

A Hybrid Stochastic and Machine-Learning Framework for the B3 Jaw Crusher at KTC: Euler–Maruyama Simulation, First-Passage Probabilities, Kurtosis Analysis and Random Forest Prediction

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Abstract: Unplanned stoppages of the B3 jaw crusher, the entry point of the comminution line at the Kamoto Concentrator (KTC) of Kamoto Copper Company, interrupt ore supply to the downstream mills and generate costly production losses. This paper treats the timing of maintenance on this ageing machine as a decision under uncertainty. A normalised performance indicator $P(t)$ is described by the Itô equation $dP(t) = -\mu P(t)dt + \sigma dW(t)$, integrated with the Euler–Maruyama scheme and explored through Monte Carlo sampling. The preventive trigger level C is selected by minimising a renewal-type cost rate that weighs planned against unplanned interventions. The full probability law of the critical time is then characterised, including its skewness and kurtosis. The cost-optimal trigger is $C^* \approx 0.42$, giving a mean cycle of about 52 days, a cost rate of 5,800 USD/day and a 70 % share of preventive interventions. The critical time is right-skewed (skewness 1.23) and leptokurtic (kurtosis $\beta_2 = 5.65$, excess 2.65), whereas the Brownian increments and the performance level at fixed dates remain mesokurtic ($\beta_2 \approx 3.0$). The probability of reaching C^* is 0.15 at day 30, 0.61 at day 52 and 0.84 at day 70, and a Weibull law ($\beta = 2.48$) fits the critical time well. Field validation over seven months gives MAE = 7.71 % and RMSE = 8.32 %. A Random Forest regressor trained on vibration, temperature, current, throughput and operating hours reaches $R^2 = 0.81$ on a chronological test set. Both approaches are complementary and can be coupled within a sensor-fed CMMS.

Keywords: Jaw Crusher; Stochastic Differential Equation; Euler–Maruyama Scheme; First-Passage Time; Failure Probability; Kurtosis; Monte Carlo; Random Forest; Condition-Based Maintenance.

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I. INTRODUCTION

At Kamoto Copper Company (KCC), in Kolwezi (Lualaba, DR Congo), ore extracted from the KOV and Mashamba East open pits and from the Kamoto underground mine is treated at the Kamoto Concentrator (KTC) before refining at Luilu, whose nameplate capacity reaches 300,000 t of copper cathode and 40,000 t of cobalt hydroxide per year. Within KTC, seven primary crushers feed six ball mills, and no mill can operate at its target feed ratio unless the upstream crusher delivers a suitable particle size. The B3 jaw crusher is therefore a single point of failure: when it stops, the grinding line it serves stops with it.

Over recent production campaigns, B3 has shown a growing number of abrupt stoppages. Corrective actions on

peripheral equipment improved operating conditions without removing these unpredictable stoppages. The machine has reached a level of wear at which failures appear almost random, yet replacement is not an immediate option. Operators must keep it running under close watch, and the maintenance team needs an objective rule that tells them when to stop the crusher for a planned intervention instead of waiting for a breakdown.

Predictive maintenance answers this need by linking the intervention decision to the measured condition of the asset rather than to the calendar (AFNOR, 2018; Jardine et al., 2006). For a degrading machine, however, the condition at a future date is not a single number but a random quantity. Ore hardness, feed variations and tramp metal introduce random shocks, so that a rule built only on average behaviour is late

for unfavourable cycles and early for favourable ones. A probabilistic description is therefore required: the planner needs to know not only the expected time to the intervention threshold but also how likely it is to be reached by a given date, and how heavy the tails of that time distribution are.

Two statistical descriptors are central to this question. The first is the probability of threshold crossing as a function of time, $P(T \leq t)$, which converts the model into a risk statement directly usable for shutdown scheduling. The second is the shape of the distribution, summarised by skewness and kurtosis. Kurtosis, the standardised fourth moment, measures the weight of the tails relative to a normal law (DeCarlo, 1997; Westfall, 2014). A leptokurtic critical-time distribution means that very early or very late crossings occur more often than a Gaussian assumption would predict, which directly affects the safety margin to be kept.

The paper contributes (i) an Itô degradation model of B3 calibrated on twelve months of KCC data and solved by Euler–Maruyama, (ii) a Monte Carlo cost-rate optimisation of the trigger level, (iii) a probabilistic characterisation of the critical time, including skewness, kurtosis and normal/Weibull comparison, and (iv) a Random Forest benchmark with a coupling scheme. Section 2 reviews the background, Section 3 presents the data and methods, Section 4 reports the results, Section 5 discusses them and Section 6 concludes.

