability factor in Eq. (2) and expected cost per cycle in Table 1 at the respective optimum values of τ for the four replacement models under consideration were used to obtain the numerical results in Table 5.

Table 5. Summary of optimal probabilities, reliability metrics, and expected costs across replacement models

Probability function	Failure-Based Replacement model 1 ($\tau_f^* = 143$)	Hazard-Based Replacement model 2 ($\tau_h^* = 137$)	Failure-Based Replacement model 3 ($\tau_f^* = 153$)	Hazard-Based Replacement model 4 ($\tau_h^* = 149$)
$f(\tau^*)$	0.00115	0.001081	0.001376	0.001145
$F(\tau^*)$	0.06256	0.056	0.093197	0.069341
$h(\tau^*)$	0.0012	0.0015	0.0015174	0.001231
$R(\tau^*)$	0.93744	0.94407	0.906803	0.930659
$A(\tau^*)$	0.9829	0.98	0.9597	0.95903
$E[\varphi(\tau^*)]$	388	392	208	166

The analytical results confirmed that the failure behaviour of the case study system follows the Birnbaum-Saunders distribution, with estimated parameters α=0.95748 and β=557.37. The failure density function of this distribution is unimodal for all values of α, and both the failure density and hazard functions are primarily governed by the shape parameter α. As α increases, the hazard rate and failure density become increasingly right skewed, indicating a higher likelihood of failure occurring at later stages of system operation. The scale parameter β, which also serves as the median of the distribution, centres the failure distribution temporally. Given these characteristics, the Birnbaum-Saunders model is well-suited for modelling the non-constant failure rates typical of complex, non-repairable electronic systems like radio transmitters. Among the preventive replacement models evaluated, those proposed by Udoh et al. (2022) outperformed earlier models by Bahrami-G et al. (2000) and Cassady et al. (2001). Notably, Model 3 from (Udoh et al., 2022) achieved the lowest expected maintenance cost, 122.93 Naira at an optimal replacement time, (τ_h^* =113), without compromising system reliability, availability, or the probability of failure. In the current study, Model 3 yielded a cost, ₦208, followed by Model 4, ₦166. Both significantly outperformed Models 1 and 2, which resulted in higher costs of ₦388 and ₦392, respectively.

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These findings confirm the selection of Models 3 and 4 as superior strategies for minimising maintenance cost and optimising replacement timing in transmitter systems. Their strong performance underscores the practical relevance of this model class for effective maintenance scheduling in high-reliability, high-availability environments.

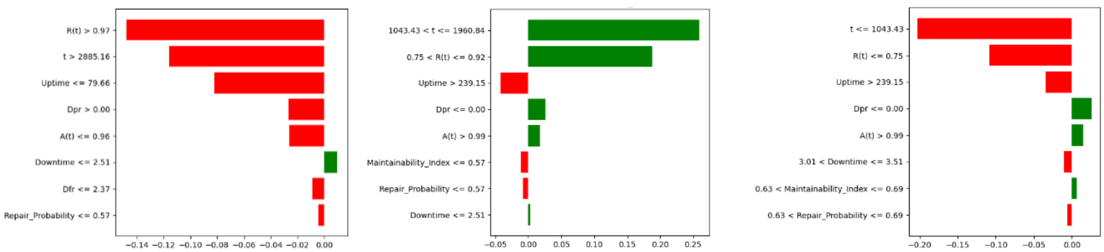
4.2 LIME-Based Explainability Analysis

To enhance interpretability and provide localised explainability for the classification outcomes, LIME was applied across the three-target metrics: Reliability, Availability, and Maintainability. An RF classifier was used as the predictive model, and LIME analysed its instance-level perturbations to identify the most influential features shaping the model's decisions within each class.

4.2.1 Reliability Target Class

LIME explanations for the Reliability class revealed coherent and interpretable patterns across both low and high reliability predictions. In Instance 3 (Fig. 3c), the model penalised short inter-failure durations ($t \leq 1043.43$) and low reliability scores ($R(t) \leq 0.75$) most heavily, consistent with expectations for systems approaching end-of-life. Uptime exceeding 239.15 hours contributed a small negative influence, while the absence of preventive maintenance ($Dpr \leq 0$) and high availability ($A(t) > 0.99$) provided slight positive offsets. Similarly, instance 1 (Fig. 3a) showed strong negative contributions from unusually high reliability scores ($R(t) > 0.97$) and extended time intervals ($t > 2885.16$), indicating possible confidence in penalising predictions at its upper bounds.

