# APPLICATION OF DEEP LEARNING TECHNIQUES IN DETECTING AND DIAGNOSIS OF POWER TRANSFORMER FAULTS

## ỨNG DỤNG KỸ THUẬT HỌC SÂU (DEEP LEARNING) TRONG PHÁT HIỆN VÀ CHẨN ĐOÁN SỰ CỐ MÁY BIẾN ÁP ĐIỆN LỰC

**Truong Chi Trung[1]*, Dinh Hoang Bach[2], Phan Thanh Tai[2]**

*[1]Quality Assurance and Testing Center 3, Vietnam*
*[2]Power System Optimization Research Group, Faculty of Electrical and Electronics Engineering, Ton Duc Thang University, Ho Chi Minh City, Vietnam*

*Corresponding author: trung.tc@quatest3.com.vn

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**Abstract -** The power sector plays a pivotal role in ensuring a stable energy supply for socio-economic activities. Power transformers are critical equipment but are susceptible to potential faults that can cause severe operational disruptions. In this context, deep learning technology has emerged as an advanced solution capable of automatically extracting and learning hidden features from operational data. This paper applies a multilayer perceptron (MLP) neural network model to detect and diagnose transformer faults based on dissolved gas analysis (DGA) data simulated according to IEC 60599 standards. Experimental results show that the deep learning model achieves high accuracy in classifying equipment conditions, thereby enhancing operational condition monitoring and supporting proactive maintenance decision-making in power systems.

**Key words -** Deep learning; transformer fault diagnosis; dissolved gas analysis; condition monitoring; multilayer perceptron.

**Tóm tắt -** Ngành điện lực đóng vai trò then chốt trong đảm bảo nguồn năng lượng ổn định cho các hoạt động kinh tế - xã hội. Máy biến áp điện lực là thiết bị trọng yếu, tuy nhiên dễ gặp phải các sự cố tiềm ẩn gây ra gián đoạn vận hành nghiêm trọng. Trong bối cảnh đó, kỹ thuật học sâu (Deep Learning) nổi lên như một công nghệ tiên tiến có khả năng tự động khai thác, học hỏi các đặc trưng ẩn sâu trong dữ liệu vận hành thiết bị. Bài báo này ứng dụng mạng nơron nhiều lớp (Multilayer Perceptron - MLP) để phát hiện và chẩn đoán sự cố máy biến áp dựa trên tập dữ liệu phân tích khí hòa tan (Dissolved Gas Analysis - DGA) mô phỏng theo tiêu chuẩn IEC 60599. Kết quả thực nghiệm cho thấy mô hình học sâu đạt độ chính xác cao trong việc phân loại tình trạng thiết bị, từ đó giúp nâng cao hiệu quả giám sát tình trạng vận hành và hỗ trợ ra quyết định bảo trì chủ động trong hệ thống điện.

**Từ khóa -** Học sâu; chẩn đoán sự cố máy biến áp; phân tích khí hòa tan; giám sát tình trạng thiết bị; mạng nơron nhiều lớp.

## 1. Introduction

Amidst the robust process of industrialization and modernization in Vietnam, the demand for stable, safe, and sustainable energy has become an urgent requirement for the nation’s socio-economic development. According to the Ministry of Industry and Trade's report in 2023, the total electricity demand in Vietnam has been growing at an average rate of approximately 8–10% per year, placing significant pressure on the power transmission and distribution system [1].

Power transformers, serving as key equipment in the transmission system, are responsible for converting voltage levels to meet usage requirements at various stages. However, during prolonged operation under high load conditions and harsh environmental factors such as temperature and humidity, transformers are prone to faults such as partial discharge, winding overheating, and degradation of insulating oil quality [2]. Statistics from the National Power Transmission Corporation (EVNNPT) indicate that, during the period from 2015 to 2020, transformer-related incidents accounted for nearly 28.7% of all faults occurring in the transmission grid [3].

Notably, severe faults can lead to widespread power outages, disrupt production activities, affect daily life, and cause estimated economic losses of hundreds of billions of VND each year [4]. The 2022 report "Assessment of Power System Reliability in Vietnam" also shows that, on average, about 40–50 transformer faults are recorded annually, most of which are due to late detection of insulation degradation or operational errors.

