Knowledge-Based Analysis of Partial Discharge Data

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This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

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Abstract

High voltage equipment, such as transformers and gas insulated substations, are important assets in the power industry. Monitoring of these assets has increased in recent years; allowing maintenance to be scheduled to resolve any problems that might exist and therefore avoid an unplanned outage, which could have serious consequences for customers' security of supply and public safety. With a shift towards condition-based maintenance, various techniques have been researched that can assess asset condition and assist in asset maintenance and management. One recognised technique utilised to identify the condition of equipment insulation is through the monitoring of partial discharge (PD) activity.

PD occurs around an insulation defect with the presence of light, sound, heat, electromagnetic waves or a chemical reaction. Monitoring and measuring PD phenomena can produce large amounts of data, the interpretation of which could unveil information about the state of the asset. The analysis of PD data has evolved from periodic, labour-intensive diagnosis by experts, to fast efficient diagnosis using advanced algorithms and artificial intelligence techniques. The move to machine diagnostics, although arguably more efficient, has diminished confidence in the diagnoses. This is due to the machine learning techniques not providing comprehensive justification for their output.

This thesis describes a knowledge-based approach to the analysis of PD data, where knowledge engineering techniques have been employed to capture expert knowledge in this field. It focuses on the elicitation, modelling and implementation of knowledge pertaining to the diagnosis of phase-resolved PD patterns. The knowledge-based system provides decision support in the classification of phase-resolved patterns by PD defect type, and offers a diagnostic explanation of the inferred PD phenomena detected within high voltage equipment insulation.

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Chapter 1

Introduction

1.0 Introduction and Justification of a Knowledge-Based Approach to the Analysis of Partial Discharge Data

As vital assets of the power transmission network, high voltage equipment, such as transformers and gas insulated substations (GIS) must perform reliably to supply secure and continuous electricity to consumers. The introduction of maintenance [Williams-94], be it the traditional time-based (scheduled) maintenance or the now more favoured condition-based (predictive) maintenance [Wang-02], assists in reducing the number of equipment failures and maintains a high-quality operating condition by assessing the health of the equipment, allowing it to be removed from service, or repaired before failure occurs. With a large number of the equipment reaching, or exceeding, their anticipated 'design life', the need for these maintenance strategies are vital to extend the life of the equipment and reduce unexpected equipment failure [James-08].

The failure of high voltage equipment could be as a consequence of the degradation of the insulation inside this equipment over time, or due to insulation defects introduced during production or maintenance activities. Early detection and diagnosis of these types of defects present numerous benefits to asset owners such as: providing time to take action; reducing unplanned power outages; improving safety of personnel; allowing scheduling of maintenance; avoidance of catastrophic equipment failure; optimising the operation of the equipment; increasing reliability and ultimately increasing the asset owner's return on their investment (ROI).

Monitoring of the insulation of electrical plant for defects provides an insight into the condition and longevity of the equipment, offering asset owners the opportunity to mitigate the risk of impact failure.

Condition monitoring and automated diagnostic systems provide a means of online condition assessment of high voltage equipment insulation [James-08][Han-03], facilitating the scheduling of maintenance when a fault is detected. This condition-based maintenance [Jardine-06] allows the apparatus to continue operation until it is deemed necessary to perform repairs, saving time and money and potentially optimising the ROI. Automated diagnostic systems must be capable of 'understanding' and 'making sense of' raw condition monitoring sensor data signals before determining the health of the equipment under surveillance. This can only be successful if there exists a way of capturing information that indicates the health of the apparatus. Analysis of partial discharge (PD) data provides one such indication.

A PD is a localised dielectric discharge that only partially bridges the insulation system between conductors, and may or may not occur adjacent to a conductor [IEC60270-00]. PD occurs at the site of a defect and can cause the production of light, sound, heat, electromagnetic waves or a chemical reaction. This range of signals emitted during a PD has led to the development of various methods of detection [James-06][IEC60270-00][Krivda-95], ranging from electrical, acoustic, thermal, chemical and, more recently, ultra high frequency (UHF) monitoring [Hampton-88][Sacha-06][Judd-05][Templeton-07]. Overtime, sustained periods of PD activity can progressively deteriorate the insulating material of electrical plant and possibly lead to electrical breakdown and risk of a catastrophic failure; making the early detection of PD activity essential.

The novel research reported in this thesis provides a method of automatically identifying defects from PD data captured using either IEC60270 [IEC60270-00] compliant measurements or UHF sensors [Judd-04]. To diagnose a defect from the raw PD sensor data, it first needs to be transformed into a generic workable format. A widely recognised method of displaying the data is to plot a period of consecutive pulses, one second in duration, generated by a defect present in the insulation, on a 3D phase-resolved pattern [Pearson-95]. These 3D patterns, known as phase-resolved patterns, describe the pulse's relative amplitude in terms of its phase position on the voltage cycle and its cycle number.

Individual defects within the insulation create specific PD signatures [Cleary-02] and using the data in this phase-resolved form allows the recognition of the PD source that created such a pattern. For several years significant research has targeted the monitoring of high voltage equipment for PDs [Kemp-95][Han-03][Bengtsson-96]; however, at present the expertise required to interpret captured PD data, be it acoustic, UHF, etc is limited. The amount of data presented to an expert for interpretation can be substantial and therefore the creation of automated systems involving artificial intelligence techniques for PD diagnosis make the task of PD diagnosis less onerous for experts [Sahoo-05][Krivda-95][Grimmelius-99].

These automated diagnostic systems originally focused on employing pattern recognition techniques to diagnose defects from phase-resolved patterns. Different types of artificial intelligence techniques, including machine learning techniques [McArthur-04], such as clustering algorithms and neural networks, although correctly classifying a defect, offered no explicit justification for the derived classification. This lack of diagnostic explanation was due to the "black box" nature of the algorithms, which transformed a defined feature vector at their inputs into classified outputs with no clear explanation of the underlying relationship between them. Other constraints of these machine learning techniques include the requirement of historical datasets to train the classifier, lack of generality due to the classifier being trained on specific apparatus, a classifier's ability to only recognise defects it was trained on and the need for a classifier to be retrained on the introduction of new defects. These data-driven techniques were employed primarily due to the lack of understanding of why and how specific defects create specific patterns.

A limited number of experts are now able to examine a 3D phase-resolved pattern and identify distinct features in the pattern that are indicative of various aspects of PD behaviour within the insulation. This allows the experts to identify the defect characteristics and subsequently infer the defect type that created the pattern. Automated PD diagnosis can be achieved by using this knowledge within a knowledge-based system, providing a number of benefits to the field of PD diagnosis.

