Partial Discharge Object Recognition using Cellualr Neural Networks on Digital Signal Processor

Javeed Ahmed Khan[#]
Research Scholar, Dr. MGR University,

Dr. S. Ravichandran,
CEO & Chief Scientist,
Trimentus Technologies,
Chennai-17.

Mr. Mallikarjunappa.K,
Joint Director,
Central Power Research Institute,
Bangalore-80.

ABSTRACT

In this paper, Object recognition of Partial Discharge (PD) occurring in High Voltage (HV) insulation system of 6.6kV, 1.5 MVA stator coils for different fault and fault conditions are analyzed using a technique of object defining using the matrix representation form and analyzing using the matrix represented Neural Networks (NN) i.e., Cellular Neural Networks (CNN) realized on a Digital Signal Processor (DSP) and data collected using PD Detector Biddle series 27000 along with Lemke's software in numerical and pictorial form is used to compare the condition of the insulation system. Comparisons of the trained CNN output in numerical and pictorial comparison are presented in results with tabulated numerical results and error graphs.

Keywords: *Object Recognition (OR), Partial Discharge(PD), Cellular Neural Networks(CNN), Digital Signal Processor (DSP), High Voltage (HV), Normal Coil (NC), End-Winding discharge coil (EWDC), Slot discharge coil (SDC) & Semi-Conductor paint (SCP)*

1. INTRODUCTION

Partial Discharge problem is a very important and challenging issue in HV and is of greater economic importance as it is related to power generation. Defining of PD in OR domain and analyzing it as numerical represented type and pictorial represented type is attempted in this paper. Different parameters linking the assessment of PD in numerical form are shown below.

- PD maximum pulse.
- Pulse Repetition rate.
- Average Discharge current.
- Quadratic rate.
- Total No. of pulses.
- Phase angle width.
- Average discharge energy.
- Skewness.

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HV insulation system used for insulation of stator windings in a generator are prone for PDs, they are deleterious to the health of the insulation system as the system may fail any moment putting the generation into jeopardy. Hence, it is very important to know the health of the insulation system before putting it into service. Different methods are devised to monitor the healthiness of the HV insulation system, all methods required extensive human intervention and careful analysis of data before certifying [1]. With the advent of processing algorithms which have reduced processing time and the intelligence part incorporated with the processing gives a very powerful tool in analyzing stochastic or probabilistic data with much better accuracy with reduced human intervention [2]. Acquired data of HV insulation system both in numerical and pictorial form was carried out at Central Power Research Institute (CPRI), Diagnostics Cables and Capacitors Division (DCCD), Bangalore.

An example of the acquired PD data in pictorial form is shown in Figure 1.1, Numerical parameters deciding

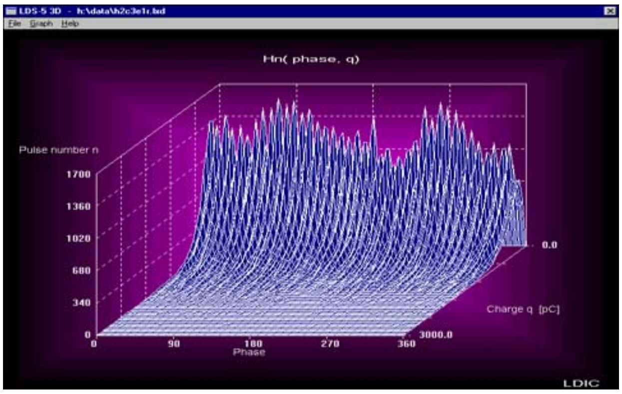

Figure 1.1 Pictorial representation of the PD pattern data is as shown below.

The condition of insulation system is subjected to a Knowledge Based Expert system whose results are given in results section of this paper. The authors have developed the algorithm on Matlab 6.1 version and the results obtained are verified using conventional techniques to know the reliability of the algorithm.

2. PD EFFECTS, DEGRADATION OF STATOR WINDING INSULATION AND PD ACQUISITION

PD is generally referred to as a discharge process in which the gap between two electrodes is partially bridged. PD can occur between two dielectric surfaces or between a dielectric and a metallic surface [3]. The dielectric constant of the void inclusion (usually a gas or mixture of gases) is often lower than that of the surrounding dielectric so that the electric stress in the void is higher than in the dielectric. Hence void breaks down at a lower stress. PD is associated with HV and can produce acoustic emissions, electromagnetic radiation and electrical pulses. In addition, PD consumes power and gives rise to the following effects:

- Ozone or nascent oxygen which are strong oxidizing agents,
- Heat in the discharge channel,
- Mechanical erosion of surfaces by ion bombardment,
- Oxalic acid and other exotic matearials in voids in plastic insulating materials and
- Nitric acid in presence of moisture[3].

