Confidence-Aware Predictive Maintenance Decision Support For Power Transformer Asset Management

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***Abstract*—Power transformer remaining useful life (RUL) prediction is most valuable when it helps engineers make safer maintenance decisions. A point prediction is not enough because the same predicted RUL can imply different actions depending on uncertainty, data quality and operating stress. This paper presents a confidence-aware predictive maintenance decision-support framework for power transformer asset management. The framework combines multi-sensor transformer evidence, supervised RUL prediction, Monte Carlo dropout uncertainty estimation, sensor-quality assessment and rule-based maintenance interpretation. A controlled physics-guided synthetic transformer degradation dataset was used to evaluate classical machine learning models, single temporal deep learning models and a hybrid CNN-LSTM-Transformer model. On the controlled synthetic validation dataset, the hybrid model achieved the best controlled-test performance, with an average RMSE of 27.6 days and an average MAE of 19.3 days across five repeated runs. Its 95 percent prediction intervals achieved 94.2 percent empirical coverage, which supported confidence-aware interpretation of model output. The decision layer maps predicted RUL, lower confidence bound, interval width and sensor-quality evidence into normal, watch, warning and critical maintenance categories. The results show that uncertainty-aware RUL prediction can provide a practical bridge between transformer prognostics and human-reviewed maintenance prioritization. Field validation with utility fleet data is still required before operational deployment.**

Keywords—predictive maintenance; transformer asset management; remaining useful life; uncertainty quantification; confidence-aware decision support; multi-sensor fusion; CNN-LSTM-Transformer.

1. Introduction

Power transformers are high-value assets in power networks. Their reliability affects continuity of supply, operating cost, outage risk and asset replacement planning. A transformer fault may lead to long repair time, expensive emergency replacement and customer interruption. These risks make predictive maintenance an important part of modern power asset management [1,28,30], [2].

Condition monitoring provides the evidence base for transformer prognostics. Dissolved gas analysis (DGA) reflects chemical decomposition and fault gases. Temperature measurements reflect thermal ageing and loading stress. Electrical measurements show operating duty and overloading. Vibration, acoustic, moisture and oil-quality indicators provide additional evidence on mechanical, insulation and dielectric health. Multi-sensor fusion is therefore useful because transformer ageing is not fully represented by one diagnostic source [3], [7], [10].

The practical value of RUL prediction lies in decision support. A predicted RUL value of 180 days can lead to different maintenance actions if the prediction interval is narrow, wide, optimistic or based on incomplete sensor evidence. Maintenance engineers need to know the predicted life, the conservative lower confidence bound, the width of the uncertainty interval and the trustworthiness of the sensor evidence before making inspection, loading, oil-treatment, spare-preparation or replacement decisions [6, 8, 33,34].

Existing transformer RUL studies often focus on prediction accuracy. Fewer studies connect predicted RUL, uncertainty bounds, sensor-quality evidence and maintenance categories in one decision-support workflow. This paper addresses that gap by proposing a confidence-aware RUL interpretation layer for transformer maintenance prioritization. The framework treats the model output as engineering evidence, not as an autonomous replacement command.

2. Main Contributions

The paper makes four main contributions. First, it presents a multi-sensor transformer RUL decision-support architecture that links condition evidence to maintenance action. Second, it compares classical machine learning, single temporal deep learning and hybrid temporal learning models under a common controlled workflow. Third, it uses Monte Carlo dropout to express prediction uncertainty through confidence bounds and interval width. Fourth, it formalizes a rule-based maintenance mapping that combines predicted RUL, conservative risk, interval width and sensor-quality flags.

Table 1. Main contributions of the paper

Contribution	Description
Confidence-aware decision support	Links predicted RUL, lower confidence bound, interval width and sensor-quality evidence to maintenance categories.
Multi-sensor prognostic architecture	Fuses DGA, thermal, electrical, mechanical, acoustic, moisture and oil-quality evidence for transformer health representation.
Hybrid temporal learning	Uses a CNN-LSTM-Transformer model to capture local degradation patterns, sequential dependencies and long-range temporal attention.
Uncertainty-aware interpretation	Converts point prediction into prediction intervals using Monte Carlo dropout.
Maintenance action mapping	Maps model evidence into normal, watch, warning and critical categories for human engineering review.

