DGA-Based Stochastic Degradation Modeling and Maintenance Optimization for Power Transformers

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***Abstract*—Power transformers are critical assets whose degradation monitoring and maintenance optimization remain key challenges in reliability engineering. This study proposes an integrated condition-based maintenance (CBM) and predictive maintenance (PdM) framework for power transformers by combining dissolved gas analysis (DGA), health index (HI) construction, stochastic degradation modeling, and long-run cost optimization. A real 110 kV transformer dataset is used to construct a time-series HI capturing degradation dynamics, including maintenance-induced resets. Three stochastic processes, Gamma, Wiener with drift, and Inverse Gaussian (IG), are fitted to increment data under a renewal-aware framework; the IG process yields the best fit based on Akaike information criterion (AIC) and Bayesian information criterion (BIC). Both CBM and PdM strategies are optimized using the renewal-reward theorem. Results show that both strategies converge to the same optimal inspection interval, and although PdM achieves a marginally lower long-run cost rate, well-tuned CBM remains competitive. The proposed framework supports practical, data-driven, and risk-informed maintenance decision-making in power transformer asset management.**

Keywords-Power transformer; Dissolved gas analysis; Health index; Stochastic degradation modeling; Inverse Gaussian process; Condition-based maintenance

I. INTRODUCTION

Power transformers are among the most critical and capital-intensive assets in electric power systems, and their unexpected failure may cause severe economic losses, extended outages, collateral equipment damage, and significant reliability consequences for downstream loads. Because these assets usually operate over long service lives under diverse electrical, thermal, and environmental stresses, maintenance decisions must balance technical risk, service continuity, and life-cycle cost. For this reason, transformer condition assessment and maintenance optimization have become central topics in modern asset management and reliability engineering. More broadly, the maintenance literature has consistently shown that moving from age-based maintenance toward condition-informed decision-making is essential for improving both reliability and economic performance [1,2].

Traditional time-based maintenance (TBM) remains widely used in practice because of its operational simplicity. However, TBM ignores the actual condition of an individual transformer and therefore suffers from two well-known limitations: maintenance may be performed too early, wasting residual useful life, or too late, increasing the probability of in-service failure. These limitations have motivated the development of condition-based maintenance (CBM), in which inspection or monitoring information is used to support maintenance actions. In CBM, maintenance is no longer determined solely by chronological age, but by evidence of deterioration. Predictive maintenance (PdM) extends this idea further by incorporating prognostic information such as conditional reliability or remaining useful life (RUL), thereby enabling decisions based not only on the present state but also on expected future degradation [1,3,4].

Among the available transformer monitoring techniques, dissolved gas analysis (DGA) is widely recognized as one of the most informative and practical methods for diagnosing incipient internal faults in oil-filled transformers. The basic rationale is that thermal and electrical defects decompose oil and solid insulation into characteristic gases, whose concentrations and relative proportions reflect different fault mechanisms. Classical DGA interpretation therefore relies on both gas levels and gas patterns to identify conditions such as partial discharge, low- and high-energy discharges, and thermal faults at different temperature ranges. This diagnostic role is formalized in international standards and guides, including IEEE Std C57.104 and IEC 60599, and has been reinforced by foundational and review literature on transformer fault interpretation and DGA-based predictive maintenance [5–9].

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However, although DGA is highly effective for diagnostics, DGA interpretation alone does not directly yield a maintenance policy. In practice, utilities often need a scalar condition indicator that can summarize multi-source evidence and support inspection, maintenance, refurbishment, or replacement decisions across individual units or fleets. This need has led to the growing use of the transformer health index (HI), which aggregates heterogeneous condition indicators into a unified representation of asset health. Early HI methods were typically based on weighted-score-sum formulations, while later studies expanded toward fuzzy, data-driven, and hybrid approaches. Recent reviews and case studies have shown that HI has become an important bridge between condition assessment and strategic asset management, yet HI design remains method-dependent and can produce significantly different results depending on variable selection, weighting, and aggregation logic [10–15].

A further challenge is that maintenance decisions require more than a static HI score at a single time instant. Once a transformer condition history is available, the central question becomes how to model the evolution of degradation over time and how to translate that evolution into a rational maintenance policy. In the degradation modeling literature, stochastic process models play a major role because they explicitly capture uncertainty in deterioration trajectories. Wiener process-based models are widely studied in prognostics and RUL estimation, especially for systems with fluctuating degradation paths, but they allow negative increments and may therefore be physically inconsistent with strictly cumulative damage mechanisms. By contrast, the Gamma process has long been regarded as a strong candidate for monotonic degradation because its increments are non-negative, independent, and stationary under the homogeneous formulation. For maintenance applications, the Gamma process is particularly attractive because it supports physically interpretable degradation modeling and tractable reliability calculations [4,16,17]. More recently, the Inverse Gaussian (IG) process has emerged as an additional candidate, offering greater flexibility in capturing empirical variability while preserving non-negative increment behavior [18]. However, applying these models directly to transformer field data introduces additional challenges specific to the asset and its operational context.