II. BACKGROUND AND RELATED WORK

➤ Reliability, Hazard and Maintenance Policies

Following AFNOR X60-500, reliability is the ability of an item to perform a required function under stated conditions for a stated period (AFNOR, 1988; Villemeur, 1995). If T denotes the random life of the item, the reliability function and the hazard rate are:

$$R(t) = P(T > t) = 1 - F(t), \quad \lambda(t) = f(t) / R(t), \quad R(t) = \exp[-\int_0^t \lambda(u) du]$$

Where F is the cumulative distribution function and f the density. The bathtub curve distinguishes early failures, a useful-life period with a roughly constant hazard (exponential law) and a wear-out period with an increasing hazard, usually represented by a Weibull law $\lambda(t) = (\beta/\eta)(t/\eta)^{\beta-1}$ with $\beta > 1$ (Birolini, 2023; O'Connor & Kleyner, 2012). Catalectic failures appear without warning, whereas progressive failures give observable precursors and can be anticipated (Elsayed, 2021; Kumar et al., 2023); availability follows $A = MTBF/(MTBF + MTTR)$. The B3 crusher combines both behaviours: a steady wear trend on which random shocks are superimposed.

Maintenance policies range from purely corrective to time-based preventive, condition-based and predictive strategies (Jardine et al., 2006; Bousdekis & Kokkinis, 2024). Barlow and Hunter (1960) formalised the trade-off: planned actions are cheaper than failures, but frequent ones waste useful life. Condition-based policies transpose this trade-off to a threshold on a condition indicator: the equipment is serviced when the indicator crosses a preventive level C ,

before it reaches a failure level S (Wang, 2025). The interval between the two levels defines three operating zones: green ($P > C$, normal running), amber ($S < P \leq C$, planned intervention to be prepared) and red ($P \leq S$, forced stop).

➤ Stochastic Degradation Processes

Degradation is usually modelled with Markov chains, whose two-state availability is $\mu/(\lambda + \mu)$ (Trivedi & Bobbio, 2017), Poisson processes, with $P(N(t) = k) = (\lambda t)^k e^{-(\lambda t)}/k!$ in the homogeneous case (Sudadiyo, 2025), or diffusion processes (Ye & Xie, 2015; Si et al., 2011). The Wiener process $X(t) = x_0 + \mu t + \sigma W(t)$ suits wear that accumulates gradually but irregularly (Hu et al., 2025). For a linear drift, the first-passage time to a fixed level follows an inverse Gaussian law (Chhikara & Folks, 1989), which is right-skewed and has a heavier right tail than the normal law. When the drift is proportional to the state, as in the Ornstein–Uhlenbeck family (Uhlenbeck & Ornstein, 1930), no simple closed form is available and simulation becomes the practical route (Kloeden & Platen, 1992).

➤ Higher-Order Moments and Kurtosis

The first two moments of a random variable X , the mean m and the standard deviation s , describe its location and dispersion. Its shape is summarised by the standardised third and fourth moments:

$$\gamma_1 = E[(X - m)^3] / s^3, \quad \beta_2 = E[(X - m)^4] / s^4, \quad \gamma_2 = \beta_2 - 3$$

The skewness γ_1 measures asymmetry. The kurtosis β_2 equals 3 for any normal law; a distribution with $\beta_2 > 3$ (positive excess kurtosis γ_2) is called leptokurtic and places more probability in its tails, whereas $\beta_2 < 3$ characterises a platykurtic law (DeCarlo, 1997). Although often described as “peakedness”, kurtosis is mainly a measure of tail weight and propensity to produce outliers (Westfall, 2014). For reference, the exponential law has $\beta_2 = 9$ and the Weibull law with $\beta \approx 2.5$ has $\beta_2 \approx 2.9$. Bias-corrected sample estimates are used (Joanes & Gill, 1998), and normality is tested with the Jarque–Bera statistic $JB = n[\gamma_1^2/6 + \gamma_2^2/24]$. In machinery diagnostics, kurtosis of vibration signals has been used since the work of Dyer and Stewart (1978) to detect impulsive bearing damage, a value well above 3 signalling shocks that a Gaussian description cannot explain (Randall, 2011).

III. MATERIALS AND METHODS

➤ Case Study and Field Data

Twelve months of operating records of the B3 crusher were extracted from the KCC maintenance history, from 3 October 2024 to 3 October 2025 (Kamoto Copper Company, 2025). Over 8,760 h (365 days), the machine was stopped for 2,256 h (94 days) and experienced 11 major failures. The 271 effective operating days give $MTBF \approx 271/11 \approx 25$ days, hence a failure-frequency rate $\mu = 1/MTBF = 0.04 \text{ day}^{-1}$, and $MTTR \approx 8.5$ days. Failure families were ranked by work-order (NT) analysis. Throughput records between October 2024 and April 2025 ranged from 350 to 600 t/h, with a mean of 457.85 t/h and a standard deviation of 11.4 t/h. Relative to the nominal 800 t/h obtained with both primary feeder pumps

running, a representative current throughput of 600 t/h gives an initial performance $P_0 = 0.75$.

