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Deep Learning-Based Transformer Moisture Diagnostics Using Long Short-Term Memory Networks

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Abstract: Power transformers play a crucial role in maintaining the stability and reliability of energy systems. Accurate moisture assessment of transformer oil-paper insulation is critical for ensuring safe operating conditions and power transformers' longevity in large interconnected electrical grids. The moisture can be predicted and quantified by extracting moisture-sensitive dielectric feature parameters. This article suggests a deep learning technique for transformer moisture diagnostics based on long short-term memory (LSTM) networks. The proposed method was tested using a dataset of transformer oil moisture readings, and the analysis revealed that the LSTM network performed well in diagnosing oil insulation moisture. The method's performance was assessed using various metrics, such as R-squared, mean absolute error, mean squared error, root mean squared error, and mean signed difference. The performance of the proposed model was also compared with linear regression and random forest (RF) models to evaluate its effectiveness. It was determined that the proposed method outperformed traditional methods in terms of accuracy and efficiency. This investigation demonstrates the potential of a deep learning approach for identifying transformer oil insulation moisture with a R^2 value of 0.899, thus providing a valuable tool for power system operators to monitor and manage the integrity of their transformer fleet.

Keywords: power transformer; oil-immersed insulation; moisture forecasting; long short-term memory

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1. Introduction

The prognostic health management (PHM) of transformers is essential since it enables the early detection of possible faults, thus preventing unanticipated downtime and expensive repairs [1]. PHM can also help optimize the transformers' maintenance schedule, which reduces costs and improves overall reliability. Additionally, PHM also helps to extend the lifespan of transformers by identifying and addressing potential issues at embryonic stages. Consequently, PHM contributes to transformers' safe and dependable operation, which is essential for preserving the power supply and preventing power outages.

The transformer's insulation can deteriorate due to moisture, which could result in arcing and electrical discharge [2]. It causes corrosion in the transformer tank, which lowers insulating performance, thus potentially leading the transformer to break down. When a significant moisture content is present, paper insulation ages more quickly, decreasing transformers insulating efficiency and life expectancy [3]. According to existing literature, moisture is not only responsible for the loss of the dielectric strength of the transformers, but it also upsurges power loss due to deterioration in insulating qualities, such as an increase in acidity and a fall in the flash point of transformer oil. The insulating performance of transformers is dynamic, which has been immensely quantified in the existing literature by estimating moisture and aging degrees [4]. Due to the detrimental effects moisture has on a transformer's operation and lifespan, assessing moisture levels is a crucial part of transformer condition monitoring processes.

Transformer oil-paper insulation is used in electrical transformers to insulate and protect electrical components from moisture. Moisture in the transformer oil-paper insulation causes a reduction in the transformer's efficiency, which leads to electrical failures. Thus, moisture forecasting in transformer oil-paper insulation helps to predict and prevent these issues and save energy. Maintenance schedules can be optimized by forecasting the moisture levels in transformer oil-paper insulation, preventing moisture from reaching harmful levels [5]. Therefore moisture forecasting can help prolong the transformer's life and reduce the prerequisite for repairs or replacements, ultimately saving energy [6]. Additionally, by monitoring and controlling the moisture levels in the transformer, the transformer's efficiency can be maintained, which in turn will help to reduce energy losses and improve the overall performance of the electrical grid. Furthermore, moisture forecasting can be used to anticipate the likelihood of moisture-induced defects, which can be used to plan transformer maintenance. Therefore, the danger of unplanned outages is reduced, and energy distribution can be planned appropriately.

Several methods for predicting moisture in transformer oil-paper insulation have been put forth in the literature. Dielectric frequency domain spectroscopy (DFDS), a non-destructive testing method used to assess the state of transformer oil-paper insulation, is one of the most frequently employed techniques [7]. The loss factor (tan delta), which is associated with the transformer oil-paper insulation's dielectric properties, is a measurement of the energy dissipation of the insulation. Another technique that has been proposed in the literature is the usage of sensors, such as capacitive sensors [8], resistive sensors [9], and optical sensors [10]. The moisture level in the oil-paper insulation of a transformer can be measured with these sensors. However, the intrusive nature of these sensors can compromise the transformer's oil-paper insulation integrity. Recently, machine learning-based approaches have been utilized for predictive health monitoring in transformer oil-paper insulation [11]. These methods predict the crucial factor in the transformer oil-paper insulation by using features obtained from the dielectric properties as inputs to a machine learning model, such as neural networks. Some studies have shown that these machine learning-based approaches can effectively anticipate crucial health-sensitive parameters and can be applied for the prognostic health monitoring of transformer oil-paper insulation. Implementing predictive maintenance is anticipating when moisture levels may be high and taking precautions before problems arise; this is done by analyzing historical information and applying machine learning algorithms. In terms of managing numerous correlated time series, long short-term memory (LSTM), a form of recurrent neural network (RNN), is frequently seen as being superior at prediction compared to conventional statistical techniques, such as autoregressive integrated moving average (ARIMA) [12,13]. Additionally, LSTM networks can learn and represent non-linear correlations in the data, which is challenging to perform with conventional statistical techniques. Based on the content of existing literature, a novel method of a moisture determination-based DFDS test conducted on a small number of samples is presented in this paper. The findings suggest that the reported technique can predict oil-paper insulation moisture to obtain feature parameters for training the LSTM model. The key novelty of this research is to adopt a hybrid DFDS-LSTM-based approach to transformer moisture diagnosis.