For power transformers, this modeling issue is especially important because real field data often does not behave like a clean, single-lifetime trajectory. Instead, condition histories may undergo maintenance-induced resets, partial recoveries, or regime changes caused by oil treatment, operational intervention, or changes in loading and environment. Consequently, many transformer datasets are better interpreted as renewal-type or segmented degradation histories rather than as uninterrupted lifetime records. This creates a methodological gap: on one hand, the transformer asset-management literature increasingly emphasizes condition assessment, health indexing, and risk-informed decision-making; on the other hand, comparatively fewer studies provide a transparent, end-to-end framework that links DGA-derived HI, stochastic degradation modeling, and explicit optimization of both CBM and PdM under the same data and cost assumptions [12,14,19].

Despite substantial progress in transformer diagnostics and maintenance research, three gaps remain particularly relevant to the present study. First, many DGA-based studies remain diagnostic rather than decision-oriented: they identify the likely fault mode but stop short of optimizing maintenance actions. Second, many condition assessment studies develop HI formulations without explicitly demonstrating how those indices can be integrated into stochastic degradation and long-run maintenance cost models. Third, although CBM and PdM are frequently discussed conceptually, direct quantitative comparisons between threshold-based CBM and reliability-based PdM on the same transformer dataset are still limited, especially when the comparison is performed under a common renewal-reward cost framework. These gaps are important because a prognostic layer does not automatically guarantee lower maintenance cost; its benefit depends on the interaction between degradation uncertainty, data quality, inspection interval, decision threshold, and the relative magnitudes of preventive, corrective maintenance, and consequential downtime costs [2,3,20].

To address these gaps, this study proposes a comprehensive framework that integrates DGA-based health assessment, renewal-aware stochastic degradation modeling, and cost-based maintenance optimization. The main contributions of this work are summarized as follows: (i) A renewal-aware degradation modeling approach is developed by detecting maintenance-induced resets in the HI trajectory and segmenting the data into independent degradation cycles; (ii) Multiple stochastic process models, including Gamma, Wiener, and Inverse Gaussian (IG) processes, are systematically compared using both statistical criteria and physical interpretability considerations; (iii) A unified optimization framework is established for both CBM and PdM strategies using a renewal-reward cost model and Monte Carlo simulation; (iv) A quantitative comparison between CBM and PdM is conducted using real transformer DGA data, providing practical insights into their relative performance and economic benefits.

The remainder of this paper is organized as follows. Section 2 presents the methodology, including HI construction, degradation modeling, and maintenance optimization. Section 3 reports the results of model comparison and policy optimization. Section 4 discusses the implications of the findings and concludes the paper.

II. METHODOLOGY

A. *Data Description and Preprocessing*

The case study is based on periodic DGA data collected from an operating 110 kV oil-immersed transformer in Vietnam. The dataset consists of 36 inspection records spanning multiple years, with non-uniform inspection intervals typical of practical maintenance environments.

The monitored gases include hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), carbon monoxide (CO), carbon dioxide (CO_2), and total dissolved combustible gas (TDCG). These gases are widely recognized as key indicators of transformer internal faults according to IEC 60599 and IEEE C57.104 standards [8,9].

The preprocessing stage includes: (i) chronological ordering of inspection data, (ii) validation of measurement consistency, (iii) handling of missing or inconsistent values when necessary, and (iv) transformation of gas concentrations into severity scores using threshold-based classification.

The resulting dataset provides a structured time series suitable for degradation modeling and maintenance decision analysis.

B. Health Index Construction

To enable quantitative degradation modeling, the multi-dimensional DGA data are transformed into a scalar HI. A score–weight aggregation scheme is adopted, where each gas concentration is mapped to a discrete severity score based on predefined threshold bands in Table 1.

The HI is defined as:

$$HI(t) = 100 \times \frac{\sum_{i=1}^{8} W_i \times \left(S_i\left(G_i(t)\right) - 1\right)}{\left(S_{\max} - 1\right)\sum_{i=1}^{8} W_i}, \quad S_{\max} = 6 \quad (1)$$

where W_i represents the relative importance of gas *i*, $S_i\left(G_i(t)\right)$ is the severity score assigned to gas i at time t.

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Table 1. DGA scoring thresholds and weighting factors [21,22]

Gas (ppm)	Score (S_i)						W_i
	1	2	3	4	5	6	
H_2	≤100	100-200	200-300	300-500	500-700	>700	3
CH_4	≤75	75-125	125-200	200-400	400-600	>600	2
C_2H_6	≤65	65-80	80-100	100-120	120-150	>150	2
C_2H_4	≤50	50-80	80-100	100-150	150-200	>200	4
C_2H_2	≤3	3-7	7-35	35-50	50-80	>80	6
CO	≤350	350-700	700-900	900-1100	1100-1400	>1400	3
CO_2	≤2500	≤3000	≤4000	≤5000	≤7000	>7000	2
TDCG	≤690	691-1251	1252-1785	1786-2720	2721-4360	>4360	3

The severity scores and weighting factors for H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, CO, and CO_2 are adopted from the authors' prior empirical study [21], which was developed based on threshold classifications in IEC 60599 and IEEE C57.104. The inclusion of TDCG as an additional diagnostic variable follows Pandey et al. [22], which defines condition-based threshold levels for total dissolved combustible gas as a composite fault severity indicator.