➤ Performance Indicator and Stochastic Model

Impact loads, abrasion and thermal cycling progressively wear the jaw plates, bearings and fasteners. The mechanical health $H(t)$, equal to 1 in new condition and tending to 0 at failure, evolves according to $dH/dt = -\lambda(t)H(t)$, in which the hazard combines a base wear term, a load-induced term proportional to the crushing force and an abrasion term proportional to ore abrasivity and throughput (Mobley, 2002). The functional performance used as the decision variable is the product $P(t) = H(t) \cdot E(t)$ of this slow health component and a fast operational-efficiency component $E(t)$, which separates irreversible wear from recoverable operating losses (Li & Anderson, 2016).

Random disturbances (tramp metal, hardness changes, feed surges) are introduced through an Itô stochastic differential equation with a state-proportional drift and an additive diffusion (Si et al., 2011; Saxena et al., 2008):

$$dP(t) = -\mu P(t) dt + \sigma dW(t)$$

Where μ (day^{-1}) is the degradation rate, σ ($\text{day}^{-1/2}$) the volatility and $W(t)$ a standard Brownian motion. The volatility was derived from the load-dependent form $\sigma = \sigma_0 \cdot Q/Q_0$ with $\sigma_0 = 0.05$ and $Q = 458$ t/h, which gives $\sigma \approx 0.02$, consistent with the relative throughput variability observed on site ($\sigma_Q/Q \approx 2.4\%$). The trigger level C was initially set to 0.40, below the value of 0.50 often recommended for ageing crushers, because field performance fluctuated between 43 % and 75 %; the failure level was fixed at $S = 0.25$.

➤ Euler–Maruyama Discretisation and Monte Carlo Sampling

Because the equation has no convenient closed-form first-passage law, it is integrated numerically with the Euler–Maruyama scheme (Maruyama, 1955; Higham, 2001; Kloeden & Platen, 1992):

$$P_{n+1} = P_n - \mu P_n \Delta t + \sigma \sqrt{\Delta t} \cdot Z_n, \quad Z_n \sim N(0, 1) \text{ i.i.d.}$$

Each Z_n is a standard normal draw representing the random shock received during one time step. Of the constant, wear-dependent and load-dependent volatility forms, the last was retained. The step size was chosen relative to the characteristic time $\tau = 1/\mu$: $\Delta t \leq 0.1\tau$ for routine runs and smaller steps for verification (Giles, 2008). In the MATLAB runs, $\Delta t = 2.5$ days, a 200-day horizon and a fixed seed $\text{rng}(42)$ were used. Crossing times were located by sequential scanning of each path and refined by linear interpolation between the two steps bracketing the level: $t_c = t_n + \Delta t (P_n - C)/(P_n - P_{n+1})$.

➤ Cost-Rate Optimisation of the Trigger Level

For each candidate level C , M simulated cycles are classified as preventive (C reached before S) or corrective (S reached first). This yields the preventive-maintenance probability $\text{PMP}(C)$, the corrective probability $\text{PDP}(C) = 1 -$

$\text{PMP}(C)$ and the expected cycle length $E(T | C)$. Following renewal–reward theory (Barlow & Hunter, 1960), the long-run cost per unit time is:

$$J(C) = [C_{\text{prev}} \cdot \text{PMP}(C) + C_{\text{corr}} \cdot \text{PDP}(C)] / E(T | C)$$

With $C_{\text{prev}} = 5,000$ USD for a planned intervention and $C_{\text{corr}} = 15,000$ USD for an unplanned one, values based on KCC practice. The optimal level C^* minimises $J(C)$ over a grid of candidate thresholds. A constrained variant, $\text{PDP}(C) \leq \alpha_{\text{max}}$, caps the forced-stop risk (Zhang & Liu, 2025).

➤ Probabilistic Characterisation of the Critical Time

The critical time T_c is the first date at which $P(t)$ reaches C^* . Its distribution was characterised with an additional Python replication of 10,000 paths ($\Delta t = 0.25$ day, horizon 300 days, seed 42). To express the distribution on the same time scale as the MATLAB cycle estimate $E(T | C^*) \approx 52$ days, the drift of the replication was set to the effective value $\mu_{\text{eff}} = \ln(P_0/C^*)/52 \approx 0.0112 \text{ day}^{-1}$, with $\sigma = 0.02$ unchanged; skewness and kurtosis being dimensionless, they do not depend on this time scaling. The descriptors computed were the distribution function $F(t) = P(T_c \leq t)$, the zone-occupancy probabilities of paths left without intervention, the moments (m, s, γ_1, β_2) of T_c , of Z_n and of $P(t)$ at fixed dates, a maximum-likelihood Weibull fit and the Jarque–Bera test. The standard error of the sample kurtosis, approximately $\sqrt{(24/n)} \approx 0.05$ for $n = 10,000$, provides the reference to judge whether β_2 differs from 3.

➤ Random Forest Benchmark

A Random Forest regressor (Breiman, 2001) was trained to predict the remaining time before the next intervention without assuming a degradation law. The twelve-month history was resampled to daily values ($n = 365$) with five inputs: vibration level (mm/s, ISO 10816), bearing temperature ($^{\circ}\text{C}$), motor current (A), throughput $Q(t)$ (t/h) and cumulative operating hours since the last intervention. The target, in days, was reconstructed backwards from the 11 recorded interventions. To avoid leakage of future information, the data were split chronologically: the first 292 days for training and the last 73 days for testing. The scikit-learn model (Pedregosa et al., 2011) used 300 trees, a maximum depth of 8 and 5 samples per leaf, tuned by five-fold time-series cross-validation.