2. Materials and Methods

The current density within insulation can be expressed in terms of the conduction current, the vacuum, and polarization displacement currents. The transition from the time to the frequency domain can be achieved analytically by the Fourier transform. The relationship between the total current density, $J(t)$, and the electric field intensity, $E(t)$, within an insulation system is expressed in the s domain as follows [14]:

$$J(\omega) = \sigma_o \overline{E}(\omega) + j\omega\epsilon_o \overline{E}(\omega) + j\omega\epsilon_o \overline{F}(\omega)\overline{E}(\omega) \tag{1}$$

The Fourier transform of the dielectric response function is denoted as $\overline{F}(\omega)$, which is equivalent to the complex susceptibility $\overline{\chi}(\omega)$ [15], where $\overline{\chi}(\omega)$ can be represented as imaginary and real components ($\overline{\chi}(\omega) = \chi'(\omega) - j\,\chi''(\omega)$) as follows:

$$J(\omega) = \omega\epsilon_o \left\{ \left[\frac{\sigma_o}{\omega\epsilon_o} + \chi''(\omega) \right] + j[1 + \chi'(\omega)] \right\} \overline{E}(\omega) \tag{2}$$

In terms of the complex relative dielectric permeability, ($\overline{\varepsilon}_r = \epsilon_r{}'(\omega) - j\,\epsilon_r{}''(\omega)$) can be expressed as follows:

$$J(\omega) = j\omega\epsilon_o[\epsilon_r{}''(\omega) - j\,\epsilon_r{}''(\omega)]\overline{E}(\omega) \tag{3}$$

By comparing Equations (2) and (3), the frequency-dependent dielectric dissipation factor can be given as follows:

$$tan\delta = \frac{\epsilon_r{}''(\omega)}{\epsilon_r{}'(\omega)} = \frac{\frac{\sigma_o}{\omega\epsilon_o} + \chi''(\omega)}{1 + \chi'(\omega)} \tag{4}$$

Transformer oil-paper insulation is examined using DFDS, a non-destructive testing method. As shown in Figure 1, the procedure comprises supplying the transformer with a variable-frequency alternating current (AC) voltage and measuring the transformer oil-paper insulation's complex permittivity and loss factor in the frequency domain. The transformer oil-paper insulation has abnormalities, including moisture retention, partial discharge, and other impurities, which can be found and located using the DFDS procedure, which is a robust tool for monitoring the insulation condition.

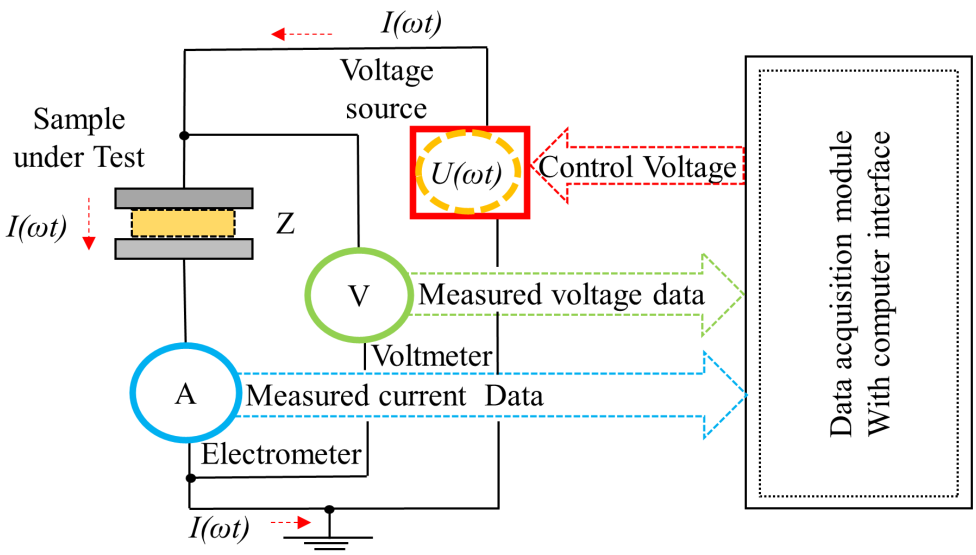

Figure 1. Schematic diagram of the dielectric frequency domain spectroscopy (DFDS) system.

The loss factor and the energy loss of the transformer insulation can also be directly correlated with energy dissipation.

The simplified expression for the energy loss per unit volume (E) can be expressed as:

$$E = 2\pi f * \varepsilon_o \varepsilon_r'' * E_o^2 \tag{5}$$

where f is the frequency, and the electric field strength is represented by E_o.

2.1. Accelerated Aging Experiment

The insulation samples used for the accelerated aging of transformer oil-paper insulation samples are prepared in a laboratory by simulating the conditions that cause aging in real-world transformers. A flowchart of the experiment design for extracting the DFDS dataset for the transformer moisture diagnostics technique is shown in Figure 2. The experimental setup for conducting accelerated thermal aging and dielectric frequency domain spectroscopy (DFDS) analysis of various aging samples is demonstrated in Figure 3a. The OPI aging samples use copper foil to replicate the high and low-voltage transformer windings (C, D). The composite insulation system is also simulated using a pressboard cylinder (A) and kraft paper (B, E); pressboard strips are utilized to separate the B and E kraft and to imitate oil ducts, as presented in Figure 3b. The insulation samples were constructed using kraft paper, a pressboard cylinder, and mineral oil with a density of 0.89 g/cm^3 at 20 °C.