The degradation processes are

- Surface Corona in HV machines.
- Slot discharges.
- End winding corona[3].

PD detection an analysis using numerical and pictorial method is carried out using PD detector (Biddle Instruments 27000 series) and acquisition is done using Lemke's software. Setup for analysis, detection and acquisition is as shown in figures 2.1 to 2.4.

Figure 2.1 PD detection and acquisition setup 1

Figure 2.2 PD detection and acquisition setup 2

Figure 2.3 PD analysis setup

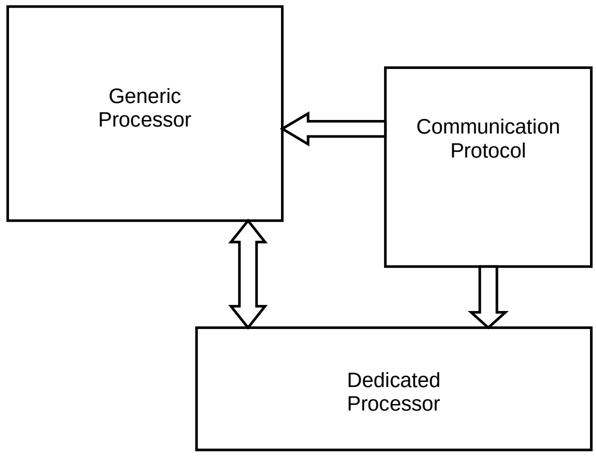

Figure 2.4 Setup of Interfacing between Generic Processor and Dedicated Processor

Fig 2.4 explains the interconnection between the generic processor and the dedicated processor. Generic processor is the Pentium IV processor in the PC as shown in the figure 2.3 PD analysis setup. Dedicated processor is the DSP processor (TMS320C542). Communication protocol is for interfacing, programming of DSP for CNN implementation is carried out in Code Composer Studio with C language, it is converted to its machine code using Code Composer Studio. Explanation is carried out in detail in methodology topic of this paper.

3. METHODOLOGY

3.1 Knowledge Based Expert System

This section gives the concept of processing using the Knowledge Based Expert System (KBES), Table 3.1 gives the different rules adapted for building of KBES.

TABLE 3.1 RULES ADAPTED IN KBES

Sl. No.	Rules
1.	If all the readings tally with the conditions of healthy insulation, then the insulation is diagnosed as healthy insulation.
2.	If all the readings tally with the conditions of faulty insulation, then the insulation in is diagnosed as faulty insulation.
3.	If all the readings fall with the conditions of ideal insulation then the insulation is ideal/virgin insulation.
4.	If skewness above satisfies the conditions given for different margins, then the insulation condition is predicted accordingly with reliability factor of 60%. for this purpose, in the developed program, this factor is given 40% weightage and other conditions of the insulation will help to decide the health/status of the insulation.
5.	If the data set satisfies case 2 requirements with total number of pulses are between 36000 to 60,000 and phase angle width is less than 90^0 then the insulation is faulty with end winding discharge.
6.	If the data set satisfies case 2 requirements with total number of discharges greater than 1 lakh and phase angle width is almost 180^0 then the insulation is faulty with slot discharge.
7.	If one or the other parameters except skewness is missing/other than the prescribed limit then the KBES gives ambiguous/wrong results. The developed software will also give a caution under such circumstances.

3.2 Cellular Neural Networks

Cellular Neural Networks is an information-processing paradigm that is inspired by the way biological nervous systems, such as the brain processes information. In here the classification of PD data is done into four groups, viz. Normal coil, End winding corona discharge coil, Slot discharge coil and Coil with semiconductor paint on 3 sides.

Mathematical modeling of the analysis tool about CNN is shown. Equations for CNN are in differential equation form.

Standard CNN differential equation is shown in eqn. 3.2.1

$$\dot{X}ij = -Xij + \sum_{k=-r}^{r}\sum_{l=-r}^{r} a_{kl}\ y_{i+k,j+l} + \sum_{k=-r}^{r}\sum_{l=-r}^{r} b_{kl}u_{i+k,j+l} + z$$

……… eqn (3.2.1)

Where $\dot{X}ij$ is the first derivative of Xij .

'a' and 'b' are the elements of the space invariant template matrices.