➤ Verification and Accuracy Metrics

Verification covered coding, convergence in Δt , normality of increments, bounds $0 \leq P \leq 1$ and response to μ and σ (Glasserman, 2004). Validation compared simulated and observed performance with the mean absolute error and the root mean square error:

$$\text{MAE} = (1/n) \sum |obs_i - sim_i|, \quad \text{RMSE} = \sqrt{[(1/n) \sum (obs_i - sim_i)^2]}$$

An RMSE below 3 % was rated excellent, 3–5 % good, 5–9 % acceptable and above 9 % insufficient (Tabatabaei, 2021; Gharaei & Salehi, 2024).

IV. RESULTS

➤ Ensemble of Performance Trajectories

Figure 1 shows forty sample paths of $P(t)$ together with the median path and the 5–95 % envelope of the 10,000 replicated cycles. All paths start at $P_0 = 0.75$ and drift

downwards, but the envelope widens steadily: after 30 days, 90 % of the paths lie between 0.38 and 0.69, and after 52 days between 0.23 and 0.60. The median path reaches $C^* = 0.42$ at about day 52 and the failure level $S = 0.25$ only after about 98 days. The width of the envelope, rather than the median alone, is what makes the intervention date uncertain.

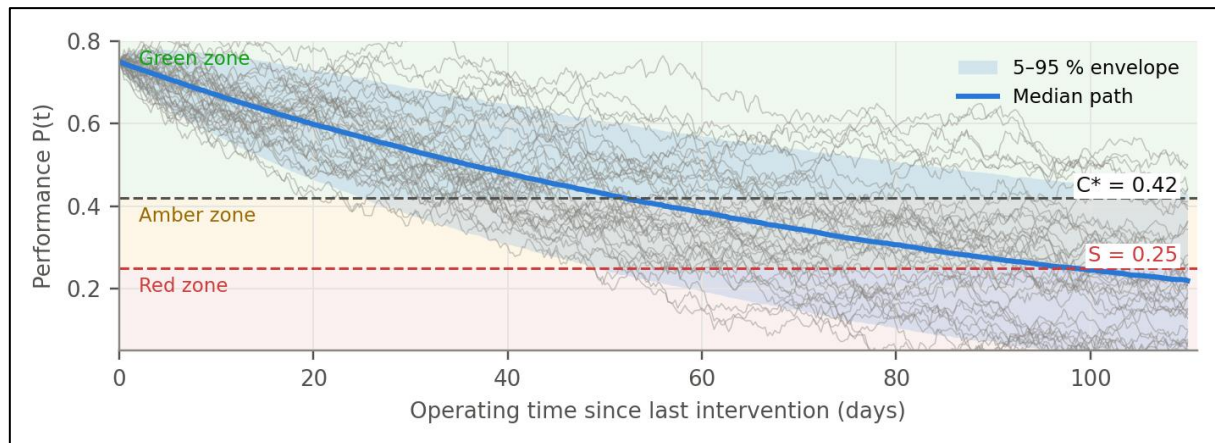


Fig 1 Forty Simulated Performance Paths (Grey), Median Path (Blue) and 5–95 % Envelope of 10,000 Euler–Maruyama Cycles, with the Green, Amber and Red Operating Zones Delimited by $C^* = 0.42$ and $S = 0.25$ ($P_0 = 0.75$, $\sigma = 0.02$).

➤ Cost-Optimal Trigger Level

Table 1 Lists, for Five Trigger Levels, the Indicators Estimated from 1,000 MATLAB Monte Carlo Cycles.

Threshold C	Mean cycle $E(T C)$ (days)	Cost rate $J(C)$ (USD/day)	PMP(C)	PDP(C)
0.35	58	6,300	0.55	0.45
0.40	55	6,000	0.65	0.35
0.42 (C^*)	52	5,800	0.70	0.30
0.45	48	6,100	0.78	0.22
0.50	43	6,500	0.85	0.15

Table 1. Mean cycle length, cost rate and maintenance shares as functions of the trigger level C (1,000 Monte Carlo cycles per level). Source: authors' MATLAB simulation.

The cost rate $J(C)$ is convex in C (Figure 2a). A low trigger lets the machine run longer but exposes it to more

forced stops, whereas a high trigger converts almost every cycle into a planned intervention at the price of shorter cycles (Figure 2b). The minimum, $J(C^*) \approx 5,800$ USD/day, is reached at $C^* \approx 0.42$ with a mean cycle of 52 days. Moving to the neighbouring levels 0.40 or 0.45 already raises the cost rate by 200 to 300 USD/day.

