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Comparative Evaluation of Artificial Neural Networks and Monte Carlo Simulation for Transformer Insulating Oil Lifetime Prediction

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Abstract: Transformer insulating oil is an important factor for the reliability and service life of power transformers. It provides electrical insulation and heat dissipation. Accurate lifetime prediction is essential for asset management and condition-based maintenance. In this study, the comparison of Artificial Neural Network (ANN) and Monte Carlo Simulation (MCS) techniques is presented to predict transformer insulating oil lifetime based on three physicochemical parameters such as acid content, moisture content and breakdown voltage. The model was developed and validated on an experimental dataset of 18 transformer insulating oil samples. The ANN model was based on a multilayer perceptron architecture with three hidden layers (80-80-40 neurons). The MCS model was run for 3000 simulation iterations to include the input uncertainty. The model performance was assessed using mean Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE) and coefficient of determination (R^2). The ANN model produced better results with a MAPE of 8.20%, an RMSE of 4.15 months and an R^2 of 0.98, surpassing the MCS model, which achieved a MAPE of 11.50%, an RMSE of 9.40 months and an R^2 of 0.89. The results presented show that ANN is a more accurate and reliable methodology for the prediction of transformer insulating oil lifetime that allows efficient condition-based maintenance and transformer asset management.

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Introduction

The insulation system is one of the most important components influencing transformer reliability and service life. Transformer insulating oil, as one of the constituent materials, plays two important roles, namely electrical insulation between energized components and dissipation of heat generated during transformer operation. During its service life, insulating oil is subjected to constant thermal stress, electrical discharge, oxidation and environmental contamination (Mharakurwa, 2022). Such aging mechanisms gradually modify the physicochemical properties of the oil resulting in deterioration of its dielectric performance. Progressive deterioration diminishes the insulation capability of the transformer and significantly increases the chance of insulation failure, partial discharge and catastrophic equipment breakdown. Therefore, continuous monitoring of transformer insulating oil has become a fundamental practice in transformer asset management (Jahromi et al., 2009; Rêma et al., 2024). The degradation process of transformer insulating oil is commonly reflected by several measurable condition indicators, among which acid content, moisture concentration, and breakdown voltage are considered the most representative. Besides the promotion of oxidation reactions and aging of cellulose insulation, acids formation is also a concern. The excessive moisture leads to a significant reduction of dielectric strength and electrical discharge in the transformer. The reducing breakdown voltage means that the insulating oil has less ability to withstand the electrical stress under the high-voltage operating conditions. These degradation parameters are highly nonlinear in their interaction which makes the accurate estimation of the transformer insulating oil lifetime much more difficult compared to traditional linear degradation analysis (Christina et al., 2018; Koksal & Ozdemir, 2016). Predictive maintenance is the latest trend in transformer condition assessment moving from the traditional time-based inspection to data-driven decision making. Instead of replacing insulating oil according to fixed maintenance schedules, predictive maintenance estimates the remaining service life based on actual degradation condition of transformer insulation. Maintenance activity can be performed only when needed, which reduces maintenance costs, prevents unexpected failures, extends transformer's lifetime and improves overall system reliability. Consequently, accurate lifetime prediction models have become an important research topic in transformer condition monitoring and asset management (Mharakurwa, 2022; Zhou et al., 2020). Various computational techniques have been developed to improve the accuracy of transformer lifetime prediction. Among these, ANN showed excellent ability to model complex non-linear relationships between multiple degradation variables without requiring explicit mathematical formulations (Krasnov et al., 2021). ANN learns iteratively from past data. This helps it to identify hidden patterns and make very accurate predictions when the relationship between variables is not easy to be expressed analytically. This capability has made ANN one of the most popular machine learning techniques in transformer health assessment and predictive maintenance applications (Maurício et al., 2023). Another approach for lifetime forecasting is the probabilistic approach based on methods such as MCS. Instead of learning directly from the historical data, MCS predicts the future system behavior by repeatedly sampling the uncertain input variables based on the specified probability distributions (Sprague & Czischek, 2024). This probabilistic approach allows the prediction uncertainty and operational risk to be estimated, which may be useful information for reliability analysis and maintenance planning. Thus, MCS has been widely applied in engineering reliability studies where uncertainty plays a significant role in equipment degradation and lifetime estimation. While ANN and MCS have shown promising performance in transformer condition assessment, most existing studies have focused on these methods separately or applied them to different prediction objectives. Comparative investigations employing identical transformer insulating oil degradation parameters under the same experimental conditions remain relatively limited. As a result, the relative predictive capability, strengths, and limitations of these two fundamentally different approaches have not yet been comprehensively established. This restriction makes it difficult for researchers and utility engineers to select the best prediction model to estimate the life of transformer insulating oil (Ang et al., 2024; Karimi & Gholipour, 2022). The objective of this study is to address this research gap by conducting a comprehensive comparative evaluation of ANN and MCS for transformer insulating oil lifetime prediction based on three important dielectric degradation indicators including acid content, moisture concentration, and breakdown voltage. Both models are developed based on the same experimental dataset to allow for a fair comparison and their predictive performance is evaluated based on MAPE, RMSE and the coefficient of determination (R^2). The results of this study provide not only a quantitative comparison between data-driven and probabilistic prediction approaches, but also practical insights into the selection of proper predictive models for transformer condition monitoring, predictive maintenance, and long-term asset management in electrical power systems.