Features such as low downtime and minimal failure rates made minor contributions but did not significantly alter the classification. However, in Instance 2 (Fig. 3b), which was classified as high reliability, the most influential factors were moderately long inter-failure times ($1043.43 < t \leq 1960.84$) and intermediate reliability levels ($0.75 < R(t) \leq 0.92$), both contributing strongly and positively. Here, high uptime (Uptime > 239.15) and low maintainability index slightly reduced confidence, showing that extreme uptime without corresponding reliability improvements may be treated cautiously by the model. Across all instances, availability and maintainability features contributed only marginally to the reliability decision, reinforcing the domain-specific importance of $R(t)$ and t in driving reliability outcomes.



(a) Instance 1 (b) Instance 2 (c) Instance 3

Fig. 3. LIME explanation for reliability class

4.2.2 Availability Target Class

LIME explanations for the Availability class closely reflected expected operational dynamics. In Instance 1 (Fig. 4a), availability scores in the mid-range ($0.96 < A(t) \leq 0.98$) were identified as the strongest negative contributors, suggesting that the model treats borderline degradation with caution. Notably, low Downtime (≤ 60 hours) and the absence of preventive maintenance ($Dpr = 0$) contributed weakly but positively, indicating a modest influence in pushing the prediction toward higher availability. In contrast, instances 2 (Fig. 4b) and 3 (Fig. 4c) showed strong positive contributions from high availability values ($A(t) > 0.99$), combined with consistently high Uptime and well-bounded inter-failure intervals. For Instance 2,

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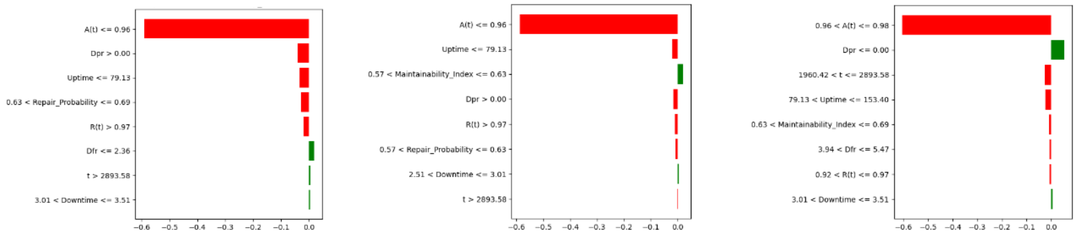
inter-failure time in the range 1043.24 < t ≤ 1960.42 and Uptime > 239.15 supported the classification as high availability. Similarly, instance 3 benefited from t ≤ 1043.24 and Uptime between 152.97 and 239.15, reinforcing the model's sensitivity to healthy operational intervals and minimal degradation signals. Across all instances, availability classification was primarily influenced by *A(t)* and its correlates (t, Uptime, Downtime), confirming that the model adheres to core reliability engineering principles when deriving availability predictions.



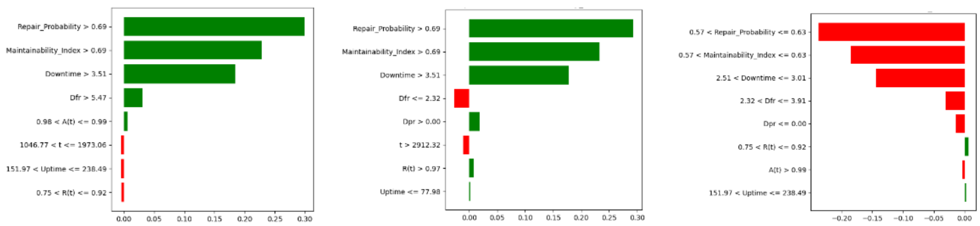
(a) Instance 1 (b) Instance 2 (c) Instance 3

Fig. 4. LIME explanation for availability class

4.2.3 Maintainability Target Class

Predictions for the Maintainability class were driven by repair-related features (Repair Probability (RP) and Maintainability Index (MI)) across three test instances (Instance 1 (Fig. 5a), Instance 2 (Fig. 5b), and Instance 3 (Fig. 5c)). These features consistently contributed the most strongly to high maintainability predictions. In Instance 2, RP > 0.69 and MI > 0.69 yielded LIME contribution scores of approximately 0.30 and 0.22, respectively, confirming their decisive roles. Furthermore, Downtime > 3.51 hours provided further positive influence, affirming the notion that longer recoverability windows may reflect successful repairs rather than system failure. In Instance 1, bounded Downtime (between 3.51 and 18.87 hours) and moderate Reliability (0.75 < *R(t)* ≤ 0.92) also exerted positive contributions, while features such as low RP and high Availability had minimal or neutral impact. Instance 3 further confirmed this trend, where MI > 0.75 and RP > 0.69 remained dominant factors in the model's decision, indicating that the classifier prioritises inherent indicators of system recoverability over external metrics.