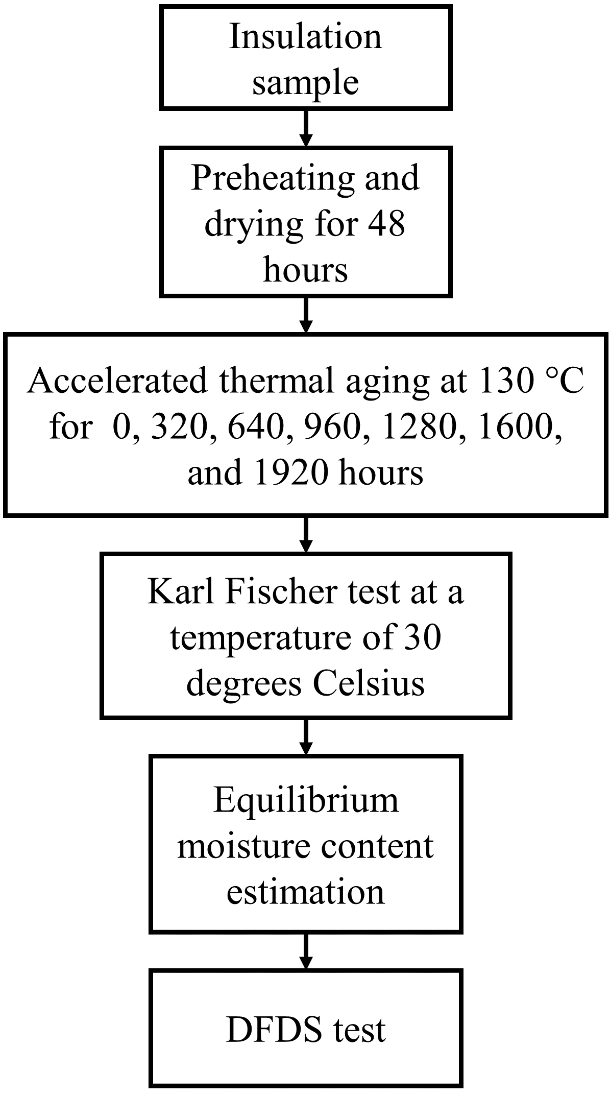

Figure 2. Schematic illustrating the experimental technique.

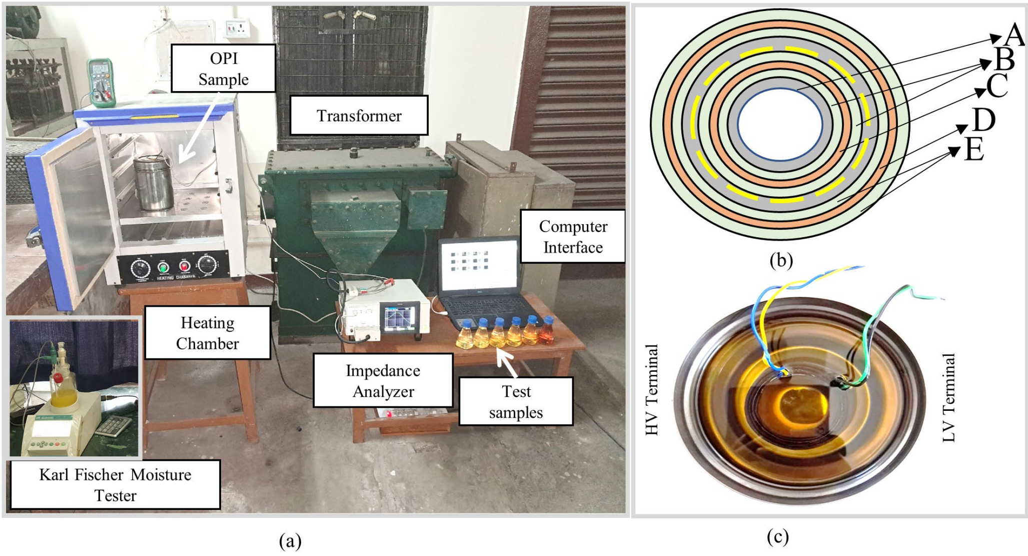

Figure 3. (**a**) Laboratory DFDS test setup with insulation sample and test oil samples, (**b**) Schematic view of the test sample, (**c**) Prepared sample.

In this study, 20 laboratory-prepared insulation samples were examined to analyze moisture variation within transformer oil-paper insulation. The samples underwent a preheating process for 48 h to remove the initial moisture content. The study utilized 14 of the 20 samples for training and 6 for validation and testing. Seven of the samples were subjected to accelerated aging at intervals of 0, 320, 640, 960, 1280, 1600, and 1920 h, and the same process was repeated for the remaining seven training samples. Notably, the training data was obtained from the 14 samples with an initial moisture content of less than 0.5%. To validate the results, accelerated aging samples were collected for testing and validation by taking out samples at various time intervals, up to 1920 h. In this research study, the oil moisture content was measured in parts per million (PPM) using the Karl Fischer test at a temperature of 30 degrees Celsius. Based on the results, the moisture content in the paper was estimated using Oommen moisture equilibrium curves. Subsequently, the dielectric frequency response of the insulation samples was measured using an impedance analyzer instrument to generate the DFDS dataset. The range of tan delta ($tan\delta$) measurements in the study was between 0.00225 and 0.383, which provides valuable insights into the electrical properties of the transformer oil-paper insulation.

