Smart Transformer for Smart Grid

– Intelligent Framework and Techniques for Power Transformer Asset Management

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Abstract-- Condition monitoring and diagnosis have become an essential part of power transformer asset management. A variety of online and offline measurements have been performed in utilities for evaluating different aspects of transformers' conditions. However, properly processing measurement data and explicitly correlating these data to transformer condition is not a trivial task. This paper proposes an intelligent framework for condition monitoring and assessment of power transformer. Within this framework, various signal processing and pattern recognition techniques are applied for automatically de-noising sensor acquired signals, extracting representative characteristics from raw data, and identifying types of faults in transformers. The paper provides case studies to demonstrate the effectiveness of the proposed framework and techniques for power transformer asset management. The hardware and software platform for implementing the proposed intelligent framework will also be presented in the paper.

Index Terms—asset management, de-noising, dielectric response, dissolved gas analysis (DGA), insulation, partial discharge (PD), pattern recognition, power transformer.

I. INTRODUCTION

POWER transformer is one of the most important assets in an electricity grid. During its operation, a power transformer is subjected to thermal, mechanical, and electrical stresses, which can eventually deteriorate the transformer and cause the failure of the whole unit. Moreover, electrical utilities around the world are currently facing an increasingly aged population of power transformers in their grids. To ensure reliable operation of a transformer, its health condition must be continuously monitored and evaluated for appropriate asset management decisions [1- 4].

A variety of measurements have been adopted in utilities for condition monitoring and assessment of power transformers [5-10]. With the oil samples collected from transformers, utilities conduct dissolved gas analysis (DGA) to identify thermal and discharge faults in transformers and adopt High Performance

Liquid Chromatography (HPLC) to measure 2-furfuraldehyde content for evaluating paper insulation ageing condition in transformers [5, 6]. Polarization based measurements including polarization and depolarization current (PDC) measurement and frequency domain spectroscopy (FDS) have been also used in utilities for estimating ageing and water content in transformer oil-paper insulation [4, 7]. Frequency response analysis (FRA) has been applied for winding deformation and displacement detection in transformers [8]. To provide dynamic behavior of a transformer's condition during its operation, online sensor based measurements have also been performed. Examples include Partial discharge (PD) measurement for transformer insulation diagnosis and acoustic measurement for transformer on-load tap-changer (OLTC) fault identification [9, 10].

Due to the complexity of a transformer's structure and its degradation mechanism, interpreting the measurement data obtained from the above techniques and subsequently evaluating the transformer's condition is a challenging task, especially for non-experts. Therefore, there is a necessity to investigate intelligent techniques and their applications for automatically analyzing measurement data and identifying fault types in the transformer. Various investigations on applying intelligent techniques to transformer monitoring and diagnosis have been reported in the literature [11- 15]. For example, numerous artificial neural networks, neural-fuzzy systems, and evolutionary algorithms have been applied for diagnosing transformer incipient faults using DGA measurement data [11-13]. Recently, intelligent algorithms have also been applied to compute health index for a transformer to provide an indication of the status of its insulation system [14-16]. Nevertheless, the above techniques scattered over different aspects of interpreting measurement data and making faults diagnosis; there is still lack of a common framework, within which different intelligent algorithms can be effectively deployed and executed to fulfil the tasks of performing sensor based transformer condition monitoring and assessment.

This paper presents an intelligent framework for transformer condition monitoring and assessment. Within this framework, a number of intelligent algorithms have been applied including: (1) digital signal processing algorithms, which concern with de-noising and extracting signals acquired by sensors during online sensor based transformer condition monitoring; (2) pattern recognition algorithms, which focus on transformer

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fault types classification and health condition evaluation. To verify the applicability of these algorithms, case studies and results of applying these algorithms to interpret online and offline measurements of transformers are provided in the paper. The case studies include: (1) de-noising signals obtained from online Partial discharge (PD) measurement; (2) recognizing types of discharge sources (insulation defects), which cause PDs in transformers; and (3) recognizing transformer faults by interpreting dissolved gas analysis (DGA) measurement data. The hardware and software platform for implementing the proposed intelligent framework and deploying the above signal processing and pattern recognition algorithms will also be presented in the paper.