Research Method

In this study, the comparative research methodology was adopted to compare the predictive performance of ANN and MCS for transformer insulating oil lifetime estimation based on dielectric degradation characteristics. The proposed methodology was developed to allow a fair and systematic comparison by applying both prediction models on the same experimental dataset with the same evaluation criteria. The research process was divided into several sequential stages, including research framework development, dataset preparation, preprocessing of data, model development, and performance evaluation. Transformer insulating oil lifetime was predicted using three major degradation indicators, namely, acid content, moisture content, and breakdown voltage. The predictive capability of each model was then compared using MAPE, RMSE, and the coefficient of determination (R^2). The overall research methodology is described in the following subsections.

Research Framework

In this study, the predictive performance of ANN and MCS in predicting the lifetime of transformer insulating oil was compared using a systematic research framework. The research framework was established to ensure the same dataset was used to implement both prediction models and both models were evaluated using the same performance criteria (Karimi & Gholipour, 2022; Romero-Quete et al., 2016). The overall research framework is illustrated in Figure 1.

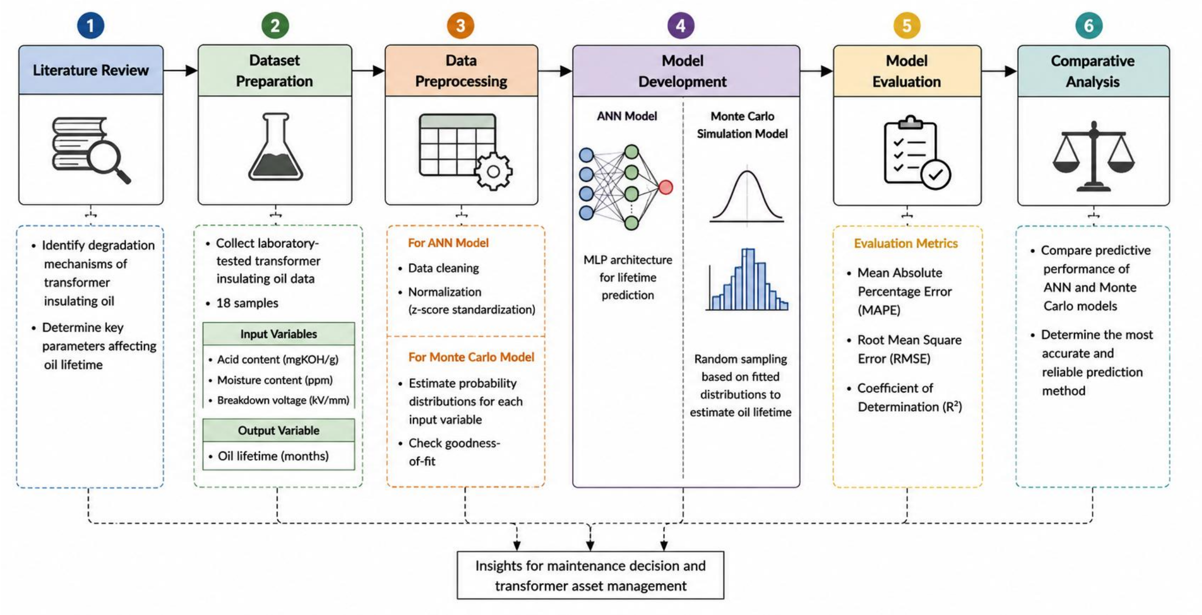

Figure 1 Research framework of the proposed study

The research consists of six consequent stages as depicted in Figure 1. The first stage involves a literature review to identify the degradation parameters and the theoretical basis of the study. The second stage is concerned with dataset preparation based on laboratory tested transformer insulating oil data (Hu et al., 2026; Jahromi et al., 2018). The third stage is the data pre-processing according to the requirements of the prediction model. The fourth stage is the development of two independent prediction models (ANN and MCS). The fifth stage is the evaluation of the predictive performance of both models based on MAPE, RMSE and the coefficient of determination (R^2). The last stage is the comparative analysis of prediction results to determine the most accurate and reliable approach for transformer insulating oil lifetime prediction.

Dataset Description

The experimental dataset used in this study consists of 18 transformer insulating oil samples obtained from laboratory testing and adopted from a previous study. Each sample represents the measured condition of transformer insulating oil at different degradation levels. The dataset was selected because it contains the principal dielectric degradation parameters that are closely associated with transformer insulating oil aging and lifetime prediction. Three degradation parameters were employed as input variables, namely acid content (mgKOH/g), moisture content (ppm), and breakdown voltage (kV/mm). The output variable was the transformer insulating oil lifetime (months). These variables were selected as they provide complementary information regarding the physicochemical condition of the transformer insulating oil: acid content gives an indication of the oxidation level of the insulating oil, moisture content indicates the presence of water contamination, which can decrease the dielectric strength, and breakdown voltage represents the oil's capacity to withstand electrical stress during operation. Prior to model development, the dataset was checked for consistency and completeness (Lal et al., 2026; Zarbipour et al., 2026). The experimental dataset was found to be free of missing values and inconsistent records. The same dataset was used in the ANN and MCS models for a fair comparison between the two prediction approaches. Table 1 summarizes the experimental dataset used in this study.