The knowledge-based system described in this thesis offers a novel automated approach to defect classification and diagnosis. This ability to justify the automatic classification sets it apart from machine learning techniques, providing confidence to the user by offering a physical explanation of the reasons for diagnosing a particular type of PD. Different levels of explanation are provided for engineers with varying levels of understanding of the equipment; from a classification of the defect, along with the characteristics that the defect exhibits, down to the physical PD phenomena occurring within the insulation and the relevant areas of the phase-resolved pattern that were examined. The knowledge-based system also provides a means of storing this valuable expert knowledge regarding PD diagnosis, which can be easily updated as new knowledge arises with regard to PD phenomena and defect classification.

The incremental knowledge-based approach [Strachan-05] to the analysis of PD data is a novel approach developed in this research, initially using knowledge pertaining to UHF sensor data. However, due to the common physical nature of PD within high voltage equipment [Fuhr-91], the knowledge-based system offers a generic approach to classifying defects from phase-resolved patterns created from IEC60270 [IEC60270-00] measurements or UHF sensors. In addition, due to the consistent physical nature of PD across different high voltage apparatus [Fuhr-91], the system has the potential to diagnose defects in several items of high voltage equipment, including power transformers and GIS. Therefore, the automated knowledge-based approach described in this thesis offers the potential of immediate online decision support to diagnose defects from a variety of sensors across various plant items.

1.1 Principal Contributions

The introduction of a knowledge-based system to the analysis of PD data (by examining a three-dimensional phase-resolved plot consisting of the *pulse's amplitude*, the *cycle number* on which the pulse appears and the *phase position* of the pulse on the voltage cycle) provides the following novel contributions:

- A knowledge-based approach to the automated classification of a defect from the aforementioned 3D phase-resolved PD pattern is in itself a novel concept that provides confidence (through explanation) of the diagnosis. Algorithms to calculate various descriptors that represent the data and highlighting the associated physical PD phenomena achieve this.

- Storage of valuable expert knowledge regarding PD phenomena, defect characteristics and PD diagnosis, which has previously not been captured, creating an evolving knowledge base, with room for expansion as knowledge regarding PD diagnosis grows.

- A novel incremental approach to the diagnosis of PD data providing explanation at each stage suitable for engineers with different levels of understanding and experience.

- The knowledge-based approached offers the potential of a generic, flexible system due to the common physical nature of PD within high voltage equipment [Fuhr-91]. Taking the phase-resolved pattern as the input, the knowledge-based system offers a generic approach to classify defects from data captured through either UHF or IEC60270 techniques, across a variety of equipment such as transformers and GIS, offering online decision support for condition monitoring.

- Examination of the phase-resolved PD pattern on a per activity basis, rather than per half cycle, to avoid the miscalculation of the descriptors that represent the data.

1.2 Thesis Overview

To emphasise the motivation for the work contained in this thesis and the benefits that it offers to the field of automated PD diagnosis, the thesis will first explore the area of condition monitoring of high voltage equipment in chapter 2. This chapter discusses different types of high voltage equipment that condition monitoring and diagnostic systems can be applied to, and the different condition monitoring technologies and techniques available. Chapter 3 proceeds to describe the state of the art artificial intelligence techniques that are presently available to automatically diagnose defects from PD data, highlighting the disadvantages of these relatively opaque techniques, and in doing so illustrating how the introduction of a relatively transparent knowledge-based approach can add justification and explanation for PD defect classification. Chapter 4 will then highlight the required knowledge engineering techniques necessary to elicit and model the knowledge required for the creation of the knowledge-based system described in this thesis.

Chapter 5 will discuss the implementation and creation of the knowledge-based system and chapter 6 will demonstrate its generic nature by showing how defects can be recognised from both the UHF and IEC60270 data, in GIS and oil-insulated transformers. This thesis highlights this generic approach by diagnosing PD defects from both UHF and IEC60270 data sources, using knowledge already captured and implemented during this research relating to the expert interpretation of UHF phase-resolved PD patterns.

Finally, chapter 7 concludes and summarises the main points of this thesis, as well as identifying areas of future work, which could benefit and advance the knowledge-based approach described in this thesis. This also includes the integration of the knowledge-based system into an overall condition monitoring architecture, which will not only assist in classification but also enhance justification of, and confidence in the classification.

1.3 Publications

The research detailed in this thesis resulted in the following publications:

1 S.M. Strachan, S. Rudd, S.D.J. McArthur, M.D. Judd, S. Meijer and E. Gulski, "Knowledge-Based Diagnosis of Partial Discharges in Power Transformers", IEEE Transactions on Dielectrics and Electrical Insulation Vol. 15, No. 1, pp259-268, February 2008.

2 S. Rudd, S.D.J. McArthur, M.D. Judd, "A Generic Knowledge-Based Approach to the Analysis of Partial Discharge Data", IEEE Transactions on Dielectrics and Electrical Insulation Vol. 17, No. 1, pp149-156, February 2010.

3 S.E. Rudd, V.M. Catterson, S.D.J. McArthur, "Agent-Based Technology for Data Management, Diagnostics and Learning within Condition Monitoring Applications", The 2nd World Congress on Engineering Asset Management (EAM) and The 4th International Conference on Condition Monitoring, pp1715-1724, June 2007 (Invited Paper).

4 S.E. Rudd, S.M. Strachan, M.D Judd and S.D.J McArthur, "An Incremental Knowledge Based Approach to the Analysis of Partial Discharge Data", XVth International Symposium on High Voltage Engineering, T5-540, August 2007.

5 V.M. Catterson, S.E. Rudd, S.D.J. McArthur and G. Moss, "On-line Transformer Condition Monitoring through Diagnostics and Anomaly Detection", The 15th International Conference on Intelligent System Application to Power Systems, paper 94, Curitiba, Brazil, November 8-12, 2009.

6 P. Baker, S. Rudd, M. Judd, S. McArthur, "A conceptual design for a low-power wireless UHF detector", Third UHVNet Colloquium on technologies for future high voltage infrastructure, 20th January 2010.

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Chapter 2

Condition Monitoring of High Voltage Equipment

2.0 Introduction to Condition Monitoring

> "Condition monitoring is based on measuring parameters that reflect the state of a machine over a given period of time." [Pearson-06]

On-line condition monitoring techniques provide a continuous indication of the health of high voltage equipment, which can be utilised to inform a predictive maintenance strategy before serious deterioration or breakdowns occur [Han-03]. As part of condition-based (predictive) maintenance, on-line condition monitoring acquires data that indicates the equipment's health, analyses this data to determine the condition of the equipment (diagnostics) and can be used to invoke appropriate maintenance based on this result. This offers many advantages, such as; avoiding catastrophic equipment failures, the ability to schedule maintenance to minimise overtime costs, optimising the operation of the equipment and increasing reliability.

