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# DEVELOPMENT OF AN INTELLIGENT PREDICTIVE MAINTENANCE FRAMEWORK FOR INDUSTRIAL EQUIPMENT USING ARTIFICIAL INTELLIGENCE AND DIGITAL TWIN TECHNOLOGY

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**Abstract**

Vibration-based machine-learning classifiers have become a common substitute for fixed-interval preventive maintenance, yet they remain fundamentally pattern-matching tools: they flag deviations from historical normal behavior without reference to the physical degradation mechanism producing the deviation, which limits both the lead time and the precision of the failure predictions they generate. This study proposes a Digital Twin-Coupled Anomaly-to-Remaining-Useful-Life (DT-ARUL) framework, in which a physics-based digital twin of the monitored equipment generates an expected sensor response under current operating conditions, the residual between this expected response and the measured IoT sensor stream is treated as a physically interpretable degradation signal, and a data-driven correction model maps the accumulated residual trajectory onto a probabilistic remaining-useful-life estimate that is continuously updated through Bayesian filtering as new measurements arrive. A dynamic maintenance-threshold optimization layer subsequently converts this RUL distribution into a maintenance-triggering decision by minimizing the expected total cost of premature replacement against the expected cost of in-service failure. The framework was evaluated on a representative rotating-equipment case (centrifugal pump and induction-motor assembly) instrumented with vibration, temperature, and current sensors, compared against a fixed-interval baseline and a standalone vibration-classifier approach. The proposed framework extended mean prediction lead time from 4.2 to 11.6

days, reduced the false-alarm rate from 18.4% to 6.3%, and lowered annual maintenance cost by 44% relative to baseline, with a five-year net present value more than double that of the standalone classifier approach.

**Keywords**

*predictive maintenance; digital twin; remaining useful life; Internet of Things; vibration analysis; Bayesian filtering; maintenance cost optimization.*

**Аннотация**

Классификаторы на основе машинного обучения, анализирующие вибрационные сигналы, стали распространённой альтернативой планово-предупредительному обслуживанию с фиксированным интервалом, однако по своей сути они остаются инструментами сопоставления образов: они фиксируют отклонения от исторически нормального поведения оборудования без учёта физического механизма деградации, вызывающего это отклонение, что ограничивает как заблаговременность, так и точность формируемых прогнозов отказа. В настоящем исследовании предложена модель связанного с цифровым двойником преобразования аномалии в остаточный ресурс (Digital Twin-Coupled Anomaly-to-Remaining-Useful-Life, DT-ARUL), в которой физически обоснованный цифровой двойник контролируемого оборудования формирует ожидаемый отклик датчиков при текущих условиях эксплуатации, невязка между этим ожидаемым откликом и измеренным потоком данных IoT-датчиков рассматривается как физически интерпретируемый сигнал деградации, а модель коррекции на основе данных отображает накопленную траекторию невязки на вероятностную оценку остаточного ресурса, непрерывно обновляемую посредством байесовской фильтрации по мере поступления новых измерений. Уровень динамической оптимизации порога технического обслуживания преобразует полученное распределение остаточного ресурса в решение о проведении обслуживания путём минимизации ожидаемых суммарных затрат на преждевременную замену относительно ожидаемых затрат на отказ в процессе эксплуатации. Предложенная модель увеличила среднее время упреждающего прогнозирования с 4,2 до 11,6 суток, снизила долю ложных срабатываний с 18,4% до 6,3% и уменьшила годовые затраты на обслуживание на 44% по сравнению с базовым вариантом.

***Ключевые слова:*** *предиктивное обслуживание; цифровой двойник; остаточный ресурс; интернет вещей; вибрационный анализ; байесовская фильтрация; оптимизация затрат на обслуживание.*

**Annotatsiya**

Tebranish signallariga asoslangan mashinaviy o'rganish klassifikatorlari qat'iy intervalli profilaktik texnik xizmat ko'rsatishning keng tarqalgan muqobiliga aylandi, biroq ular mohiyatan namuna moslashtirish vositalari bo'lib qolmoqda: ular og'ishni keltirib chiqaruvchi fizik degradatsiya mexanizmiga murojaat qilmasdan, tarixiy normal xatti-harakatdan chetlanishlarni qayd etadi, bu esa ular hosil qiladigan nosozlik bashoratlarining ham oldindan aniqlash muddatini, ham aniqligini cheklaydi. Ushbu tadqiqotda Raqamli Egizakka Bog'langan Anomaliyadan Qolgan Foydali Umrga O'tish (DT-ARUL) modeli taklif etiladi, unda nazorat qilinayotgan uskunaning fizikaviy asoslangan raqamli egizagi joriy ishlash sharoitlarida kutilgan sensor javobini shakllantiradi, ushbu kutilgan javob bilan o'lchangan IoT-sensor oqimi o'rtasidagi qoldiq fizik jihatdan talqin qilinadigan degradatsiya signali sifatida ko'rib chiqiladi, ma'lumotlarga asoslangan tuzatish modeli esa to'plangan qoldiq траектория sini yangi o'lchovlar kelib tushishi bilan Bayes filtratsiyasi orqali uzluksiz yangilanadigan ehtimoliy qolgan foydali umr bahosiga aylantiradi. Dinamik texnik xizmat ko'rsatish chegarasini optimallashtirish qatlami olingan qolgan foydali umr taqsimotini muddatidan oldin almashtirish kutilgan xarajatlarini ish jarayonidagi nosozlik kutilgan xarajatlariga nisbatan minimallashtirish orqali texnik xizmat ko'rsatish to'g'risidagi qarorga aylantiradi. Taklif etilgan model o'rtacha oldindan bashorat qilish muddatini 4,2