Table 1 Experimental dataset of transformer insulating oil characteristics

Sample	Acid Content (mgKOH/g)	Moisture Content (ppm)	Breakdown Voltage (kV/mm)	Oil Lifetime (Months)
1	0.040	16.0	67	12
2	0.048	22.0	61	36
3	0.060	24.0	57	48
4	0.080	28.0	56	60
5	0.090	32.0	50	69
6	0.090	33.0	51	72
7	0.100	36.0	49	75
8	0.110	37.0	50	78
9	0.120	36.0	50	81
10	0.122	36.0	49	84
11	0.128	36.3	49	87

12	0.128	36.0	50	93
13	0.130	36.0	48	99
14	0.142	36.0	48	105
15	0.144	37.5	46	111
16	0.148	37.0	46	117
17	0.148	37.0	46	123
18	0.140	37.0	45	129

The experimental dataset used in this work consists of 18 samples of laboratory tested transformer insulating oil with different degradation characteristics as presented in Table 1. The acid content ranges from 0.040 to 0.148 mgKOH/g and the moisture content ranges from 16.0 to 37.5 ppm. The breakdown voltage ranges from 45 to 67 kV/mm, indicating different levels of dielectric performance. Therefore, the transformer insulating oil lifetime ranges from 12 to 129 months. These variations demonstrate that the dataset includes multiple degradation conditions and is therefore suitable for the development and evaluation of predictive models based on both ANN and MCS.

Data Preprocessing

Data processing was performed to enhance data quality and to satisfy the needs of the prediction models. First, the experimental dataset was checked for completeness and consistency. All the observations were complete and no missing values or inconsistent records were found (Ma et al., 2026; Yang et al., 2026). Descriptive statistical analysis was then conducted to lay out the characteristics of each variable, such as the minimum, maximum, mean and standard deviation. The descriptive statistics of the experimental dataset are shown in Table 2.

Table 2 Descriptive statistics of the experimental dataset

Variable	Unit	Minimum	Maximum	Mean	Standard Deviation
Acid Content	mgKOH/g	0.040	0.148	0.109	0.035
Moisture Content	ppm	16.0	37.5	32.933	6.259
Breakdown Voltage	kV/mm	45	67	51.000	5.750
Oil Lifetime	Months	12	129	82.167	30.597

The input variables were measured in different units and numerical scales; therefore, the data normalization process was performed before developing the ANN model. In this study, the z-score standardization was used to convert each input variable into a standardized scale with zero mean and unit variance. This step of the preprocessing of data improves the numerical stability, accelerates the model convergence and avoids variables with bigger numerical values from dominating the learning process. The normalized value of each variable was calculated using Equation (1).

$$z = \frac{x - \mu}{\sigma} \tag{1}$$

where the normalized value is obtained by subtracting the mean of each variable from the original observation and dividing the result by the corresponding standard deviation. This standardization puts all input variables on a common scale with zero mean and unit variance, which improves the numerical stability and eases the learning process of the ANN. MCS was used for the original dataset as opposed to the ANN model, as the simulation was constructed based on the statistical characteristics and probability distributions of the observed variables.Thus, the original values were preserved to estimate the probability distributions that were required for stochastic sampling in the simulation process.The same experimental dataset was used for the development of ANN and MCS by implementing specific preprocessing procedures to the characteristics of each prediction model for the purpose of comparison, ensuring methodological consistency.

Artificial Neural Network Model

The ANN based on the Multilayer Perceptron (MLP) architecture was developed to predict the lifetime of transformer insulating oil from its dielectric degradation characteristics. The model was designed to capture the nonlinear relationship between the selected degradation parameters and the corresponding oil lifetime. Three input variables, namely acid content, moisture content, and breakdown voltage, were used as predictors, while transformer insulating oil lifetime served as the output variable. The proposed ANN architecture consists of one input layer, three hidden layers, and one output layer. The hidden layers contain 80, 80, and 40 neurons, respectively, while the output layer contains a single neuron representing the predicted transformer insulating oil lifetime. The Rectified Linear Unit (ReLU) activation function was employed in all hidden layers because of its computational efficiency and its ability to improve convergence during the training process. Model training was performed using the Limited-memory Broyden–Fletcher–Goldfarb–Shanno (L-BFGS) optimization algorithm with a maximum of 5,000 iterations. A learning rate of 0.005 and L2 regularization were adopted to improve model generalization and reduce the risk of overfitting. The input variables were standardized using z-score normalization prior to training, while the network parameters were iteratively updated until the optimization process converged. The architecture and hyperparameters were selected based on preliminary experimental evaluation to provide stable convergence and satisfactory prediction performance for the available experimental dataset. The overall architecture of the proposed ANN model is illustrated in Figure 2.