3. Related Work

Transformer RUL prediction has received increasing attention because transformer failures are costly, disruptive and difficult to manage after they occur.[19, 21, 22] Recent studies have used machine learning and deep learning models to estimate transformer health state or remaining service life from condition-monitoring records [1], [3], [4], [5]. These studies show that data-driven prognostics can support asset planning, but many of them still emphasize prediction accuracy more than maintenance interpretation.

Multi-sensor transformer health assessment is important because no single diagnostic source describes every ageing process. DGA is valuable for detecting chemical decomposition and fault gases, while thermal, electrical, moisture, acoustic, vibration and oil-quality measurements provide complementary evidence about loading stress, insulation condition and mechanical behaviour [3], [7], [10], [15]. This supports the use of fusion-based models for transformer decision support.

Temporal deep learning models are suitable for RUL prediction because transformer degradation is progressive and time-dependent. LSTM, GRU, CNN and Transformer-based models can represent different aspects of historical sensor patterns, including local changes, long-term memory and attention across time steps [5], [9], [14]. Hybrid models are therefore useful when the aim is to capture both short-term diagnostic changes and longer degradation trends.

Uncertainty quantification is also needed because maintenance decisions should not depend only on a point prediction. Prediction intervals, lower confidence bounds and uncertainty scores help engineers identify whether a low RUL estimate is reliable or whether additional inspection is needed before costly action is taken [6], [8], [20], [29]. The remaining gap is the direct link between RUL prediction, uncertainty, sensor-quality evidence and practical maintenance categories. This paper addresses that gap by adding a confidence-aware decision layer to the predictive maintenance workflow.

4. System Model Architecture

The proposed system contains seven linked layers. The sensor layer collects transformer condition evidence from chemical, thermal, electrical, mechanical, acoustic, moisture and oil-quality sources[16,17,18]. The preprocessing layer aligns records, removes physically impossible values, scales variables, constructs time windows and records missingness indicators. The fusion layer combines sensor groups into a unified health representation. The prediction layer estimates RUL using baseline and temporal learning models [7,11,13]. The uncertainty layer estimates confidence intervals through Monte Carlo dropout. The reliability layer checks interval width, sensor quality and robustness under imperfect records. The decision layer maps these outputs to maintenance categories.

Figure 1. Confidence-aware transformer RUL decision-support architecture.

The architecture is designed for supervised predictive maintenance. It does not issue automatic replacement commands. High-risk predictions are treated as evidence that must be checked by engineers using diagnostic tests, loading records, maintenance history and utility risk policy.

5. Materials, Dataset and Preprocessing

5.1 Dataset Generation and Label Construction

Real utility transformer fleet records were not available for this study. The experiments therefore used a controlled physics-guided synthetic transformer degradation dataset generated from the research workflow. The dataset was designed to reproduce progressive ageing patterns, loading stress, thermal stress, DGA trend growth, oil-quality deterioration, random noise and incomplete sensor records in a controlled manner.

The simulated dataset contained 50 transformer degradation trajectories and 50,000 time-stamped samples. Each trajectory represented one transformer ageing path from healthy operation to end-of-life condition. The sampling interval was one day. The degradation duration varied from 900 to 1,800 days across trajectories to avoid a single fixed failure pattern. The random seed used for the final controlled experiment was 42.[6, 26, 27] A transformer-wise split was applied, with 70 percent of trajectories used for training, 15 percent for validation and 15 percent for testing. This split was used to reduce information leakage because samples from the same simulated transformer were not shared across the training and test subsets[32,22].

The RUL label was computed as the number of days between the current time step and the simulated end-of-life point for the corresponding transformer trajectory. End-of-life was triggered when the latent health index crossed the failure threshold or when the simulated degradation process reached its assigned terminal condition. Sensor noise, missing records and sensor-group dropout were added after label generation so that robustness tests reflected realistic data-quality problems.