Solving of standard differential equation like

$\dot{x} = h(x;w)$

$x = x(t)$

$x(0) = x_0$ ………. eqn (3.2.2)

This can be solved by standard numerical integration methods; the simples one is the forward Euler formula which calculates the value of $x(t+\Delta t)$ from $x(t)$, Δt being the time step.

$$x(t+\Delta t) \cong x(t) + \Delta t\dot{x}(t) = x(t) + \Delta t h(x(t);w)$$
……… eqn (3.2.3)

From, eqn(3.2.3) it is qualitatively correct and accurate enough if we use a small time step Δt, small enough that the CNN dynamics range when known in advance states will give good convergence, advance states meaning the group to which the PD pattern belongs.

The above equations 3.2.1 to 3.2.3 can be represented in figure 3.1 form as shown below.

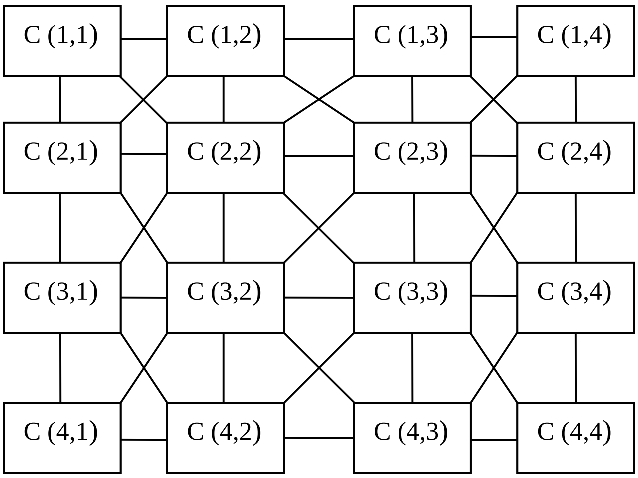

Fig 3.1 A two dimensional fully connected Cellular Neural Network

In figure 3.1, it is seen that the basic circuit unit of Cellular Neural Networks is called a cell. It contains linear and nonlinear circuit elements. The structure of Cellular Neural Networks is similar to that found in Cellular automata: namely, any cell in a cellular neural network is connected only to its neighbour cells. The connected cells can interact directly with each other [4]. Cells not directly connected together may affect each other indirectly because of the propagation effects of the continuous time dynamics of cellular neural networks.

Consider an MxN Cellular Neural Network, having MxN cells arranged in M rows and N columns. We call the cell on the i^{th} and the j^{th} column cell (i,j), and denote it C(i,j) as in figure 3.1.

3.3 Digital Signal Processor

Generic Processors use Von-neumann architecture where in the data bus and address bus are multiplexed this hampers the processing speed for repetitive processes like the one represented in eqn. (3.2.1)[5][6]. Digital Signal Processors are made on Super Harvard Architecture (SHARK) where in the data bus and address bus are separate and that the stored program and stored data are separate but interlinked. This is ideal for repetitive task like the multiply and accumulate task (MAC). The DSP used here for processing, i.e., computing the distances or weights after repetitive feed forward training was of fixed point origin, the software developed for DSP was written in high level language and later converted to assembly level language and finally to machine level language.

4. RESULTS

Results in tables 1 to 4 shown knowledge based comparison of results show the numerical data of the PD acquired of a HV insulation system was diagnosed and is interpreted, table 5 & 6 gives the output along with figures, Fig 4 gives the NN setup used for numerical analyses of PD with eight parameters as input. DSP analysis was carried out and the decimation of image into its RGB value was done using "uiimport" command in matlab and this decimated value was transferred on to the DSP board (TMS320C542) fixed point processor. Figure 4.1 gives an example of the error graph obtained after running analysis.

Table 1: Results of parametric analysis for normal coil

Learning rate (α)	Momentum (β)	No. Of iterations	O/p or convergence
0.1	0.5	450	0.9
0.2	0.6	250	0.899999
0.3	0.7	250	0.900900
0.4	0.8	350	0.900900
0.5	0.9	100	0.90022

Table 2: Results of parametric analysis for end winding corona discharge coil:

Learning rate (α)	Momentum (β)	No. Of iterations	O/p or convergence
0.1	0.5	130	0.9
0.2	0.6	130	0.9
0.3	0.7	130	0.9
0.4	0.8	100	0.9
0.5	0.9	90	0.9

Table 3: Results of parametric analysis for slot discharge coil:

Learning rate (α)	Momentum (β)	No. Of iterations	O/p or convergence
0.1	0.5	50	0.9
0.2	0.6	50	0.9
0.3	0.7	50	0.9
0.4	0.8	48	0.9
0.5	0.9	45	0.9

Table 4: Results of parametric analysis for coils with semi-conductor paint on 3 sides:

Learning rate (α)	Momentum (β)	No. Of iterations	O/p or convergence
0.1	0.5	70	0.85
0.2	0.6	70	0.85
0.3	0.7	65	0.85
0.4	0.8	65	0.85
0.5	0.9	60	0.85

Observation of tables 1 to 4 reveal that, the learning rate (α) for NN of 0.5 and the momentum (β) of 0.9 will give faster and better convergence, compared to the other learning rates and momentums.