This formulation follows the widely used concept of health indexing for asset condition assessment, which aggregates heterogeneous condition indicators into a single interpretable metric [10,11]. The resulting HI serves as the degradation variable for subsequent stochastic modeling.

C. Renewal-aware degradation representation

Inspection of the HI time series reveals a significant downward shift exceeding a predefined reset threshold, which is interpreted as a maintenance-induced reset or operational intervention. Therefore, the degradation history is modeled as a sequence of renewal-type cycles rather than as a single uninterrupted lifetime trajectory.

Let τ_j denote the start time of cycle j. Under the absolute-HI formulation adopted in this study, the degradation state within each cycle is defined as

$$X_j(t) = HI_j(t), \quad t \ge \tau_j \quad (2)$$

To ensure compatibility with monotonic degradation assumptions within each renewal cycle, a cumulative-maximum transformation is applied:

$$X_j^*(t) = \max_{\tau_j \le s \le t} X_j(s) = \max_{\tau_j \le s \le t} HI_j(s) \quad (3)$$

This approach removes artificial decreases caused by measurement noise or partial recovery effects and ensures that degradation increments remain non-negative.

Such renewal-aware modeling is essential when maintenance actions or operational changes alter the condition trajectory, and it aligns with stochastic maintenance theory for repairable systems [2,16].

D. Stochastic Degradation Models

The degradation process $X(t)$ is modeled using stochastic processes with independent and stationary increments. Three candidate models are considered:

- Gamma process:

$$X(t+s) - X(t) \sim Gamma(\alpha s, \beta) \quad (4)$$

where α is the shape-rate parameter and β is the scale parameter

- Wiener process with drift:

$$X(t+s) - X(t) = \mu t + \sigma\left[W(t+s) - W(t)\right] \sim \mathrm{N}\ (\mu s, \sigma^2 s) \quad (5)$$

where μ is the drift coeffiient, σ is the diffusion coeffiient, and $W(t)$ denotes a standard Brownian motion.

- Inverse Gaussian process:

$$X(t+s) - X(t) \sim IG\left(\mu s, \lambda s^2\right) \quad (6)$$

where μ governs the mean degradation rate and λ controls the dispersion of the degradation increments.

While the Gamma and IG processes produce strictly non-negative increments suitable for monotone degradation, the

Wiener process with drift accommodates non-monotone trajectories through its Gaussian noise term [23].

These three models are selected because they represent different stochastic degradation assumptions commonly used in maintenance and prognostics literature. The Gamma and IG processes both preserve non-negative increments and are therefore compatible with cumulative degradation behavior, whereas the Wiener process allows negative increments and is included mainly as a reference model for comparison [16,24].

Rather than selecting a model a priori, all candidate processes are estimated from the same renewal-aware degradation increment dataset and compared using statistical goodness-of-fit criteria. The process with the best empirical fit is then adopted as the primary degradation model for subsequent reliability evaluation and maintenance optimization. In this study, the IG process is ultimately selected for policy analysis because it provides the best overall fit to the observed transformer degradation data.

E. Parameter Estimation

Model parameters are estimated using maximum likelihood estimation (MLE) based on degradation increments:

$$\Delta X_{j,k} = X_j^*\left(t_{j,k}\right) - X_j^*\left(t_{j,k-1}\right) \tag{7}$$

For each candidate process, the likelihood function is constructed from the observed renewal-aware increments and numerically maximized to obtain the corresponding parameter estimates. Bootstrap resampling is further used to assess parameter uncertainty and estimation stability.

The estimated parameters are subsequently used for model comparison based on information criteria. After the comparison stage, the best-fitting model is carried forward as the core stochastic representation of degradation. In the present study, the IG process is selected as the primary model and is used consistently in the conditional reliability analysis, Monte Carlo simulation, and maintenance optimization steps.

F. Failure Threshold Definition

Failure is defined when the degradation level exceeds a threshold L_0:

$$\tau_j^F = \inf\left\{t \geq \tau_j : X_j^*\left(t\right) \geq L_0\right\} \tag{8}$$

The threshold L_0 is determined based on empirical HI observations and engineering judgment. In this study, L_0 is set to 81, corresponding to the upper range of severe degradation observed in the dataset.

A preventive maintenance (PM) threshold L_{PM} is defined such that:

$$0 < L_{PM} < L_0 \tag{9}$$

This threshold is treated as a decision variable in the CBM optimization framework.

G. CBM Model

Under periodic inspection with interval ΔT, the degradation state is observed at inspection times $t_k = k\Delta T$.