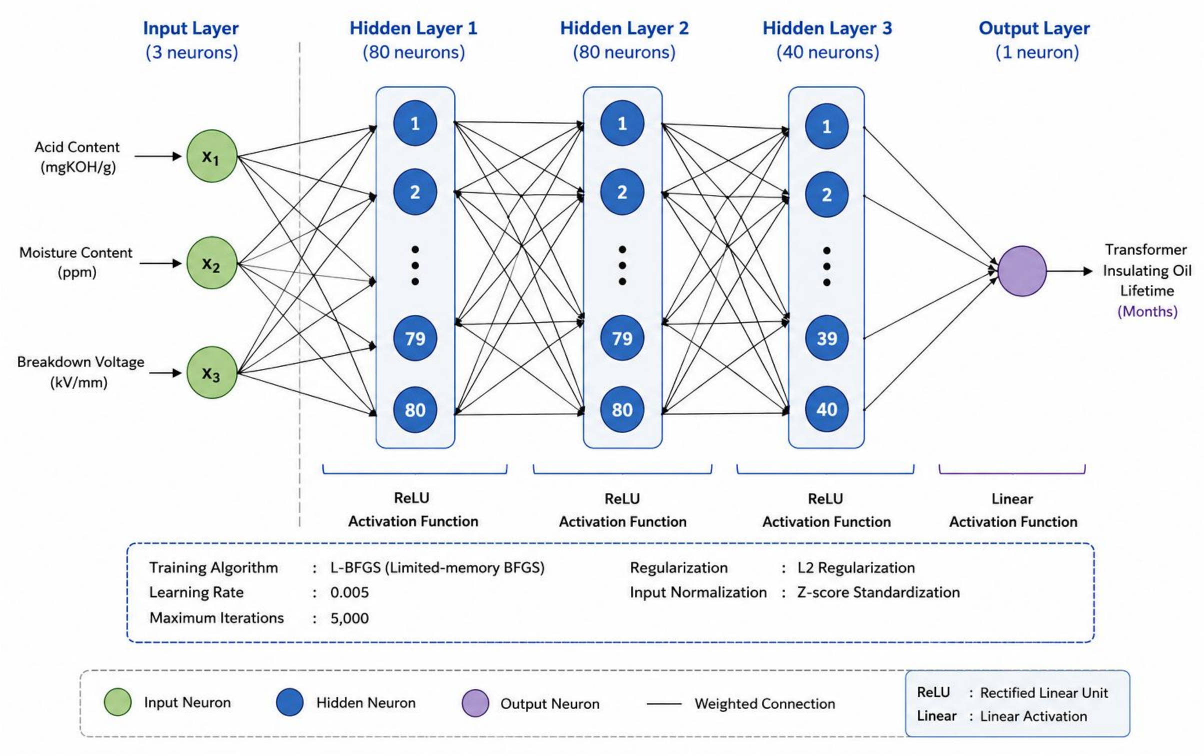

Figure 2 Architecture of the proposed Artificial Neural Network model

The inputs to the proposed ANN model are the three normalized input variables defining the degradation of the transformer insulating oil as shown in Figure 2. The inputs are passed through three fully connected hidden layers with the ReLU activation function which are then passed through a single output neuron predicting the lifetime of the transformer insulating oil. The network parameters are iteratively optimized using the L-BFGS algorithm during training in an effort to decrease the prediction error.

Monte Carlo Simulation Model

The MCS was used as a probabilistic method to estimate the lifetime of transformer insulating oil by considering the uncertainty of the degradation parameters. Unlike ANN that learns the nonlinear relationships from historical observations, MCS predicts the output by repeatedly generating random samples from the probability distributions of the input variables. This approach allows the evaluation of the variability of prediction and uncertainty due to the stochastic behavior of transformer insulating oil degradation.

The simulation model used three degradation parameters, acid content, moisture content and breakdown voltage as inputs. Acid content and moisture content were modeled by log-normal probability distributions as both variables are non-negative and usually increase during the transformer aging process. Conversely, the breakdown voltage was represented by a normal distribution because its variation around the observed mean is relatively symmetric. The predicted transformer insulating oil lifetime was then estimated by a Weibull distribution, which is widely used in reliability engineering and lifetime analysis. The number of simulation iterations was selected as 3000 to obtain stable estimation of the transformer insulating oil lifetime. Random values of the degradation parameters were generated for each iteration according to their probability distributions and used to calculate the transformer insulating oil lifetime. This sampling procedure was repeated to produce a probability distribution of the predicted lifetime values, allowing for a quantitative assessment of the uncertainty in the transformer insulating oil degradation with preserved computational efficiency. The workflow of the proposed MCS model is presented in Figure. 3.

