Electric Power Systems Research 110 (2014) 154–162

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Review

Application of an ensemble neural network for classifying partial discharge patterns

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ARTICLE INFO

Article history:
Received 5 August 2013
Received in revised form 6 January 2014
Accepted 9 January 2014
Available online 15 February 2014

Keywords:
Partial discharge
Ensemble neural network
Single neural network

ABSTRACT

This paper proposes a technique for classifying partial discharge (PD) patterns based on ensemble neural network (ENN) learning. The ENN technique is based on training a number of neural network (NN) models with statistical parameters from PD patterns and combining their predictions. In this paper, six constituent NN models form the ensemble. Combining the outputs of the constituent NNs through an aggregating unit using dynamically weighted averaging strategy gives a final evaluation of PD patterns in relation to a range of PD fault types. Using the data sets of measured PD patterns as the system input fingerprints, the classification performance of the ENN has been compared statistically and quantitatively with a single neural network (SNN). This is achieved through evaluating the average, variance and standard error of the means of ENN and SNN recognition performances over 100 different initial states of the NNs thus providing an effective comparison to be made. The result shows that the ENN appears to be more robust with statistically improved performance in recognizing untrained PD patterns for a number of PD fault geometries.

Contents

1. Introduction

Localized partial discharge (PD) often occurs within high voltage (HV) systems when insulation materials start to degrade under conditions of high electrical stress [1]. Once PD initiates, it becomes a driver of further insulation degradation, which may ultimately lead to complete breakdown or failure of HV equipment. It is therefore important that PD activity is monitored and trended so that decision on the state of the insulation can be made. PD pulses are normally measured over individual power cycles with both the magnitude of the discharge (normally the apparent charge (i.e. IEC60270 Standard [2])) and the phase of occurrence being captured by digital systems. From these measurements often φ–q–n (phase–amplitude–number) patterns are produced as a means of diagnosis, e.g., [3]. As different insulation fault mechanisms and

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http://dx.doi.org/10.1016/j.epsr.2014.01.010

fault geometries produce different φ–q–n patterns it is therefore possible to determine from these patterns the nature of the fault, e.g., void, corona, surface discharges, etc. On this basis several approaches and classification techniques have gradually appeared for automatic recognition in order to exclude the need for experienced operators to interpret fault patterns. One of the most common automated approaches for PD monitoring is the neural network (NN), e.g., [3–6].

The NN has been extensively applied for classifying complex stochastic PD patterns because of its ability to learn from a few trained fault examples [3,6]. However, the fundamental issue in NN learning and classification is generalization, i.e. the potential of the NN to function reliably well for some unknown or unseen PD data. Many NN topology algorithms have been applied for PD classification and these include: the back-propagation (BP) algorithm [3,5–7]; the Kohonen self-organizing map and learning vector quantization [3]; modular neural networks [8]; adaptive resonance theory [9]; the counter propagation NN [10]; hidden Markov models [11]; fuzzy logic controllers [12] and more recently the probabilistic neural network [13]. These methods have produced recognition performances of more than 90% when testing has been performed on some unseen PD data set. However, generalization of patterns remains an issue for these NN implementations.

In an attempt to improve the situation, this paper aims at developing an ensemble neural network (ENN) for classifying PD patterns. ENNs have not, until recently, been considered for PD fault classification. The inspiration for ENN methods is based on the premise that by combining the prediction of several individual NN models, the generalization error of the widely applied single neural network (SNN) might be improved. It has been shown that this is only possible if constituent NNs in the ensemble are concurrently diverse and accurate [14]. Some recent research within the field of PD has shown improved recognition performance of an ENN over an SNN for a few selected PD fault geometries e.g., [15–17]. However, the ability of an ENN to classify a collection of well-known insulation PD fault types has not yet been widely explored or effectively quantitatively assessed in relation to SNN performance. Such an investigation forms the basis of this paper.

The normal practice for PD NN methods is for statistical measures of φ–q–n patterns to form the training and testing fingerprints to the networks. However, one drawback of the SNN for PD classification is the trial and error approach in choosing initial states (i.e., weights and biases) as different initial states produce different performance evaluations. To establish a truly effective ENN prediction scheme, a certified level of statistical confidence is thus required based on different initial state assignments. In order to understand and compare the general performances of an ENN and SNN in this regard, this paper calculates the averages, variances and standard errors of the mean (SEM) of the recognition rates as a function of varying the initial weights and biases of the networks. Some previous work has attempted to establish error tolerances on selected statistical φ–q–n parameters for SNN investigations [3]. However, these evaluations were of limited application and restricted in experimental scope to a selected number of fault geometries. Therefore, as a further contribution to the field of PD, this paper provides an associated quantitative statistical comparison of the ENN and SNN recognition and discrimination rates for several well-established PD faults as well as some less known NN evaluated fault geometries. The PD faults investigated include corona in air, corona in oil, oil and air surface discharges, voids in insulation and an electrode bounded cavity. For these fault geometries, laboratory φ–q–n data captures over extended testing periods have been obtained for the evaluations. These extended data sets are then applied for both training and testing the SNN and ENN developed within this work.

The paper is organized as follows. Section 2 presents the experimental test geometries and summarizes the statistical input parameters used for the SNN and ENN. Section 3 summarizes the background theory of ENNs; Section 4 outlines the training strategy and development of the SNN and ENN models employed within this work; Section 5 evaluates and compares the quantitative ENN and SNN performance discrimination capabilities and discusses some of the implications of the work to the field of PD. Section 6 summarizes the conclusions of the paper.

2. Experimental set-up and input parameters for the SNN and ENN

2.1. The PD measurement

Measurements of PD were made using an optically isolated wide-band PD detection system based on the IEC 60270 Standard [2], designed and built at Glasgow Caledonian University. The measurement system transmits separately the wideband IEC 60270 detected PD impulse and the synchronized measured power cycle over optical fibre to optical electrical receivers to provide isolation of the measurement system from the high voltage environment. The receiver system software measures the apparent charge from the peak of the impulse signal and generates φ–q–n patterns over specified time intervals which can be stored for future analysis.

2.2. PD fault geometries

PD fingerprints required for fault recognition are normally obtained under laboratory conditions by means of specially manufactured PD fault model geometries. In this work, six PD fault geometries have been constructed and are described below. The first four geometries have previously been evaluated in the literature for SNNs e.g., [3,16,17]. The last two have not previously been evaluated in NN investigations.

(1) Corona in oil

This is produced by a point-plane configuration immersed in Castrol insulating oil [18] (see Fig. 1a). Measurements were carried out at 28 kV for a period of 2 h and the point needle placed at a distance of 25 mm from a solid ground plane. Changing gap distance has minimal effect on the φ–q–n behaviour for oil corona discharges e.g., [19].

(2) Surface discharge in air

This fault type was produced by placing a small brass conductor ball of 55 mm diameter onto Perspex insulation as shown in Fig. 1b. Measurements were conducted at approximately 5 kV and the Perspex was stressed continuously for 4 h, up to the level of its initial stage of degradation, i.e. when chemical particles appeared on the Perspex surface.

(3) Single void in PET

A single void of 0.6 mm diameter was created as an artificial cylindrical void in the centre layer of a nine layer poly-ethylene-terephthalate (PET) sample as shown in Fig. 1c. Each layer was 50 μm in thickness. One layer of PET was attached to the top and bottom electrodes using epoxy while the remaining seven PET layers were compressed between the two electrodes. All measurements were taken at 3.6 kV and PD data captured from the start of the test up to 7 h at which point some degradation of the insulation had started. To ensure reliability of the manufacture process of the