Table 5: Comparison between desired output and actual output of NN, for similar data set

Coils being compared	Training set		Epochs	testing set	
	Desired o/p	Actual o/p	Iterations	Desired o/p	Actual o/p
NC v/s NC	0.9	0.899996	500	0.9	0.900175
EWDC v/s EWDC	0.9	0.9	500	0.9	0.9
SDC V/S SDC	0.9	0.9	500	0.9	0.9
SCP on 3 sides coil v/s SCP on 3 sides coil	0.85	0.85	500	0.85	0.85

Table 6: Comparision between desired o/p and actual o/p NN, for dissimilar data set.

Training set			Epochs	Testing set		
Type of coil	Desired output	Actual output	Ite-Rations	Type of coil	Desired output	Actual output
NC	0.99	0.97825775	500	SDC	0.9	0.141121
NC	0.99	0.97716175	500	EWDC	0.9	0.1652
NC	0.99	0.96565475	500	SCP on 3 sides coil	0.9	0.1429
SDC	0.99	0.9786	500	NC	0.9	0.13
SDC	0.99	0.9092	500	EWDC	0.9	0.2135
SDC	0.99	0.909278	500	SCP on 3 sides	0.9	0.12
EWDC	0.99	0.974766	500	NC	0.9	0.15
EWDC	0.99	0.974766	500	SDC	0.9	0.1254711
EWDC	0.99	0.974766	500	SCP on 3 sides coil	0.9	0.33
SCP on 3 sides coil	0.99	0.976369	500	NC	0.9	0.3715
SCP on 3 sides coil	0.99	0.976369	500	SDC	0.9	0.33275
SCP on 3 sides coil	0.99	0.9776369	500	EWDC	0.9	0.2612

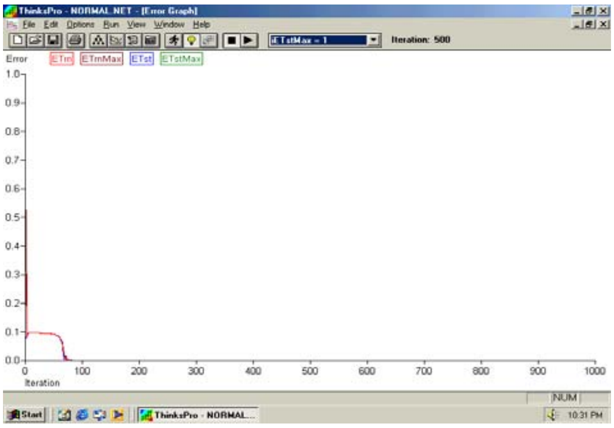

Fig 4.1 Error graphs of similar coils

5. CONCLUSION

Artificial Intelligence paradigms are constantly been developed to incorporate intelligence and make process of automation more effective with less human intervention, the automation process of analysis of PD data in this paper presented was successful in interpreting the healthiness of the HV insulation system, by different paradigms, Knowledge Based Expert System (KBES) results obtained were compared with the results obtained through the CNN paradigm with minimum error. Further the speed of analysis was not very high in this approach as the experimental setup used a fixed point DSP for incorporating CNN. If CNN was realized on a floating point DSP or dedicatedly fabricated on the same board, the processing speed will be drastically improved.

6. REFERENCES

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Javeed Ahmed Khan received Bachelor of Engineering degree from Bangalore University, Bangalore in 2001 and Master of Technology (M.Tech) degree from VTU, Belgaum in 2003. In 2003, he joined for academia and started working towards his Ph.d and registered as a Ph.d scholar in 2004, he is teaching classes in Signals and Systems, Digital Signal Processing, Neural Networks and all electrical power related subjects.

Dr. S. Ravichandran received his Master of Engineering and PhD degrees in Physics / Engineering (interdisciplinary) from REC, Tiruchy. He started his career with the Atomic Energy Commission and Nuclear Power Corporation. He is currently the CEO and Chief Scientist of Trimentus Technologies.

Mr. K. Mallikarjunappa received his Bachelor of Engineering degree from Mysore University, Mysore and Master of Science (Engg) by research degree from IISc, Bangalore. He is currently working as Joint Director at CPRI, Bangalore.