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Reliability and Ageing Assessment of XLPE Power Cables Using Bayesian Neural Network

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With the global growth of electrification, there is an increased reliance on underground power cable networks. Due to new electrical loads, e.g., Data Centers, Heat Pumps, etc., this significant increase and variation in distribution and patterns of demand, utilities face escalating challenges in ensuring the long-term reliability of ageing cross-linked polyethylene (XLPE) power cables,. Traditional condition assessment approaches rely heavily on deterministic indicators that fail to account for uncertainty in degradation processes, often leading to conservative or suboptimal maintenance decisions. Moreover, existing diagnostic-based models typically provide single-point health estimates, offering limited insight into confidence levels and risk, which constrains effective reliability-centered asset management. This paper proposes a probabilistic framework for enhancing the reliability of XLPE power cables using a Bayesian Neural Network (BNN). Unlike traditional deterministic models that provide point estimates of asset health, the proposed BNN explicitly quantifies the uncertainty inherent in cable degradation. The framework utilizes a dataset of 5732 real power cable samples, incorporating 7 critical diagnostic indicators: operational age, partial discharge, tangent delta characteristics, visual condition, and neutral corrosion. The model targets the health index (HI) as a continuous output variable. Model architecture is optimized through a comprehensive sensitivity analysis for hyperparameter tuning, evaluating the impact of prior distributions and network depth on predictive stability. Generalization capability is evaluated by excluding a 5% subset of the dataset, which served as unseen samples for final validation. The BNN outputs a posterior predictive distribution for each power cable, yielding a mean predicted HI and a 95% confidence interval. The model achieves $R^2 = 0.991$. The impact of this study lies in transforming power cable maintenance and asset management planning from a reactive to a risk-based paradigm. By providing uncertainty bounds, the model enables utility operators to distinguish between confident safe and uncertain/high-risk assets. This probabilistic output facilitates precise maintenance scheduling and optimized lifecycle management, ensuring interventions are targeted based on both the predicted condition and the confidence of that prediction.

Keywords: Asset management, Bayesian neural network, Health condition, Lifecycle management, Maintenance scheduling, Reliability.

1. Introduction

The International Energy Agency (IEA) has reported that investment trends are being shaped by the onset of the 'Age of Electricity'. Driven by the rapid rise in electricity demand for industry, cooling, electric mobility, data centers and artificial intelligence (AI). Investment in Grids and storage in 2025 reached \$419B (IEA 2025). The expansion of modern power systems through extensive electrification, renewable integration, and digitalization has increased the complexity and reliability-requirements of the underpinning transmission and distribution networks (Orton 2013; Dinmohammadi *et al.* 2019). Underground power cables play a critical role in ensuring continuous power delivery in urban, industrial, and renewable-energy corridors (Song *et al.* 2022). Subsea power cables and overhead lines can be subjected to dynamic and extreme environmental disturbances. Due to this a range of advanced inspection and evaluation technologies have been developed (Munro *et al.* 2024; Odo *et al.* 2021). Although less exposed to environmental disturbances underground power cable failures can be more severe due to long repair times, limited accessibility and visibility, and high economic impact, making underground cable reliability a key concern for utilities and regulators (Emdadi *et al.* 2025).

Among available insulation technologies, cross-linked polyethylene (XLPE) has become the dominant choice for medium- and high-voltage underground power cables, largely due to its favorable dielectric strength, low dielectric losses, thermal stability, and reduced maintenance requirements compared to oil-impregnated paper insulation systems (Orton 2013; Nemati *et al.* 2019; Vahedi *et al.* 2010). Nevertheless, despite their superior material properties, XLPE-insulated cables are not immune to degradation (Tang *et al.* 2018). From a reliability perspective, the insulation system remains the most failure-prone component of the cable, ultimately governing the probability of failure (PoF) and the usable service life of the asset (Atiq *et al.* 2025).