Alternatively, off-line condition monitoring may be invoked to inform a combination of time and condition-based maintenance. For example, dissolved gas analysis (DGA) on transformers [Duval-01] can be carried out periodically to set intervals for maintenance (time-based maintenance) or to indicate the health of the equipment (condition-based maintenance), following which an informed decision on whether to, and how to maintain the transformer may be taken.

In the past, condition monitoring required the physical presence of the engineers onsite. The fact that the operators worked in close proximity to the equipment meant that they could observe or hear any faults. However, the onsite workforce has depleted in recent years and rather than wait for plant items to fail (failure-based maintenance), it is more beneficial to avoid failures and subsequent replacement costs (particularly for expensive items of transmission equipment such as transformers). Condition monitoring enables the capture of data from which incipient faults/defects may be observed and therefore the need for automated diagnostic systems and condition monitoring has increased, making condition monitoring a significant issue for electrical utilities [Judd-02].

However, there are many strategic issues faced by utilities when deciding on whether to adopt condition monitoring. These include risk management issues regarding the utility's reputation, safety of personnel as well as expense. Due to the number of issues an asset manager faces when trying to maintain and maximise the return from assets, a publically available specification [PAS55-08] was constructed to standardise and assist asset management. According to [Montanari-08] the amount of money that an asset manager can invest in diagnostic systems and condition monitoring is the difference between the economic losses when diagnostics are incorporated in the maintenance regime minus the economic losses for a regime without diagnostics. Both calculations of losses take into account the mean time to repair after a fault, the cost associated with scheduled or condition-driven maintenance activities, the energy cost, the replacement cost and the average power demanded by the system. While the economic losses with diagnostics also takes into account the mean time to restore in service after a false alarm, which is a disadvantage of condition monitoring. While such methods for quantifying potential benefits of diagnostics and condition monitoring exist, each case must be considered individually from economic, operational and safety perspectives before a decision as to whether such systems be introduced is taken.

If adopted, condition monitoring is intended to extend the life of high voltage equipment by observing and measuring conditions within the equipment, as well as detecting and monitoring any signs of defects. To achieve this, the process of condition monitoring involves four main stages [Han-03], these are:

1. Sensing – sensors are used to convert a physical occurrence inside the high voltage equipment into an electrical signal.
2. Data acquisition – converts the raw signal by amplification, recording and pre-processing.
3. Fault detection – identifies whether any abnormalities are present within the system.
4. Diagnosis – classifies the fault through the use of human expertise or computers to identify the type of fault and location.

The knowledge-based system described in this thesis addresses the fourth stage of this condition monitoring paradigm. However, in order to diagnose defects within high voltage equipment there must first exist a way of capturing information that indicates the health of the apparatus. One way in which this can be achieved is by monitoring PD activity within the insulation. This chapter will describe a range of different equipment that condition monitoring can be performed on, as well as the diverse methods that can be used to capture various PD signals, which offer an insight into the condition of the equipment.

2.1 High Voltage Equipment

Various types of high voltage equipment perform important roles in the power industry. With the design life of most of the equipment ranging from 20 to 50 years, and with a significant proportion of installed equipment already reaching the end of their design life, it is important to monitor high voltage equipment for any signs of deterioration [James-08]. Condition monitoring can be used to identify these signs of deterioration, which undetected could potentially lead to a fault arising within the equipment. This approach allows asset managers or maintenance staff to take appropriate measures to avoid the occurrence of faults, such as maintenance or replacement of the asset.

Although condition monitoring can be used as a fault prevention technique, it can also be used for post fault diagnosis. Defects can occur at any time in the equipment's life, due to the deterioration of the insulation over time. They can happen immediately after manufacturing or occur because of high electrical stress, and can also be dependent on operating conditions. Defects occurring within the insulation of the equipment could be in the form of loose bolts, or metal particles building up on the conductors over time. Therefore, the monitoring of the insulation within the equipment can provide useful information about the condition of the apparatus [Abu-Elanien-07].

This section discusses two of the main types of high voltage transmission equipment (considered in this thesis) that condition monitoring is applied to: power transformers; and gas insulated substations (GIS).

2.1.1 Power Transformers

> Power transformers "are probably the most important equipment in an electrical transmission system" [James-08]

Typically found in power stations and substations, transformers (an example of which is shown in Figure 2.1) form part of the high voltage transmission network, helping to supply consumers with secure and continuous electricity. They are used to transfer electrical energy from one circuit to another, usually with a change in the voltage and currents. To do this transformers have an iron core, which is normally formed from laminated sheets into a series of rings with two coils wound around each vertical 'limb'. The 'primary coil' is connected to an electrical source and the 'secondary coil' supplies the power to a load. Three phase transformers, an example of which can be see in Figure 2.2, contain three pairs of coils, with each 'limb' having a primary and secondary winding.

When an ac voltage is applied to the primary coil of a loaded power transformer, a current flows in the coil and establishes a magnetic field. This changing magnetic field then induces a current in the secondary coil, which produces a voltage across the terminals of the secondary winding.

Figure 2.1. 120MVA SGT1 Transformer at Easterhouse, Glasgow, Scotland, which converts 275kV to 33kV (courtesy of V. Catterson, University of Strathclyde)

Step down transformers have fewer turns on the secondary coil than on the primary coil. This creates an output voltage that is smaller than the input voltage (in the same proportion as the turns ratio), which is used when migrating from a high voltage to a low voltage. The converse applies for a step up transformer. During transformation the current and magnetic losses heat the coils so an insulating material, such as oil, circulates around fans and the coils to keep them cool.

[Stigant-73] indicated that “the day is now past when a transformer is looked upon as a piece of apparatus which requires no attention whatever because its parts are stationary”. Defects can occur at any stage of the transformer’s life, for example, sharp objects lodging on the high voltage structures, loose nuts and bolts in the core clamping structures, floating metal components or gas filled cavity in solid or liquid insulation. Early detection of these kinds of defects, through the use of on-line condition monitoring and PD diagnosis, offers economic benefits such as; providing time to take action, reducing unplanned power outages and improving safety of personnel.