To enable early detection of potential transformer failures, DGA is considered a standard method, regulated by international standards such as IEC 60599 and IEEE C57.104-2019 [5]. DGA allows the identification of fault types by analyzing the components and ratios of gases generated in insulating oil. However, traditional methods such as the gas ratio method and Duval triangle, while providing significant support, still have certain limitations: their accuracy heavily depends on expert experience, automation is difficult, and precise identification in complex situations remains challenging [6].

In the era of digital transformation and the Fourth Industrial Revolution, the application of artificial intelligence (AI) technologies in monitoring and diagnosing electrical equipment, particularly deep learning techniques, is expected to open new approaches. Deep learning models are capable of learning complex nonlinear relationships in data, automatically extracting hidden features, thereby improving diagnostic accuracy and speed [7].

Globally, numerous studies have demonstrated the effectiveness of machine learning models based on neural networks in diagnosing electrical equipment faults through DGA data analysis [8]. In Vietnam, the National Strategy for Renewable Energy Development and Power System Reliability Enhancement for the period 2021–2030, with a vision to 2045, also emphasizes the need to promote the application of intelligent technologies such as artificial intelligence in the operation and maintenance of critical equipment like transformers [9].

Based on these practical needs, this study proposes a MLP neural network model for the task of detecting and diagnosing transformer faults using DGA data simulated according to IEC 60599 standards. The contribution of this research lies in standardizing the DGA processing and training procedure per IEC 60599 with a simple MLP architecture, which is easy to implement under limited data and computational infrastructure conditions in Vietnam, thereby laying the groundwork for practical applications in transformer condition monitoring.

The model is trained and evaluated on a dataset simulated according to IEC 60599 standards, achieving an accuracy of approximately 96.0% on the test set, thereby validating the effectiveness of deep learning techniques in monitoring power transformer operations.

Although MLP is a basic architecture and has been investigated in several international studies, this paper focuses on demonstrating the effectiveness of IEC-standardized MLP deployment in the context of limited data, while also establishing a foundation for extending to advanced architectures (CNN, RNN, Transformer) in future research.

## 2. Multilayer Perceptron (MLP) for transformer fault diagnosis

### *2.1. Multilayer Perceptron (MLP) Model*

The Multilayer Perceptron (MLP) architecture is selected to perform transformer fault classification due to its capability to model nonlinear relationships between dissolved gas components (DGA) and transformer operating conditions. The model receives seven input features, including the concentrations of $H_2$, $CH_4$, $C_2H_2$, $C_2H_4$, $C_2H_6$, $CO$, and $CO_2$. All features are normalized to ensure numerical stability and improve convergence during training. The overall neural network structure consists of one input layer with seven nodes, three hidden layers activated by ReLU, and one output layer with three nodes corresponding to the operating states: normal, partial discharge, and thermal fault. The schematic diagram of the MLP architecture is shown in Figure 1.

The model configuration uses seven input parameters, including the concentrations of the following gases: $H_2$, $CH_4$, $C_2H_2$, $C_2H_4$, $C_2H_6$, $CO$, and $CO_2$. These features are normalized prior to training to ensure scale consistency and optimize the convergence rate of the neural network.

The overall network structure includes one input layer with seven nodes, three hidden layers using the ReLU activation function, and one output layer with three output nodes corresponding to three transformer operating states: normal, partial discharge, and thermal fault.

The general architecture of the neural network is illustrated in Figure 1.