Table 2. Multi-sensor evidence used in the dataset

Sensor group	Variables used	Condition evidence
DGA evidence	Hydrogen, methane, ethane, ethylene, acetylene, carbon monoxide and carbon dioxide	Chemical decomposition, arcing, overheating and insulation stress
Thermal evidence	Oil temperature, winding temperature and ambient temperature	Thermal ageing and cooling stress
Electrical evidence	Load current, voltage, apparent power and loading ratio	Operating stress and overload exposure
Mechanical evidence	Vibration descriptors and trend features	Mechanical looseness, winding movement and abnormal operating condition
Acoustic evidence	Acoustic energy and spectral descriptors	Partial discharge and abnormal internal activity
Moisture and oil evidence	Moisture content, dielectric strength, acidity and interfacial tension	Insulation ageing and oil-quality deterioration

Table 3. Dataset and experimental design summary

Item	**Configuration used in the controlled study**
Data source	Physics-guided synthetic transformer degradation records generated from the research workflow
Simulated transformer trajectories	50 trajectories
Total samples	50,000 time-stamped samples
Sampling interval	One day
Degradation-duration range	900 to 1,800 days
Prediction target	Remaining useful life in days
Input form	Fixed-length multi-sensor time windows for temporal models and engineered descriptors for classical models
Sequence window length	60 historical time steps
Data split	Transformer-wise split of 70 percent training, 15 percent validation and 15 percent testing
Random seed	42 for the final controlled experiment
Validation design	Model comparison, sensor ablation, uncertainty evaluation, missing-data testing, noise testing and domain-shift analysis
Main limitation	Synthetic data supported controlled validation but did not replace field validation with real transformer fleets

5.2 Preprocessing

The preprocessing stage followed a leakage-safe protocol. Sensor records were aligned in time, physically impossible values were removed and missing values were handled with training-set statistics only. Scaling parameters were fitted on the training set and then applied to the validation and test sets. Missingness indicators were retained because missing sensor evidence can itself signal a reliability problem in practical monitoring systems.

For temporal models, the processed records were converted into 60-day historical windows. Each window contained the available sensor variables, missingness masks and engineered trend descriptors. For classical models, statistical summaries were extracted from each window, including means, standard deviations, slopes, maximum values and recent-change descriptors.

6. Model Architectures Used in the Paper

The study compared classical machine learning baselines, single temporal deep learning models and a hybrid temporal model. The classical baselines were Support Vector Regression (SVR), Random Forest and XGBoost. The temporal deep learning models were CNN, LSTM, GRU, Transformer and the proposed CNN-LSTM-Transformer hybrid model. These models were selected because they represent common approaches to nonlinear regression, ensemble learning and temporal degradation modelling [5], [9], [14].

The hybrid model first used one-dimensional convolution to learn local degradation patterns within the time window. The LSTM layer then represented ordered degradation memory. The Transformer encoder added self-attention so that the model could learn longer-range relationships across the historical window. A dropout-enabled regression head produced stochastic RUL estimates during inference for uncertainty quantification.

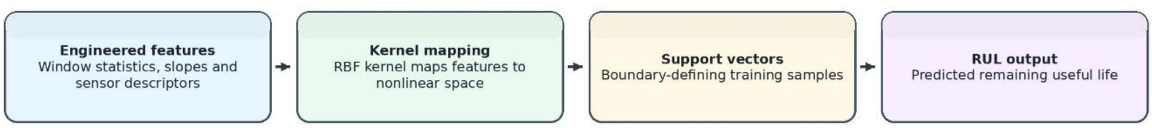

Figure 2. Support Vector Regression model architecture.

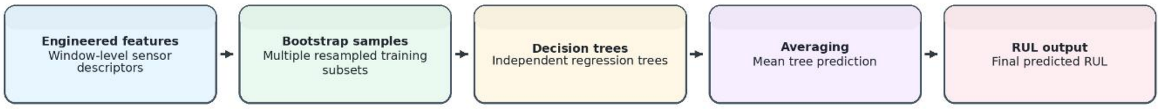

Figure 3. Random Forest model architecture.

