# Transformers Fault Detection Using Artificial Intelligence Technique

**Nagpal Tapsi**
Department of Electrical and Instrumentation Engineer,
Tapar University, Patiala, Punjab
tapsiarora@gmail.com

**Y.S. Brar**
Department of Electrical and Instrumentation Engineering,
Guru Nanak Dev Engineering College, Ludhiana
braryadwinder@yahoo.co.in

***Abstract:*** *An artificial recognition system of defective type for epoxy-resin insulation based transformers through acoustic emission (AE) from partial discharge (PD) experiment is proposed. Most of the PD detection methods could be performed only at the shutdown period of equipments. By using Acoustic Emission (AE), the real-time and online detection could be achieved. Therefore, in this paper a series of high voltage tests were conducted on pre-faulty transformers to collect transformer mechanical data such as vibration from the faulty transformer. These vibration signals can be gathered with the help of accelerometer (50 kHz) which can be further used for recognition needed. The selected features can be extracted from the experimental AE signals and used as input to the recognition system. According to these features, effective identification of their faulty types can be done using the proposed particle swarm optimization combined with neural network. To demonstrate the effectiveness and feasibility of the proposed approach, the artificial intelligence identification system is applied on both noisy and noiseless circumstances,the recognition rates of the two being 80% and 86% respectively.*

***Keywords:*** *Acoustic Emission, Partial Discharge, Particle Swarm Optimization, Neural Network, Transformer.*

## I. INTRODUCTION

Accidental or unscheduled transformer shutdowns cause serious impacts and significant financial losses. A variety of defects can lead to the failure of a transformer, including the occurrence of partial discharges, which are the subject of discussion in this paper.

The occurrence of partial discharge (PD) in transformers may result from a defect or an incipient fault, which can produce an unexpected interruption and which appears and develops without being easily detectable.

Aging and faults in insulating systems of electrical equipment originate from chemical, mechanical, thermal and electrical processes that can occur during operation and even in the manufacture of the equipment. During these processes, defects appear that can lead to localized reduction of the dielectric capacity of the insulating system [1].

When the insulation of equipments has some defection, the local partial discharge might happen when on duty. Some energy release will occur in many different ways such as acoustic emission (AE) and current impulse [1]. If the AE wave can be analyzed and processed, it should be possible to identify the nature of failure, thus making breakthrough contribution on defective detection. Any breakdown of running transformer will lead to a dramatic loss and negative influence. In an attempt to prevent and identify occasional accidents, degrading diagnosis and failure identification of transformer are urgently required based on a safe, real-time and accurate solution.

Recently, the use of the global optimization technique called particle swarm optimization (PSO) (Kennedy & Eberhart, 1995) to solve real world problems has aroused researchers' interest due to its flexibility and efficiency. Limitations regarding the form of the objective function employed and the continuity of variables used for the classical greedy search technique can be completely eliminated. Considering the complexity of error curve of back propagation (BP) neural network and its sensitivity to initial weights (Amir & Chuanyi, 1997), in this paper PSO is applied as the first optimization stage to get better initial weights and bias for BP neural network. When the initial weights and bias are set from PSO, the artificial neural network with BP training is used as the recognition system. This recognition system in combination with PSO and BP for neural network training is then called PSO–BP hybrid algorithm[2-3].

In this paper, a real-time online detection system is set up that is based on AE signal diagnosis method, and also an approach to obtain the status of equipments as well as relevant information and reference for possible defective types to prevent and diagnose any electric equipment failure is provided to the end users. Simulation results show that using PSO–BP approach on the proposed artificial recognition system is possible to have a higher accuracy and better noise tolerance ability.

## II. AE TECHNOLOGY

The ASTM standard E610-82 gave a detailed description as ‘‘AE is a transient elastic waves generated by the rapid release of energy form localized sources within a material”. PD detection is basically considered as a pulse phenomenon of energy release, and the subsequent sound release is named AE from the perspective of supersonic wave. Therefore, an ideal way to judge the performance of transformer online is based on computer-aided AE method for PD detection. The following are three highlights of AE methods in PD detection for transformer (Boczar & Zmarzly, 2004; Chen, Tsao, & Lin, 2005; Grossmann & Feser, 2005; Gupta & Ramu, 2001; Lundgaard, 2001).