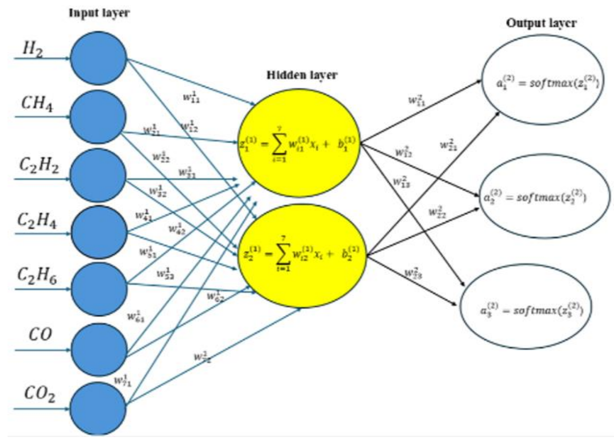


***Figure 1.*** *Schematic diagram of the MLP neural network architecture*

#### *2.1.1. Input Data*

In this study, input data are collected from DGA results of insulating oil in power transformers, including the following gas components: $H_2$ (Hydrogen), $CH_4$ (Methane), $C_2H_2$ (Acetylene), $C_2H_4$ (Ethylene), $C_2H_6$ (Ethane), $CO$ (Carbon monoxide), and $CO_2$ (Carbon dioxide) [4], [5]. All data are normalized before being fed into the training process to ensure stable convergence of the neural network and limit scale deviation among input variables.

#### *2.1.2. Formula for total input signal calculation*

At each node of the first hidden layer, the total input signal is calculated as the weighted sum of all input variables plus a bias term. The general formula is expressed as follows:

$$z_j = \sum_{i=1}^{7} w_{ij}\, x_i + b_j \tag{1}$$

where: $w_{ij}$ is the weight connecting input $i$ to hidden node $j$, $b_j$ is the bias of hidden node $j$, $x_i$is the value of the $i$-th dissolved gas input.

The signal is then passed through the ReLU activation function:

$$a_j = max(0,\ z_j) \tag{2}$$

The output nodes use the Softmax function to calculate the probability for each class:

$$z_j = \frac{e^{z_k}}{\sum_{t=1}^{K} e^{z_t}} \tag{3}$$

where $K = 3$ is the number of output classes (normal, partial discharge, thermal fault).

#### *2.1.3. Network output variables*

The neural network produces three output variables corresponding to three transformer operating states:

$a_1^{(2)}$ : normal state,

$a_2^{(2)}$ : partial discharge state,

$a_3^{(2)}$ : thermal fault state.

These outputs are computed by passing the total input signal of each output node through the Softmax function:

$$a_k^{(2)} = Softmax\left(z_k^{(2)}\right) = \frac{e^{z_k^{(2)}}}{\sum_{l=1}^{3} e^{z_l^{(2)}}}$$

with $k = 1, 2, 3$.

*2.1.4. Hidden layers*

Three hidden layers are used in the model to learn complex nonlinear features of the data. Each layer uses the ReLU activation function to enhance nonlinear separation between operating states.

*2.1.5. Output layer*

The output layer consists of three nodes, corresponding to three diagnostic states. The output nodes use the Softmax activation function to distribute probabilities across the classes.

*2.1.6. Activation functions*

The ReLU activation function is used for the hidden layers to optimize convergence and mitigate the vanishing gradient phenomenon. The Softmax activation function in the output layer is applied to model the multiclass classification problem.

***2.2. Training method for MLP in transformer fault diagnosis***

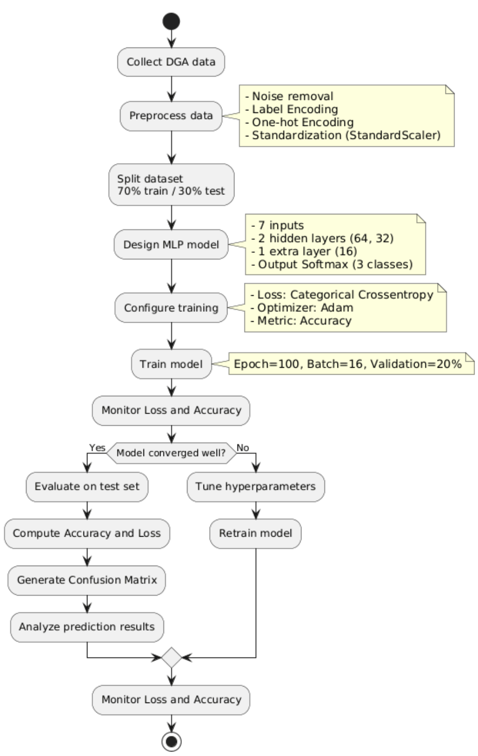


***Figure 2.*** *Flowchart of MLP training for transformer fault diagnosis*

The data used in this study are collected from the DGA dataset of insulating oil in power transformers, simulated according to IEC 60599 standards.