The CBM decision rule is defined as follows: If $X(t_k) < L_{PM}$, no action is taken; if $L_{PM} \leq X(t_k) < L_0$: PM action is performed; otherwise $X(t_k) \geq L_0$: corrective maintenance (CM) is triggered.

After either PM or CM, the transformer is assumed to be restored to an as-good-as-new condition, initiating a new renewal cycle.

This three-region decision structure follows the standard CBM formulation for single-component systems under periodic inspection [1,2].

H. PdM Model

In the PdM framework, maintenance decisions are based on conditional reliability rather than solely on the currently observed degradation level.

The conditional reliability is defined as:

$$R\left(t_{j,k} + \Delta T \mid X\left(t_{j,k}\right)\right) = P\left(X\left(t_k + \Delta T\right) < L_0 \mid X\left(t_{j,k}\right)\right) \tag{10}$$

After model comparison, the degradation process is represented by the selected IG model. Accordingly, the conditional reliability is evaluated from the IG increment distribution over the next inspection interval. This probability reflects the likelihood that the degradation state remains below the failure threshold L_0 during the interval $[t_k,\ t_k + \Delta T]$.

The PdM decision rule is defined as follows: if $R(t_{j,k} + \Delta T) \geq R_{PM}$, the transformer continues operating until the next inspection; if $R(t_{j,k} + \Delta T) < R_{PM}$, PM action is performed.

Therefore, the PdM policy incorporates both the current degradation state and the model-based future failure risk derived from the selected IG degradation process. This forward-looking rule enables maintenance actions to be triggered before the degradation trajectory reaches the failure threshold [3,4].

I. Cost Model and Optimization

The long-run average maintenance cost per unit time is evaluated using the renewal-reward theorem:

$$C_\infty = E\left[C\right] / E\left[H\right] \tag{11}$$

where C denotes the total cost incurred in a renewal cycle, including inspection, preventive maintenance, and corrective maintenance costs, and H is the corresponding cycle length, measured from the start of operation to the next renewal point.

The cost components include:

$$C = c_i N_i + c_p N_p + c_c N_c + c_d W \tag{12}$$

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where c_i, c_p, and c_c are the costs per inspection, PM action, and CM action, respectively; N_i, N_p, and N_c are the corresponding number of occurrences per renewal cycle; c_d is the downtime cost rate (cost per unit time); and W is the total downtime duration per renewal cycle.

The optimization problem is formulated as

$$\Delta T(\Delta T^*, \theta^*) = \arg\min(C_\infty(\Delta T, \theta)) \quad (13)$$

where $\theta = L_{PM}$ for CBM strategy and $\theta = R_{PM}$ for PdM strategy.

Because analytical solutions are generally intractable, Monte Carlo simulation is used: *(i)* simulate degradation trajectories, *(ii)* apply maintenance decision rules, *(iii)* compute cycle costs, *(iv)* estimate long-run average cost. This approach is consistent with the renewal-reward framework widely used in maintenance optimization.

III. RESULTS

A. DGA Characteristics and Health Index Behavior

The temporal evolution of dissolved gas concentrations and the derived HI are shown in Fig. 1. The HI is constructed from eight key gases to capture overall insulation condition severity.

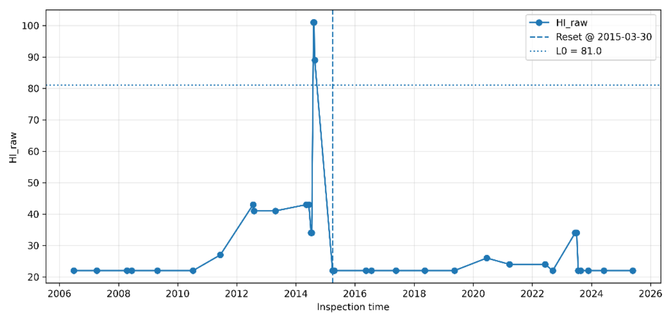

Figure 1. *HI trajectory with detected reset point and empirical failure threshold*

As illustrated in Fig. 1, the HI trajectory exhibits pronounced non-stationary behavior, including a sharp peak followed by a sudden drop around March 2015. This drop corresponds to a major maintenance intervention, indicating that the degradation process cannot be adequately described as a single monotonic trajectory. Instead, the system behavior is better interpreted as a sequence of degradation–renewal cycles.

The empirical failure threshold is defined as (L_0 = 81), corresponding to the maximum observed HI level prior to the detected reset. This threshold serves as a reference for failure modeling in subsequent stochastic degradation analysis.

B. Renewal-aware Degradation Analysis

To account for maintenance-induced resets, the HI trajectory is segmented into renewal cycles using a threshold-based change detection method. The processed dataset consists of 36 observations and is divided into two distinct cycles, with the reset point identified on March 30, 2015.

Within each cycle, a cumulative maximum transformation is applied to enforce monotonicity, yielding a degradation signal suitable for stochastic modeling. The resulting cycle-wise degradation trajectories are shown on Fig. 2.