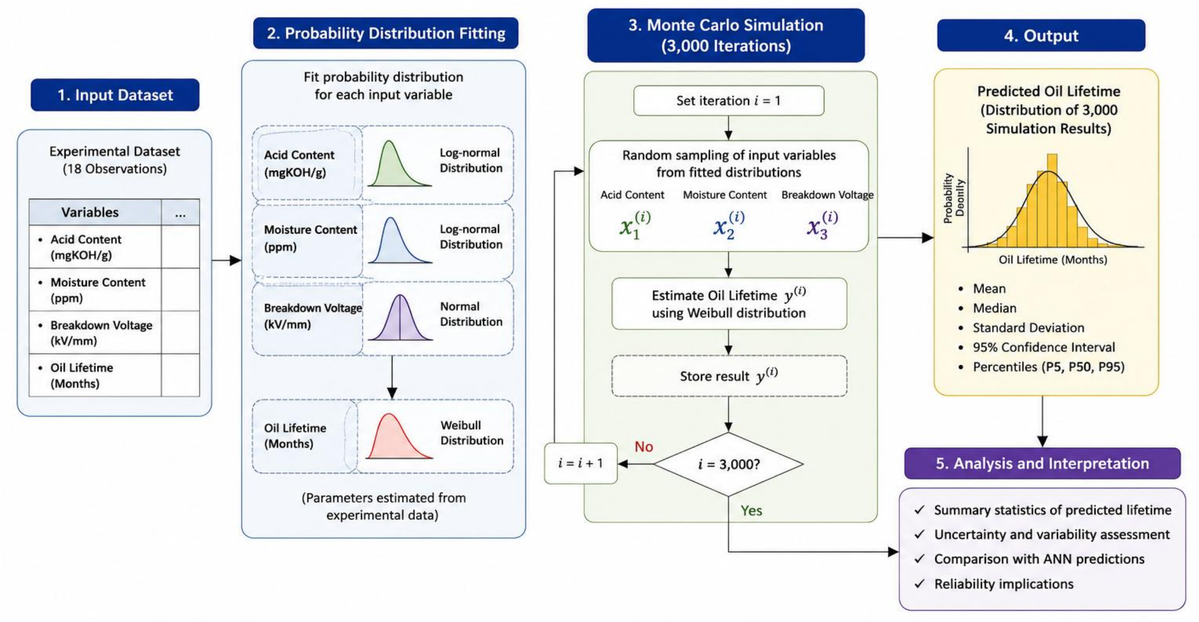

Figure 3 Flowchart of the proposed Monte Carlo Simulation model

The simulation procedure is illustrated in Figure 3; the procedure starts with the estimation of the probability distributions of the degradation parameters based on the experimental dataset. In each simulation iteration, the random samples are generated through the repeated stochastic sampling process, and then the sampled values are used to estimate the transformer insulating oil lifetime, and the predicted results are stored during the entire simulation process. Once all 3,000 iterations are finished, the predicted lifetime distribution is analyzed to obtain the representative statistical measures and to evaluate the uncertainty of the transformer insulating oil lifetime prediction.

Performance Evaluation

The predictive performance of the ANN and MCS models were assessed by using three commonly used statistical performance indicators: MAPE, RMSE and coefficient of determination (R²). These metrics have been chosen so that they provide a complete evaluation of the prediction accuracy, the prediction error and the ability of each model to capture the relationship between the degradation parameters and the lifetime of the transformer insulating oil. The Average Relative Error (ARE) was used to measure the average of the relative deviation of the predicted and observed lifetime values. Lower MAPE values indicate higher accuracy of prediction. The MAPE is computed as per Equation (2).

$$\mathrm{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{2}$$

where $n$is the total number of observations, $y_i$represents the observed transformer insulating oil lifetime, and $\hat{y}_i$denotes the corresponding predicted lifetime. The MAPE quantifies the average percentage difference between the predicted and observed values, providing an intuitive measure of prediction accuracy. A lower MAPE value indicates that the predicted lifetime is closer to the observed lifetime, with a value of zero representing a perfect prediction. The RMSE was used to quantify the magnitude of prediction errors by assigning greater penalties to larger deviations. A lower RMSE value indicates better predictive performance. The RMSE is defined in Equation (3).

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

where n is the total number of observations, y_i denotes the observed transformer insulating oil lifetime, and $\hat{y}_i$represents the corresponding predicted lifetime. The RMSE measures the average magnitude of prediction errors by assigning greater weight to larger deviations through the squaring operation. Consequently, lower RMSE values indicate better predictive performance and a closer agreement between the predicted and observed transformer insulating oil lifetime. The coefficient of determination (R^2) was employed to evaluate the proportion of variance in the observed lifetime that can be explained by the prediction model. An R^2value closer to one indicates a better agreement between the predicted and observed values. The coefficient of determination is calculated using Equation (4).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{4}$$

where y_i represents the observed transformer insulating oil lifetime, $\hat{y}_i$ denotes the predicted lifetime, $\bar{y}$ is the mean of the observed lifetime values, and n is the total number of observations. The coefficient of determination (R^2) evaluates the proportion of variance in the observed data that is explained by the prediction model. An R^2 value closer to 1 indicates a stronger agreement between the predicted and observed lifetime values, reflecting better predictive performance.

Result and Discussion

In this section, the experimental results for the ANN and MCS models are presented to predict the lifetime of transformer insulating oil. The predictive performance of both approaches is evaluated using MAPE, RMSE and coefficient of determination (R^2). Moreover, a comparative study is performed to evaluate the pros and cons of the approaches in terms of prediction accuracy, model reliability and applicability to transformer condition assessment.