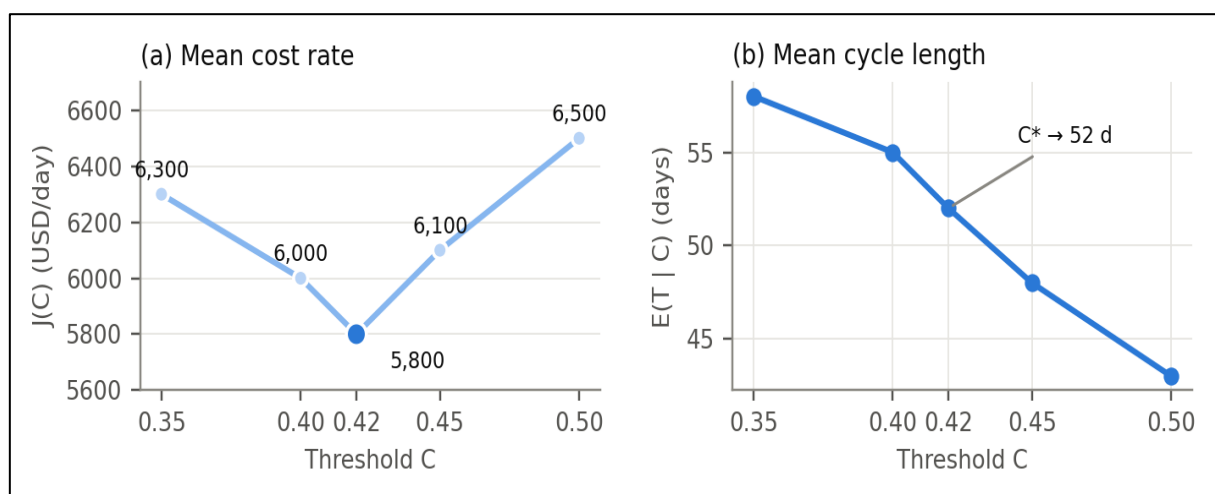


Fig 2 (a) Cost Rate $J(C)$ and (b) Mean Cycle Length $E(T | C)$ as Functions of the Trigger Level; the Optimum $C^* = 0.42$ is Highlighted (Values from Table 1).

➤ Preventive versus Corrective Shares

In Table 1, the preventive share rises from 55 % at $C = 0.35$ to 85 % at $C = 0.50$. At the optimum, 70 % of the cycles end with a planned intervention and 30 % with a forced stop. The optimum thus accepts a residual corrective risk rather than intervening too often.

➤ Distribution, Skewness and Kurtosis of the Critical Time

Table 2 summarises the moments of the main simulated quantities. The standard normal draws Z_n and the performance increments ΔP have a kurtosis of 3.00, within 0.01 of the theoretical value, which confirms that the random generator and the scheme behave as intended. The performance level observed at fixed dates also remains close to normal: $\beta_2 = 3.11$ at day 30 and 3.03 at day 52, i.e. within about two standard errors of 3.

Table 2 Moments of the Simulated Quantities (Python Replication, 10,000 Paths, $\Delta t = 0.25$ Day). $\beta_2 = 3$ and $\gamma_2 = 0$ for a Normal Law; the Standard Error of β_2 is About 0.05.

Quantity	Mean	Std. dev.	Skewness γ_1	Kurtosis β_2	Excess γ_2
Brownian draws Z_n	0.000	1.000	0.00	3.00	0.00
Increments ΔP ($\Delta t = 0.25$ d)	-0.0016	0.0100	0.00	3.00	0.00
Performance $P(30$ d)	0.535	0.094	-0.07	3.11	0.11
Performance $P(52$ d)	0.419	0.111	-0.06	3.03	0.03
Critical time T_C (days)	50.3	21.2	1.23	5.65	2.65

The critical time behaves differently. Although generated by Gaussian shocks, T_C is a first-passage time, a non-linear functional of the path. Its distribution (Figure 3) is clearly right-skewed ($\gamma_1 = 1.23$) and leptokurtic ($\beta_2 = 5.65$, i.e. an excess kurtosis of 2.65, more than fifty standard errors above zero). The mean (50.3 days) exceeds the median (46.4 days); the 90 % interval spans 23.7–90.5 days. The Jarque–

Bera statistic ($JB = 5,448$, $p < 0.001$) rejects normality. A normal law with the same mean and standard deviation would place about 2 % of the cycles before day 7, including almost 1 % at negative times, although no simulated cycle crosses C^* before day 12, and it would underestimate the long right tail; whereas the Weibull fit ($\beta = 2.48$, $\eta = 56.8$ days) follows the mode and the tails more closely.