II. INTELLIGENT FRAMEWORK FOR POWER TRANSFORMER ASSET MANAGEMENT

Figure 1 presents the proposed intelligent framework for transformer asset management with the focus on transformer condition monitoring and diagnosis. The key components included in the framework will be discussed in this section.

Fig. 1. Intelligent Framework for Power Transformer Asset Management

The first component of the proposed framework is an integration of various online sensor measurements to provide dynamic information of a transformer's condition. These measurements may include current and voltage measurements, temperature measurement, water content in oil measurement, Partial discharge (PD) detection, and acoustic/vibration monitoring. Necessary data acquisition hardware, which can acquire sensor measured signals, and then transmit these signals through communication peripherals for further data processing will be incorporated.

For practical transformer condition monitoring in a substation environment, various interference and noise can be imposed on the sensor acquired signals. The interference and noise can significantly affect the sensitivity and reliability of sensor measurement and consequently has reverse impacts on correctly identifying the faults occurring in transformers. Therefore, the second component of the proposed framework is a suite of signal processing algorithms, which can remove noise from original measured signals.

With the modern sensing and data acquisition technologies, it is relatively easier for gathering, storing, and accessing raw data in a more straightforward manner. However, the huge volume of raw data may consist of erroneous records, redundant information, and even incomplete records. Therefore, it is necessary to perform feature extraction, which aims to select representative characteristics from raw data. The selected features are embedded with more condensed and smaller amount information, which will be more suitable and manageable for further information processing to support transformer condition assessment. Feature extraction forms the third component of the proposed framework.

After feature extraction, pattern recognition algorithms are adopted as the fourth component for classifying faults types and evaluating health conditions of transformers. The merit of pattern recognition algorithms is the learning from data, which can make use of a historic database to obtain the knowledge regarding the correlation between the measurement data and transformers' conditions. Subsequent condition assessment on the transformer of interest can be performed based on such knowledge.

By combining the results of various measurements, the overall dynamic condition of a transformer can be evaluated. Within the proposed framework, a data and information fusion component will be implemented, which will integrate pattern recognition results of individual measurement to estimate the probability of different types of faults that might occur in a transformer.

The following sections will detail the above key components of the proposed frameworks, i.e. signal processing algorithms, feature extraction, and pattern recognition algorithms for transformer condition monitoring and assessment. Case studies and results will also be provided in each section to demonstrate the applicability of these algorithms.

III. SIGNAL PROCESSING FOR ONLINE SENSOR BASED TRANSFORMER CONDITION MONITORING

This section presents signal processing algorithms for de-noising sensor acquired signals (i.e. original signals), which are prone to environmental interference and noise. These algorithms are applied for de-noising Partial discharge (PD) signals, which are acquired from PD measurements performed on experimental PD models and transformers.

PD is the localized breakdown in insulation systems and its measurement can provide a means of online monitoring and diagnosis of a transformer's insulation system [9, 17]. Fig.2 depicts two types of PD measurement set-ups: (1) RLC impedance in series with a coupling capacitor for acquiring PD signals, the PD signals are recorded by a commercial measurement system complying with IEC60270 [17]; and (2) high frequency current transformer (HFCT), which clamps on a grounding wire of the transformer for acquiring PD signals, the PD signals are recorded by using a digital oscilloscope.

During online PD measurement, different types of noise may exist including white noise, periodic noise, and stochastic

noise. A number of techniques for removing noise from measured PD signals have been proposed in the literature [9, 18 - 22]. The following sections (III.A and III.B) will review two novel de-noising algorithms proposed by the authors of this paper [21, 22]. Section III. C will provide results of de-noising PD signals collected from experimental PD models and transformers. Due to the space limitation, mathematic derivations of these algorithms will be omitted and readers can refer to [21, 22] for the details.