*Step 1: Data Preprocessing* – Input data include the gas features: $H_2$, $CH_4$, $C_2H_2$, $C_2H_4$, $C_2H_6$, $CO$, and $CO_2$. The transformer condition labels are encoded as integers using Label Encoding, then converted to one-hot vectors using One-Hot Encoding for multiclass classification. Input variables are normalized using the StandardScaler method to bring the data to a standardized distribution (mean 0, standard deviation 1), helping to accelerate convergence and stabilize the model.

*Step 2: Dataset Splitting* – The processed data are divided into two sets: 70.0% for training and 30.0% for testing, ensuring good generalization capability for the model.

*Step 3: Neural Network Construction* – The MLP is designed with:

- One input layer with seven nodes, corresponding to seven DGA gas parameters.

- Two hidden layers with 64 and 32 neurons, respectively, both using the ReLU activation function to enhance nonlinear learning.

- A third hidden layer with 16 neurons, also using ReLU.

One output layer with three nodes, corresponding to three transformer operating states, using the Softmax activation function for multiclass classification.

*Step 4: Model Configuration and Training* – The model is compiled with:

Adam optimization algorithm.

Categorical cross-entropy loss function suitable for multiclass classification.

Accuracy as the main evaluation metric. The model is trained for 100 epochs, with a batch size of 16, and 20% of the training data used for validation to monitor learning progress and detect early overfitting.

*Step 5: Model Evaluation* – After training, the model is evaluated on the test set, with loss and accuracy metrics recorded. Additionally, the loss and accuracy progression over epochs is plotted to analyze the model's convergence.

$$Accuracy = \frac{Number\ of\ correctly\ predicted\ samples}{Total\ number\ of\ test\ samples} \text{x}100\%$$

*Step 6: Prediction and Result Analysis* – After training, the model is used to predict the operating state labels of transformers on the test set. The steps include:

Probability prediction for each class: For each sample $i$, the model outputs a probability vector $p_i = [p_{i1}, p_{i2}, p_{i3}]$ corresponding to three states (Normal, Partial Discharge, Thermal Fault).

Label assignment: The predicted label $\widehat{y_i}$ for sample $i$ is determined by selecting the index of the highest probability:

$\widehat{y_i} = \arg\max p_{ik}$

Comparison with actual labels: Predicted labels $\widehat{y_i}$ are compared with actual labels $y_i$ to calculate accuracy and plot comparison charts.

Confusion matrix construction: The confusion matrix is built to analyze the number of samples correctly and incorrectly classified for each state group.

## 3. Experimental results and evaluation

### *3.1. Model training results*

The IEC 60599-simulated DGA dataset comprises three transformer operating state classes, with an uneven sample distribution: the Normal class accounts for about 70% of the total samples, while the two fault classes (Partial Discharge and Thermal Fault) each account for 15%. This results in data imbalance among the labels and may artificially inflate average accuracy if not evaluated per class.

The MLP neural network model using the Adam optimizer was trained on the DGA dataset for power transformers. The training process was conducted over 100 epochs, with a data split of 70% for training and 30% for testing to ensure the model's generalization capability.

All data processing and model training procedures were implemented in Python, using the Google Colab platform combined with open-source libraries such as TensorFlow, Keras, and Scikit-learn. Utilizing Google Colab allowed for free GPU resources to accelerate training and conveniently monitor model convergence.

The training progress chart (Figure 3) presents the variation of loss and accuracy as area charts:

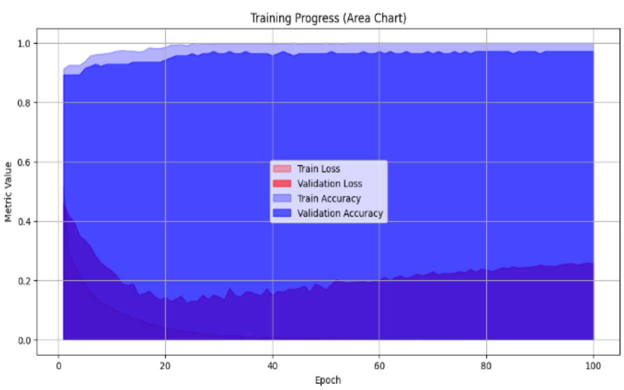


***Figure 3.*** *Training process: Area Chart of Loss and Accuracy by Epoch*

The loss metric on both training and test sets decreases rapidly during the initial phase (0–20 epochs), reaching a stable low level after about 30 epochs.