The radar plot in Figure 4 provides valuable insights into the aging behavior of the tan delta values. It can be determined that the tan delta is higher in the low-frequency regions, except for the initial samples with low moisture content. Additionally, the plot reveals that the tan delta of the samples increases as the aging process advances in a clockwise direction. It is apparent that the aging conditions affect the dielectric properties of the insulation, specifically in the lower frequencies, and it helps monitor the state of the transformer oil-paper insulation and identify potential problems before they lead to significant failures. It is clearly evident from Figure 4 that the variation in tan delta with aging at varying frequencies is barely noticeable. This fact highlights the difficulty in extracting moisture-sensitive features from the dielectric frequency domain spectroscopy data using conventional statistical methods.

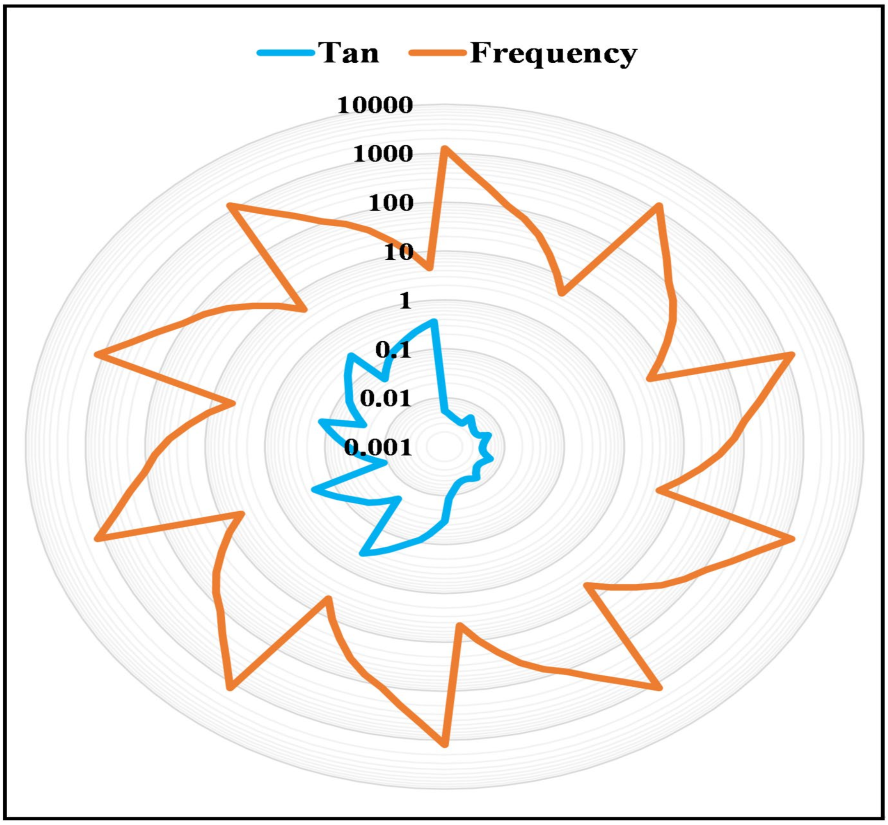

Figure 4. Radar plot of frequency and tan delta variations over the aging of transformer oil-paper insulation.

Moisture content is an essential indicator of the condition and aging of the transformer oil-paper insulation, and it is crucial to forecast it accurately. However, the stability of the dielectric properties makes it difficult to extract moisture-sensitive features from the DFDS data. Therefore, this paper proposes using an LSTM-based deep learning method for forecasting moisture variation inside the transformer tank through non-intrusive DFDS feature parameters. LSTM is a recurrent neural network that can capture temporal dependencies in the data, allowing it to make accurate predictions even when the data is not easily interpretable using conventional statistical methods [16]. Although insulation DFDS is also affected by the aging duration, the literature suggests that the effect of moisture on DFDS is significantly higher than aging [17]. This disparity becomes even smaller for oil-immersed insulation, thus justifying the proposed approach for moisture estimation through learning non-linear temporal dependencies using LSTM. Several accelerated aging tests of varying durations were carried out to study the impact of thermal aging on transformer oil. Utilizing a coulombmeter setup based on the Karl Fischer titration (KFT) technique, the moisture content of the oil is estimated. An impedance analyzer instrument was employed to measure the curves' DFDS characteristics of insulation samples. Predictive maintenance for transformer moisture assessment using machine learning algorithms involves several steps:

- Collecting historical data on moisture levels in the transformer oil and paper insulation while relevant variables.
- Data preprocessing through cleaning and transforming the data to remove any missing or inaccurate values.
- Training the ML model through preprocessed data to predict moisture levels based on the input variables.
- Validating the model through a separate dataset ensures generality and accurate prediction of different moisture levels.