Fig. 2. Set-ups of PD measurements of power transformer

A. Hybrid Algorithm for Adaptive Signal De-noising

Discrete wavelet transform (DWT) has been widely adopted for PD signal de-noising [20, 21]. Based on the convolution between original signals and a selected mother wavelet, DWT decomposes the original signals into many coefficients residing at different frequency bands. One of major challenges of DWT based signal de-noising is the proper selection of mother wavelet. DWT can attain desirable de-noising performance given the mother wavelet has high correlation with pure PD signals. However, for the signals with low signal-to-noise ratios (SNRs), a mother wavelet which correlates to the noise rather than the pure PD signals may be chosen. Also, for practical online measurement, a fixed mother wavelet may not be feasible as it cannot match different types of PD signals generated by different insulation defects [21].

To provide an adaptive and automatic PD de-noising method, the authors of this paper proposed a hybrid algorithm, which is based on ensemble empirical mode decomposition (EEMD) and morphological morphology [21]. In this hybrid algorithm, the sensor measured signals are decomposed into a series of mono-component signals, which are named as intrinsic mode functions (IMFs), for PD signals extraction from noise. Pre-selection of mother wavelet is not required. Moreover, an automatic morphological thresholding (AMT) is used to create threshold for further separating noise from PD signals. The procedure of this hybrid algorithm is listed as follows [21].

1. Obtaining sensor measured signals, which consists of PD signal, white noise, and periodic noise.
2. Setting reconstructed signal, $REC = 0$, and IMF number, $N = 1$.

3. Performing EEMD on the measured signals.
4. If $N = 1$, setting $REC = IMF(N)$ and $N = N + 1$, and going to Step 5.
5. If kurtosis of IMF, $K(N) \geq K(N-1)/2$, then setting $REC = REC + IMF(N)$ and $N = N + 1$, going to Step 5; otherwise, going to Step 6.
6. Executing AMT on REC to remove noise.
7. Reconstructing PD signals (de-noised signals).

As shown above, the hybrid algorithm firstly decomposing sensor acquired signals into IMFs. After signal decomposition, kurtosis of each IMF is calculated as

$$k = \sum_{i=1}^L (I_i - \bar{I})^4 / (L-1)\sigma^4 \quad (1)$$

In the above equation, the mean, length, and standard deviation of IMF are denoted as $\bar{I}$, L , and σ respectively. The larger value of kurtosis implies the signals consisting of abruptly changed impulses while smaller value of kurtosis refers to the slowly fluctuated signals or signals with evenly distributed amplitudes. As Kurtosis is sensitive to transient signals, it is used to select IMFs for reconstructing PD signals with noise removed.

The Kurtosis based selection process starts from the first IMF, which embeds the highest frequency component of the measured signals. If an IMF's kurtosis value decreases to half compared to the previous IMF, it implies that this IMF consists of slow fluctuations due to periodic noise and/or white noise. As a result, this IMF is considered as noise without containing any PD signals and thus can be discarded in the reconstruction. Otherwise, it is regarded as PD signal and added to the previous IMF for PD signals reconstruction. Such IMF selection process will be continued on the remaining IMFs. With the completion of the above selection process, most noise can be removed and the PD signals are reconstructed.

However, it is not uncommon that the reconstructed signals may still consist of some noise, which has the same frequency scales of the selected IMFs. To deal with this problem, automatic morphological thresholding (AMT) is proposed, which can create thresholds for removing noise originated signals having similar frequency scales as pure PD signals [21]. Therefore, the hybrid algorithm based on EEMD and morphological morphology is an automatic signal de-noising method, which is suitable for online PD measurement of transformer.

B. Algorithm for Removing Stochastic Noise

The frequency characteristic of stochastic noise has considerable similarity with that of pure PD signal. As such, stochastic noise is relatively more difficult to remove compared to other types of noise such as periodical noise and Gaussian noise. The authors of this paper developed an algorithm based on fractal dimension and entropy analyses for removing stochastic noise [22].

This algorithm starts with transforming the original sensor measured signals, i.e. stochastic noise corrupted PD signals,

into two-dimensional signals. Then, on the transformed signals, a fractal dimension is computed for each power cycle. For a power cycle with severe noise, the value of its fractal dimension will be significantly different from that of other power cycles. Thus, fractal dimension can be used to locate and accordingly remove the noise. However, in PD measurement some stochastic noise may appear at most of power cycles and have similar fractal dimension values compared to PD signals. For such situation, it may not be able to completely identify and remove noise from PD signals by only using fractal dimension.