Cycle 1 exhibits a rapid increase in degradation, approaching the failure threshold, while cycle 2 shows a significantly slower degradation pattern. This contrast highlights the importance of renewal-aware modeling, as ignoring cycle boundaries would lead to biased parameter estimation and misleading reliability predictions.

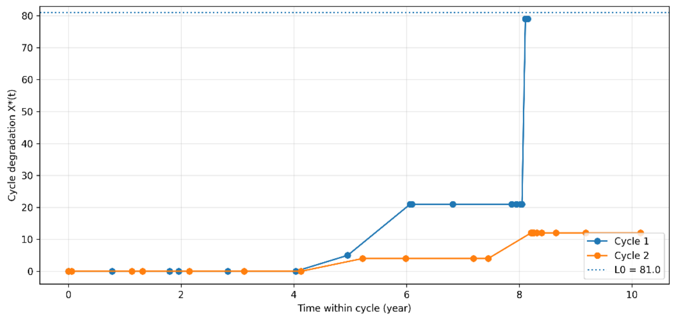

Figure 2. *Renewal-aware degradation trajectories after cumulative-maximum transformation*

C. Stochastic Degradation Model Comparison

Three stochastic degradation models, namely the Gamma process, Wiener process with drift, and IG process, were fitted to the renewal-aware degradation increment dataset using maximum likelihood estimation. Model selection is performed using the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), defined as: $\mathrm{AIC} = -2\ln(\hat{L}) + 2k$ and $\mathrm{BIC} = -2\ln(\hat{L}) + k\ln(n)$, where $\hat{L}$ is the maximized likelihood value, k is the number of estimated parameters, and n is the number of observations. Lower AIC and BIC values indicate a better trade-off between goodness-of-fit and model complexity. The quantitative comparison results are summarized in Table 2, which presents the estimated parameters, log-likelihood values, and information criteria for each model. Fig. 3 provides a visual illustration of the AIC and BIC differences among the candidate models.

Table 2. Statistical evaluation and selection criteria (AIC, BIC) for the proposed degradation processes

Criteria	**Gamma**		**Wiener with drift**		**Inverse Gaussian**	
Estimated parameters	α	β	μ	σ	μ	λ
	0.67	0.03	20.65	110.13	849.78	6.25
LogLik	-26.69		-35.26		-25.67	
AIC	57.39		74.52		55.35	
BIC	56.97		75.80		54.93	
n_{used}	6		14		6	
Note	Candidate for final selection		Allows negative increments		Candidate for final selection	

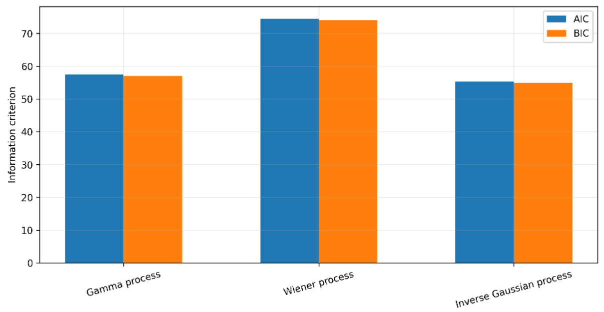

Figure 3. *Information-criterion comparison among process-level degradation models*

Among the three candidate models, the IG process achieved the best statistical fit, with the lowest AIC (55.35) and BIC (54.93). The Gamma process showed slightly higher values (AIC = 57.39, BIC = 56.97), while the Wiener process performed substantially worse (AIC = 74.52, BIC = 74.41). The inferior performance of the Wiener model is also consistent with its allowance for negative increments, which is less compatible with cumulative degradation behavior.

Based on these results, the IG process is selected as the primary degradation model for all subsequent analyses. Conditional reliability evaluation, maintenance decision-making, and cost optimization are therefore conducted under the IG-based representation. Although the Gamma process remains physically interpretable and consistent with cumulative degradation behavior, its slightly higher AIC and BIC values indicate a less precise fit to the observed increment data, and it is accordingly retained only as a reference benchmark.

D. Conditional Reliability Analysis

Based on the selected Inverse Gaussian (IG) process, the conditional reliability function is defined as the probability that the degradation level remains below the failure threshold over a future inspection interval. This reliability depends on both the current degradation state and the inspection interval length.

For a given observed state $X(t_k)$, the conditional reliability quantifies the probability that the future degradation trajectory will remain below L_0 during the next interval ΔT. Under the IG-based degradation model, this probability provides a direct measure of near-future operational risk and serves as the core decision variable in the PdM strategy.

The reliability function decreases monotonically as the current degradation level increases or as the inspection horizon becomes longer. This property supports predictive maintenance decisions that dynamically adapt to both present condition and anticipated short-term deterioration.

E. Maintenance Optimization Results

The long-run cost performance of maintenance strategies is evaluated using a renewal-reward framework combined with Monte Carlo simulation with cost assumptions as shown in Table 3. Two strategies are considered: Condition-Based Maintenance (CBM) is based on a fixed degradation threshold; Predictive Maintenance (PdM) is based on a reliability threshold.