Across all instances, *Dpr* (degree of preventive repair) and *Dfr* (failure rate) consistently exhibited weak or negligible contributions. This suggests that the classifier's logic is narrowly focused on system-internal indicators of maintainability, rather than more general preventive or failure-related variables. Similarly, negative features such as *R(t)* ≤ 0.75 or *A(t)* > 0.99 had limited influence, affirming the model's ability to distinguish maintainability drivers from overlapping reliability or availability metrics.



(a) Instance 1 (b) Instance 2 (c) Instance 3

Fig. 5. LIME explanation for maintainability class

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4.2.4 Feature Importance Analysis Across Classification Targets

To interpret the role of different features in model decisions, we present in Fig. 6 a bar chart of normalised feature importance scores derived using the RF model. This enables visualisation of how different operational features influenced predictions for the various target classes. Fig. 6 shows that Reliability classification was primarily influenced by inter-failure time (t) and uptime, reaffirming the classical reliability theory. These features jointly contributed over 50% of the model's explainability. Availability predictions were most affected by *A(t)* itself and Uptime, with minor influences from Downtime and Inter-failure time, showing strong operational alignment. Maintainability classification was predominantly driven by RP (34.1%) and MI (21.3%), with Downtime (15.9%) also showing substantial influence. This affirms that Maintainability operates independently of system-level Availability or Reliability, relying instead on direct measures of repair effectiveness and intervention outcomes. Our results strengthen the role of LIME in translating machine-learned patterns into interpretable, actionable insights. By surfacing the contribution of each feature across decision contexts, LIME provides a clearer understanding of how maintenance decisions may be rationalised across different operational objectives.

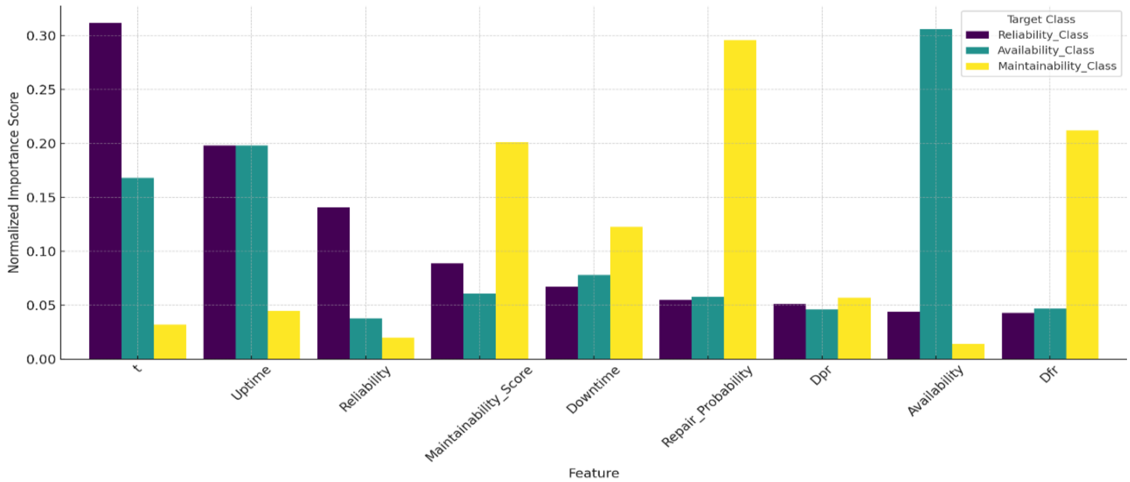

Fig. 6. LIME feature importance by classification targets

4.3 Discussion

The analytical results presented in Section 4.1 established an understanding of optimal replacement strategies within classical age-based maintenance frameworks. These models, which were built upon statistical failure distributions and cost functions, offer insights into theoretically optimal replacement intervals. Specifically, using the Birnbaum-Saunders distribution with $\alpha = 0.95748$ and $\beta = 557.37$, the optimal preventive replacement threshold was computed at $\tau = 113$ hours*, resulting in a minimum expected maintenance cost of 122.93 Naira and a corresponding reliability of approximately 0.838 at replacement. However, the analytical approach typically treats inter-failure times as isolated, discrete events, abstracting from the continuous degradation dynamics experienced by real-world systems. It also does not account for the active degradation interval, nor does it capture contextual operational conditions between failures.

