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REVIEWS - LETTERS - REPORTS

NEURAL NETWORKS AND THEIR ROLE IN PARTIAL DISCHARGE RECOGNITION IN GAS INSULATED SWITCHGEAR AND TRANSFORMERS: A SHORT REVIEW

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In this paper a short review of the work performed in the field of partial discharge (PD) pattern recognition with the aid of neural networks in gas insulated switchgears and in power transformers is presented. The role of neural networks in shaping modern approaches to PD pattern recognition is discussed. Comments about various types of neural networks are offered as well as about the separation of PD events from noise signals. Possible remaining problem areas are discussed.

K e y w o r d s: neural networks, partial discharges, pulse height analysis, phase analysis

1 INTRODUCTION

It is well known that partial discharges (PD) are one of the main causes of degradation of insulating materials [1]. PD — depending on the application — may occur in a variety of places and under a variety of conditions, rendering thus their detection and measurement one of the main tasks of insulation engineers and scientists. It is nevertheless a task which is particularly challenging since PD are inherently stochastic in nature [2]. PD effect on insulating materials or systems is of a cumulative nature and causes their deterioration in the long run [3].

During the past years PD diagnostic techniques were further developed and parameters such as pulse height and phase analysis techniques became fashionable [4, 5]. Statistical parameters extracted from the aforementioned techniques were used in order to better interpret and estimate PD behaviour with ageing and the state of insulation under question [6, 7]. PD measurements are affected by interfering signals and consequently the resulting histograms and/or related parameters must be interpreted with due care. PD pattern recognition is thus a rather demanding task from the part of the operator.

In recent years, the neural network (NN) has become one of the main PD recognition methods. The basic idea is that a NN may learn the required input-output mapping information from a variety of examples. It is the aim of the present paper to give a short review of the research activities in the field of PD pattern recognition regarding gas insulated switchgears (GIS) and transformers. Comments on aspects of certain algorithms regarding their ability to rightly recognize new inputs are given. Problems arising from the existence of multiple defects in insulations and the difficulty of the recognition are also discussed.

2 WHY TO USE NEURAL NETWORKS?

The question which is often asked is the following: Why do we have to use NN for PD recognition? Is it not, after all, the well known philosopher D. Hofstadter who pointed out that "neural networks are nothing else but another way to organize a program. The principle is simple, the neurons exchange signals with each other. [However] these procedures can also be carried out with a normal program description " [8].

The answer is that a NN has the capability of non-linear mapping. It may simulate the human learning process (which is not exactly a precise process) and therefore it may learn without difficulty the various PD patterns. Even though the PD pattern may at times be not well defined — or if it resembles to other PD patterns — a NN may still continue the recognition procedure. We do not have these advantages with a conventional computer programme. As it was noted in [9, 10] regarding input data, in a NN computation, numerical but also perceptual representation is allowed whereas with conventional computation we have only numerical representation. In a NN computation the procedure of knowledge acquisition is training and not — as in conventional computation — just programming. Furthermore, and most important of all, regarding computation, low-precision non-linear mapping is needed and not as in conventional computation, high-precision arithmetic.

Although the above may seem to be rather general comments about the usefulness of the NN, they hold true also for PD recognition. PD recognition is a particularly difficult problem requiring from the part of the operator skill and experience, especially if one has to deal with various sources of PD and if the operator is confronted with interference. This task can be undertaken by a NN.

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As is put in [11], "[because] the PD phenomenon is inherently random and influenced by the nature of insulation aging amplitude of applied voltage [noise] the resulting 3-d pattern is quite complex [All these consist] a very challenging pattern recognition task ".

It is the purpose of this paper to offer a short review on the aspects of PD recognition with the aid of NN. The present paper is not to be understood as a general review paper on NN and their relation to PD recognition neither it will give an extended view of the basics of NN. It does not describe the various neural networks (back propagation, Kohonen self organizing map *etc*). Such presentations and detailed descriptions have been made elsewhere [12]. This paper concentrates rather on specific high voltage applications, such as gas insulated switchgear and transformers. It discusses specific problems related to the aforementioned applications and tries to put the PD recognition problems regarding the nature and variety of defects in a wider context.