Table 3. Cost components used in maintenance evaluation

Cost	Value (VND)	Normalized cost
Inspection cost (c_i)	8,000,000	1
PM cost (c_p)	250,000,000	31.25
CM cost (c_c)	900,000,000	112.5
Downtime loss (c_d)	1,000,000,000	125

a) CBM optimization results

The cost surface of CBM is shown in Fig. 4, where the long-run average cost is evaluated over combinations of inspection intervals and preventive thresholds.

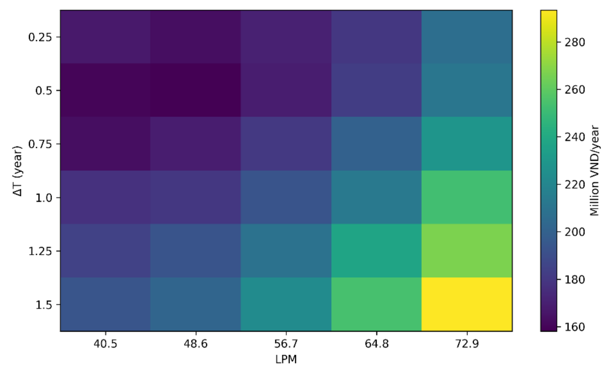

Figure 4. *Cost surface of CBM over inspection interval and preventive threshold*

The optimal CBM policy is obtained at $\Delta T^* = 0.5$ years and $L_{PM}^* = 48.6$ with a minimum cost of approximately 158.08 million VND/year.

The cost surface reveals a well-defined optimum region, with costs increasing for both excessively short inspection intervals (due to frequent inspections) and excessively long intervals (due to increased CM and downtime).

b) PdM optimization results

The cost surface of PdM is shown in Fig. 5, where maintenance decisions are based on reliability thresholds instead of fixed degradation levels.

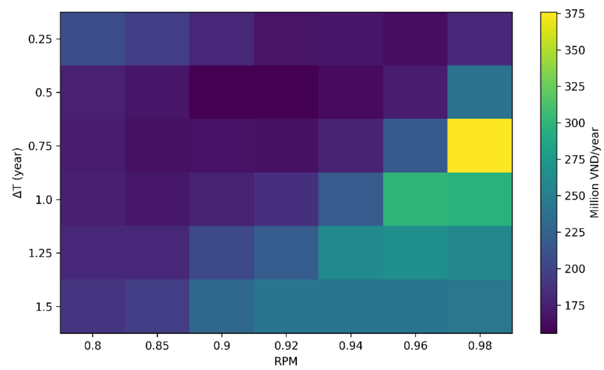

Figure 5. *Cost surface of PdM over inspection interval and reliability threshold*

The optimal PdM policy is $\Delta T^* = 0.5$ years and $R^*_{PM} = 0.92$ with a minimum cost of approximately 155.66 million VND/year.

Compared to CBM, PdM demonstrates a slightly lower cost by adjusting maintenance decisions based on predicted failure risk rather than solely on observed degradation levels.

F. Comparative Analysis of CBM and PdM

The optimal policies for CBM and PdM are summarized in Table 4. Both strategies converge to the same optimal inspection interval of 0.5 years, indicating that inspection scheduling is the dominant factor in cost optimization.

However, PdM achieves a marginally lower cost than CBM, with an absolute reduction of approximately 2.41 million VND/year, corresponding to a relative improvement of about 1.53%. This improvement is achieved through a slight increase in PM action and a corresponding reduction in CM events. The results suggest that PdM provides incremental economic benefits by incorporating predictive information, particularly in regions where degradation is close to the failure threshold.

Overall, the performance difference between CBM and PdM is modest, indicating that well-calibrated threshold-based CBM already captures most of the achievable cost savings under the given degradation and cost conditions.

Table 4. Optimal maintenance policies and cost-performance summary for CBM and PdM frameworks

Metric	CBM	PdM
Optimal inspection interval ΔT^* (year)	0.5	0.5
Optimal preventive threshold L^*_{PM}	48.6	–
Optimal reliability threshold R^*_{PM}	–	0.92
Long-run cost (million VND/year)	158.08	155.66
PM count	4,006	4,188
CM count	994	812
Inspection count	29,800	28,008
Average cycle length (year)	2.98	2.80
Average cycle cost (VND)	471,064,000	435,976,800
PM rate	0.80	0.84
CM rate	0.20	0.16

IV. DISCUSSION

The results provide several important insights into transformer degradation behavior and maintenance decision-making under real operating conditions.

First, the observed reset in the HI trajectory confirms that transformer degradation cannot be adequately modeled as a single continuous process. The sharp drop in HI around March 2015 indicates a major maintenance intervention, supporting the adoption of a renewal-aware representation. This modeling approach enables the separation of distinct degradation regimes and avoids biased parameter estimation that would arise from treating the entire dataset as a single monotonic trajectory.