Training accuracy saturates near 1.0, while test accuracy remains stable around 0.96. To better reflect classification performance for each class, Precision, Recall, and F1-score metrics are calculated separately for the three labels. Results are summarized in Table 1.

***Table 1.*** *Performance metrics of the MLP model by class*

| Class | Precision | Recall | F1-score |
|---|---|---|---|
| Normal | 0.98 | 0.97 | 0.97 |
| Partial Discharge | 0.75 | 0.67 | 0.70 |
| Thermal Fault | 0.78 | 0.67 | 0.72 |
| Average | 0.84 | 0.77 | 0.80 |

These results indicate that the model classifies the Normal class well but requires improvement for the two fault classes due to insufficient training samples.

The Radar Chart (Figure 4) summarizes Accuracy, Validation Accuracy, Loss, and Validation Loss metrics. Results show that the model achieves very high accuracy on both training and test sets, with low loss values, reflecting stable training and no significant overfitting. This confirms the model's good generalization ability for new data.

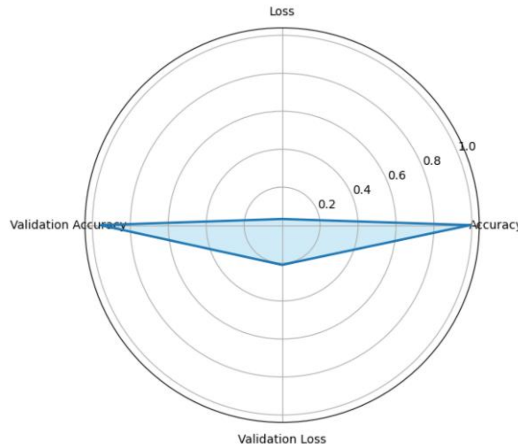


***Figure 4.*** *Radar Chart summarizing overall model performance*

### *3.2. Prediction results evaluation*

The Scatter Plot combined with Trend Line (Figure 5) illustrates the variation of Validation Loss over epochs.

Data points indicate that Validation Loss decreases rapidly in the initial phase, reaching a minimum around epochs 20–30. After this phase, Validation Loss shows a slight increase, reflecting a tendency toward overfitting if training continues for too long.

Accurate prediction of fault state groups (0: Normal, 1: Partial Discharge, 2: Thermal Fault) with minimal deviation at individual time points demonstrates that the model has effectively learned nonlinear features between DGA gas components and transformer operating states.

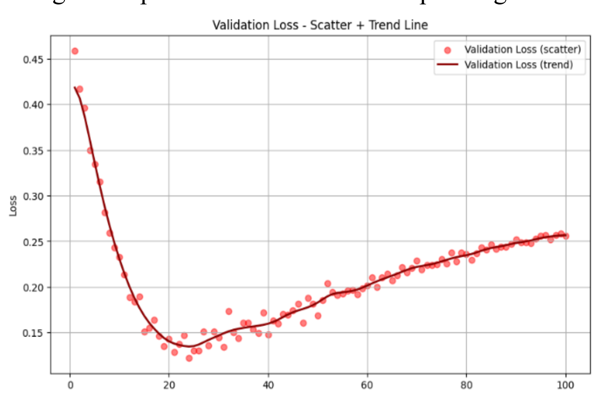


***Figure 5.*** *Validation Loss variation by Epochs (Scatter Plot + Trend Line)*

### *3.3. Confusion matrix and model performance analysis*

To evaluate the model's classification effectiveness in detail, the confusion matrix on the test set is constructed and presented in Figure 6.