The simulated dataset introduced in this study incorporates these degradation dynamics. It models t, *Dpr*, and *Dfr* as interacting continuous variables. This real-time simulation framework enables a more realistic and scalable representation of system behaviour. Notably, Reliability across the 10,000 simulated events displayed a broader and more flexible range: [0.00-1.00], with a mean of 0.855, thereby closely

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aligning but slightly exceeding the analytical benchmark (0.838). This divergence captures the benefit of considering real-world dynamics beyond what static analytical models provide.

The integration of LIME (detailed in Section 4.2) adds further interpretive power. While analytical models identify global optima (e.g., minimising expected cost $E[\phi(\tau)]$ at τ^*), they do not explain the local reasoning behind specific classification outcomes. LIME addresses this by generating instance-specific explanations, illuminating the feature contributions behind every prediction. For example, LIME analysis showed that operational time (t) consistently dominates reliability classification, while *Dfr* plays a more decisive role in predicting availability ($A(t)$). These insights confirm domain expectations (e.g., longer t reduces reliability, higher *Dfr* lowers availability) and reveal compensatory interactions such as moderate *Dpr* mitigating the reliability penalties associated with mid-range operational times. Such complexity remains hidden in closed-form equations. The combined analytical simulation approach, therefore, offers the following contributions:

- Theoretical evidence through validated failure models (e.g., Birnbaum-Saunders) used for both simulation and decision thresholds.
- Realistic system representation by capturing degradation dynamics, mutual maintenance exclusivity, and interdependent performance metrics in continuous time.
- Instance-level transparency, enabled by LIME, enhances auditable, explainable, and risk-aware maintenance strategies.

5. CONCLUSION AND FUTURE WORK

This study presented a framework for interpreting maintenance decisions in non-repairable systems by integrating analytical reliability modelling, Monte Carlo simulation, and explainable machine learning. Traditional age-based replacement strategies using the Birnbaum-Saunders distribution yielded optimal preventive thresholds with validated reliability, availability, and cost metrics. Analytical formulations operate on discrete events and under-represent continuous degradation between failures. To address this, we implemented symbolic data generation to simulate real-time scenarios that include both preventive servicing and failure replacement. Integrating LIME provided instance-level transparency, identifying and quantifying feature effects that drive maintainability decisions, critical for high-reliability systems where safety, cost efficiency, and uptime must be balanced. Future directions for this study include validation on other non-repairable electronics, benchmarking alternative classifiers (e.g., gradient boosting, SVM), and exploring alternative lifetime models and maintenance policies beyond age-based approaches.

6. ACKNOWLEDGEMENT/FUNDING

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7. CONFLICT OF INTEREST STATEMENT

The authors agree that this research was conducted in the absence of any personal benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

8. AUTHORS' CONTRIBUTION

Moses Ekpenyong was responsible for conceptualisation, methodology, software, visualisation, writing, reviewing and editing of the original draft. Nse Udoh acquired funding and performed investigation, data

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curation, formal analysis and validation. Elisha Inyang gathered resources, performed formal analysis and investigation as well as data curation and validation. Uko Jim gathered resources, performed formal analysis and investigation as well as data curation and validation. Nsikak Udoenoh also gathered resources, performed formal analysis and investigation as well as data curation and validation. All authors read and approved the final manuscript.

9. DECLARATION OF GENERATIVE AI IN THE WRITING PROCESS

The authors declare that generative artificial intelligence (AI) tools may have been used solely to support language refinement during the preparation of this manuscript. Such tools were used only to improve grammar, sentence structure, clarity, and overall readability. All aspects of the research, including the study design, data collection, data extraction, analysis, interpretation of findings, and final academic decisions, were conducted, reviewed, and approved by the authors. The authors take full responsibility for the accuracy, integrity, originality, and scholarly content of this manuscript.

10. DATA AVAILABILITY/SUPPLEMENTARY MATERIALS

The data and/or supplementary materials supporting the findings of this study are available from the corresponding author upon reasonable request, where applicable.

11. ETHICS STATEMENT

The authors declare that this study did not involve human participants or animal subjects. Where applicable, all procedures were conducted in accordance with relevant institutional guidelines, safety requirements, and ethical standards.

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