2.2. Proposed Model

Long Short-term Memory (LSTM) is a recurrent neural network that excels at forecasting time series data. LSTMs have been demonstrated to perform effectively well on time series forecasting tasks. Furthermore, they have been employed in various industrial applications, including power system monitoring and control [18]. LSTMs are intended to respond with sequential data with many dependencies and long-term trends. An LSTM's central concept is to utilize gates to control the flow of information across the network, allowing it to recall specific information for more extended periods. An LSTM model is trained using specific information and data, which in this investigation includes historical data of oil moisture measurements, dielectric loss factor, aging hour, and cyclic features. These features are then extracted from the data to predict insulation conditions in terms of forecasting transformer oil moisture levels.

The input-output equation of an LSTM model can be represented as follows:

$$y(t) = f(x(t), h(t-1), c(t-1)) \tag{6}$$

where $y(t)$, $x(t)$, $h(t-1)$, $c(t-1)$, and $f(.)$ is the output at time step t, the input at time step t, the hidden state at time step t-1, the memory cell state at time step t-1, and the LSTM function, respectively. The LSTM function maps the input, hidden state, and memory cell state to the output at time step t [19]. The LSTM model takes in the input $x(t)$ at each time step t and uses it along with the hidden state $h(t-1)$ and memory cell state $c(t-1)$ from the previous time step to calculate the output $y(t)$ at the current time step. The hidden state and memory cell state is updated at each time step based on the input and previous hidden state, allowing the LSTM to maintain a certain level of information for an extended period. In more detail, the LSTM model takes the input features, the DFDS, and the aging hours (AH), and processes them through multiple layers of LSTM cells and fully connected layers. The LSTM cells capture the temporal dependencies in the data, while the fully connected layers map the input features to the output, which is the moisture concentration. Figure 5 provides a visual representation of the comprehensive training process for the whole moisture diagnosis algorithm. The training operation of an LSTM-based model for forecasting moisture variation inside the transformer tank using aging hour and tan delta as feature parameters involves several steps:

- Data preparation: the first step is to prepare the data for training, which includes collecting and preprocessing the data, such as cleaning, normalizing, and segmenting the data. The data is divided into input and output sets, with the aging hour and tan delta as the input features and moisture as the target or output.
- Model architecture: the LSTM model architecture is defined, including the number of layers, the number of units in each layer, and the activation functions used. The model architecture is designed to handle the input data, with the input layer reshaped to match the shape of the input data and the output layer designed to output the moisture values.
- Training: the model is then trained using the input-output data sets, where the input is the aging hour and tan delta data, and the output is the corresponding moisture content. The model is trained to learn the non-linear relationship between the input features and the output and make accurate moisture content predictions.
- Optimization: during the training process, the model is optimized using a chosen optimization algorithm, such as Adadelta, to minimize the error between the predicted and actual moisture content. The learning rate of the optimizer is a hyperparameter that is adjusted to optimize the model's performance.
- Evaluation: the model is evaluated using a validation set to assess its performance and accuracy after the training process, and it is fine-tuned by adjusting the hyperparameters.

- Forecasting: once the model is trained and optimized, it can forecast moisture content in transformer oil-paper insulation. The model takes an aging hour and tan delta as inputs and forecasts the moisture content.

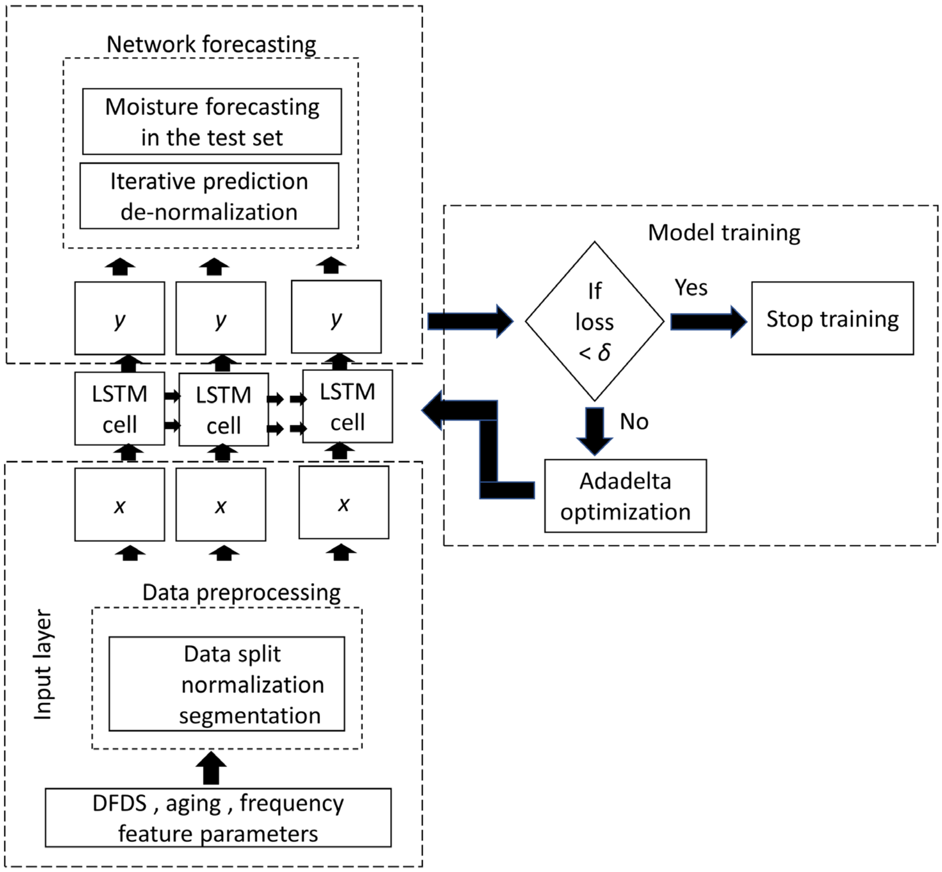

Figure 5. The flowchart of the moisture diagnosis algorithm.