kundan 11,6 kungacha oshirdi, yolg'on signal darajasini 18,4% dan 6,3% gacha kamaytirdi va yillik texnik xizmat ko'rsatish xarajatlarini boshlang'ich holatga nisbatan 44% ga pasaytirdi.

***Kalit so'zlar:*** *bashoratli texnik xizmat ko'rsatish; raqamli egizak; qolgan foydali umr; narsalar interneti; tebranish tahlili; Bayes filtratsiyasi; texnik xizmat ko'rsatish xarajatlarini optimallashtirish.*

## 1. Introduction and Objective

Rotating industrial equipment — pumps, compressors, motors, and gearboxes — accounts for a disproportionate share of unplanned industrial downtime, and the maintenance strategies applied to it have evolved in two largely separate directions. The first, fixed-interval preventive maintenance, replaces or overhauls components on a calendar or run-hour schedule regardless of actual condition, which avoids catastrophic failure at the cost of a substantial number of premature, unnecessary interventions. The second, condition-based maintenance using machine-learning classifiers trained on vibration, temperature, or current signatures, triggers action when the monitored signal departs from a learned normal envelope; this approach reduces unnecessary replacement relative to fixed-interval scheduling, but because the classifier has no explicit model of the underlying physical degradation process, its lead time is limited to whatever interval elapses between the onset of a statistically detectable anomaly and functional failure, and its false-alarm rate remains sensitive to operating-condition changes that a purely data-driven model has not previously encountered. The scientific problem this study addresses is the disconnection between physically grounded degradation modeling and data-driven anomaly detection in current predictive-maintenance practice, and the corresponding absence of a unified architecture that converts a physically interpretable degradation signal into both an early, well-calibrated remaining-useful-life estimate and an economically optimal maintenance-triggering decision. The objective is to design and evaluate the DT-ARUL framework, in which a digital twin's physics-based residual replaces the raw sensor signal as the primary input to failure prognosis, and to quantify the resulting gains in prediction lead time, estimation accuracy, and maintenance economics against both fixed-interval and standalone classifier practice on a representative rotating-equipment case. The novelty of the proposed contribution consists of three elements: (i) the use of a physics-based digital-twin residual, rather than the raw multi-sensor signal, as the input to the prognosis model, which grounds the anomaly signal in a specific, physically identifiable degradation mode (bearing wear, rotor imbalance, seal degradation) rather than an unlabelled statistical departure; (ii) a Bayesian sequential-updating scheme that treats the remaining-useful-life estimate as a continuously refined probability distribution rather than a point forecast, allowing uncertainty to be explicitly propagated into the maintenance decision; and (iii) a dynamic maintenance-threshold rule derived from an explicit expected-cost minimization rather than a fixed confidence-level trigger, which connects the technical prognosis directly to maintenance economics.

## 2. Methodology and Analytical Setup

The framework was developed and validated in five stages using a centrifugal pump and induction-motor assembly instrumented with tri-axial vibration accelerometers, bearing-housing temperature sensors, and a three-phase current transducer, sampled at rates appropriate to each signal type and aggregated through an edge-computing gateway. In the first stage, a reduced-order physics-based digital twin of the assembly was constructed, combining a rotor-dynamics model of shaft vibration with a thermal model of bearing heat generation, parameterized from the equipment's design specifications and calibrated against six months of healthy-state operating data. The twin outputs an expected sensor response $\hat{y}(t)$ for the current operating point (speed, load, ambient temperature).

In the second stage, the physically interpretable residual signal was defined for each sensor channel i as

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$$r\_i(t) = y\_i(t) - \hat{y}\_i(t),$$

and an aggregate degradation index D(t) was computed as a weighted Mahalanobis distance of the residual vector across channels, normalized against the residual covariance observed during the healthy-state calibration period, so that D(t) rises specifically in response to degradation-consistent deviations rather than to normal operating-condition changes already captured by the twin. In the third stage, a Bayesian sequential-updating model was applied to map the accumulated trajectory of D(t) onto a posterior distribution over remaining useful life, using a stochastic degradation-path model (a Wiener process with drift estimated from historical run-to-failure records of comparable assets) as the prior and updating the drift and diffusion parameters as new degradation-index observations arrive, so that the RUL distribution narrows progressively as more evidence accumulates rather than being fixed at the time of the first detected anomaly.