3 NEURAL NETWORKS IN SWITCHGEAR

The problems of pD diagnostics and pattern recognition in GIS was tackled in [13]. The authors used the well known pulse height and phase resolved approach. For classification purposes they used the L2-distance classification. The average results of 150 test classifications of 15 different fault types were offered. Numerous defects for both SF_6 and air installations were investigated. Important defects, such as detached electrode at ground potential, tips at high potential, multiple and/or single internal cavities, fixed conducting particles on the dielectric, bouncing particles and surface discharges, were investigated. They reported that relatively high probabilities of recognition were obtained and no misclassifications were observed. Further results from the same author were reported in [14]. Noise suppression was a major feature in this paper. The back-error propagation (BEP) algorithm was used. Orthogonal transforms (Fourier, Walsh-Hadamard and Haar) extracted from pulse height and phase analysis were used for the redundant diagnostic concept. This method was very successful with PD diagnostics in commissioning tests and for triangular shaped voltage waveforms (94 % and 100 %, respectively) but it had only a moderate success for monitoring tests (63 % only). Despite the latter drawback, reference [14] posed some pertinent questions regarding the whole concept of PD recognition with the aid of NN: can, for example, a NN system be used independently of the measuring equipment and experimental conditions? Are PD patterns in internal cavities the same for various arrangements so that no misclassifications are possible? Why most of the misclassification problems appear near inception and extinction voltages? The general feeling that one gets from [13, 14] is that classification of various defect types is possible and in many cases with a high success rate. It is, however, questionable whether such high success rates can also be obtained with combined and/or multiple defects.

A different approach was used in [15], not so much regarding the NN as the PD data. Instead of pulse height and phase analysis data, the authors used POW (point-on-wave) records from the UHF method. A POW waveform represents the peak hold amplitude of any short lived discharge pulse ($< 10\,\mu s$) occurring on a mains cycle when recorded using the maximum hold facility of the spectrum analyzer, with the complete waveform built up over a large number of cycles. A NN of the feed-forward type was used. Three types of defects were investigated, namely, a free metallic particle bouncing asynchronously with respect to the mains cycle across the floor of the chamber, a fixed protrusion on the high voltage conductor or on the chamber wall and a fixed wire on the surface of the spacer. Pre-processing of the PD data was employed in the context of this work. The authors showed their preference for the single hidden layer approach with three hidden neurons. High classification rates were reported (up to 98 %). It should, however, be noted that in this work, three types of defects only were investigated (and these not in conjunction with each other). The approach of the authors of collecting PD data with UHF method should be seen favourably especially in the light of some criticism regarding PD data by using pulse height and phase analysis techniques [16, 17]. In the opinion of the authors of [16, 17], PD pulse height and phase distributions depend on the previous history of the sample under test and consequently one may look for other parameters suitable to feed into a NN. The authors of [16], for example, claim that parameters such as the voltage difference between consecutive discharges furnish the operator with more reliable information about the development of PD. Moreover, it is stated by some researchers [16, 18] that, contrary to the general belief, PD in systems that contain solid dielectrics are not statistical events but very deterministic processes. Certainly the problem of stochasticity of PD is a major one and studies were carried out indicating that time-resolved discharge sequences may be capable to define a discharge regime parametric situation that could be used to monitor the state of SF_6 insulation over time. Pulse-to-pulse information (such as the ratio of the largest pulse over the first pulse in a pulse sequence, the pulse ratio with respect to the nth consecutive event etc.) may illuminate the complex nature of the PD phenomena [19] and, according to the opinion of the authors of the present paper, it should be taken into account in future attempts of PD recognition with NN.

The authors of [20] approached the problem of PD recognition with the aid of NN from another point of view. They used data obtained from a simulation PD injection method as instructor data in order to detect and locate PD with a three-layer back propagation NN. Actual faults were restricted to aluminium needles of given dimensions on the surface of the high voltage conductor. Location was proved accurate when PD were generated near the spacer and rather low with remotely generated

PD. This can possibly be explained by the fact that existing frequency components decrease at locations away from the point of simulated pulse injection or the site of PD generation causing the scatter of waveforms to increase. Although high accuracies in detection and location were reported, no details were given. It is to be noted that the authors did not use any pulse height and phase analysis techniques but they concentrated on the UHF method and the related analysis with the spectrum analyzer. In this respect their approach had similarities with [15].