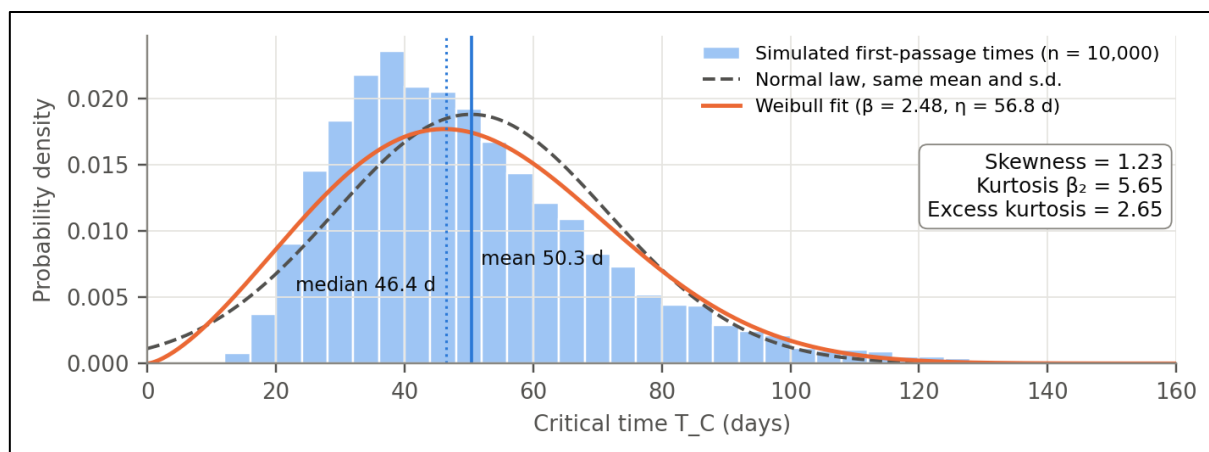


Fig 3 Histogram of the Critical Time T_C (10,000 cycles) with the Normal Law of Equal Mean and Standard Deviation (Dashed) and the Fitted Weibull Law (Orange). Mean, Median, Skewness and Kurtosis are Reported on the Chart.

➤ Time-Dependent Crossing and Zone Probabilities

Table 3 and Figure 4 translate the distribution into probabilities that can be read directly by planners. The probability that the trigger has been reached is only 0.15 at day 30, rises to 0.37 at day 40, exceeds one half near day 47

and reaches 0.61 at day 52 and 0.84 at day 70. If no intervention is made, the probability that performance has already fallen to the failure level S is 0.3 % at day 30, 9.1 % at day 52 and 30.2 % at day 70.

Table 3 Probability that the Trigger $C^* = 0.42$ has been Reached and Zone-Occupancy Probabilities without Intervention, as Functions of Time (10,000 Simulated Paths).

Day t	$P(T_C \leq t)$	Still above C^*	Reached C^* , not S	Reached S
30	0.145	0.855	0.142	0.003
40	0.366	0.634	0.345	0.022
52	0.608	0.392	0.517	0.091
60	0.733	0.268	0.560	0.173
70	0.842	0.158	0.540	0.302
90	0.949	0.052	0.383	0.565

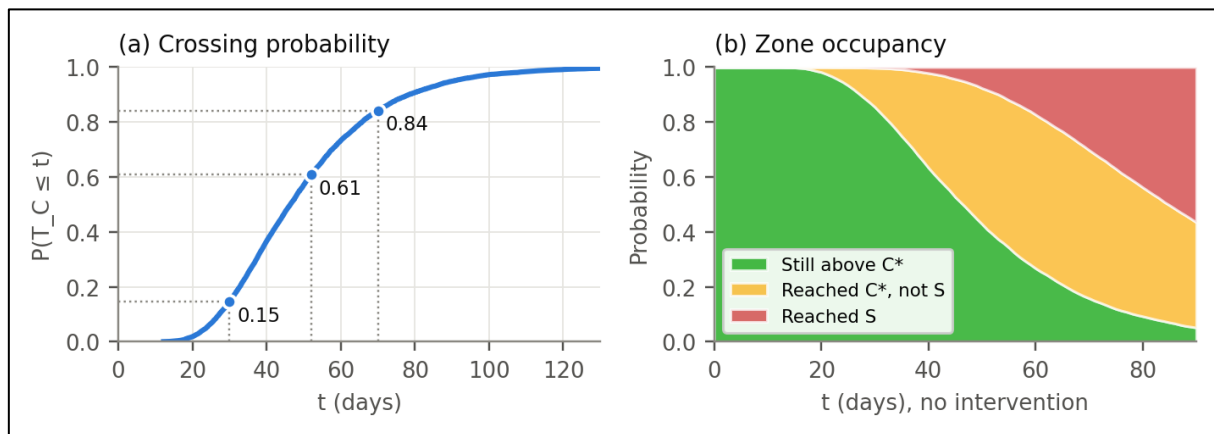


Fig 4 (a) Cumulative Probability $P(T_C \leq t)$ of Reaching $C^* = 0.42$, with Values at Days 30, 52 and 70; (b) Probability of Still being above C^* , of Having Reached C^* but Not S, and of having Reached S, for Paths Left without Intervention.