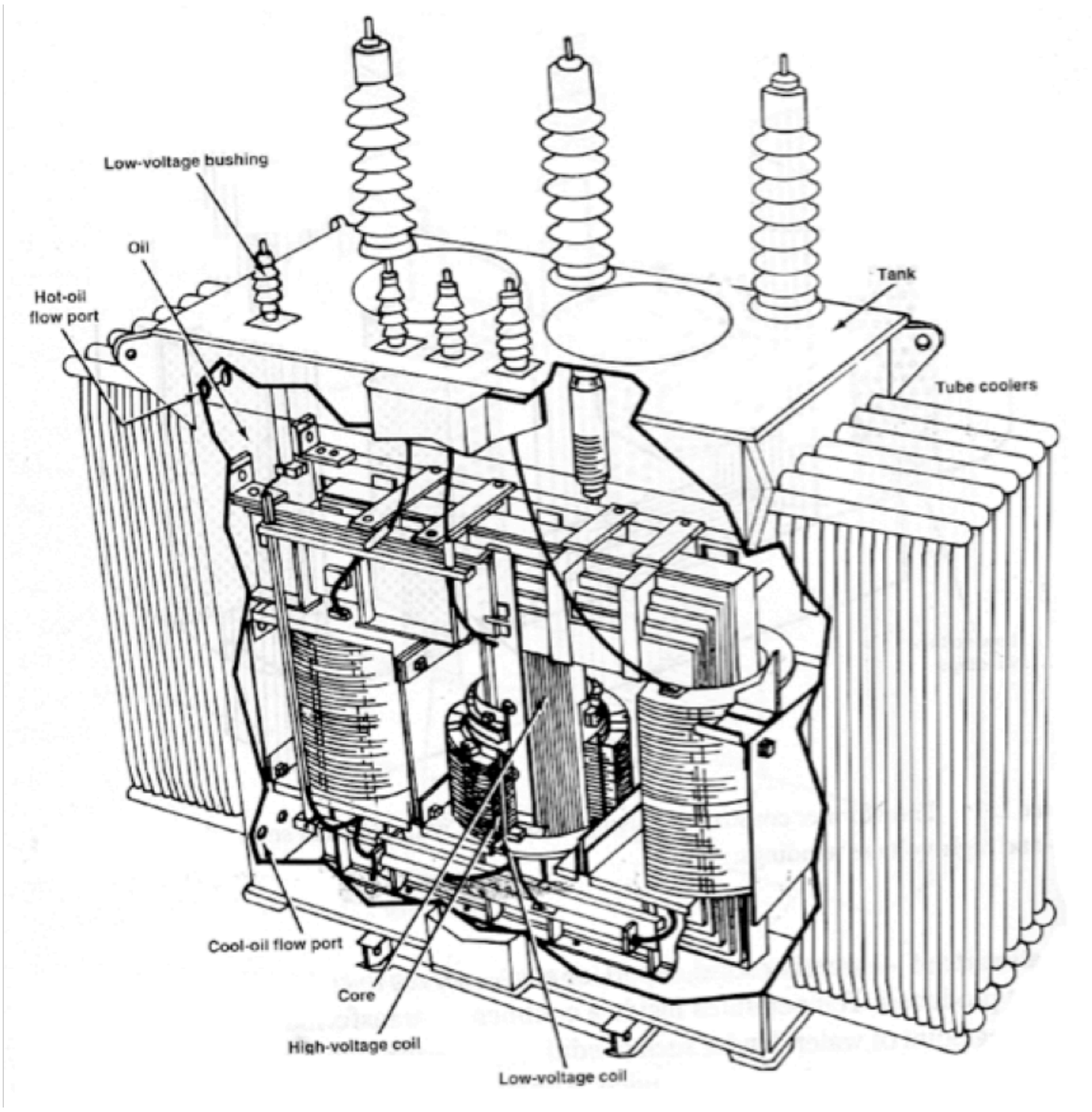

Figure 2.2. Cutaway of a transformer [Seevers-91]

Condition monitoring of transformers can be achieved through the measurement and analysis of a variety of signals that indicate the condition of the asset, ranging from top oil temperature and main tank temperature, to PD [CIGRE343-08]. Traditionally, oil sampling has been an important indication of transformer insulation health [Heathcote-98], originally through visual inspection of the sample for odour, appearance and colour. [Heathcote-98] proposed that "by far the most worthwhile test of the oil sample for all important transformers is to carry out dissolved gas analysis".

This can be carried out offline or more recently online to identify the condition of the oil insulation and therefore the condition of the asset (discussed in section 2.2.2.1.4). In 2003, CIGRE recognised the benefits of condition monitoring of transformers and created working group A2.18, which published a document [GIGRE227-03] sharing knowledge regarding diagnostics and monitoring techniques for transformers.

With growing interest in the area of condition monitoring of transformers, CIGRE Working Group A2.27 published "Recommendations for Condition Monitoring and Condition Assessment Facilities for Transformers" in April 2008 [CIGRE343-08]. This guide recognised the importance of condition monitoring and stated that a combination of sensors could offer better insight into the health of the transformer. To assist in the identification of the correct sensor set for transformers in different circumstances, [CIGRE343-08] recommends and describes a variety of sensors to capture the main indicators highlighting the transformer's health, proposing DGA and PD as two of the main techniques that should be included in the monitoring of transformers.

2.1.2 Gas Insulated Substation

Gas insulated substations (GIS) have been in operation for more than 30 years [Achatz-05]. Designed to overcome space limitations, GIS integrate circuit breakers, other switchgear, disconnectors (isolators), instrument transformers, surge arresters and busbars into an enclosed metal-earthed chamber for electrical power distribution (see Figure 2.3). Consisting of a network of coaxial busbars, GIS contain compressed sulphur hexafluoride (SF_6) gas as the electrical insulation. SF_6 is used in this instance due to its superior dielectric strength, its successful application in high voltage power equipment since the early 1960s and the relative safety of its use [CIGRE276-05].

The present design of GIS has benefited from previous experience gained from earlier versions, making them more reliable than before [Pearson-95].

Although GIS were designed to be maintenance free [James-08], there are still several defects that may exist within the GIS. Defects present in GIS include voids in solid insulation components, stress-raising protrusions, capacitive sparking from bad contacts and free metallic particles. When a fault does occur, the GIS would be out of action, with the typical repair time being more than a week. This could lead to circuit disruption and loss of supply [Achatz-05].

Figure 2.3. 400 kV Gas insulated substation at Torness nuclear generation station

In 1992, CIGRE working group 15.03 recognised that diagnostic methods (discussed in section 2.2.2.1) based on different physical or chemical phenomena could provide valuable information about the state of the GIS insulation, enabling identification of the defect types and their location [CIGRE23-01-92]. It is said in [Pearson-95] that "the common feature of all these defects is that they generate PD activity in advance of complete breakdown". This is the key aspect that enrols PD detection as the basis of all dielectric diagnostics in GIS.

2.2.2 PD Monitoring

> "The most effective technique for signalling imminent failure in electrical apparatus is the detection and measurement of partial discharges." [Ward-01]

As highlighted above, many different defects can occur in high voltage equipment during any stage of their life. Condition monitoring can be used to monitor the equipment for any signs of defects, allowing time to take action if such indicators should arise. Condition monitoring has been an area of extensive research and as a result there are several methods for each of the four stages of condition monitoring [Han-03][Bengtsson-96]. Different parameters can be monitored to assess the condition of the equipment depending upon the type of diagnostic monitoring method used. A common indicator of the deterioration of the insulation in power transformers and GIS is the monitoring of PD activity, which (depending on the method used) can provide a diagnosis of the type, severity and location of the PD source. The existence of PD can also be used to diagnose other equipment where insulation is subjected to high electric stress, such as cables.