The reliability of XLPE power cables deteriorates under combined electrical, thermal, mechanical, and environmental stresses, with aging mechanisms such as water and electrical treeing, thermal oxidation, and metallic screen corrosion driving insulation breakdown and fault initiation (Steennis *et al.* 2002; Xu *et al.* 2022). In practice, degradation mechanisms interact nonlinearly, producing asset-specific trajectories that make deterministic life estimation unreliable (Mariut *et al.* 2012). Their progression and impact on cable condition are represented by the P–F Interval Curve (see Fig. 1).

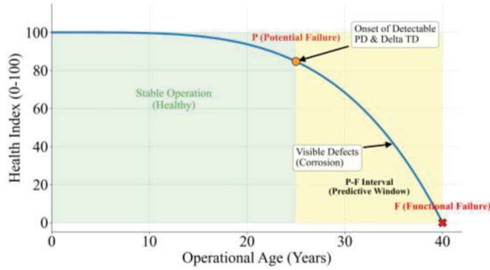


Fig. 1. The P-F Interval Curve illustrating the degradation of an XLPE cable over its operational life.

Traditional reliability assessment of power cables has relied on physics-based and statistical approaches, including Arrhenius thermal aging models, Weibull time-to-failure analysis, Monte Carlo simulations, and proportional hazard models (Mazzanti 2009, 2023; Santhosh *et al.* 2018; Zhang *et al.* 2025; Bendell 1985). While these methods have provided good results at the network level, they typically assume homogeneous asset behavior, require strong parametric assumptions, and offer limited adaptability to evolving operating conditions.

In modern asset management in power systems, these limitations are increasingly restrictive (Tang *et al.* 2023). Underground cable networks operate under heterogeneous installation, loading, and environmental conditions, rendering reliability a dynamic quantity that must be updated as new data become available (Billinton *et al.* 2003). An added complexity, is that electricity network operators, especially within the distribution and low voltage networks, have incomplete underground cable information. Due both to the high volume and significant age of typical electric network assets. Wherein, historic maintenance and repair cycles relied on the effectiveness of human operators performing repairs to report on the most recent asset information (Park *et al.* 2018; Mokhtar *et al.* 2019).

Data-driven approaches have gained attention with the acceleration in network and asset digitalization (Yazdani-Asrami *et al.* 2015; Tsotsopoulou *et al.* 2022; Yazdani-Asrami, Fang, *et al.* 2023; Yazdani-Asrami, Song, *et al.* 2023). Widespread deployment of online and offline monitoring systems providing indicators such as partial discharge (PD), tangent delta (TD), sheath currents, and thermal measurements (Gulski *et al.* 2021; IEEE 5 Feb. 2007; Ahmed *et al.* 2002). Machine learning (ML) methods—including ensembles and neural networks—have shown promise in mapping diagnostic features to health indices (Abdolahi *et al.* 2025a; Sundsgaard 2025; Pan *et al.* 2023; Abdolahi *et al.* 2025b). However, conventional ML models remain deterministic, failing to quantify uncertainty in safety-critical applications. In reliability engineering, uncertainty-aware decision-making is essential, as deterministic predictions without confidence measures are inadequate for safety-critical infrastructure (Hashemi *et al.* 2024).

In this paper, a probabilistic reliability framework is developed for XLPE power cables, integrating multiple diagnostic indicators—

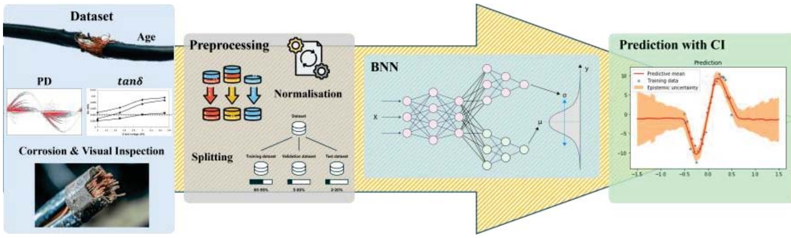


Fig. 2. The proposed framework of reliability assessment of XLPE power cables using BNN.