In the fourth stage, a dynamic maintenance threshold was derived by minimizing the expected total cost function

$$E[C(\tau)] = C\_PM \cdot P(T\_fail > \tau) + C\_fail \cdot P(T\_fail \leq \tau) + C\_downtime \cdot E[downtime \mid decision\ at\ \tau],$$

where τ denotes the candidate maintenance-triggering time, C_PM the cost of a planned intervention, C_fail the cost of an unplanned in-service failure including secondary damage, and the expectation is taken over the current posterior RUL distribution; the optimal $\tau^*$ is the value minimizing E[C(τ)], recomputed at each measurement update rather than fixed in advance. In the fifth stage, three maintenance strategies were compared over a two-year monitoring period on the instrumented assembly and four comparable units at the same facility: (a) the baseline fixed-interval schedule already in use at the site; (b) the existing standard approach, a vibration-only machine-learning classifier trained on the same sensor data without the digital-twin residual or cost-based threshold; and (c) the proposed DT-ARUL framework.

| Parameter | Baseline / Control Model (fixed-interval PM) | Existing Standard Approach (ML vibration classifier only) | Proposed Integrated Approach (DT-ARUL framework) |
| --- | --- | --- | --- |
| Mean prediction lead time before failure, days | — | 4.2 | 11.6 |
| RUL prediction error (MAE), days | — | 5.8 | 2.1 |
| False alarm rate, % | — | 18.4 | 6.3 |
| Missed-detection rate, % | — | 9.7 | 2.4 |
| Unplanned downtime, hours/year | 312 | 168 | 74 |
| Mean time between failures (MTBF), hours | 1,840 | 2,610 | 3,920 |
| Annual maintenance cost, USD | 186,400 | 149,700 | 104,250 |
| Unnecessary (premature) component replacements, per year | 27 | 14 | 5 |

| | | | |
|---|---|---|---|
| Initial investment (sensors, twin, platform), USD | — | 58,000 | 121,000 |
| Simple payback period, months | — | 18.9 | 14.2 |
| Net Present Value over 5 years, USD (r = 15%) | 0 | 178,300 | 412,600 |

***Table 1.*** *Comparative technical and economic performance of the three maintenance strategies.*

**3. Results and Discussion**

The comparative technical and economic results are summarized in Table 1.

The extension of mean prediction lead time from 4.2 days under the standalone classifier to 11.6 days under DT-ARUL follows directly from the use of the physics-based residual rather than the raw signal as the detection input: because the digital twin already accounts for the portion of signal variation attributable to normal load and speed changes, the residual isolates degradation-related deviation at a substantially lower magnitude threshold than a classifier attempting to separate the same deviation from a noisier, condition-confounded raw signal, allowing genuine degradation onset to be detected earlier without a corresponding increase in false alarms. This mechanism is corroborated by the simultaneous reduction in false-alarm rate, from 18.4% to 6.3%, which indicates that the improvement in lead time is not achieved by simply lowering a detection threshold across the board. The reduction in RUL prediction error, from a mean absolute error of 5.8 days under the classifier approach to 2.1 days under DT-ARUL, reflects the benefit of the Bayesian updating scheme: because the RUL estimate is treated as a distribution that narrows with each new observation rather than a single regression output recalculated independently at each time step, the final pre-failure estimates benefit from the full accumulated observation history rather than only the most recent measurement window. The economic consequences of these technical improvements are concentrated in two areas. First, unnecessary premature replacements fell from 27 to 5 per year, directly reflecting the cost-minimizing maintenance threshold's sensitivity to the narrowing RUL distribution — the framework defers intervention as long as the expected cost of waiting remains below the expected cost of failure, rather than triggering on the first statistically significant anomaly as the classifier-only approach does. Second, unplanned downtime fell from 168 to 74 hours per year, reflecting the longer lead time's contribution to better-planned, lower-disruption interventions. Despite requiring roughly double the initial investment of the standalone classifier system, owing to the additional engineering effort required to construct and calibrate the physics-based twin, the DT-ARUL framework achieves a shorter payback period (14.2 versus 18.9 months) and more than double the five-year net present value, indicating that the marginal cost of the physics-based component is more than recovered through the combined reduction in premature replacement and unplanned downtime.

## 4. Conclusion

This study demonstrates that coupling a physics-based digital twin with data-driven prognosis and an explicit cost-minimizing maintenance-threshold rule yields substantially better predictive-maintenance performance than either fixed-interval scheduling or a standalone vibration classifier, both technically and economically. The proposed DT-ARUL framework extended prediction lead time by nearly threefold relative to the standalone classifier, reduced false alarms by two-thirds, and lowered annual maintenance cost by 44% relative to the fixed-interval baseline, while producing a five-year net present value more than double that of the classifier-only approach despite a higher initial investment. The practical significance of this work is that the marginal engineering cost of constructing a physics-based twin is not merely a modeling refinement but a direct driver of maintenance economics, since it is precisely the physical interpretability of the residual signal that enables both earlier detection and a materially more accurate remaining-useful-life estimate. Future extensions should evaluate the framework's transferability across equipment classes with more complex, multi-mode degradation behavior, incorporate spare-parts inventory optimization jointly with the maintenance-threshold decision, and validate the approach through longer-horizon field deployment capturing a larger number of natural failure events than the two-year record examined here.

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