The problem of noise rejection is of paramount importance. In [21], PD pulses from various sources and disturbing pulses were investigated by an unsupervized working clustering algorithm. A feed forward neural network (FFNN) was trained in the predetermined clusters [22, 23]. Tests were carried out with a 245 kV SF_6-switchgear. PD signals were measured with two broadband field probes. The authors of [21] claimed that it was possible to distinguish real external disturbing pulses from artificial internal PD pulses without, however, giving any hints as to the recognition rate of their method. They pointed out that by their method internal PD activity could be evaluated up to an average noise to signal ratio of $10:1$. Consequently, one is entitled to say that such a system may distinguish between interference and real PD signals only under certain conditions.

Protrusions on the inner conductor and the enclosure cannot be distinguished from each other easily [24]. The narrow-band UHF method, according to [24], seems to be appropriate for the detection of PD signals in GIS. These authors experimented with a GIS set-up with a rated voltage of 362 kV. Interpretation and classification of PD signals may be carried out with the aid of orthogonal functions (other functions, such as Walsh-Hadamard, Haar, Slant and Hybrid Walsh functions can also be used). A NN used for the classification was a feed-forward network trained with the back-propagation momentum. For the most suitable topology a genetic algorithm was applied. The aforementioned work did not give any details on the recognition rate of the used NN or on its comparison with the results obtained from the classification with a fuzzy system.

Generally speaking, although much progress has already been made, very high recognition rates have not yet been reported for all possible defects and/or all possible combinations of defects in GIS. The multitude of possible combinations is too large for that. In the words of a recent paper, "any expert system can detect some failures sometimes, but no expert system can detect every failure every time" [25]. Although the latter sentence runs contrary to the optimism expressed by one of other researchers in this field [14], we think that it still holds true. Having said that, we should also point out that in the same paper [25], a combination of both human experts and computer diagnostics is proposed for the best outcome since in the words of the authors " ... when either of them is wrong the other could be right".

4 NEURAL NETWORKS IN TRANSFORMERS

Since the reliable operation of power transformers is directly related to the reliability of power systems, it is to be expected that a lot of research was devoted to the study of PD signals and their possible sources as well as to the gases evolved because of some electrical, thermal and/or chemical processes (it is not to forget that deterioration of the transformer insulation because of PD may manifest itself as evolved gases). It is thus imperative in the case of power transformers to be interested not only purely in the PD activity but also to the byproducts which possibly result from such an activity.

Oil quality in power transformers plays a predominant role in determining their performance [26, 27]. Data gas analysis (DGA) is one of the main techniques furnishing results on the state of a power transformer. In [28], an approach involving cluster visualization in order to attain an intuitive understanding of the problem data space was presented. Data of DGA was selected with (as the authors of [28] state) " ... elegance and consistency among a set of results from several investigations ... ". As a clustering technique, the Kohonen self organizing feature map (SOFM) was preferred. This technique mapped the data as best it could into two dimensions, folding and stretching it during the mapping so as to minimize the inevitable mismatches. The authors used a large number of neurons, comparable to or even greater than the number of training samples. The results were attributed to two main types of fault: overheating and arcing. No details on the recognition rate were given. The authors claimed that they were able to see some credible trends in terms of trajectories across the Kohonen map. High recognition rates, however, were reported in [29]. The authors of the said publication studied power transformer DGA data in conjunction with PD parameters such as PD counts and average and maximum PD magnitude *wrt* the phase angle. Three gas ratios were chosen as the input attributes to classify the fault conditions of the transformers. A main conclusion drawn from this work is that a possible combination of fuzzy logic and NN structure would give better results than either fuzzy logic or NN alone. The authors proposed a fuzzy learning vector quantization network (FLVQ) which showed superior learning capability (of 100 %) as opposed to either the fuzzy system (88.06 %) or the back-propagation NN (80.59 %). A weakness of this work was that it was carried out in laboratory conditions, in other words in conditions of a rather low noise. In laboratory conditions was also carried the work reported in [30] with circular disc shaped oil impregnated pressboard insulation under uniform field electrodes. The advantage of this work was that it emphasized the stressing of the samples at different levels in order to enhance the classification accuracy. The work was carried out with a back-propagation learning based multi-layer perceptron (MLP) NN. Comparisons between such networks with two hidden layers and with a single hidden layer were made. The authors concluded that a