Second, the stochastic model comparison shows that the IG process provides the best statistical fit to the renewal-aware degradation increments among the candidate models considered. While the Gamma process remains physically consistent with cumulative degradation, the IG model offers greater flexibility in capturing the empirical variability observed in field data. This result highlights that model selection in practical asset management should balance physical interpretability with statistical adequacy, particularly when dealing with real operational datasets. It is acknowledged that the number of independent renewal-aware increments available for model fitting is limited ($n = 6$), which is a direct consequence of the single-asset, two-cycle renewal segmentation applied to the 36-observation dataset. While this limits the absolute statistical power of the AIC/BIC comparison, the relative ordering of the three candidate models is consistent with both information criteria and aligns with the physical expectation that cumulative degradation processes should exhibit non-negative increments. Bootstrap resampling was further employed to assess estimation stability under this limited-sample condition.

Third, the maintenance optimization results reveal that both CBM and PdM strategies converge to the same optimal inspection interval of 0.5 years. This finding indicates that inspection scheduling is the dominant factor influencing long-run cost performance. In contrast, the additional predictive capability in PdM leads only to a modest cost reduction (approximately 1.53%), primarily through a shift from corrective to PM action.

Finally, the modest cost advantage of PdM over CBM (~1.53%) should be interpreted in the context of the prevailing cost structure and degradation conditions. The relative economic benefit of PdM over CBM is expected to increase under three conditions: (i) a high corrective-to-preventive cost ratio (c_c / c_p), reflecting severe failure consequences; (ii) a high downtime loss rate c_d, representative of critical supply infrastructure; and (iii) elevated degradation uncertainty, where the stochastic spread of remaining useful life is large. In the present case study, the moderate cost ratios and relatively stable degradation behavior of cycle 2 limit the marginal value of predictive information. A systematic sensitivity analysis across these cost dimensions is identified as an important direction for future work.

V. CONCLUSIONS

This study proposes an integrated framework for power transformer maintenance optimization by combining DGA-based health index construction, renewal-aware stochastic degradation modeling, and long-run cost optimization under a renewal-reward structure. A key methodological contribution is the explicit detection and treatment of maintenance-induced resets in the HI trajectory, enabling more accurate degradation modeling through cycle-wise segmentation.

Among the three candidate stochastic processes evaluated, the Inverse Gaussian process provides the best statistical fit to the observed renewal-aware degradation increments, outperforming both the Gamma and Wiener processes based on AIC and BIC criteria. Both CBM and PdM strategies converge to the same optimal inspection interval of 0.5 years, confirming that inspection scheduling is the dominant factor in long-run cost minimization. Although PdM achieves a marginally lower cost rate (approximately 1.53% reduction), the improvement is modest, indicating that well-calibrated CBM remains a competitive and practical alternative.

The proposed framework provides a transparent and data-driven approach to transformer asset management. Nevertheless, the current results are derived from a single 110 kV transformer dataset with limited observations. Future work should address multi-asset validation, sensitivity analysis of cost parameters, and incorporation of additional condition indicators to improve generalizability and practical applicability. Future work should focus on: (i) multi-asset validation across transformer fleets with diverse operating conditions to improve generalizability; (ii) systematic sensitivity analysis of key cost parameters, particularly the c_c / c_p ratio and downtime loss rate c_d, to identify operational regimes where PdM provides substantial economic benefits; and (iii) integration of additional condition indicators beyond DGA, such as oil quality and insulation aging metrics, to enhance the robustness of the health index and degradation modeling framework.

References

[1] A. K. S. Jardine, D. Lin, and D. Banjevic, "A review on machinery diagnostics and prognostics implementing condition-based maintenance," Mech. Syst. Signal Process., vol. 20, no. 7, pp. 1483-1510, 2006. https://doi.org/10.1016/j.ymssp.2005.09.012.

[2] B. De Jonge and P. A. Scarf, "A review on maintenance optimization," Eur. J. Oper. Res., vol. 285, no. 3, pp. 805–824, 2020. https://doi.org/10.1016/j.ejor.2019.09.047.

[3] Y. Peng, M. Dong, and M. J. Zuo, "Current status of machine prognostics in condition-based maintenance: A review," Int. J. Adv. Manuf. Technol., vol. 50, nos. 1–4, pp. 297–313, 2010. https://doi.org/10.1007/s00170-009-2482-0.

[4] X.-S. Si, W. Wang, C.-H. Hu, and D.-H. Zhou, "Remaining useful life estimation—A review on the statistical data-driven approaches," Eur. J. Oper. Res., vol. 213, no. 1, pp. 1–14, Aug. 2011. https://doi.org/10.1016/j.ejor.2010.11.018.

[5] H. V. Tran and K. A. Nguyen, "A hybrid ensemble approach for dissolved gas analysis-based power transformer fault diagnosis using SMOTE and GBDT," Arab. J. Sci. Eng., Nov. 2025. https://doi.org/10.1007/s13369-025-10772-z.