For a PD signal it has high chance to appear at the same phase location of different power cycles. In contrast, for stochastic noise, if it appears in a particular phase location of a power cycle, it will have low chance to appear at that phase location in the subsequent power cycles [22]. Therefore, at each phase location, the entropy values of noise is significantly different from the entropy values of PD signals. Based on this observation, entropy value is used with fractal dimension to distinguish and remove stochastic noise from PD signals.

C. Case Studies of PD Signal De-noising

This section presents the results of de-noising measured PD signals using the above signal processing algorithms. The PD signals were collected from experimental PD models and transformers [21].

Fig. 3 presents the de-noising results of measured PD signals by using hybrid algorithm based on EEMD and morphological morphology. The original signals were collected from PD measurement on the experimental PD model of internal discharge using PD measurement set-up one (Fig. 2).

Fig.3. De-noising results of PD experimental model of internal discharge (a) measured signals (noise corrupted PD signals) in time domain; (b) measured signals with respect to the phase angles of power cycle; (c) de-noised PD signals in time domain; and (d) de-noised PD signals with respect to the phase angles of power cycle.

It can be seen from Fig.3 that the hybrid algorithm can effectively extract PD signals from noise and also preserve the phase locations of these extracted PD signals. This can assist pattern recognition algorithm to recognize different types of PD sources, which caused by different types of insulation defects in transformers [23].

Fig. 4 presents stochastic noise removal results by using fractal dimension and entropy analyses. In the figure, the PD signals were also acquired by using PD measurement set-up one (Fig. 2) with the experimental model of internal discharge over ten power cycles. It can be observed from the figure that PD signals locate periodically in most of power cycles. Severe stochastic noise occurs at the first and second power cycles where relatively insignificant noise can be found at other power cycles.

Fig.4. Stochastic noise removal results of PD signals collected from PD models of internal discharge (a) measured signals (noise corrupted PD signals) in time domain over ten power cycles; (b) measured signals with respect to phase angles of power cycle; (c) de-noised PD signals with respect to phase angles of power cycle. Pulses in bright color are de-noised PD signals whereas pulses at background are noise.

Fig. 4b is the original signals with respect to phase angles (all signals in ten power frequency cycles were mapped into 0° to 360° phase angles, which is referred to as phase resolved PD, PRPD) without applying the de-noising algorithm. It indicates that PRPD before signal de-noising is contaminated by stochastic noise. Fig. 4c is the noise removed PRPD, which proves that fractal dimension and entropy analyses are capable of identifying and removing stochastic noise.

Fig. 5 presents the results of using fractal dimension and entropy analyses to de-noising PD signals, which were collected from PD measurement performed on a 5 MVA transformer (using PD measurement set-up one, Fig.2). It can be observed from Fig. 5a and Fig. 5b that the measured PD signals are embedded with heavy noise, which causes considerable difficulties for the identification of PD signals. However, as shown in Fig. 5c, the proposed fractal dimension and entropy analyses method can effectively reveal PD signals. In Fig. 5c, the PD signals appear at the negative power cycle

(180° to 360°) may be generated by corona and/or surface discharge; the PD signals appear at both positive (0° to 180°) and negative (180° to 360°) power cycles may be due to internal discharge. A pattern recognition algorithm can be trained to classify the above types of PD pattern. This will be discussed in the next section.

Fig.5. Stochastic noise removal results of PD signals collected from a transformer (a) measured signals (noise corrupted PD signals) in time domain over ten power cycles; (b) measured signals with respect to the phase angles of power cycle; (c) de-noised PD signals with respect to the phase angles of power cycle. Pulses in bright color are de-noised PD signals whereas pulses in background are noise generated signals.

Though the above signal processing algorithms were applied to PD monitoring and diagnosis of transformer, they can also be applied to other types of sensor based online measurement for transformer condition monitoring. Example is the acoustic measurement for transformer on-load tap-changer (OLTC) fault identification.