➤ Sensitivity Analysis

For Δt between 1 and 3 days, C^* stays at 0.40–0.41, the mean cycle at 52 days and the cost rate within 5,727–5,899 USD/day, which justifies $\Delta t = 2.5$ days. The degradation rate has a stronger influence. For a slower machine ($\mu = 0.02 \text{ day}^{-1}$) the optimum moves down to $C^* \approx 0.34$ with a cost rate of 4,435 USD/day; the reference rate $\mu = 0.04 \text{ day}^{-1}$ gives C^*

$= 0.42$ and 5,800 USD/day; a fast-degrading machine ($\mu = 0.08 \text{ day}^{-1}$) requires $C^* \approx 0.49$ at 9,134 USD/day.

Volatility barely moves the position of C^* for σ between 0.02 and 0.08, but it changes the shape of the critical-time distribution markedly (Table 4). As σ increases from 0.01 to 0.05, the standard deviation of T_C triples, the skewness rises from 0.70 to 1.84 and the kurtosis from 3.71 to 7.07.

Table 4 Effect of the Volatility σ on the Distribution of the Critical Time (5,000 Paths Per Case, $\mu_{\text{eff}} = 0.0112 \text{ Day}^{-1}$).

Volatility σ	Mean T_C (days)	Std. dev. (days)	Skewness γ_1	Kurtosis β_2
0.010	51.8	11.5	0.70	3.71
0.020 (reference)	50.5	21.2	1.26	5.69
0.035	47.3	31.1	1.68	6.92
0.050	43.9	36.4	1.84	7.07

➤ Field Validation

Simulated performance was compared with the values measured every 30 days over 210 days (October 2024 to April 2025). The seven absolute deviations sum to 0.54, giving $\text{MAE} = 0.54/7 \approx 7.71\%$, and the sum of squared deviations (0.006914) gives $\text{RMSE} \approx 8.32\%$. Both errors fall in the acceptable class: the model reproduces the trend of degradation, but operational decisions should keep a margin of about $\pm 8\%$ on the performance level.

➤ Random Forest Benchmark

The relative importance of the inputs in the Random Forest is shown in Figure 5. Vibration (38 %) and cumulative operating hours (27 %) dominate, followed by bearing temperature (18 %), throughput (11 %) and motor current (6 %), which agrees with the physical view that mechanical wear signals carry most of the information.

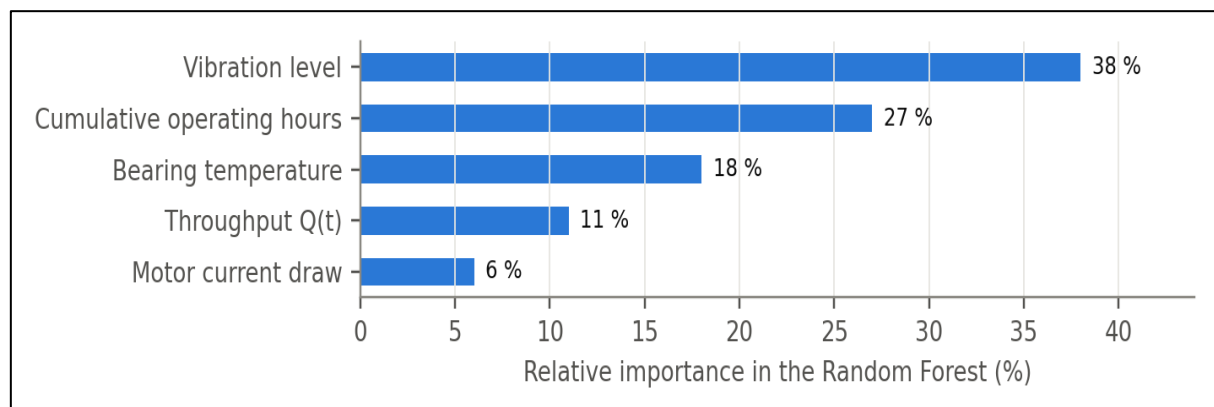


Fig 5 Relative Importance of the Five Inputs of the Random Forest Regressor (Chronological Test Set).

Table 5 Accuracy of the Stochastic Model and of the Random Forest on the Chronological Test Set (73 Days).

Model	MAE (days)	RMSE (days)	R ² (test set)
Stochastic model (Euler–Maruyama, threshold crossing)	4.8	6.1	n/a
Random Forest regression	3.9	5.2	0.81

Source: Authors' MATLAB and Python Analysis.

The Random Forest achieves a lower error (MAE 3.9 days against 4.8 days) and explains 81 % of the variance of the remaining time, because it exploits non-linear interactions between several sensors that the univariate equation ignores. It gives, however, no explicit trigger or probability law and needs a labelled intervention history, whereas the stochastic model needs only μ and σ and remains transparent to engineers.

➤ Economic Impact

Before optimisation, interventions were mostly corrective (about 15,000 USD each, one every 60 to 70 days), for an estimated 75,000 to 90,000 USD per year. With $C^* = 0.42$, about seven mostly preventive interventions per year at 5,000 USD each bring the direct cost to about 35,000 USD per year. The direct saving is therefore estimated at 40,000 to 55,000 USD per year, plus indirect benefits from fewer unplanned stoppages.