including operational age, PD, TD characteristics, and neutral corrosion—into a unified Bayesian learning architecture (MacKay 1992). In addition, a Bayesian updating strategy is implemented to imitate real-world asset management scenarios, enabling dynamic refinement of reliability estimates as new inspection and monitoring data become available. Finally, the proposed framework facilitates a transition from reactive maintenance strategies to a risk-based paradigm, in which maintenance prioritization is guided by both the predicted PoF and the associated uncertainty. This distinction allows operators to systematically identify assets that are confidently healthy, assets that are high-risk, and assets whose condition remains uncertain and therefore require further investigation.

2. Methodology

2.1.*Proposed Framework*

The proposed methodology introduces a probabilistic reliability assessment framework for uncertainty-aware decision support in underground power cable asset management. Instead of producing a single point estimate, the framework derives the posterior predictive distribution (Kononenko 1989; Bishop 1997):

$$p(y^* \mid x^*, \mathcal{D}) \quad (1)$$

where x^* is the diagnostic feature vector, y^* represents the corresponding health index (HI), and $\mathcal{D} = [(x_i, y_i)]_{i=1}^{N}$ is the observed dataset. This posterior predictive distribution simultaneously captures the expected health condition of the asset and the associated uncertainty arising from measurement noise and limited data.

The workflow begins with the acquisition of diagnostic indicators, which are temporally ordered to ensure evaluation on future unseen data. A BNN is then used to model the nonlinear relationship between diagnostic features and cable health while explicitly quantifying uncertainty through probabilistic network weights. This formulation enables risk-based interpretation of asset condition by estimating the probability that the HI falls below a critical threshold. As a result, maintenance actions can be prioritized based on both degradation severity and confidence, supporting risk-based asset management. The overall framework is shown in Fig. 2.

2.2.*Dataset Description and Preprocessing*

The dataset consists of 5732 XLPE-insulated power cable samples obtained from field inspections and condition monitoring systems (Alden 2020), which are mapped to an expert-evaluated, continuous health index (0–100). Each sample is characterized by 7 diagnostic features derived from international testing standards (e.g., IEC 60270, IEEE 400.2) describing the electrical, chemical, and physical condition of the insulation, including operational age, PD magnitude, three TD indicators (mean, frequency variation, and stability), visual condition, and neutral corrosion severity. Prior to training of the model, all features were preprocessed to ensure numerical consistency. The corrosion indicator was normalized from percentage values to floating-point form to support neural network learning. The samples were ordered chronologically by inspection ID and partitioned into training (76%), sequential update (19%), and hold-out test (5%) sets, ensuring that all test samples correspond to later inspections than those used for training. All continuous features were standardized using Z-score normalization as follows:

$$z = \frac{x - \mu}{\sigma} \quad (2)$$

where μ and σ represent the mean and standard deviation of each feature, respectively. Importantly, these statistics are computed exclusively from the initial training set to ensure that the model has no prior knowledge of future observations, preventing data leakage.

2.3. *Bayesian Neural Network*

The core of the proposed framework is a BNN, which extends conventional neural networks by modeling uncertainty in the network parameters. In a standard neural network, the weights are treated as deterministic parameters obtained by minimizing a loss function, resulting in a single optimal estimate $\widehat{w}$. In contrast, a BNN treats the weights as random variables and seeks to derive their posterior distribution conditioned on the observed data. Using Bayes' theorem, the posterior distribution of the weights is given by (Kononenko 1989; Bishop 1997):

$$p(w \mid \mathcal{D}) = \frac{p(\mathcal{D} \mid w)\, p(w)}{p(\mathcal{D})} \quad (3)$$

where $p(w)$ is the prior distribution over the weights, $p(\mathcal{D} \mid w)$ is the likelihood of the observed data given the weights, and equation 4 is the marginal likelihood (evidence) (Kononenko 1989; Bishop 1997):

