Deep Neural Network for Fault Diagnosis of Power Transformers using Dissolved Gas Analysis

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ABSTRACT

The dissolved gas analysis, produced by deterioration of insulating oil, is the most popular diagnostic tool to detect various incipient faults in power transformers. So far, the handcrafted DGA features, such as DGA composition ratios (i.e., C2H2/C2H4, C2H4/C2H6, CH4/H2), have been often used as the input features of shallow learning or used to identify diagnostic criteria (i.e., Dornenburg Ratio, Rogers Ratio, IEC ratio) for the fault diagnosis of power transformers. However, a false alarm rate is relatively large due to the limitations of the handcrafted features because they are made up of two or three gas combinations that can classify the fault types in a low dimensional space that can be analyzed by the human inspection. To enhance DGA-based diagnostic accuracy, a novel method using deep neural network (DNN) is proposed to determine high-level features without relying on the handcrafted features. Specifically, many layers of nonlinear transforms in a DNN convert the raw DGA data into a highly invariant and discriminative representation without losing high-dimensional information that human cannot analyze in high dimensional space. This makes health classification more effective. A proposed method is validated from the reference database of IEC TC 10, which is the visual inspection data of transformer faults. The results indicate that the proposed DNN approach achieves higher accuracy than the existing methods based on shallow learning with the handcrafted features.

1. INTRODUCTION

The stable operation of the power system depends on the reliable operation of the various individual components within the power grid network. Power transformer plays a vital role in the transmission and distribution levels of a power system and its unexpected breakdown could cause a plant shutdown with substantial societal expenses. It is thus of great importance to accurately detect incipient faults of the power transformer.

The transformer transforms the alternating current supplied to one winding by the electromagnetic induction action to the alternating current voltage of the same frequency to the other winding, and the inside of the transformer is composed of winding, coil, and insulating oil. The major role of transformer insulation oil is electrical insulation and cooling. The objective of insulation is to insulate the transformer outer case and the winding inside the transformer, and the cooling is to cool the heat generated during the transforming process. This insulating oil is decomposed by aging or due to the harsh operating conditions such as, too high temperature, too high voltage or exposed to high current external faults etc. From the decomposed oil, the gas generated from the condensate is called dissolved gas and it is used as the most important factor in diagnosing the incipient faults of the transformer. The dissolved gas analysis is well-known method to diagnose six widely known incipient faults (Partial Discharge (PD), Low Discharge (D1), High Discharge (D2), Thermal Fault 1 (T1), Thermal Fault 2 (T2), Thermal Fault3 (T3)). Traditionally, for transformer incipient faults detection, a knowledge-based rules are applied to make handcrafted features from the dissolved gas profile. These handcrafted features, such as DGA composition ratios (i.e., C_2H_2/C_2H_4, C_2H_4/C_2H_6, CH_4/H_2), have been often used as the input features of shallow learning or used to identify diagnostic criteria (i.e., Dornenburg Ratio, Rogers Ratio, IEC ratio) for the fault diagnosis of power transformers. However, handcrafted features not only have relatively large false alarm rate, but also complicated to rule out and laborious to design appropriate features. Thus, it would be of great value to automatically learn features from low-level features or signatures from raw sensor measurements.

Instead of training shallow learning algorithm (KNN, SVM, Random forest, Naïve Bayesian etc.) by designing appropriate input features with statistical method or the knowledge based method, deep Learning can learn the features automatically. Deep Learning, known as a state of the art in machine learning, represents high-level features from low-level features through multiple layers of hidden layers. This ability can be seen from the deep learning research area, which shows that speech recognition, natural language process, and image recognition have achieved remarkably higher performance and proven outstanding performance.

To enhance diagnosis of accuracy in power transformer, inspired by the success of deep learning, we applied this deep learning technique to determine high-level features without relying on the handcrafted features.

The remaining of the paper is organized as follows. Section 2 presents related work; Section 3 describes our Experimental setup and model design; Section 4 presents our experimental results to demonstrate its applications. Finally, we conclude the study in Section 5.

2. RELATED WORK

The following section outlines the study of handcrafted features through dissolved gas and feature learning through deep learning.

2.1. Handcrafted Features from Dissolved Gas Concentration

Transformer fault diagnosis extracts handcrafted features that are related to faults types. Domain experts extract handcrafted features through manual process which were analyzed by the transformer faults and eight types of dissolved gas concentration (H_2, CH_4, C_2H_2, C_2H_4, C_2H_6, CO, CO_2, TCG). Specifically, these handcrafted features are made up of two or three gas combinations that can classify the fault types in a low dimensional space that can be analyzed by the human inspection. The boundary surface formed in the lower dimension helps to diagnose intuitively. However, since it is not a high-level features represented by using all eight types of dissolved gas, there are limitations in fault diagnosis.

2.2. Feature Learning in Deep Learning

In deep learning, feature learning transforms a raw data input to a highly invariant representative features that can be effectively exploited in machine learning tasks. This method could be done by using “dropout” and “Relu”, and can be applied to supervised learning or unsupervised learning, learning through the hidden layers of the neural network. Both are known to be robust in regularization.