V. DISCUSSION

➤ From Mean Values to Risk-Based Scheduling

The mean cycle of 52 days is a useful summary, but the probabilistic results show that planning on this value alone would be misleading. At day 52, the trigger has been reached in only 61 % of the cycles, while 15 % of them already reach it before day 30. Because the distribution is right-skewed, the median (46 days) is a better planning reference than the mean, and because it is leptokurtic, extreme dates occur more frequently than a normal model suggests. In practice, these results support a staged policy: routine inspections until about day 25 (5th percentile), intensified condition checks and preparation of spare parts from day 30, and a planned stop no later than the date at which the forced-stop probability exceeds an accepted limit (for instance 10 %, reached at about day 54).

➤ What the Kurtosis Reveals

The kurtosis results separate two sources of non-normality. The shocks and the performance level at a fixed date are mesokurtic by construction, since the model uses Gaussian Brownian motion. The excess kurtosis of the critical time is produced by the threshold mechanism itself: paths that happen to degrade slowly spend a long time near the trigger, which stretches the right tail. This effect grows with volatility (Table 4), so that a noisier crusher is not only less predictable on average but also more prone to extreme cycle lengths. Field shocks on a jaw crusher, such as uncrushable tramp metal or sudden feed surges, are impulsive rather than Gaussian. If the increments observed on site show a kurtosis well above 3, as is common for vibration signals of damaged machinery (Dyer & Stewart, 1978; Randall, 2011), the present model will underestimate the tails, and a jump-diffusion or Lévy-driven formulation should be preferred.

Monitoring the kurtosis of measured increments in the CMMS is thus a simple adequacy test.

➤ Simulation Versus Field Observations

Field observations differ from the simulation on four points. The observed cycle, 55–65 days, is longer than the simulated mean because ore type, load and operating conditions vary between campaigns (Silva & Ferreira, 2024), and it lies well inside the 90 % interval of Section 4.4. The corrective share observed on site (25–40 %) exceeds the predicted 30 % in unfavourable periods, since budget limits and spare-parts availability often delay planned actions that the model assumes to be executed on time. The actual cost, close to 15,000 USD/day, is much higher than the simulated 5,800 USD/day because production losses and supply lead times are not modelled; the model remains valid for ranking policies. Finally, weekly or monthly inspections amount to a far larger Δt than in the simulation, which delays detection on site.

➤ Complementarity of the Stochastic and Learning Approaches

The Random Forest estimates how much time remains; the stochastic model states at which level to intervene and with what probability that level is reached by a given date. A coupled architecture is therefore proposed, in which the Random Forest prediction continuously re-estimates the degradation rate, $\hat{\mu}(t) = \mu_0 \cdot (T_{\text{opt}} / \text{RF_predicted_time}(t))$, and the updated rate is fed into the Euler–Maruyama engine to refresh the trigger level, the crossing probabilities and the kurtosis of the critical time.

VI. LIMITATIONS

Several assumptions limit the scope of the results. The state-proportional drift does not represent the acceleration of wear often observed at end of life. The parameters μ and σ are assumed constant, whereas they depend on load, ore and maintenance history. Gaussian noise excludes impulsive shocks, a restriction that the kurtosis analysis makes explicit. The model is Markovian and univariate, so it neither remembers past fatigue nor distinguishes vibration, temperature and energy signals. Interventions are assumed instantaneous, costs constant and cycles independent. The probabilistic analysis uses an effective drift calibrated on the MATLAB mean cycle, which should be confirmed with a longer data set. The Random Forest relies on one year of data from one machine.

VII. CONCLUSION

This study proposed a hybrid framework to decide when the B3 jaw crusher at KTC should be stopped for maintenance. An Itô model of performance solved by Euler–Maruyama was combined with Monte Carlo threshold

optimisation, a probabilistic study of the critical time and a Random Forest benchmark.

The cost-optimal trigger is $C^* \approx 0.42$, with a mean cycle of about 52 days, a cost rate of 5,800 USD/day and 70 % of cycles ending with a planned intervention, which represents an estimated saving of 40,000 to 55,000 USD per year. The critical time is right-skewed ($\gamma_1 = 1.23$) and leptokurtic ($\beta_2 = 5.65$), and is better described by a Weibull law ($\beta = 2.48$) than by a normal law. The probability of reaching the trigger is 0.15 at day 30, 0.61 at day 52 and 0.84 at day 70, and the forced-stop probability without intervention reaches 9.1 % at day 52. Field validation (MAE = 7.71 %, RMSE = 8.32 %) confirms that the model captures the degradation trend within a margin of about ± 8 %. The Random Forest predicts more accurately ($R^2 = 0.81$) but is less interpretable.

Future work will couple both models in an IoT-fed CMMS, extend the formulation to multivariate and jump-diffusion processes able to reproduce heavy-tailed shocks, and recalibrate μ and σ on a longer KCC data campaign within a doctoral programme. The framework gives maintenance managers a transparent, risk-based decision tool for the Congolese mining industry.

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