$$p(\mathcal{D}) = \int p(\mathcal{D} \mid w)\, p(w)\, dw \quad (4)$$

For deep neural networks, this integral is analytically intractable due to the high dimensionality and non-linearity of the parameter space. To address this challenge, variational inference is employed to approximate the true posterior $p(w \mid \mathcal{D})$ with a tractable variational distribution $q_\theta(w)$, parameterized by θ (Graves 2011). Here, a mean-field approximation is adopted, in which the posterior is modeled as a factorized Gaussian distribution (Kononenko 1989; Bishop 1997). The variational parameters are optimized by maximizing the evidence lower bound as follows (Sun *et al.* 2019):

$$\mathcal{L}(\theta) = \mathbb{E}_{q_\theta(w)}[\log p(\mathcal{D} \mid w)] - \mathrm{KL}\big(q_\theta(w) \parallel p(w)\big) \quad (5)$$

where $\mathrm{KL}(\cdot)$ denotes the Kullback–Leibler divergence. In equation 5, the first term supports accurate data fitting, while the second term regularizes the solution by penalizing deviations from the prior, thereby mitigating overconfidence and overfitting. Given a new input x^*, the posterior predictive distribution of the HI is obtained by marginalizing over the posterior weight distribution as follows:

$$p(y^* \mid x^*, \mathcal{D}) = \int p(y^* \mid x^*, w)\, q_\theta(w)\, dw \quad (6)$$

Table 1. The BNN parameters during training stage.

Parameter	Configuration / Value
Hidden layers	3
Neurons	20
Activation function	ReLU and Linear
Optimizer	Adam
Learning rate	0.001 → 0.0001
Batch size	Full Batch
Training epochs	5000 → 2000
Inference posterior	1000 samples

This integral is approximated using Monte Carlo sampling, resulting in a predictive distribution characterized by a mean μ and a variance σ^2. The predictive variance naturally decomposes into epistemic uncertainty, arising from uncertainty in the model parameters, and aleatoric uncertainty, arising from inherent noise and variability in the degradation process. The BNN is first trained on the initial dataset using a wide Gaussian prior $p(w) = \mathcal{N}(0,5)$, representing limited prior knowledge. After training, the resulting variational posterior $q_{\theta^*}(w)$ is extracted and reused as the prior for the next learning stage as indicated in the following:

$$p_{\mathrm{new}}(w) = q_{\theta^*}(w) \quad (7)$$

The model is then updated using the subsequent batch of diagnostic data, allowing it to incorporate new information while preserving previously learned knowledge. This sequential updating process ensures temporal consistency and enables continuous refinement of reliability estimates as additional data become available. The architecture and hyperparameters used in the BNN are listed in Table 1.

2.4. *Evaluation Metrics*

Model performance is evaluated using two metrics that addresses both predictive accuracy and reliability relevance. First, conventional regression metrics are employed to assess point prediction performance using the mean of the posterior predictive distribution. The coefficient of determination (R^2) is defined as:

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \tag{8}$$

where y_i is the observed HI, $\hat{y}_i$ is the predicted mean, and $\bar{y}$ is the sample mean. The Mean Absolute Error (MAE) is given by:

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} \mid y_i - \hat{y}_i \mid \tag{9}$$

While these metrics quantify predictive accuracy, they do not account for uncertainty. Therefore, a second reliability-oriented metric is introduced based on the PoF. For each cable sample i, PoF is defined as the probability that the HI falls below a critical threshold $HI_{\text{crit}} = 40$ (Atiq *et al.* 2025):

$$\text{PoF}_i = P(y_i < HI_{\text{crit}}) = \int_{-\infty}^{HI_{\text{crit}}} \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left(-\frac{(y-\mu_i)^2}{2\sigma_i^2}\right) dy \tag{10}$$

where μ_i and σ_i are the predicted mean and standard deviation, respectively. This probability provides a direct, interpretable measure of risk for power cable.

3. Results and Discussion

This section presents a comprehensive evaluation of the proposed BNN-based framework, assessing its predictive accuracy, reliability quantification capabilities, and stability for real-world deployment scenarios. All computations were conducted on a personal laptop equipped with an Intel Core i7 processor and 16 GB of RAM, running the Windows 11 and Python 3.13.