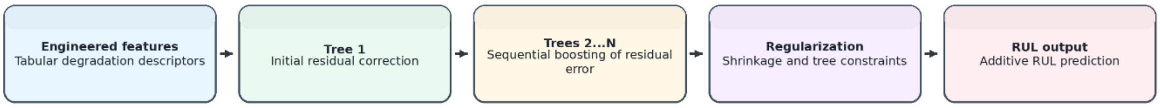

Figure 4. XGBoost model architecture.

Figure 5. CNN model architecture.

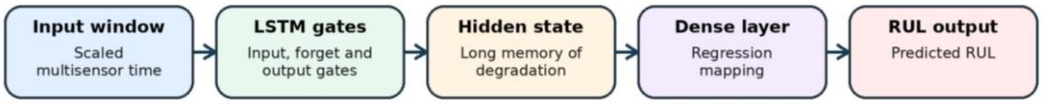

Figure 6. LSTM model architecture.

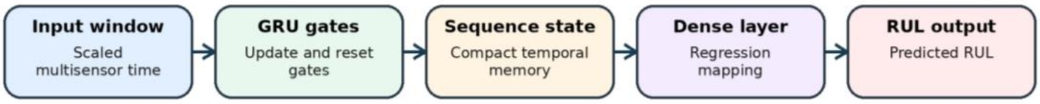

Figure 7. GRU model architecture.

Figure 8. Transformer model architecture.

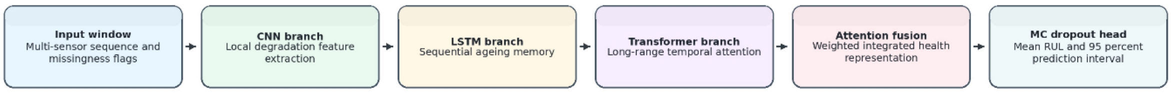

Figure 9. Hybrid CNN-LSTM-Transformer model with uncertainty layer.

7. Model Training Procedure and Result-Generation Workflow

The results were obtained from a controlled training and testing workflow. The workflow was designed to prevent leakage between training and testing records, preserve the temporal structure of degradation histories and allow fair comparison across models. Classical models were trained on engineered descriptors extracted from the same 60-day windows used by the deep learning models. Deep learning models were trained directly on normalized multi-sensor sequences.

Table 4. Model training hyperparameters

Parameter	Final configuration used in the controlled experiment
Sequence window length	60 historical time steps
Train-validation-test split	70 percent, 15 percent and 15 percent by transformer trajectory
Batch size	64
Optimizer	Adam

Parameter	Final configuration used in the controlled experiment
Initial learning rate	0.001
Learning-rate scheduling	Reduce learning rate by factor of 0.5 after 10 validation epochs without improvement
Maximum epochs	150
Early stopping patience	20 validation epochs
Loss function	Mean squared error for point RUL prediction
CNN block	64 one-dimensional filters, kernel size of 3 and ReLU activation
LSTM hidden units	128 hidden units
GRU hidden units	128 hidden units
Transformer encoder	2 encoder layers, 4 attention heads, 128-dimensional embedding and 256-dimensional feed-forward layer
Dropout rate	0.20 in temporal blocks and regression head
MC dropout passes	100 stochastic forward passes during inference
Classical model tuning	Grid search on the validation set for SVR, Random Forest and XGBoost
Software environment	Python workflow using common machine learning and deep learning libraries
Hardware environment	Workstation-class CPU/GPU environment used for research experimentation