(1) Online and real-time supervision: AE can be detected online without switching off, or any special arrangements of equipments.

(2) High safety: AE can be detected from a contact-free or outside contact manner, thereby helping to improve greatly the safety of maintenance personnel compared with high voltage testing.

(3) Perfect trouble shooting: In the case of new or unknown troubles of electric equipments, only AE data shall be required for future identification and prevention [4-6].

Therefore, in this paper, applying AE principle to analyse PD of transformers which is difficult to diagnose online by other methods is intended.

### A. *PSO Neural Network*

The weight and bias training of neural network involves actually complex continuous optimization of parameters. The feed-forward network being widely developed is based on Back Propagation (BP) initiated by Rumelhart et al. Notwithstanding it has simple and flexible advantages, BP based on gradient descent is extremely sensitive to initial weight and bias vector. So, different initial weight and bias vectors may lead to totally different results or even falling into local minimum. To prevent the outputs turning into local optimum, the neural network generally allows for setting randomly the initial value. In such case, it’s required to consider if the weight and bias are optimum one after training. Trial and error method has been applied by some researchers to find out better initial weight settings [7]. In addition, selection of dynamic optimal learning rate, etc, depends upon test and experience. The network cannot be converged if the value is improperly set, or even in the case of convergence, the slow convergence speed may lead to longer training and local optimum without optimal weight and bias distribution. Recently, the use of the global optimization technique called PSO, to solve real world problems have aroused researchers’ interest due to its flexibility and efficiency. Limitations regarding the form of the objective function employed and the continuity of variables used for the classical greedy search technique can be completely eliminated [20-22]. Considering the complexity of error curve of BP neural network and its sensitivity to initial weight, as well as the global searching advantage of PSO, PSO is applied as the training method to get the weight and bias of neural network. PSO algorithm is mainly used to train the neural network. When the weight and bias are set, the feed forward neural network is used for recognition. By combining these advantages of two algorithms, higher accuracy and quicker convergence is possible. This algorithm combining PSO and neural network together is called PSO-NN hybrid algorithm.

### B. *Brief review of PSO*

Particle swarm optimization (PSO), first introduced by Kennedy and Eberhart, is one of the modern heuristic algorithms. It was developed through simulation of a simplified social system, and has been found to be robust in solving continuous nonlinear optimization problems [8-9]. The PSO technique can generate a high-quality solution within shorter calculation time and stable convergence characteristic than other stochastic methods [10-12]. Much research is still in progress for proving the potential of the PSO in solving complex power system operation problems. Researchers including Yoshida et al. have presented a PSO for reactive power and voltage control considering voltage security assessment. The feasibility of their method is compared with the reactive tabu system and enumeration method on practical power system, and has shown promising results [13]. Some researchers have presented the use of a hybrid PSO method for solving efficiently the practical distribution state estimation problem.

## III. PROPOSED MODEL/RESEARCH METHODOLOGY

The major purpose of this research is to set up a real-time online detection unit based on AE detection method, and also provide the end users with an approach to obtain the status of objects as well as relevant information and reference for failure prevention and diagnosis of any electric equipment. Based upon the transformers with discharge failure and a trouble-free transformer, this research analysed the data on the MATLAB platform and artificial neural network, and then identified the presence of or otherwise the nature of failure. To put it bluntly, "AE" represents supersonic wave of PD within transformer.

The whole procedure for the proposed method in detail has been stated below:

### A. Acquisition of AE Data

PD data, if obtained from computer simulation testing, may differ from those derived from field test research. In this research we use field experiment, and employs epoxy resin transformers with designated defects to get the defect type pattern of PD. Five types of defects designed which include model A- improper solder on high voltage side, model B and C- improper soft copper wire on grounding and high voltage panel, model D and E- improper bubble within insulating material on low and high voltage side. To reduce interference from noise and to make a very high level of dependability, the experiment is conducted mainly in a control room and a magnetically shielded room. The conceptual diagram of equipment configuration is shown in Fig. 1 and the proposed process is in Fig. 2 [14-16].