IV. FEATURE EXTRACTION AND PATTERN RECOGNITION FOR TRANSFORMER FAULT TYPES CLASSIFICATION

After signal de-noising, the next step within the proposed intelligent framework for transformer asset management involves feature extraction and pattern recognition, which aim to identify types of faults occurring in transformers.

Starting with the mathematic formulation of feature extraction and pattern recognition, this section will present several techniques and their applications on PD sources classification and transformer faults diagnosis.

A. Mathematic Formulation of Feature Extraction and Pattern Recognition

After signals acquisition and de-noising, the resultant measurement records form a $N \times D$ dataset of $\mathbf{X} = [\mathbf{x}_1, \dots, \mathbf{x}_N]$, where $\mathbf{x}_i = [x_i^1, \dots, x_i^D]$ is a D dimensional vector with each dimension is regarded as a feature. Feature extraction reduces the dimensionality of dataset $\mathbf{X}$ and transforms it to a $N \times d$ dataset

of $\mathbf{Y} = [\mathbf{y}_1, \dots, \mathbf{y}_N]$, where $\mathbf{y}_i = [y_i^1, \dots, y_i^d]$ and $d \ll D$. Though substantial features are removed from the dataset $\mathbf{X}$ in feature extraction, the remaining features in dataset $\mathbf{Y}$ can still provide essential characteristics for discriminating different types of faults [23].

Each record in dataset $\mathbf{Y}$ can be categorized into one of K independent classes, $C_k \in \{1, \dots, K\}$ with each class corresponds to one type of transformer faults. A pattern recognition algorithm can be evoked to learn the correlation between records (i.e. features in dataset $\mathbf{Y}$) and the corresponding types of faults occurring in transformers. It involves exploring the function of $f: \mathbf{y}_j \rightarrow C_k, j = 1, \dots, N, C_k \in \{1, \dots, K\}$. The algorithm can be subsequently used to identify the fault types of transformers, which are not included in the above training dataset $\mathbf{X}$ or $\mathbf{Y}$.

B. Classification of PD Sources in Transformer

PD source classification is to distinguish the types of defects that cause discharge in transformer insulation system. The conventional approach for PD source classification involves several steps: (1) collecting PD signals from PD measurements on different types of experimental PD models; (2) constructing phase resolved PD pattern (PRPD), i.e. PD pulses distribution of magnitude and number count with respect to phase angles of power cycle for all acquired PD signals; (3) using statistic operators to characterize the PD patterns and forming a training database of different PD sources; and (4) training pattern recognition algorithms, which are used to identify the PD sources in transformers [23].

Instead of using the above phase resolved PD pattern, this paper adopts EEMD for feature extraction because it can perform two tasks, PD signal de-noising and feature extraction, in one step. Firstly, data are extracted from IMFs with nine-level decomposition. To reduce the high dimensionality introduced by decomposition (a power cycle may have several hundred discharge pulses, and each discharge pulses is represented by nine coefficients), the first four moment statistics including mean, variance, skewness, and kurtosis are computed for the distribution formed by the nine coefficients of discharge pulses. As a result, 36 features ($4 \times 9 = 36$) are used to represent each record of PD measurement.

A training database having 1000 records for five PD sources (internal discharge, surface discharge, discharge in oil, discharge in air, and discharge due to floating particles) has been constructed [23]. Each record consists of the above 36 features and the corresponding types of PD sources. Therefore, the $\mathbf{Y}$ dataset for training is with the dimension of 1000×36 . To visualize data distribution in this dataset, principle component analysis (PCA) is adopted as shown in Fig. 6.

From Fig. 6 it can be seen that the records of different PD sources exhibit a certain degree of overlapping. This implies the necessities of adopting algorithms with nonlinear discriminability, i.e. artificial neural networks (ANNs) or support vector machine (SVM) algorithm, for PD sources

classification. The validation results show that SVM (with EEMD feature extraction) can achieve 97% classification accuracy on this training dataset (70% records in the dataset are used for training SVM while the remaining 30% records are used for validating the trained SVM algorithm) [23].