3.1.*Predictive performance and generalization capability*

To first establish the baseline predictive capability of the proposed framework, the regression performance of the updated BNN is evaluated on the unseen generalization test set in Fig. 3. The red markers represent the mean predicted HI for each cable sample, while the vertical bars denote the 95% confidence interval ($\mu \pm 1.96\sigma$), capturing the aleatoric uncertainty inherent in the diagnostics. The tight clustering of data points along the diagonal ideal fit line ($y = x$) validates the model's accuracy in terms of R^2 = 0.991, demonstrating a strong ability to map complex inputs to the correct health condition. Crucially, the uncertainty bounds consistently

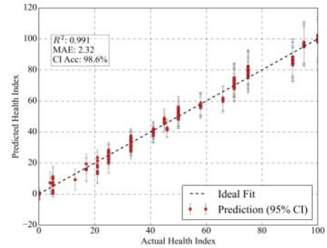


Fig. 3. The regression performance of BNN on unseen samples.

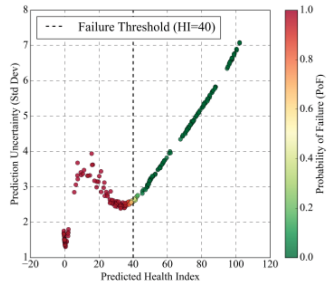


Fig. 4. Multidimensional risk assessment based on the probabilistic outputs of the BNN.

Table 2. Performance and calibration of the proposed framework against MLP.

Metrics	BNN	MLP
R^2	0.991	0.982
MAE	2.32	3.351
ECE	0.16	-
NLL	2.61	-
CI width	19.8	-
Uncertainty	Yes	No
Seq. updating	Posterior to prior	Full retraining

capture the true HI values even when the mean prediction shows minor deviations; this effect is particularly evident in the higher HI range (80–100), where wider confidence intervals appropriately reflect the inherent variability of healthy cable data compared with the more deterministic behavior observed in failed cables. To benchmark the proposed framework, a deterministic multilayer perceptron (MLP) with the same architecture was trained as an empirical baseline. As reported in Table 2, the BNN achieves higher point-prediction accuracy than the MLP. More importantly, the deterministic baseline produces only point estimates and cannot quantify confidence in any individual prediction, leaving operators unable to distinguish high-confidence diagnoses from uncertain ones or to compute probability of failure for risk-based prioritization. Furthermore, the BNN provides a calibrated posterior predictive distribution and supports sequential posterior-to-prior updating without full retraining. In addition, the results of calibration using expected calibration error (ECE), negative log-likelihood (NLL), and sharpness via predictive interval width parameters are presented in Table 2, showing BNN to be slightly under-confident.

3.2. *Probabilistic risk mapping and uncertainty quantification*

Based on the demonstrated predictive accuracy, the reliability significance of the probabilistic outputs is analyzed using a multidimensional risk representation as shown in Fig. 4. The results show a clear heteroscedastic pattern, where cables in the healthy region (HI > 70) display substantially higher prediction uncertainty than cables in the critical failure region (HI < 40). This observation indicates that the model produces high confidence when identifying degraded assets, which are clustered in the bottom-left quadrant with low uncertainty and high probability of failure, while appropriately assigning higher uncertainty to healthy assets where degradation patterns are less clearly defined. Here, a failure threshold of 40% is assumed for separating the safe operating region from the critical intervention region. From an asset management perspective, probabilistic risk may trigger premature replacement for borderline HI values, the proposed framework differentiates