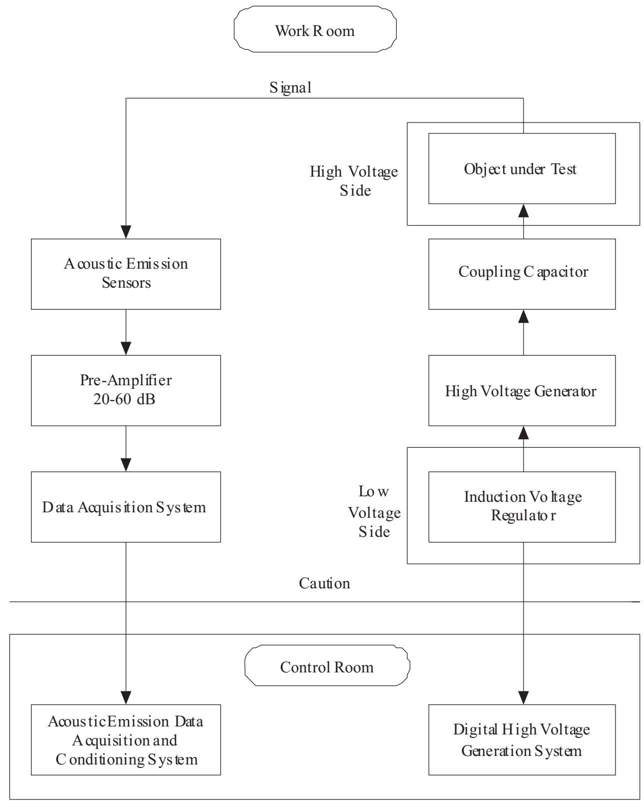


**Fig. 1: Hardware structure for PD measurement of AE**

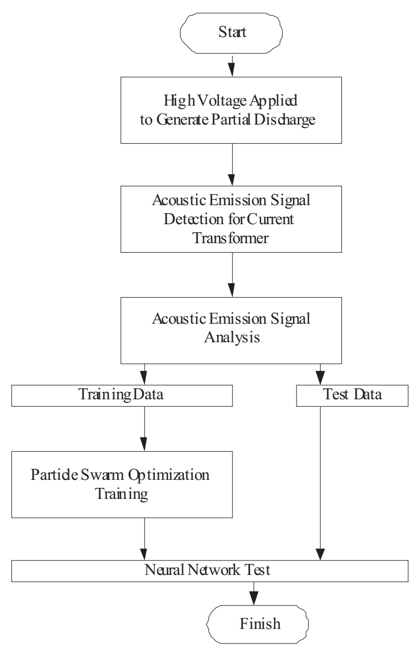


**Fig. 2: Flowchart of the proposed approach for defect types recognition by PD signal**

When the test sample (epoxy-resin transformer) generates PD and AE phenomenon, the voltage value obtained from sensor will be transmitted to amplifier and then AE data capture card for A/D conversion. Finally, the digital data pattern is stored in database.

*B. Searching procedures by PSO*

Searching procedures by PSO based on the above concept can be described as follows:

A flock of individuals optimizes a certain objective function. Each individual knows its best value $p_{best}$ so far and its position. Moreover, each individual knows the best value in the group $g_{best}$ among $p_{best}$, namely the best value so far of the group. The modified velocity of each individual can be calculated using the current velocity and the distance from $p_{best}$ and $g_{best}$ as shown below:

$$V_i^{k+1} = \omega V_i^k + c_1 rand_1 (...) \times (P_{best_i} - s_i^k) + c_2 rand_2 (...) \times (g_{best} - s_i^k) \quad ...1$$

$$s_i^{k+1} = s_i^k + V_i^{k+1} \quad ...2$$

where $V_i^k$ is the current velocity of individual i at iteration k; $V_i^{k+1}$, modified velocity of individual i at iteration k+1; $rand_i(\ )$, random number between 0 and 1;$S_i^k$,current position of individual i at iteration k;$p_{best}$, $p_{best}$ of individual i until iteration k;$g_{best}$, $g_{best}$ of the group until iteration k; $c_i$, weight coefficients for the stochastic acceleration terms.