Artificial Neural Network Prediction Results

An ANN model was developed to predict the lifetime of transformer insulating oil using acid content, moisture content, and breakdown voltage as input variables. After data preprocessing, the normalized dataset was used to train a (MLP consisting of three hidden layers with 80, 80, and 40 neurons, respectively. The model was optimized using the L-BFGS algorithm with a maximum of 5000 training iterations. The predictive performance of the developed ANN model was evaluated using the MAPE, RMSE, and coefficient of determination (R^2). The corresponding performance metrics are summarized in Table 3, while the relationship between the observed and predicted transformer insulating oil lifetime values is illustrated in Figure 4.

Table 3 Performance evaluation of the proposed Artificial Neural Network model

Performance Metric	Value
MAPE	8.20%
RMSE	4.15 months
(R^2)	0.98

As presented in Table 3, the proposed ANN model achieved excellent predictive performance, as indicated by the low MAPE and RMSE values together with a high coefficient of determination (R^2). To provide a visual assessment of the model performance, the relationship between the observed and predicted transformer insulating oil lifetime values is illustrated in Figure 4.

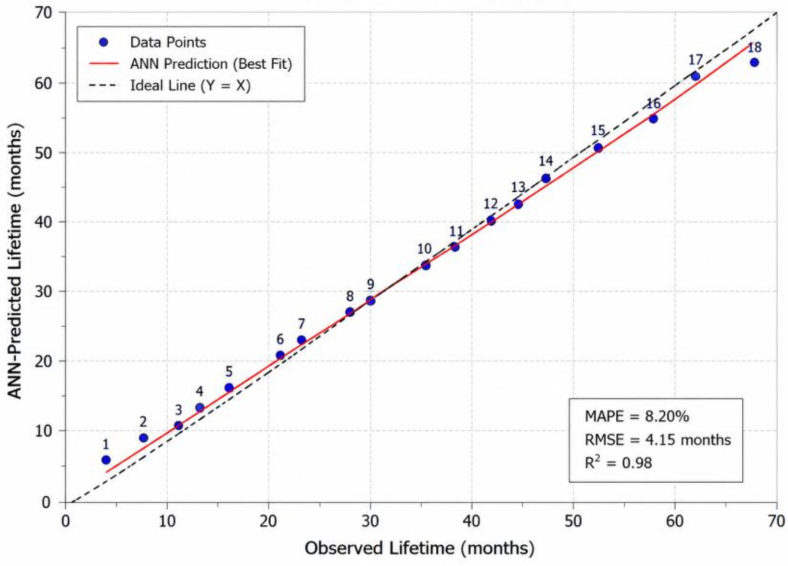

Figure 4 Relationship between observed and ANN-predicted transformer insulating oil lifetime values

As shown in Figure 4, there is a good agreement between the measured and predicted lifetime of the transformer insulating oil. Most of the data points are close to the reference line, which indicates that the ANN model has successfully learned the nonlinear relationship between the physicochemical properties of the transformer insulating oil and its working life. The high degree of agreement between the observed and predicted values agrees with the evaluation results presented in Table 3 which confirms the robustness and reliability of the presented ANN model in predicting lifetime.

Monte Carlo Simulation Results

The MCS model was employed to predict the lifetime of transformer insulating oil considering the uncertainty of input parameters such as acid content, moisture content and breakdown voltage. Unlike the ANN model that learns the nonlinear relationship directly from the experimental data, the MCS model generates many random samples from the probability distributions of the input parameters to simulate the variability of transformer insulating oil lifetime. In this study, 3000 simulation iterations were conducted to ensure the convergence and statistical stability of the prediction results. The predictive performance of the MCS model was evaluated by the MAPE, RMSE and coefficient of determination (R^2). The corresponding performance indicators are summarized in Table 4, and the relationship between the observed and Monte Carlo-predicted transformer insulating oil lifetime values are illustrated in Figure 5.

Table 4 Performance evaluation results of the Monte Carlo Simulation model

Performance Metric	Value
MAPE	11.50%
RMSE	9.40 months
(R^2)	0.89

The MCS model was effective for predicting the lifetime of transformer insulating oil as displayed in Table 4. Although the model was able to simulate the general trend of the observed data, the prediction accuracy of the model was less than that of the ANN model as evidenced by the higher MAPE and RMSE values and the lower coefficient of determination. The observed and predicted values of the transformer insulating oil lifetime are plotted in Figure 5 to give a visual evaluation of the model performance.