[6] N. Abu Bakar, A. Abu-Siada, and S. Islam, "A review of dissolved gas analysis measurement and interpretation techniques," IEEE Electr. Insul. Mag., vol. 30, no. 3, pp. 39–49, May/Jun. 2014. https://doi.org/10.1109/MEI.2014.6804740.

[7] H. De Faria, Jr., J. G. S. Costa, and J. L. M. Olivas, "A review of monitoring methods for predictive maintenance of electric power transformers based on dissolved gas analysis," Renew. Sustain. Energy Rev., vol. 46, pp. 201–209, Jun. 2015. https://doi.org/10.1016/j.rser.2015.02.052.

[8] IEEE Guide for the Interpretation of Gases Generated in Mineral Oil-Immersed Transformers, IEEE Std C57.104-2019, IEEE Power & Energy Society, 2019.

[9] Mineral Oil-Filled Electrical Equipment in Service—Guidance on the Interpretation of Dissolved and Free Gases Analysis, IEC 60599:2022, International Electrotechnical Commission, 2022.

[10] A. Naderian, S. Cress, R. Piercy, F. Wang, and J. Service, "An approach to determine the health index of power transformers," in Proc. 2008 IEEE Int. Symp. Electr. Insul., 2008, pp. 192–196. https://doi.org/10.1109/ELINSL.2008.4570308.

[11] P. Bohatyrewicz, J. Płowucha, and J. Subocz, "Condition assessment of power transformers based on health index value," Appl. Sci., vol. 9, no. 22, p. 4877, 2019. https://doi.org/10.3390/app9224877.

[12] J. Foros and M. Istad, "Health index, risk and remaining lifetime estimation of power transformers," IEEE Trans. Power Deliv., vol. 35, no. 6, pp. 2612–2620, Dec. 2020. https://doi.org/10.1109/TPWRD.2020.2972976.

[13] H. Guo and L. Guo, "Health index for power transformer condition assessment based on operation history and test data," Energy Rep., vol. 8, pp. 9038–9045, Nov. 2022. https://doi.org/10.1016/j.egyr.2022.07.041.

[14] S. Li, X. Li, Y. Cui, and H. Li, "Review of transformer health index from the perspective of survivability and condition assessment," Electronics, vol. 12, no. 11, p. 2407, 2023. https://doi.org/10.3390/electronics12112407.

[15] D. A. Zaldívar and A. A. Romero, "Health index for power transformer condition assessment: A comparison of three different techniques," J. Appl. Res. Technol., vol. 20, no. 5, pp. 536–545, 2022. https://doi.org/10.22201/icat.24486736e.2022.20.5.1606.

[16] J. M. Van Noortwijk, "A survey of the application of gamma processes in maintenance," Reliab. Eng. Syst. Saf., vol. 94, no. 1, pp. 2–21, Jan. 2009. https://doi.org/10.1016/j.ress.2007.03.019.

[17] Z. Zhang, X. Si, C. Hu, and Y. Lei, "Degradation data analysis and remaining useful life estimation: A review on Wiener-process-based methods," Eur. J. Oper. Res., vol. 271, no. 3, pp. 775–796, Dec. 2018. https://doi.org/10.1016/j.ejor.2018.02.033.

[18] Z.-S. Ye and N. Chen, "The inverse Gaussian process as a degradation model," Technometrics, vol. 56, no. 3, pp. 302–311, 2014. https://doi.org/10.1080/00401706.2013.830074.

[19] Condition Assessment of Power Transformers, CIGRE Tech. Brochure 761, Working Group A2.49, Paris, France: CIGRE, 2019.

[20] M. C. A. Olde Keizer, S. D. P. Flapper, and R. H. Teunter, "Condition-based maintenance policies for systems with multiple dependent components: A review," Eur. J. Oper. Res., vol. 261, no. 2, pp. 405–420, Sep. 2017. https://doi.org/10.1016/j.ejor.2017.02.044.

[21] H. V. Tran, K. A. Nguyen, D. H. Dinh, D. D. Le, H. T. Le, and P. Do, "Evaluation of the health state of oil-immersed transformer based on dissolved gas analysis: An empirical study," in Proceedings of the 13th IMA International Conference on Modelling in Industrial Maintenance and Reliability (MIMAR), 2025. https://doi.org/10.19124/ima.2025.01.67.

[22] P. K. Pandey, H. Singh, M. Rao, and R. K. Jarial, "Emerging trends in diagnosis and condition assessment of power transformers based on health index," in Proc. 2nd Int. Conf. Emerging Trends Eng. Technol. (ICETET'2014), London, U.K., May 2014, https://doi.org/10.15242/IIE.E0514591.

[23] K. A. Nguyen, "Développement de stratégies de maintenance prévisionnelle de systèmes multi-composants avec structure complexe," Ph.D. dissertation, Université de Technologie de Troyes, France, 2015.

[24] K.-A. Nguyen, P. Do, and A. Grall, "Multi-level predictive maintenance for multi-component systems," Reliab. Eng. Syst. Saf., vol. 144, pp. 83–94, Dec. 2015. https://doi.org/10.1016/j.ress.2015.07.017.