The constants $c_1$ and $c_2$ represent the weighting of the stochastic acceleration terms that pull each individual toward the $p_{best}$ and $g_{best}$ positions. Low values allow individual to roam far from the target regions before being tugged back. On the other hand, high values result in abrupt movement toward target regions. Hence, the acceleration constants $c_1$ and $c_2$ were often set to be 2.0 according to simulation experiences. Suitable selection of inertia weight ω in (3) provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution [17-19]. As originally developed ω often decreases linearly from about 0.9 to 0.4 during a run. In general, the inertia weight ω is set according to the following equation:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{Iter_{max}} \times Iter \quad ...3$$

where $\omega_{max}$,initial weight; $\omega_{min}$, final weight;$Iter_{max}$, maximum number of iterations; and Iter, current number of iterations.

*C. Processing Steps of PSO-NN hybrid algorithm*

The following describes the detail steps of PSO-NN process:

1. Treating each weight and bias of multi-layer neural networks as the particle of PSO.
2. Initialize N particles using random generator.
3. Evaluate each particle by MSE.
4. Modify *gbest* and *pbest* by simply comparison their fitness values.
5. Calculate velocities for each particle by Eq. (1).
6. Renew each particle to the new position by Eq. (2) that including random search phenomenon.
7. If the evolution process reach to a satisfy condition (or maximum evolution number is reached) then go on to step 9, else modify the inertia weight ù by Eq. (3) and go back to step 5.
8. Using the best particle as the weight and bias for multi-layer neural network.
9. Performing test data to evaluate the performance of this PSO-NN.

## IV. RESULTS AND DISCUSSION

The experimental and research results for the proposed artificial recognition system by PSO–BP neural network are divided into two different parts.

Six hundred sets of data obtained in shielding room without noise distortion undergo PSO–BP recognition, 400 of which are for training purposes, 200 of which for testing. Two different inputs that include noisy and noiseless are all applied to the same PD recognition problem. The results of the recognition rates are listed out in Table 1 and their comparison (Kuo,2007) is made in Fig. 3. From these recognition results, noise-free recognition rate is as high as 82-89% while the noise-added situations contribute to 80% using the proposed approach. These encouraged rates should be high enough for practical use.

**Table 1: Recognition rates (%age) for different inputs (noisy and noiseless)**

| Input | Defective Types | | | | |
|---|---|---|---|---|---|
| | A | B | C | D | E |
| Noisy | 83 | 77 | 85 | 76 | 73 |
| Noiseless | 88 | 78 | 84 | 89 | 82 |

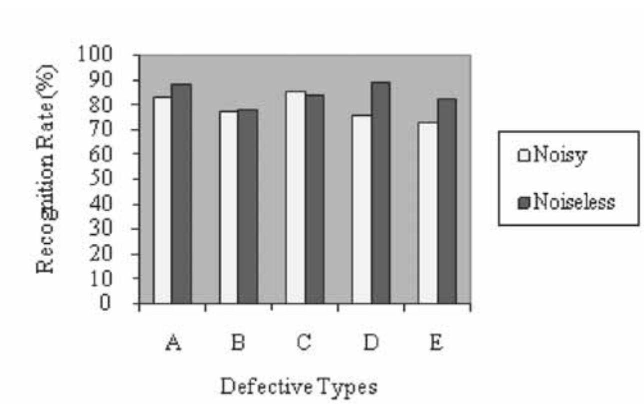


**Fig. 3 : Recognition rates using different inputs**

## V. CONCLUSIONS

Most of the PD detection methods can be applied on offline period of equipment. By using AE, the real-time and online detection could be easily performed. Therefore, a top-down experimental procedure of epoxy-resin transformers for defective types recognition by PD is developed in this paper. High voltage test on pre-faulty transformers is conducted and PD signals are measured for defect recognition and type classification. Five selected features are used in this paper to increase the successful probability of recognition rate. A PSO–BP approach is also provided for better recognition results. The whole proposed procedure can be easily extended to other electrical equipments for online defect detection and type classification. To show the effectiveness of the proposed approach, several classification and identification simulations are used to evaluate. The results show that the recognition rate is as high as 82-89% under noise-free circumstances. It should be high enough for practical use to reduce system failure probability.

Although, noise may interfere with or overlap the PD pattern, and likewise influence the recognition rate. In our research, even on 30% noise-added situation, at least 80% recognition rate can be guaranteed. These encouraging results show that this paper can provide a feasible and effective way to early detect the possible failure of epoxy-resin transformers and can also determine the types of failure to help utility for maintenance needed.

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