The model architecture and hyperparameters, determined empirically in this study, are fine-tuned during the training phase to achieve the best outcomes. In this investigation, the moisture content of transformers was predicted using a long short-term memory network model. The model's architecture comprised an input layer, an LSTM layer, and a dense output layer. The input layer had the shape of (5, 6), which is implemented using the Keras library. This input layer reshaped the input data to a specific shape that the LSTM layer could handle. The LSTM layer had 100 units, and it is responsible for capturing the temporal dependencies in the data. The loss function used in the study was the mean absolute error (MAE).

A sigmoid activation function, a prevalent choice for this type of problem, was utilized by the LSTM layer. The sigmoid function is utilized to introduce non-linearity to the model, enabling it to learn intricate connections between the input and output properties. The output layer is a dense layer with a single unit that maps the output of the LSTM layer to the final predicted moisture content. The dense layer is connected to the LSTM layer with fully connected weights, allowing it to make a final prediction based on the output of the LSTM layer. The LSTM model was trained to utilize a series of input-output pairs consisting of dielectric frequency domain spectroscopy and aging hour data as inputs and the corresponding moisture content as the output. Through utilizing this technique, accurate moisture forecasting was acquired for oil-paper transformer insulation.

2.3. Model Optimization

Recurrent neural networks, such as LSTM, primarily excel at time series forecasting. However, adequate tuning of the LSTM model is required for excellent performance. Hyperparameters are adjustable parameters of a machine learning model that are established before the training process and do not undergo modification during training. A combination of hyperparameters, including the number of LSTM layers, learning rate, and sequence length, were employed in a deep-learning model to predict transformer insulation conditions through moisture forecasting. The selection of the optimal hyperparameters was achieved using a combination of techniques, such as grid search, error, and the reduce on plateau method.

The Adadelta optimizer is a popular method for tuning LSTM models. Adadelta is an adaptive learning rate optimization algorithm that modifies the learning rate automatically during training. It makes use of the gradient and past data to adjust the learning rate on the run. Adadelta is very effective for deep neural network training, such as LSTM, because it can help overcome diminishing or exploding gradients [20]. In this study, an Adadelta optimizer was utilized to tune the LSTM model. The initial learning rate was set to 0.01, and ρ and ε values were kept to 0.98 and 1×10^{-8}, respectively. The optimal learning rate that yields the best performance is chosen using a grid search method by evaluating its performance on a validation set. Also, Adadelta has the advantage of requiring less memory and processing than other optimization techniques, such as Adam, RMSprop, and Adagrad. Furthermore, it is less sensitive to the initial learning rate, making it more resistant to hyperparameter selection [21]. The Adadelta optimizer increased the performance of the proposed LSTM model for obtaining accurate moisture forecasting results in transformer oil-paper insulation.

3. Results

The proposed LSTM-based transformer's insulation moisture forecasting model was trained and evaluated on a compiled dataset of dielectric frequency domain spectroscopy measurements of oil-paper insulation, which empowers the model to predict future moisture levels in the insulation accurately. During the model training, 70% of the dataset was used, while the remaining 30% was split into a 15% test set and a 15% validation set, the former was used to evaluate the model's performance, and the latter was used for hyperparameter tuning and overfitting prevention. An LSTM model on the dielectric aging DFDS dataset is trained in this study, and its performance is assessed by depicting the loss curve. The loss curve shown in Figure 6 demonstrates that the model's error lowers consistently as the training iterations are increased, demonstrating that the system effectively learns from the training data. The final training loss achieved by the model is 0.027, which is relatively low compared to the range of possible loss values. Additionally, the curve also exhibits a progressive decline in fluctuations, indicating that the model is not overfitting the training set of data. These outcomes show how well the LSTM model generalizes well to new information and, therefore, is effective at learning the features in the dataset. After the training operation is complete, the model validation is carried out independently on a previously intact sample. Quantifiable metrics, including the R-squared (R^2) value, are used to assess the performance and generalization capabilities of the proposed moisture level forecasting model. R-squared is a statistical measure that shows the percentage of the variance in the dependent variable that can be predicted by the independent variable. R-squared is typically used to measure the fraction of the variance in observed oil moisture levels that are predictable from the historical data provided as input to the LSTM model when forecasting transformer oil moisture.