Results show that the model achieves high classification accuracy: a total of 276 Normal samples are correctly predicted. Misclassification errors mainly occur between the Normal and Partial Discharge classes, with six Normal samples misclassified and three Partial Discharge samples misclassified. The Thermal Fault class has six samples correctly predicted and three misclassified as Normal.

No direct confusion between the two fault classes is recorded; however, the misclassification rate between the Normal and Partial Discharge classes remains significant (six Normal and three Partial Discharge samples misclassified). This clearly reflects the impact of data imbalance and explains why the average accuracy of 96.0% does not fully represent the model's comprehensive performance.

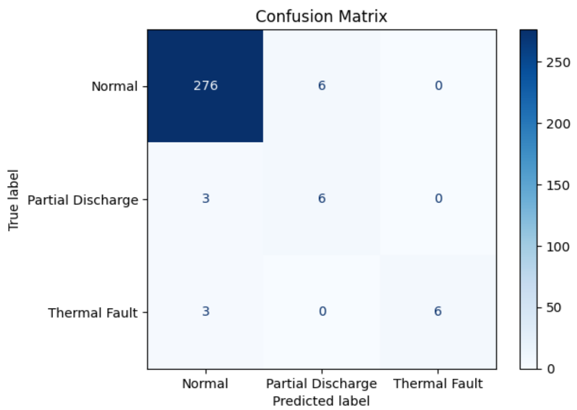


***Figure 6.*** *Confusion Matrix of transformer fault classification*

## 4. Conclusion

In this study, a MLP neural network model was developed and implemented to diagnose power transformer faults, based on DGA data following IEC 60599 standards [5]. The gas parameters $H_2$, $CH_4$, $C_2H_2$, $C_2H_4$, $C_2H_6$, CO, and $CO_2$ were selected as input variables for the model.

Experimental results show that the model achieves high accuracy, averaging about 96.0% on the test set, with loss maintained at a low level (~0.09). The model converges stably after about 20 to 30 epochs and does not exhibit significant overfitting. The training process chart and confusion matrix confirm that the model can effectively classify transformer operating states, including normal, partial discharge, and thermal fault, with a low misclassification rate.

The application of deep learning techniques in electrical equipment diagnosis, as demonstrated in this study, affirms the strong potential of automated models in enhancing power grid operational reliability. For performance comparison, the authors compared the proposed MLP model with two traditional machine learning methods: Support Vector Machine (SVM) and Decision Tree. Results show that MLP achieves 96.0% accuracy, outperforming SVM (90.0%) and Decision Tree (85.0%), demonstrating the superior effectiveness of deep learning models in DGA classification tasks. The proposed model supports real-time equipment condition monitoring and provides direction for proactive maintenance strategies, aligning with the modern digitalization trend in the power sector.

In the future, research can be expanded by experimenting with more advanced neural network architectures such as CNN, RNN, or Transformer, as well as applying automated hyperparameter optimization methods to further improve diagnostic performance on larger datasets.

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## REFERENCES

[1] Ministry of Industry and Trade of Vietnam, *Vietnam Electricity Development Report 2023*, Annual Report, 2023.

[2] National Power Transmission Corporation (EVNNPT), *Summary Report on the Operation of the Power Transmission Grid for the Period 2015–2020*, 2021.

[3] Institute of Energy, *Reliability Assessment Report of Vietnam Power System in 2022*, 2022.

[4] International Electrotechnical Commission (IEC), *"Interpretation of the analysis of gases in oil-filled transformers*," IEC 60599, 2015.

[5] Institute of Electrical and Electronics Engineers (IEEE), *Guide for the Interpretation of Gases Generated in Oil-Immersed Transformers*, IEEE Std C57.104-2019, 2019.

[6] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*, MIT Press, 2016.

[7] J. Zhang, Y. Liu, and W. Yang, "Transformer fault diagnosis based on dissolved gas analysis and deep learning models," *IEEE Transactions on Power Delivery*, vol. 35, no. 3, pp. 1231–1240, 2020.

[8] Ministry of Industry and Trade of Vietnam, *National Strategy for the Development of Renewable Energy to 2030 with a Vision to 2045*, Decision No. 2068/QD-TTg, Nov. 25, 2015.