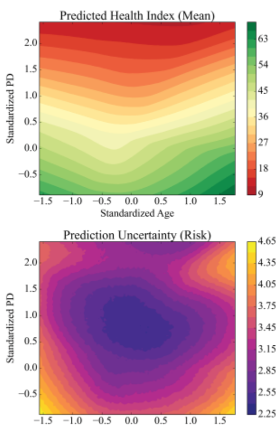
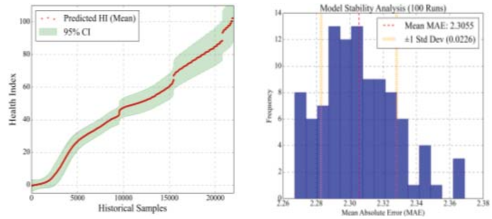


Fig. 5. the BNN-predicted health index (top) and associated uncertainty (bottom) over standardized age and PD, illustrating higher risk and lower confidence in out-of-distribution regions.



(a) (b)

Fig. 6. (a) the fleet health profile from historical deployment of unlabeled samples and (b) model stochastic stability over 100 inference runs on the test set.

stratification directly informs maintenance prioritization. Unlike deterministic methods that between confident failures and uncertain high-risk assets by explicitly modeling uncertainty. This enables immediate replacement of confirmed failures while directing uncertain cases toward targeted inspections rather than disposal, thereby improving maintenance efficiency and reducing unnecessary capital expenditure.

3.3. *Degradation dynamics*

To examine the degradation mechanisms associated with the predicted reliability trends, the joint influence of operational age and PD activity was analyzed, as shown in Fig. 5. The resulting contour map of the predicted HI reveals a nonlinear decision boundary within the standardized feature space. A stable healthy region is observed at low PD levels, where moderate aging has limited impact on reliability, whereas a sharp transition to the critical region occurs when age and PD increase concurrently. The corresponding uncertainty map further highlights regions of elevated epistemic uncertainty, particularly for newer cables with atypically high PD activity, indicating that the model appropriately identifies rare or out-of-distribution conditions rather than producing overconfident predictions. The interaction of age and PD directly defines dynamic safe operating zones. Conventional age-based policies are inefficient, as aged cables can remain healthy under low PD, while newer cables may fail under elevated PD. By capturing these combined effects, the BNN framework enables life extension of safe assets and early detection of newer, high-risk cables overlooked by deterministic approaches.

3.4. *Fleet-scale deployment simulation and stochastic stability*

Following validation under controlled conditions, the operational utility of the framework was assessed using a historical fleet deployment scenario, as shown in Fig. 6(a). Unlabeled samples were ranked by predicted health state to generate a continuous fleet health profile with associated uncertainty. Consistent with prior results, wider confidence intervals the test set, as illustrated in Fig. 6(b). The resulting MAE distribution exhibited a narrow spread around the nominal error with negligible variance, demonstrating that the Bayesian inference process does not compromise prediction stability. This reproducibility supports regulatory acceptance and confirms the suitability of the proposed framework for large-scale asset management and long-term infrastructure planning.

4. Conclusion

This paper developed and validated a probabilistic reliability assessment framework for XLPE power cables based on BNN, enabling uncertainty-aware diagnostics beyond deterministic machine learning approaches. The proposed model achieved $R^2 = 0.991$ on unseen data, with calibrated predictive intervals (ECE = 0.16) supporting uncertainty-aware diagnostics. Moreover, heteroscedastic degradation behavior was identified, characterized by higher aleatoric uncertainty in healthy assets and lower variance in failing cables, thereby improving the interpretation of diagnostic noise. The results further demonstrated that operational age alone is an inadequate reliability indicator, while the combined effect of age and PD activity governs failure risk and defines a dynamic safe operating zone. Fleet-level validation and a 100-run Monte Carlo stability analysis confirmed the scalability, robustness, and reproducibility of the framework, supporting its applicability in regulatory environments. Overall, the proposed Bayesian approach provides a rigorous basis for risk-based asset management, enabling optimized maintenance planning, reduced premature capital investment, and enhanced distribution network resilience. Future work will focus on integrating BNN with temporal deep learning architectures to enable dynamic, uncertainty-aware reliability assessment over the full service life of power cables.

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Data availability statement

All data that support the findings of this study are included within the article.

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