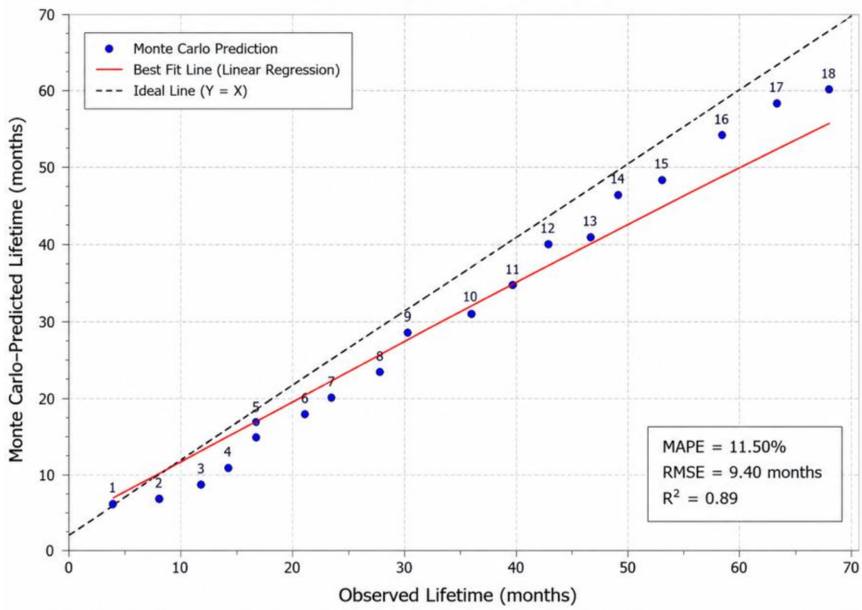

Figure 5 Relationship between observed and Monte Carlo-predicted transformer insulating oil lifetime values

Figure 5 shows that the MCS model generally follows the observed transformer insulating oil lifetime values, although a greater dispersion of data points around the ideal prediction line can be observed compared with the ANN model. This indicates that the probabilistic simulation approach can represent the uncertainty of transformer insulating oil degradation but produces larger prediction deviations for several samples. Nevertheless, the obtained prediction results demonstrate that the MCS model provides a reasonable estimation of transformer insulating oil lifetime and can serve as an alternative prediction approach when uncertainty analysis is required.

Comparative Performance Analysis

The performance of ANN and MCS models were thoroughly compared using MAPE, RMSE and coefficient of determination (R^2) as the evaluation criteria for the prediction approaches. These evaluation metrics are used collectively to assess the prediction accuracy, average prediction error and the ability of each model to capture the variations in the transformer insulating oil lifetime. The comparative results are presented in Table 5, and the overall performance comparison between the two prediction models is presented in Figure 6.

Table 5 Comparative performance of the ANN and Monte Carlo Simulation models

Performance Metric	ANN	Monte Carlo Simulation
MAPE	8.20%	11.50%
RMSE	4.15 months	9.40 months
(R^2)	0.98	0.89

The ANN model outperforms the MCS model for all evaluation metrics as presented in Table 5. The ANN possessed a lower MAPE and RMSE, which implies a higher prediction accuracy and a smaller prediction error. Also, the higher coefficient of determination (R^2 = 0.98) shows that the ANN model explained a considerably higher proportion of the variability in transformer insulating oil lifetime compared to the MCS model. A graphical comparison of the prediction performance is shown in Figure 6.

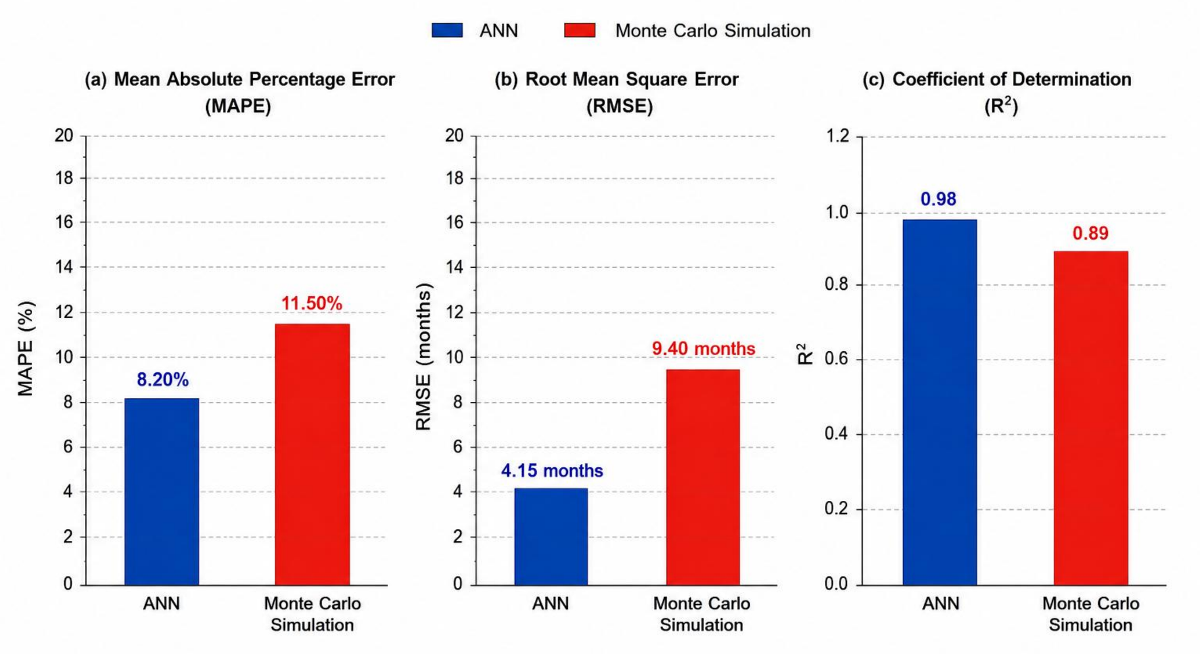

Figure 6 Coparison of the predictive performance of the ANN and Monte Carlo Simulation models