2.2.1. Dropout

It is one of the most powerful regularization techniques at this time. Dropout improves the generalization error of large neural network. In the learning phase of Deep Neural Network, dropout drastically improves regularization by randomly omitting a fraction of the hidden units in hidden layers.

2.2.2. Rectified Linear Unit

This is also the most powerful activation function at this point in place of sigmoid function. The use of the rectifier as a non-linearity has shown to enable training deep supervised learning faster and efficient for gradient propagation, no vanishing gradient problems occurs. As a result, it has a powerful for regularization and representation.

3. EXPERIMENTAL SETUP AND MODEL DESIGN

The most fundamental problem in building diagnostic model through data-driven method in engineering system is the lack of labeled training data. In this study, the unlabeled data of 88,000 which were obtained from the Korea Electric Power Corporation were labeled using the Duval triangle known as the international diagnostic method. Classes are classified into seven categories, PD, D1, D2, T1, T2, T3 and normal state. The test data which were to be verified IEC TC 10 database, the labels T1 and T2 were classified in the same category, thus it is assumed that T1 and T2 is true when the test data was diagnosed in the diagnostic model. We compared shallow learning and Deep Neural Network.

DNN was used as a supervised learning, and we designed 4 layers to learn feature learning. The first layer is the input layer, the next four hidden layers were Relu function, and the last layer was output layer, applied softmax regression. Dropout was applied only to the 4th layer. For the input values, 8 raw data (H_2, CH_4, C_2H_2, C_2H_4, C_2H_6, CO, CO_2, TCG) were used as dissolved gas and they were all normalized. In the case of shallow learning (KNN, RBF-SVM, Linear SVM, Naïve Bayesian, Random Forest), we constructed a model using

$$R1 = \frac{CH_4}{CH_4 + C_2H_2 + C_2H_4}$$

$$R2 = \frac{C_2H_2}{CH_4 + C_2H_2 + C_2H_4}$$

$$R3 = \frac{C_2H_4}{CH_4 + C_2H_2 + C_2H_4}$$

features which were used for Duval triangle and the other shallow learning algorithm that were only used raw data same as the initial setting of DNN

4. RESULTS

The following sections describes the results of shallow learning and the results of Deep Neural Network.

4.1. Shallow Learning Accuracy

In the first experiment, we evaluate the fault diagnosis of power transformer using shallow learning results presented in Table 1. Shallow learning (1) using handcrafted features of R1, R2, and R3 as input values and shallow learning (2) using raw data as input values were compared. We used KNN, Linear-SVM, RBF-SVM, Naïve Bayesian, Random Forest for shallow learning. From fig we observe that shallow learning algorithms using handcrafted features have better accuracy.

Table 1. Shallow learning accuracy of IEC TC 10 database results using raw data and handcrafted features

Shallow learning with raw data	Accuracy (%)
KNN	43.4
Naïve Bayesian	74.4
Linear SVM	20.4
RBM SVM	30.5
Random Forest	66.2

Shallow learning with handcrafted features	Accuracy (%)
KNN	87.1
Naïve Bayesian	87.1
Linear SVM	87.1
RBM SVM	89.6
Random Forest	87.1

4.2. Deep Neural Network Accuracy

We evaluate the DNN diagnostic accuracy proposed in this study with the results of the shallow learning with handcrafted features that we have conducted. To analyze the results in more detail, we show the confusion matrix for the IEC TC 10 database using RBF-SVM (Table 2) and DNN (Table 3). The two confusion matrices indicate that many of the prediction errors are due to confusion between these four incipient faults “T1 or T2”, “T3”, “D1”, “D2”. This is because “T1 or T2” and “T3” are relatively similar, also “D1” and “D2”. However, from the results we can observe that the DNN model outperforms the RBF-SVM due to the feature learning through non-linear activation function of Relu and dropout method.

5. CONCLUSION

In this paper, we have proposed a DNN approach, which extracts high-level features from raw data. Although it is impossible to visualize high-level features like image data, the experimental results have shown that DNN outperforms shallow learning with the handcrafted features.

Experiments with larger test datasets are needed to further study the robustness of the proposed technique. Further improvements will be adapted by using unsupervised pre-training and repeating pooling raw data into high-level features.

Table 2. Confusion matrix for RBF SVM on IEC TC 10 database

		Predict Class				
		PD	D1	D2	T1 or T2	T3
Class Actual	PD	1	0	0	0	0
	D1	0	9	4	0	0
	D2	1	1	25	0	0
	T1 or T2	0	0	0	6	1
	T3	0	0	0	2	10

Table 3. Confusion matrix for DNN on IEC TC 10 database

		Predict Class				
		PD	D1	D2	T1 or T2	T3
Class Actual	PD	1	0	0	0	0
	D1	0	10	0	0	0
	D2	0	0	27	0	0
	T1 or T2	0	0	0	6	1
	T3	0	0	0	2	11

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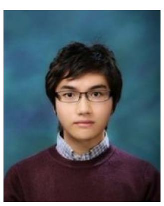
BIOGRAPHIES



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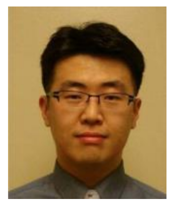

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