Fig.6. PCA visualizations of PD sources dataset constructed using EEMD feature extraction method

Different types PD sources can co-exist in a transformer. SVM algorithm can estimate the probability of existence of each type of PD sources. Fig. 7 depicts PRPD pattern of an experimental model of multiple PD sources, which is due to simultaneous occurrence of internal discharge and discharge due to floating particles. A SVM algorithm trained by the above dataset shown in Fig. 6 indicates the probability of discharge due to floating discharge and internal discharge are 67% and 17%, respectively.

Fig.7. Multiple PD sources obtained from internal discharge and discharge due to floating particles (a) PD pattern of multiple PD sources of internal discharge and discharge due to floating particle; (b) PD pattern of internal discharge; and (c) PD pattern of discharge due to floating particles.

The above trained SVM is also applied to make PD sources classification for the PD measurement on a 5 MVA power transformer, which was shown in Fig. 5 in Section III. It indicates that the internal discharge accounts for 54%, surface discharge accounts for 34%, and corona accounts for 14% of discharges in this transformer.

C. Transformer Faults Diagnosis using Dissolved Gas Analysis (DGA) data

DGA has been in use in utilities for diagnosing transformer faults such as overheating, discharge fault, and Partial discharge (PD). As mentioned in Section I, pattern recognition techniques have also been applied for DGA data interpretation and transformer faults diagnosis [11-13]. A pattern recognition algorithm is trained by a historic DGA database, which consists of DGA measurement records and the fault types of corresponding transformers. After training the algorithm is able to identify the fault type of a transformer with its DGA data [24].

In utilities, transformers' faulty rate is generally low. Thus, the records belonging to some faults types can be insufficient, which leads to an imbalanced DGA training database, i.e. the number of records of some faults types (majority classes) are quite larger than that of other faults types (minority classes). An algorithm trained by such an unbalanced database will be biased in that it can lead to higher misclassification rate on the minority classes [25].

To tackle the above class imbalanced problem, this paper applies synthetic over-sampling technique (SMOTE) to reduce the degree of imbalance among different classes (i.e. faults types) and subsequently facilitate pattern recognition algorithms consistently achieving desirable classification accuracy [26]. SMOTE is implemented in three steps: (1) computing the imbalance ratio between majority and minority classes in the original database, which is then used to decide the number of synthesized samples; (2) computing the Euclidean distance between a sample and its closest neighbours in a minority class; and (3) generating the synthesized samples according to:

$$\mathbf{m}_i = \mathbf{x} + \text{rand}(0,1) \times d(\mathbf{x}, \mathbf{x}_i^*) \quad (2)$$

In the above equation $\mathbf{m}_i$ denotes the synthesized sample, $\text{rand}(0, 1)$ is referred to as a random number within the range from zero to one, $d(\mathbf{x}, \mathbf{x}_i^*)$ is the Euclidean distance between sample $\mathbf{x}$ and its neighbour $\mathbf{x}_i^*$.

To further improve the performance of pattern recognition algorithms, a boosting approach is adopted. Boosting is a meta-learning technique, which constructs a high-performance ensemble of algorithms to attain desirable performance [27]. Boosting is implemented as follows: (1) performing initial training, in which all samples are with equal weights; (2) assigning higher weights to the samples, which are incorrectly classified in the previous step; and (3) the training iterations continue until the ensemble attains the desirable classification accuracy. A case study of applying SMOTE and boosting to transformer fault diagnosis is as follows.

A DGA database provided by a utility company is presented in Table I. The first and second rows of the table are records distribution before and after performing SMOTE operation, respectively. It is apparently the original database shown in Table I is class imbalanced. After SMOTE process,

the database achieves approximate equal distribution of records throughout different faults types.

The SVM and radial basis function network (RBF) algorithms were trained using the above database. The inputs (features) to the algorithms are concentrations of dissolved gases C_2H_4 , C_2H_2 , C_2H_6 , CH_4 , and H_2 [15]. Descriptions of SVM and RBF algorithms are given in [28]. After the algorithms were trained they were used to identify the faults types of 206 transformers, of which DGA data are provided by another utility. The records of these 206 transformers form a testing dataset and were not included in the training database (Table I). Table II shows the fault types of eight transformers amongst these 206 transformers classified by the trained SVM and RBF algorithms.