There are a variety of defect types that can lead to electrical failure; for example metallic protrusions, poor or loose electrical contacts, electrically floating parts and free moving particles [CIGRE226-03][CIGRE23-01-92]. One of the earliest signs that a defect is occurring within electrical equipment is the existence of PD [IEC60270-00]. PD arises in the insulation as a consequence of local electrical stress, where the electric field exceeds the dielectric strength of the insulation. Due to the nature of the PD it can progressively damage the insulating material and possibly lead to electrical breakdown within minutes, hours or years after the initial PD activity; therefore, the early detection of the PD is crucial.

2.2.2.1 PD Monitoring Techniques

PD is a pulse of electrical current that occurs at the site of the defect with the possible production of light, sound, heat, electromagnetic waves or a chemical reaction. The variety of signals emitted during PD means that there are various methods to capture such occurrences [James-08][Kemp-95][Krivda-95]. Measurement of PD phenomena include electrical, acoustic, thermal, chemical and more recently ultra high frequency (UHF) monitoring, each of which will be discussed in this section.

2.2.2.1.1 Electrical Measurement

The field of electrical detection of PDs is a mature area of measurement encapsulated in the IEC60270 standard [IEC60270-00]. The IEC60270 standard provides an electrical method for measuring PDs. This is achieved by measuring small current pulses using specialised equipment to acquire the apparent charge levels.

The apparent charge is usually expressed in picocoulombs (pC) and is not a direct measure of the PD current (since it cannot be physically accessed inside the equipment), but is obtained from the transient voltage drop across the test object terminals [CIGRE366-08]. The basic testing circuit recommended by IEC60270, where the measuring impedance Z_m is in series with the coupling capacitor C_k, is shown in Figure 2.4 [CIGRE366-08]. This is one of three circuits recommended for measuring PD. Two further circuits can be found in the IEC60270 standard or in [CIGRE366-08]. These circuits differ in the arrangement of the measuring impedance Z_m. The use of these alternative circuits can increase the PD sensitivity and remove external electromagnetic noise.

The circuit in Figure 2.4 comprises an ac voltage source U, an impedance Z, a coupling capacitor C_k, a measuring impedance Z_m and a test object C_a. When a PD occurs within the test object C_a, a current flows in Z_m, meaning that a voltage V_m can be measured across it. The measuring instrument that is connected at Z_m is then used to identify the apparent charge from this change in voltage.

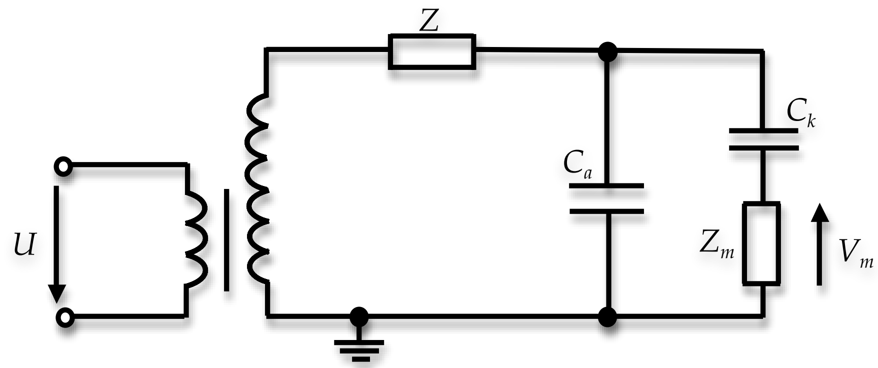

Figure 2.4. PD test circuit [CIGRE366-08]

Electric measurements in the field often have to use variations in the sensor and measurement circuit to record the current pulse. Utilising the high voltage bushing (and tap) as the coupling is one example [James-08]. In the case of transformers, a disadvantage of this technique is the requirement to connect to the transformer bushing to access the signals, requiring an outage. Further disadvantages with this measurement arise from electromagnetic interference from nearby plant [Yang-03], and the electrical method cannot provide the position of the defect within the high voltage equipment.

2.2.2.1.2 Acoustic Monitoring

Acoustic detection of PD within plant items is based on detecting the mechanical energy wave that propagates from the discharge site through the insulation [Kemp-95]. The main advantages of acoustic sensors are that they are non-invasive due to the external placement of the sensor; they are also reliable, reasonable in cost and immune to electromagnetic noise. However, a disadvantage with this technique is that the acoustic sensor is affected by environmental noise [Ward-01].

2.2.2.1.3 Thermal Monitoring

Certain developing faults cause thermal changes within high voltage equipment, and severe PD or arcing could have this effect. An increase in heat can lead to accelerated ageing and further degradation of the insulating oil [Abu-Elanien-07]. There exist two types of sensors to monitor the heat within the high voltage equipment. Firstly, an offline infrared gun [Shoureshi-04] can detect abnormal temperatures when pointed at external surfaces of the equipment. Secondly, online sensors, usually thermocouples [Shoureshi-04], can be placed on the main tank of a transformer, as well as load tap changers, bushings, pumps and fans to detect temperature changes. The main advantages of thermal monitoring are that the technique is simple and effective [Shoureshi-04], and online temperature monitoring reduces the likelihood of missing faults between checks, as is the case with the offline infrared gun.

2.2.2.1.4 Chemical Monitoring

The chemical composition of the insulation inside high voltage equipment alters when PD activity occurs [Kemp-95]. Within the GIS, PD activity results in the presence of thionyl fluoride (SOF_2) and sulfuryl fluoride (SO_2F_2) within the SF_6 insulation. Detector tubes or gas chromatographs and mass spectrometers can be used to detect the presence of these two products. However, the chemical approach is very insensitive because the large volume of SF_6 dilutes the gases that indicate PD [Pearson-95].

Within transformers, DGA can be used to detect PD activity within the hydrocarbon oil and paper insulation. Deterioration within the insulation of high voltage equipment can lead to the presence of certain gases. When PD is present within the insulation various gases can be produced, including hydrogen, methane, ethane, acetylene, ethylene, carbon dioxide, and carbon monoxide [Saha-03]. A technique that can utilise the presence and concentrations of these gases to indicate the condition of the equipment is DGA [Duval-05][Ward-01].