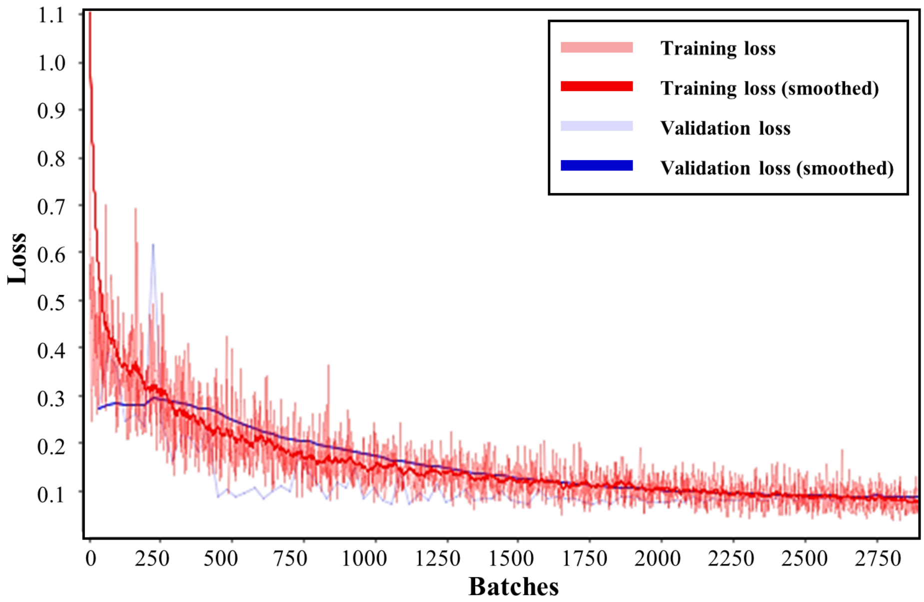

Figure 6. Loss curve vs. batches curve of the LSTM forecasting model.

The results of the LSTM-based moisture forecasting model are displayed in Figure 7. The x-axis represents the time in hours, and the y-axis represents the moisture content in percentage. The red line represents the actual moisture content, and the green line represents the forecasted moisture content. The plot illustrates the ability of the LSTM model to accurately predict the moisture content of transformer oil-paper insulation over time. The plot shows a good alignment between the actual and forecasted values, indicating that the model has a high level of accuracy and reliability.

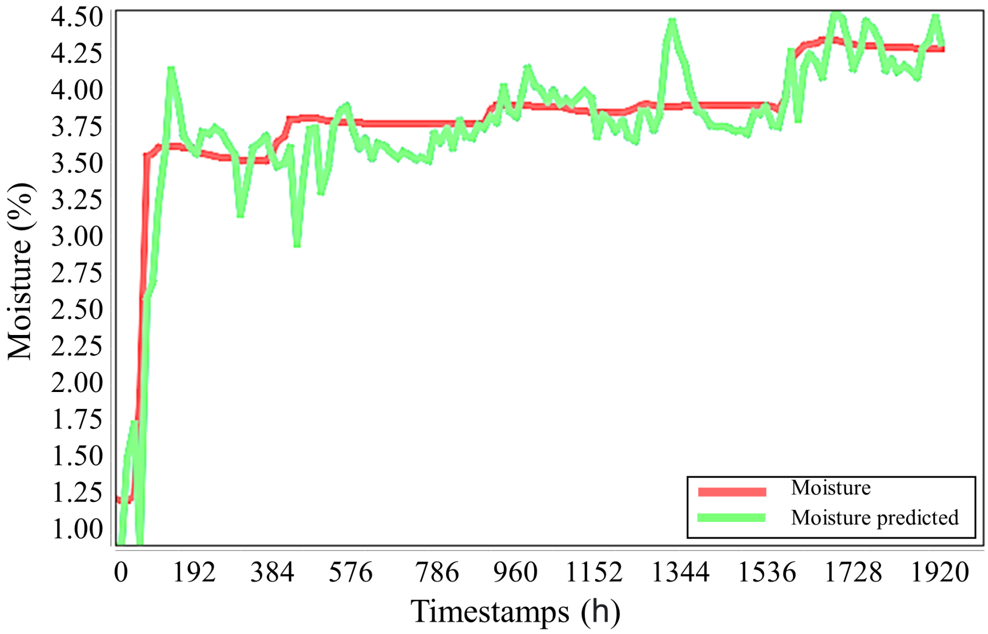

Figure 7. Results of the LSTM-based moisture forecasting model.

Table 1 summarizes the forecasting model's performance metrics using R^2, mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and mean signed difference (MSD). These metrics are commonly used to evaluate the performance of forecasting models and provide a comprehensive evaluation of the model's accuracy and consistency. The R^2 measures how well the model fits the data; it ranges between

0 and 1, where one means that the model perfectly fits the data. MAE, MSE, and RMSE are measures of the error between the predicted and actual values. MSD measures the difference between the predicted and actual values that consider the difference's sign. The values in the table represent the average error or difference across all the predictions made by the model. An R-squared value of 0.899 indicates that the model fits the data well and explains a large proportion of the variance in the observed oil moisture levels. This value indicates that the LSTM model is able to explain 89.9% of the variance in the moisture content of transformer oil-paper insulation.

Table 1. Performance metrics of the moisture forecasting model.