A comparison between the algorithm classified transformers' fault types and the utility expert's manually determined fault types is shown in Table III. The classification accuracy is the ratio between the number of transformers with correctly classified faults types and the total number of the testing transformers (i.e. 206).

Table I
Samples Distribution in Training Database (before and after SMOTE)

	Normal condition	Discharge	Thermal	Partial Discharge
Original	201	12	145	32
SMOTE	252	253	250	258

Table II
SVM Assessment Results on Eight Transformers of Testing Database

Transformer	Probability of Each Class (in percentage)	SVM Results	Utility Expert Diagnosis
TX1	[0.88 0 0.09 0.03]	Normal	Normal
TX2	[0.90 0.05 0.03 0.02]	Normal	Normal
TX3	[0.06 0.71 0.19 0.04]	DS	DS
TX4	[0.18 0.05 0.71 0.06]	OT	OT
TX5	[0.03 0.02 0.01 0.94]	PD	PD
TX6	[0.03 0.02 0.08 0.87]	PD	PD
TX7	[0.76 0.01 0.12 0.11]	Normal	Normal
TX8	[0 0.10 0.90 0]	OT	OT

[Normal DS OT PD] denotes the probability of each fault type. Normal-normal operating condition, DS-discharge fault, OT-thermal fault, and PD-partial discharge.

Table III
SVM and RBF Classification Accuracy on Testing Database

Algorithms		Overall classification accuracy (in percentage)
Without SMOTE and boosting	RBF	50
	SVM	52
With SMOTE and boosting	RBF	85
	SVM	98

It can be seen from Tables III that original RBF and SVM algorithms (i.e. without integrating SMOTE and boosting) almost failed to make classification (classification accuracy is merely above 50%). This is not surprising since the training data and testing data are collected from different utilities. However, with the integration of SMOTE and boosting, SVM and RBF algorithms can attain higher classification accuracy on the testing dataset. This demonstrates that SMOTE and

boosting can assist pattern recognition algorithms in achieving desirable generalization capability when they are applied for classifying transformer faults.

V. SMARTBOX – HARDWARE AND SOFTWARE PLATFORM FOR IMPLEMENTING PROPOSED INTELLIGENT FRAMEWORK

To implement the proposed intelligent framework and deploy signal processing and pattern recognition algorithms for transformer condition monitoring and assessment, a configurable architecture ("SmartBox") has been adopted as hardware development platform. The SmartBox consists of signal conditioning and high speed digitizer, which can acquire signals from sensor during online condition monitoring of transformer. The SmartBox can also execute signal processing algorithms and pattern recognition algorithms for signal de-noising, feature extraction, and fault pattern recognition.

To provide a platform for deploying various algorithms, multi agent system (MAS) will be adopted as shown in Fig.8. MAS can provide system extensibility to include newly installed sensors and the latest signal processing and pattern recognition algorithms as they become available.

Fig.8. Software Platform based on a multi agent system (MAS) for transformer condition monitoring and assessment.

MAS systems encompass attributes required to automate condition monitoring and diagnosis applications [29, 30]. With the integration and interaction with pattern recognition algorithms, each intelligent agent in a MAS system can learn from data for making reasoning. Also, through historical data analysis using pattern recognition algorithms, these agents can enhance their capabilities of handling uncertainties, which are important for practical intelligent condition monitoring and assessment of power transformers in substation environment.

VI. CONCLUSIONS

This paper proposed an intelligent framework for condition monitoring and assessment of power transformer using data obtained from online sensor measurement and historic database. Within the proposed intelligent framework, a variety

of signal processing and pattern recognition techniques were applied for data and information processing and transformer faults identification. Case studies were provided to verify the effectiveness of the proposed framework and applied techniques. Current work is on the implementation and deployment of the proposed intelligent framework on the SmartBox hardware and software platform.

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