To conduct DGA, small oil samples from within the high voltage equipment are drawn off via a drain plug and analysed every six to twelve months to check for the occurrence of these gases. IEEE standard C57.104-1991 [IEEE

C57. 104-91] and IEC standard 60599 [IEC60599-91] stipulate acceptable levels of gas concentration within the insulation. Two methods that can be utilised for fault diagnosis based on the concentration levels of the gases are Roger's Ratio [Wang-02] and Duval's Triangle [Duval-02], which can help with identification of the type of fault present within the insulation. For example, high levels of hydrogen indicate the presence of PD and deterioration of the insulation [Wang-02].

As well as the periodic off-line technique, DGA can be performed online. One approach to online DGA uses the Hydran sensor [Reason-95] (connected to the load tap changer) to detect the major gases produced with most faults (hydrogen and carbon monoxide, along with acetylene and ethylene) [Martin-96]. Alternatively the Kelman Transfix [Susa-09] offers the detection of hydrogen, methane, ethane, carbon dioxide, acetylene, ethylene, and carbon monoxide, along with oxygen, nitrogen and water content. The levels of gases measured with either sensor can then be used for trending and diagnosis to identify the condition of the transformer. The use of online DGA eliminates the need to visit site to take samples, as well as removing risk of contamination of the samples due to human error.

Although DGA has proven to be successful in the identification of faults within transformers [Duval-05], the offline technique is a periodic inspection that does not provide detailed in-service analysis. It can identify useful information regarding the condition of the equipment but it does not provide up to date diagnosis, i.e. detecting the PD as and when it happens. Also, in the case of offline DGA, the equipment may degrade between tests due to the long time between samples. Other disadvantages associated with this method are the lack of information regarding the position of the fault within the equipment, and the fact that online DGA requires a significant initial capital investment.

2.2.2.1.5 UHF Monitoring

The field of UHF monitoring is a developing area of research. Originally developed in the 1980s for GIS [Hampton-88], UHF sensors were designed to capture the electromagnetic waves emitted by the PD current pulse in the UHF range (300 - 3000 MHz). Now also used in power transformers, there are at least three different types of UHF sensors to capture PD signals, shown in Figure 2.5.

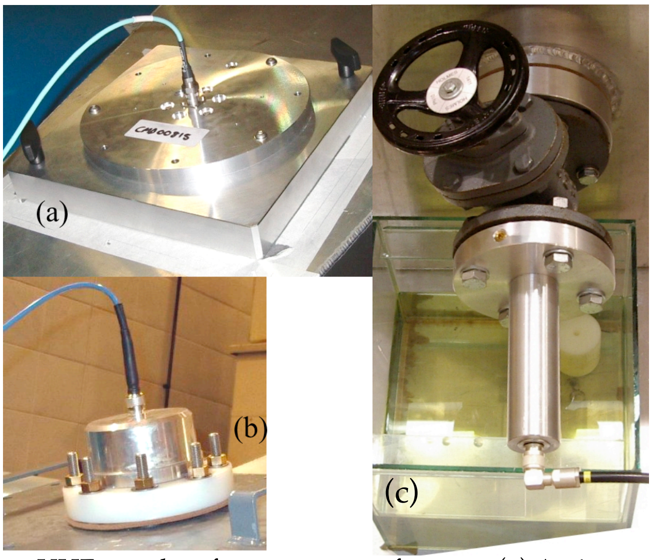

Figure 2.5. Three UHF couplers for power transformers: (a) An internal coupler (courtesy of DMS Ltd), (b) an external dielectric window type, and (c) oil valve probe type

The first is an internal coupler built into the tank at manufacture (Figure 2.5a) [Templeton-07]. The second type of sensor is a window coupler (Figure 2.5b) [Judd-05], which is mounted on a special pre-installed dielectric window, making it unintrusive and therefore not compromising the integrity of the tank, as presented in Figure 2.6. This sensor is more suited for new transformers due to the need to remove the transformer from operation to install the window. The third sensor is the drain valve sensor (Figure 2.5c) [Markalous-06], which is inserted into the oil valve of the transformer while it is still in operation.

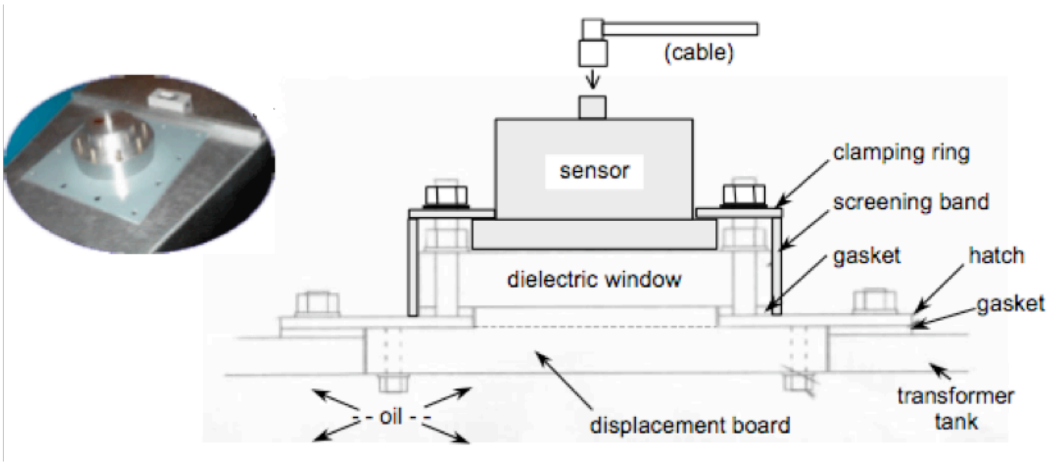

Figure 2.6. UHF sensor mounted on special dielectric window [Judd-04]

UHF monitoring of PD activity has become a recognised technique [James-08] due to its sensitivity and comparative immunity to noise. The main advantage of the UHF method is its ability to identify the location of the PD by using multiple UHF sensors and the "time-of-flight" technique [Judd-05]. This can be accomplished by placing multiple sensors on the high voltage equipment, as shown in Figure 2.7, and measuring the differences in the time it takes for the PD signal to reach each of the sensors.