two hidden layer network would be a better choice. Although this work is informative regarding the PD pulse pattern analysis comments and NN implementation, it does not give any hints as to what sort of recognition rate can be obtained. Moreover, the fact that this work was carried out with laboratory samples means that no direct extrapolation of the reported results can be done into actual working conditions.

Separation of PD from pulse-shaped noise signals with the aid of NN was reported in [31]. An ART 2-A NN (adaptive resonance theory) was used. Such a network is characterized by the fact that the connections of the neurons would only be modified if the input pattern is similar enough to an already known pattern. If the input pattern is not similar to any existing recognition category, the NN generates a new category by itself. Thus the concept of the ART network allows it to learn new patterns without forgetting those already known. In this case, two cascaded ART 2-A networks were employed. This means that there was first a separation of the PD from the noises and then a further investigation of all signals recognized by the first network as PD can begin. The aim of [31] was to distinguish PD from disturbances (*eg* PD from corona noise and from periodic noise) and to correctly locate the PD. In both the authors claimed success. They did not, however, give any recognition rates regarding the correct location of the PD signals. Their assumption, namely, that both PD and disturbances are linearly distributed about the whole winding of the transformer, although somehow justified in the context of the paper, seems questionable. In another work [33], further effort was undertaken to study the separation of PD signals from noise pulses in greater detail. The authors studied the evaluation of PD measurements with features calculated from various transforms (discrete cosine, discrete Fourier, discrete Harltley, Haar, Karhunen-Loeve, rapid, slant and Walsh-Hadamard). In [32], the usefulness of RT algorithms was again emphasized. It was, however, pointed out that a back-propagation network classifying the slant transform features would give the smallest error regarding the classification at the noise suppression. Other combinations (e.g. fuzzy-ART with discrete Fourier transform or nearest neighbour classifier with Karhunen-Loeve transform) are also possible and may give optimal results. Yet other combinations (*eg* back-propagation with Karhunen-Loeve transform or Kohonen feature map with Karhunen-Loeve transform) may give optimal results regarding the localization of the defects. Certainly, the aforementioned work is a detailed one proposing the simultaneous application of several algorithms which, each in combination with suitable feature vectors, contributes to an increase of the reliability of the evaluation. Again, in [32] no details were given as to the recognition rate of the various algorithms.

A further development of the previous work [31, 32] was given in [33]. The authors investigated the subject of PD localization in power transformers with a wide band measurement method taking into account the transfer function of the winding. Their NN was a back-propagation network. The NN was trained by sectional winding transfer functions (SWTFs) of the transformer coils for evaluating PD wide band signals. Despite the fact that misclassifications occurred, the method presented in [33] had a rather high recognition rate of about 95 %. This paper took a rather more critical and less optimistic view from that of Kranz [14] regarding our ability of what we can achieve with NN. It emphasized the importance of the transfer function, an altogether significant notion especially when we are concerned with power transformers. The merit of [33] was that it replaced the a priori knowledge of PD patterns (which in on-site situations are not known anyway) with the transfer functions of the transformer windings. Back-propagation NN was also used in [34], where the emphasis was given to the learning process of the NN. Training with multiple patterns per class resulted to a short learning time and very good classification characteristics. The importance of the quality of input data was commented upon as well as that of a large number of patterns. The authors got their PD data from on-site measurements with GIS, polyethylene cables and instrumental transformers. No details were given as to the collection of PD data from such a variety of high voltage equipment or about the obtained recognition rates. The authors relied on the registration of pulse height and phase analysis distributions.