Table 5. Training and result-generation procedure

Step	Operation	Output used in the results
1	Group sensor variables into chemical, thermal, electrical, mechanical, acoustic, moisture and oil-quality evidence.	Structured sensor evidence
2	Clean records, align sampling times, reconstruct allowable missing values and keep missingness flags.	Leakage-safe cleaned data
3	Split records by transformer identity into training, validation and test subsets.	Independent evaluation subsets
4	Fit scaling and imputation statistics on the training subset only.	Preprocessing pipeline
5	Train classical and temporal models using the training subset.	Fitted RUL prediction models
6	Tune model settings using validation RMSE, MAE and calibration behaviour.	Selected model configuration
7	Evaluate selected models on the held-out test subset.	Final performance tables
8	Run MC dropout inference for the hybrid model.	Mean RUL, standard deviation and confidence bounds
9	Test noise, missing records and missing sensor groups.	Robustness and sensor-dependence evidence
10	Apply the decision-mapping rule to the model output.	Normal, watch, warning or critical maintenance category

8. Uncertainty Quantification

The uncertainty layer was used to express prediction confidence. During inference, dropout remained active and the hybrid model was evaluated 100 times for each test sample. This produced a distribution of RUL estimates rather than a single deterministic value. Monte Carlo dropout was used because it provides a practical approximation of Bayesian uncertainty in deep learning models [12], [13].

The mean predicted RUL for sample i was computed as:

$$\hat{y}_i = \frac{1}{M}\sum_{m=1}^{M}\hat{y}_{i,m} \qquad (1)$$

where y-hat_i is the mean predicted RUL, M is the number of Monte Carlo dropout passes and y-hat_i^(m) is the m-th stochastic prediction.

The predictive standard deviation was computed as:

$$\sigma_i = \sqrt{\frac{1}{M-1}\sum_{m=1}^{M}\left(\hat{y}_{i,m} - \hat{y}_i\right)^2} \tag{2}$$

The approximate 95 percent lower and upper confidence bounds were computed as:

$$\mathrm{LCB}_i = \hat{y}_i - 1.96\sigma_i \tag{3}$$

$$\mathrm{UCB}_i = \hat{y}_i + 1.96\sigma_i \tag{4}$$

The prediction interval width was computed as:

$$W_i = \mathrm{UCB}_i - \mathrm{LCB}_i \tag{5}$$

The prediction interval coverage probability was computed as:

$$\mathrm{PICP} = \frac{1}{N}\sum_{i=1}^{N} I\left(\mathrm{LCB}_i \le y_i \le \mathrm{UCB}_i\right) \tag{6}$$

The prediction interval normalized average width was computed as:

$$\mathrm{PINAW} = \frac{1}{NR}\sum_{i=1}^{N}(\mathrm{UCB}_i - \mathrm{LCB}_i) \tag{7}$$

The Gaussian negative log-likelihood was computed as:

$$\mathrm{NLL} = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{1}{2}\log(2\pi\sigma_i^2) + \frac{(y_i - \hat{y}_i)^2}{2\sigma_i^2}\right] \tag{8}$$

In these expressions, N is the number of test samples, y_i is the observed RUL, R is the range of observed RUL in the test set and $I(\cdot)$ is the indicator function. Lower confidence bounds were used as conservative maintenance evidence because optimistic point estimates can delay necessary intervention.

9. Confidence-Aware Maintenance Decision Mapping

The decision layer uses four core evidence items. The first is the predicted mean RUL. The second is the lower confidence bound, which gives a conservative risk view. The third is the interval width, which shows whether the prediction is stable or uncertain. The fourth is the sensor-quality flag, which shows whether the evidence base is complete, noisy, missing or reconstructed.

Table 6. Evidence used for confidence-aware maintenance decision support

Evidence item	Meaning	Decision role
Predicted mean RUL	Central estimate of remaining life	Supports maintenance scheduling
Lower confidence bound	Conservative estimate under uncertainty	Protects against optimistic predictions
Interval width	Spread between upper and lower confidence bounds	Shows whether the prediction is stable or uncertain
Sensor-quality flag	Completeness, noise level, missing groups or reconstruction status	Shows whether the evidence base is trustworthy
Operating context	Load, temperature, recent maintenance, fault history and stress events	Supports engineering review of model output

The maintenance categories are rule-based and utility-calibrated. Let T_N denote the normal planning threshold, T_W denote the warning threshold and T_C denote the critical threshold, where T_C < T_W < T_N. Let W_max denote the acceptable interval-width limit. These values should not be fixed universally. Each utility should calibrate them using transformer rating, failure history, outage cost, spare availability, maintenance policy, risk tolerance and safety requirements.