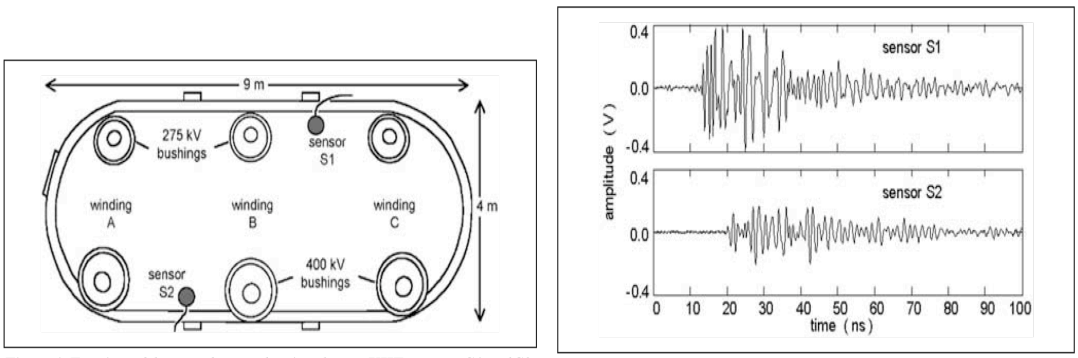

Figure 2.7. Top down view of transformer, showing sensors 1 and 2, and time domain UHF signals showing time delay between signal capture [Judd-02b]

2.2.2.2 Representation of PD data

> "In the design of a partial discharge diagnostic system, finding a set of features corresponding to an optimal classification performance (accuracy and reliability) is crucial." [Yan-05]

The representation of PD data is an important stage within PD diagnostics. The set of features/attributes that are used to classify a certain PD source need to be reliable and accurate when identifying the characteristics and behaviours of the PD. PD data captured through any of the aforementioned monitoring techniques in section 2.2.2.1 should be structured in a suitable format for effective diagnostics.

PD patterns include time and frequency domain characteristics and phase-resolved patterns, which can be used to visualise the PD data for evaluation by experts or computer systems [Lapp-00][Kranz-05]. One important approach is time-based monitoring, where changes in the PD activity are tracked to identify the progress of the PD activity. Increases in the number and amplitude of PD pulses over a particular time period, usually a week or more, could potentially highlight incipient fault development and progressive deterioration of the insulation.

The most common representation of PD activity is the phase-resolved pattern, which is the input data representation used in the knowledge-based system described in this thesis, and which will be discussed in more detail below.

2.2.2.2.1 Phase-Resolved Analysis

Phase-resolved PD analysis is the most reliable for defect identification and is used in various commercial products [Portugues-08]. In a phase-resolved pattern, the power frequency ac supply voltage is also monitored to establish where each PD pulse occurs over the 360 degrees of the voltage cycle, see Figure 2.8 [Strachan-08]. Different defects have different inception voltages and interact in different ways with electric fields around the site, meaning that different defects create different signatures in the waveform [Cleary-02]. The difference in these signatures enables artificial intelligence techniques (pattern recognition techniques) to diagnose the defect that created such a pattern; this will be discussed in chapter 3.

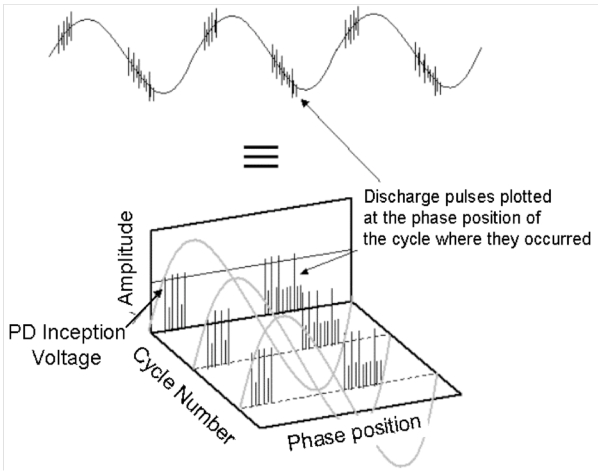

Figure 2.8. Representation of phase resolve pattern showing PD pulses occurring on voltage waveform [Strachan-08]

One widely used data format is the phase-resolved PD pattern (PRPD), otherwise known as the δ–q-n plot [Vaillancourt-89], which can be used for diagnostic purposes [Kranz-05]. This involves plotting the number of PD pulses as a function of their apparent charge and phase angle on a 3D graph, an example of this is shown in Figure 2.9.

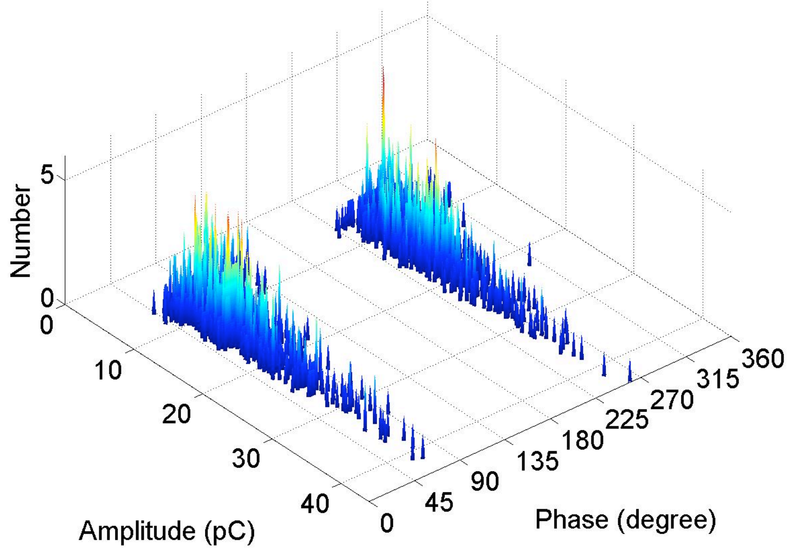

Figure 2.9. Example of a δ–q-n 3D PRPD pattern [Hao-08]

From the 3D pattern different 2D phase distribution graphs can be constructed [Gulski-91], as shown in Figure 2.10, by calculating the maximum amplitude, the mean amplitude and the pulse count for each phase position of the voltage waveform within a particular period. These derived 2D patterns show "statistical fingerprints" representing the 3D pattern and hence PD activity over the period in question can be derived and used to characterise the defect type by extracting various statistical [Gulski-91] features to classify the PD defect.

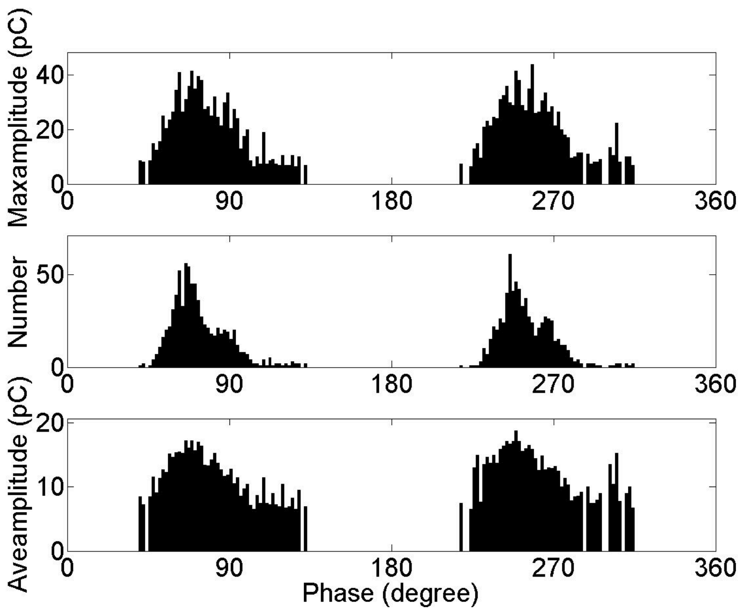

Figure 2.10. 2D examples of a maximum amplitude, pulse count and mean pulse height distribution from the PRPD pattern in Figure 2.9 [Hao-08]