In [35], another approach based on DGA data and a combination of ART network and back-propagation algorithm is proposed. The ART network implements the DGA data and is preferred because its diagnostic knowledge is not learned in trial and error manner but is consists of refining, features memorizing and merging [31]. Back-propagation algorithms are used for the sub-models which can judge the state of the transformer from measurements of its DC resistance, acidity of the oil, *etc.* Finally, fuzzy reasoning is adopted for the comprehensive diagnostic sub-models. A combination of ART, back-propagation algorithm and fuzzy logic is presented in this work. This may sound complicated but it encompasses aspects of various methods and networks offering good diagnostic capabilities. This work had as a purpose not only to offer high recognition rates but also to correctly locate the actual fault in a transformer. Results given in [35] indicate that this was obtained. The novelty about [4] is the fact that it combines various aspects of NN. It does not, however, give any details as to the recognition rates obtained.

5 DISCUSSION AND SOME PROPOSALS FOR THE FUTURE

It is understood from the above that intensive research is going on regarding the application of NN in GIS and power transformers. We think that the discussion as to whether this or that particular NN is better suited for one or the other application will not stop. Personal preferences and occasional better familiarity with a particular

NN will always be with us. Marginal improvements here and there are also possible. It is our belief that combinations of two or more types of NN to tackle massive tasks (like the PD pattern recognition and the DGA data at the same time) will also be proposed in future publications. We think, however, that this is not the main problem envisaged by the research community although this alone has some significant aspects by itself.

The main problems are the elimination as much as possible of the various noise signals in industrial applications as well as the better and more reliable recognition of PD patterns when - and this is very important - not only one defect (or one type of defects) discharges but two or more types of defects simultaneously. This aspect was not really tackled either in laboratory conditions or in industrial applications although the research community is well aware of this daunting problem. PD pattern recognition under such complicated circumstances will be a rather difficult task. The difficulty arises from the fact that it is hardly possible to establish a relationship between PD patterns and the number of defects or to recognize a single cavity PD pattern in a multi-cavity pattern [36]. In most of the cases, the defect sites were well defined and recognized as such when they were discharging one at a time [21, 37]. What is still to be done is the study with the aid of NN of complicated PD patterns coming from multiple defect sites discharging at the same time. In that sense, studies of PD time-resolved measurements from two or more defects may contribute in elucidating some aspects of the PD processes with time [38].

Attention should also be paid to the fact that pulse height and phase analysis data were put to question by some researchers [16, 17]. The main thrust of their argument is that consecutive PD resulting from an individual discharge site are not independent events because the remaining space charge from previous discharges may alter the ignition conditions of subsequent PD pulses. Such patterns may give good information on the variation of the PD magnitude and PD number with time and phase angle but no information on the time sequence of the PD events [39]. There are indeed proposals of using sequential partial discharge pattern analysis as a diagnostic tool for high voltage insulation systems [39, 40] (indeed as was shown in [39], the sequential PD pattern analysis — regarding GIS studies — may distinguish more clearly PD events stemming from a moving particle from PD events coming from a fixed particle).

Last but not least one should also mention that in order to have good recognition rates, we should bear in mind that experiments have to be performed at various voltage levels. This may seem a trivial assumption but it is not. PD events especially very near to the inception voltage level seem to be sometimes blurred. What is needed is not only PD pattern recognition well above the inception voltage level but also at values approaching the said level. Since research has shown that PD events may be possible even at voltage levels below the inception voltage, work at or around inception becomes pertinent [41-44].

6 CONCLUSIONS

This paper is a short review of the role of NN in industrial high voltage applications such as GIS and power transformers. It gives good grounds why we should use neural networks for PD recognition in high voltage systems and in GIS and power transformers in particular. It was pointed out that noise signal separation from the genuine PD is one of the main problems envisaged. Various NN were proposed by the researchers, the most popular being the back-propagation NN. Such NN are useful for PD recognition and PD location. Difficulties arising from the application of NN were also mentioned. Attention should be paid to the problem of multiple defects as well as to the effort of finding alternatives to the parameters of the pulse height and phase angle analysis. Furthermore, care should be exercized with respect to the PD events very near the inception voltage level.

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