Table 7. Rule-based maintenance decision mapping

Category	Indicative decision rule	Recommended maintenance action
Normal	Mean RUL > T_N; LCB > T_N; interval width <= W_max; sensor quality is good.	Continue routine monitoring and periodic testing.
Watch	Mean RUL remains acceptable, but interval width is increasing, stress is rising or sensor quality is partly reduced.	Increase monitoring frequency, verify key sensors and review the next diagnostic report.
Warning	Mean RUL <= T_W or LCB approaches T_W.	Schedule targeted inspection, DGA confirmation, oil-quality testing, load review and outage planning.
Critical	LCB <= T_C or mean RUL <= T_C; severe stress is present or evidence is unreliable around a high-risk state.	Carry out urgent engineering review, diagnostic confirmation, loading control, spare preparation or intervention planning.

This rule does not replace engineering responsibility. It organizes model evidence so that engineers can decide whether to continue monitoring, intensify inspection, reduce loading, treat oil, prepare spares or schedule intervention.

10. Results and Discussion

10.1 Sensor-Fusion Result Interpretation

The fusion experiment showed that single-sensor models were useful but incomplete. DGA-only modelling was informative because gas trends reflect internal fault processes. Thermal and load-only modelling captured operating stress, but it missed important chemical and oil-quality evidence. The best performance was obtained when all sensor groups were combined, because transformer degradation is caused by interacting thermal, electrical, chemical, mechanical and insulation processes.

DGA alone was not sufficient because some ageing processes appear first as thermal loading or oil-quality deterioration before severe gas accumulation becomes visible. Thermal-load evidence was also incomplete because high loading does not always produce the same insulation damage under different moisture and oil conditions. Full multi-sensor fusion improved RUL prediction because it allowed the model to interpret these interacting condition signals together.

Table 8. Sensor-fusion ablation results over five repeated runs

Configuration	RMSE days	MAE days	Interpretation
DGA only	42.8 ± 1.4	30.6 ± 1.1	Useful chemical evidence but incomplete asset view
Thermal and load only	46.2 ± 1.6	33.4 ± 1.3	Captures operating stress but misses internal chemical evidence
DGA plus thermal and load	35.9 ± 1.2	25.7 ± 0.9	Improves degradation representation
DGA, thermal, load and oil-quality evidence	31.8 ± 1.0	22.4 ± 0.8	Adds insulation and oil-condition context
Full multi-sensor fusion	27.6 ± 0.8	19.3 ± 0.7	Best overall evidence representation

10.2 Comparative Model Performance

The comparative results show that temporal deep learning improved over classical tabular baselines in the controlled validation setting. The hybrid CNN-LSTM-Transformer model produced the best test result because it combined local pattern extraction, sequential memory and attention-based long-range dependency learning.

Table 9. Comparative RUL prediction performance over five repeated runs

Model	RMSE days	MAE days	MAPE	R squared	Interpretation
SVR	58.7 ± 2.1	41.5 ± 1.8	18.6%	0.742	Baseline nonlinear regressor
Random Forest	49.3 ± 1.8	34.8 ± 1.5	15.7%	0.813	Strong tabular baseline
XGBoost	44.6 ± 1.6	31.2 ± 1.2	14.1%	0.846	Best classical baseline
CNN	39.8 ± 1.5	28.6 ± 1.1	12.9%	0.879	Captures local patterns
LSTM	35.4 ± 1.3	25.1 ± 1.0	11.4%	0.902	Captures temporal dependencies
GRU	36.1 ± 1.4	25.8 ± 1.1	11.7%	0.897	Efficient temporal baseline
Transformer	31.4 ± 1.0	22.2 ± 0.8	10.1%	0.927	Captures long-range dependencies
Hybrid CNN-LSTM-Transformer	27.6 ± 0.8	19.3 ± 0.7	8.7%	0.946	Best controlled-test performance

The RMSE reduction from 31.4 days for the Transformer baseline to 27.6 days for the hybrid model is about 12.1 percent. The result supports the use of a hybrid temporal structure, although field validation is needed before this improvement can be generalized to operational transformer fleets.