R^2	MAE	MSE	RSME	MSD
0.899	0.166	0.058	0.241	0.060

The proposed model's MAE, MSE, and RMSE values were determined to be 0.166, 0.058, and 0.241, respectively, correspondingly showing a modest average difference between predicted and actual moisture levels. The proposed approach was also compared to two regularly used moisture forecasting models: a traditional linear regression model and a random forest (RF) model. In terms of accuracy, the suggested LSTM model outperformed the classic linear regression model and the RF model, with an R-squared value of 0.899 vs. 0.376 and 0.654, respectively. The LSTM model also outperformed linear regression and RF in terms of MAE, MSE, and RMSE, with values of 0.166, 0.058, and 0.241, respectively, versus 0.226, 0.172, and 0.414, respectively, for linear regression and 0.205, 0.151, and 0.387 for RF, respectively. Table 2 compares the proposed model's performance metrics with linear regression and the random forest model.

Table 2. Comparison of the performance metrics of the proposed model with linear regression and random forest models.

MODELS	R^2	MAE	MSE	RSME
LR	0.376	0.226	0.172	0.414
RF	0.654	0.205	0.151	0.387
LSTM	0.899	0.166	0.058	0.241

Table 3 provides an average comparison of actual moisture, moisture forecast, and percentage error for different samples for ten iterations. The performance of the proposed model was evaluated using percentage error, a widely used metric to measure the accuracy of forecasting models. The percentage errors for the proposed model were calculated using the formula: percentage error = (|actual value–predicted value|/actual value) × 100. The results showed that the percentage errors for the proposed model were 3.22, 3.13, 0.54, 0.52, and 0.48 for five different samples. The proposed model achieved an average percentage error of 1.57%. These results demonstrate the potential of the proposed model to provide more accurate predictions of moisture content in transformer oil-paper insulation.

Table 3. Comparison of actual moisture, moisture forecast, and percentage error.

Moisture (%) (Actual)	Moisture (%) (Forecast)	Absolute Error (Forecast)	Percentage Error (Forecast)
1.24	1.20	0.04	3.22
1.28	1.24	0.04	3.13
3.70	3.68	0.02	0.54
3.87	3.85	0.02	0.52
4.12	4.10	0.02	0.48

4. Discussion

The maintenance and longevity of power transformers are crucial for ensuring stability in energy systems. The moisture in transformer oil-paper insulation can cause deterioration and result in electrical failures. Therefore, to prevent such issues, it is crucial to forecast the moisture levels in the insulation accurately. In this regard, this study proposes a novel approach to moisture diagnosis that uses a hybrid DFDS-LSTM method. The hybrid method combines the benefits of deep feature selection, and long short-term memory techniques have the potential to improve the accuracy of moisture prediction. The proposed method was tested using a dataset of transformer oil moisture readings. In terms of accuracy and efficiency, the proposed method performed well with an R^2 value of 0.899, thus proving itself as a valuable tool for power system operators to monitor and manage the integrity of their transformer fleet. This study highlights the potential of a deep learning approach for accurately identifying transformer oil insulation moisture and contributes to developing effective prognostic health management systems for transformers.

In this study, the performance of long short-term memory (LSTM) networks was compared with linear regression and random forest models for forecasting transformer moisture. According to the findings, the LSTM model performed significantly better in performing accurate predictions than the linear regression or the random forest models. LSTM networks could capture long-term dependencies in the data by using a memory cell, which allows them to maintain a certain level of information for an extended period. Hence it is beneficial for transformer moisture forecasting, as the moisture content of the transformer oil-paper insulation is affected by both short-term and long-term factors, such as temperature, aging, and dielectric properties. In contrast, linear regression and random forest models are not intended to handle time series data and cannot capture long-term dependencies within the data [22]. In this investigation, the linear regression model failed to capture the non-linear relationship between input characteristics and moisture content. The random forest model captured the non-linear relationship between the input features and the moisture content, although it performed worse than the LSTM model. As a result of their ability to capture long-term dependencies in the data, LSTM networks are especially suited for transformer moisture forecasting tasks. Furthermore, their capacity to handle non-linear relationships between input features and output makes them a better alternative for transformer moisture predictions than linear regression and random forest models.

5. Conclusions

In this research, accelerated aging insulation samples were prepared in the laboratory to rapidly obtain the moisture-effected aging characteristics of the transformer insulation. Dielectric spectroscopy of oil-paper samples was obtained; however, moisture-sensitive features are complex to extract for accurate moisture forecasting. A deep learning method based on LSTM was proposed to forecast moisture variations inside the transformer tank through non-intrusive DFDS feature parameters. The proposed model was validated by collecting data from a real-life transformer, and the results showed that the proposed model was able to accurately predict moisture variations inside the transformer tank. The DFDS dataset was analyzed to extract moisture-sensitive features, and the LSTM-based deep learning method was proposed to forecast the moisture variation inside the transformer tank. The model was trained and validated using the DFDS dataset and the moisture measurements of the samples. The results of this study provide insight into the moisture variation inside the transformer oil-paper insulation and demonstrate the potential of the proposed LSTM-based model to provide accurate and non-intrusive moisture forecasting.

Overall, this research demonstrates the effectiveness of using LSTM-based deep learning for forecasting moisture variations in transformer oil-paper insulation. The proposed model can be used for prognostic monitoring of transformer oil-paper insulation and predicting the transformer's health status. This study can help prolong the transformer's life and reduce the need for unplanned repairs or replacements, eventually saving energy.

Furthermore, the results of this research can potentially improve the electrical grid's overall performance by reducing energy losses and minimizing the risk of unexpected outages.

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