Figure 6 also demonstrates the out-performance of the ANN model over the MCS model. ANN showed lower prediction errors and stronger correlation with observed values of transformer insulating oil lifetime. The results show that the ANN model is better for capturing the nonlinear relationships between acid content, moisture content, breakdown voltage and transformer insulating oil lifetime. The MCS model, in contrast, gives a probabilistic representation of the prediction uncertainty but has higher deviations from the observed values. Thus, both methods can be used for lifetime prediction, but the ANN model provides better predictive accuracy and reliability for the experimental dataset used in this study.

Discussion

The experimental results showed that the ANN model always performed better than the MCS model in the lifetime prediction of transformer insulating oil. As shown in Table 5, the ANN model had less MAPE of 8.20% and RMSE of 4.15 months in the lifetime prediction of transformer insulating oil whereas the MCS model had MAPE of 11.50% and RMSE of 9.40 months. Besides, the coefficient of determination (R^2 =0.98) obtained from the ANN model was higher than the MCS model, which means the ANN model has a better ability to explain the variability of transformer insulating oil lifetime. These results demonstrated that the ANN model could provide more accurate and reliable lifetime prediction for the dataset studied. The ANN model has been performed better, since it is able to learn the complex nonlinear relations between the physicochemical properties of the transformer insulating oil and its service lifetime. The degradation of transformer oil is affected by various inter-related factors such as acid formation, moisture formation and reduction of dielectric strength. The multilayer perceptron architecture can effectively capture these nonlinear interactions during the training process, allowing for more accurate lifetime estimation. The prediction values obtained from the ANN model were very close to the observed lifetime values as shown in Figure 4. In contrast, the MCS model estimates the transformer insulating oil lifetime by repeated sampling from the input variables probability distributions. This probabilistic approach can effectively capture the uncertainty and variability of the degradation process; however, its prediction accuracy mostly depends on the assumed statistical distributions rather than learning the underlying nonlinear relationships of the experimental data. The MCS model showed larger prediction errors and higher dispersion between the observed and predicted lifetime values, as demonstrated in Figure 5.

The comparison also indicates that both prediction approaches have their own advantages depending on the intended application. The ANN model has better predictive performance which makes it more suitable for accurate prediction of lifetime and condition assessment. In contrast, the MCS model can give useful information about the uncertainty related to the degradation of transformer insulating oil and it can be used for probabilistic risk assessment and reliability analysis. Therefore, the choice of a suitable prediction method should consider the specific objectives of transformer asset management. Results of this study show that the proposed ANN model is a practical and efficient solution for transformer insulating oil lifetime prediction. The high prediction accuracy of the ANN model shows the potential to enable a condition-based maintenance and improve maintenance planning with reliable estimates of the transformer insulating oil lifetime. Future works can further improve prediction performance by integrating more oil condition parameters, larger datasets under various operating conditions, and advanced deep learning architectures to enhance the generalization capability of the prediction model.

Conclusions

This paper presents a comparative evaluation of ANN and MCS for the prediction of transformer insulating oil life based on three key physicochemical parameters including acid value, moisture content and breakdown voltage. Both prediction models were successfully developed and evaluated using a laboratory-based experimental dataset and their prediction performance was measured using MAPE, RMSE and coefficient of determination (R^2). The experimental results showed that the ANN model performed better than the MCS model in terms of all the evaluation metrics. The ANN model reported a MAPE of 8.20%, RMSE of 4.15 months and R^2 value of 0.98, while the MCS model reported a MAPE of 11.50%, RMSE of 9.40 months and R^2 value of 0.89. The results showed that the ANN model has higher prediction accuracy and better agreement with the observed transformer insulating oil life compared to the probabilistic simulation approach. The results confirm that ANN are an efficient and robust technique for estimating the lifespan of transformer insulating oil, through accurate simulation of the nonlinear interconnections between the studied oil condition parameters. However, MCS is still beneficial to demonstrate uncertainty in the degradation of transformer oil, albeit with somewhat lower prediction accuracy. Thus, the ANN model is more appropriate for condition-based maintenance planning and transformer asset management, where the accurate estimation of lifespan is crucial for enhancing operational reliability and lowering maintenance expenditures. Future works should explore the expansion of the experimental dataset by increasing the range of transformer operating conditions and other oil quality parameters such as the dissolved gas analysis (DGA), interfacial tension, and dielectric dissipation factor. Furthermore, the study of advanced machine learning and deep learning techniques together with hybrid prediction models that combine data-driven and probabilistic methods can provide further improvement of the prediction accuracy and better applicability of the transformer lifetime assessment in real power system scenarios.

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