10.3 Repeatability and Statistical Validation

The reported results are the mean and standard deviation from five repeated training runs using different random seeds. The repeated runs were used to check that the ranking of the models did not depend on one favourable initialization. The hybrid model remained the best-performing model in all five runs. The small standard deviation in Table 9 suggests that the improvement was stable under the controlled synthetic validation setting. A formal statistical test with a larger number of real transformer trajectories should still be carried out when field data become available. Because only five repeated runs were conducted, the repeated-run statistics were used as stability evidence rather than as a full inferential test. A paired statistical significance test should be conducted when larger field datasets become available.

10.4 Uncertainty Evaluation

The uncertainty module changed the output from a single RUL number into a confidence-aware result. Repeated stochastic forward passes with dropout active produced a mean RUL estimate, a standard deviation, a lower confidence bound and an upper confidence bound. This was important because transformers with similar mean RUL values may require different actions when one prediction is confident and another is uncertain [6], [8], [12].

Table 10. Uncertainty evaluation results for the hybrid model

Metric	**Value**	**Interpretation**
Nominal confidence level	95%	Target interval level
MC dropout passes	100	Number of stochastic predictions per test sample
Prediction interval coverage probability	94.2%	Coverage close to nominal level
PINAW	0.118	Moderate interval width relative to RUL range
NLL	2.41	Reasonable calibration under controlled data

10.5 Robustness and Deployment Meaning

The robustness tests evaluated noisy data, missing records, missing sensor groups and domain shift. Performance degraded under imperfect records, as expected. The largest degradation occurred when DGA evidence was missing because DGA variables carried strong information about internal chemical fault processes. This shows that the sensor-quality flag is not a minor addition. It is essential for responsible interpretation of RUL predictions.

Table 11. Robustness test summary

Test condition	Observed behaviour	Deployment meaning
Added sensor noise	RMSE increased moderately	Prediction should be interpreted with wider confidence intervals
Random missing records	Performance degraded but remained usable when missingness masks were included	Missingness indicators should be retained as model evidence
Missing DGA group	Larger error increase was observed	Critical chemical evidence should be restored or confirmed by laboratory testing
Missing oil-quality group	Moderate error increase was observed	Oil sampling and dielectric tests remain important
Simulated domain shift	Calibration became weaker	Field calibration should be performed before deployment

The controlled results support framework validation. They do not prove final field performance. Real field data will include irregular oil sampling, sensor drift, inconsistent maintenance records, different loading practices and utility-specific operating policies. The framework should therefore be recalibrated with local utility data before operational use.

11. Practical Implications for Asset Management

The framework can support transformer asset management in four ways. First, it helps rank assets by RUL risk and uncertainty. Second, it separates confident low-risk cases from uncertain cases that need more diagnostic evidence. Third, it gives engineers a conservative lower-bound view that reduces overreliance on optimistic point estimates. Fourth, it provides a common language for data scientists and maintenance engineers.

Transformers with low predicted RUL and narrow high-risk intervals can move higher in the maintenance queue. Transformers with moderate RUL but wide intervals can be assigned for additional testing before costly intervention is taken. The framework therefore supports both risk reduction and cost control.

12. Conclusion

This paper presented a confidence-aware predictive maintenance decision-support framework for power transformer asset management. The framework links multi-sensor transformer evidence, hybrid temporal RUL prediction, uncertainty quantification, sensor-quality checking and maintenance category interpretation.

The central contribution of the paper is the integration of RUL prediction, uncertainty estimation, sensor-quality assessment and maintenance interpretation in one decision-support workflow. This makes the framework useful for maintenance prioritization while preserving human engineering review. Future validation with real transformer fleet data is required before operational deployment.

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