[Pearson-95] showed that both the amplitude and repetition rate of discharge pulses over a number of cycles are fundamental to the interpretation of the data. Therefore an alternative way to represent the raw PD data is to plot the amplitude of each pulse (for UHF data), or the apparent charge (in the case of the IEC data), on a three-dimensional axis consisting of the *pulse's amplitude*, the *cycle number* on which the pulse appears and the *phase position* of the pulse on the voltage cycle. Plotting consecutive pulses generated by a defect present in the insulation generates an alternative 3D phase-resolved pattern, for example, representing a one second (50 cycle at 50Hz) snapshot of PD activity. An example of such a phase-resolved pattern can be seen in Figure 2.11. This phase-resolved pattern allows ready correlation of the PD pulses with the cycle of the high voltage. The positive half cycle appears first, between 0 and 180 degrees and then the negative half cycle between 180 and 360 degrees. This type of phase-resolved pattern can highlight specific PD behaviour occurring within the insulation through the features of the pattern and is therefore examined and utilised in this research for PD diagnosis.

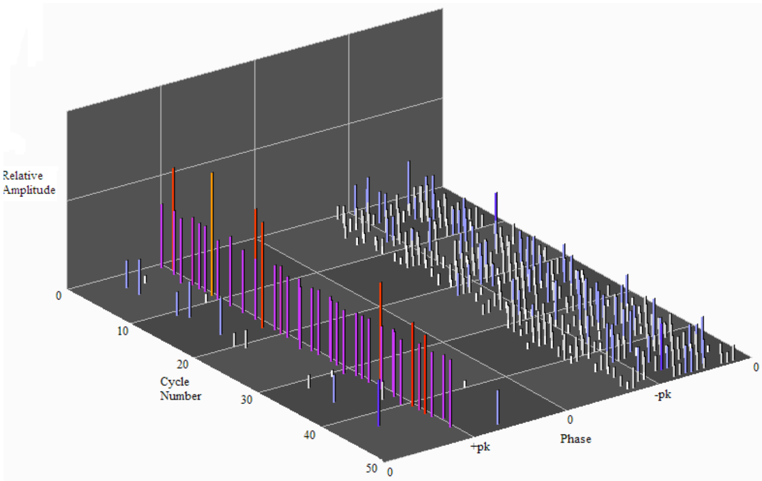

Figure 2.11. Example of an alternative phase-resolved PD pattern

2.3 Conclusion

Whilst this thesis focuses on the later stages of the condition monitoring process, the preceding sections in this chapter have highlighted the requirement for condition monitoring as a means to offer an insight into the condition of high voltage equipment. This constant awareness of the state of the apparatus has benefited the industry [Montanari-08] by “decreasing in inspection frequency and duration, and reducing the frequency and impact of failure” [CIGRE23-202-96].

The preceding sections also demonstrated the variety of sensors and monitoring technology available to acquire PD data, which offer an insight into the health of the equipment. UHF monitoring for PD data provides a sensitive and a comparative immunity to noise, as well as the opportunity of identifying the defect location, making it a recognised PD monitoring technique being currently researched. This thesis therefore concentrates on the automated identification of defects within high voltage equipment from PD data captured through the UHF method. However, the IEC60270 measurement is a standard measurement utilised in industry and therefore this research also evaluates the ability of the newly developed knowledge-based approach to diagnose phase-resolved patterns captured through this technique.

The latter stages of this chapter were included to explain the data acquisition process and representation stage (including the statistical feature extraction), since it is this representation (the phase-resolved pattern) which characterises the PD activity and provides a basis for classifying the defect type. Since every PD generates a specific phase-resolved pattern, various artificial intelligence techniques can be utilised to extract meaningful information from these patterns and automate the classification of the PD source. This will be discussed in chapter 3.

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Chapter 3

Artificial Intelligence Application to Partial Discharge Diagnosis

3.0 Introduction to Artificial Intelligence

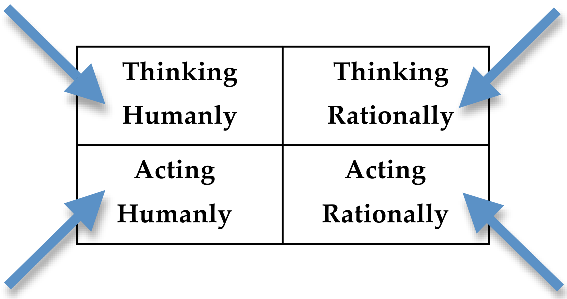
"Artificial Intelligence is the study of ideas that enable computers to be intelligent."[Winston-84].

Artificial intelligence (AI) techniques can be employed to automate the diagnostic process of condition monitoring and identify certain defects that occur within the insulation of high voltage apparatus. These defects emit PD signals, as explained in the previous chapter, which, once captured, can be represented as 3D and 2D phase-resolved patterns depicting the PD activity generated by the insulation defect. During previous research it was identified that individual defects exhibit certain characteristics represented as specific phase-resolved patterns [Sahoo-05][Cleary-02], enabling AI based pattern recognition techniques to be employed to distinguish the defects behind the patterns. This chapter will first define what is generally understood by the term AI and subsequently detail a variety of AI techniques that have been previously utilised in PD diagnosis, and their perceived advantages and disadvantages.

The term AI was originally coined in 1956 and has been the subject of extensive research and discussion ever since. The question "what is AI?" is not easily answered, but may be thought of as one of the four definitions shown in Figure 3.1. These definitions show different ways in which computers can be employed to act or 'think' intelligently. One such definition, which is appropriate for this thesis, is that "AI may be defined as the branch of computer science that is concerned with the automation of intelligent behaviour" [Luger-98]. This quote is appropriate due to the knowledge-based system described in this thesis utilising knowledge from experts to diagnose defects intelligently. This then leads onto the question "what is intelligence?".

Cognitive Approach:
Cognitive science looks into the psychology of the human mind. It is able to link aspects of human thinking into computers.

"Laws of thought" Approach:
Aristotle, the Greek philosopher, was among the first to attempt the process of "right thinking".



Turing Test:
In 1950 Alan Turing designed the Turing Test [Russell-03], otherwise known as the imitation game, to test whether a system could be described as acting humanly. A human examiner tried to identify if the communication he held over a terminal device in natural language was with a computer or a human. If the examiner could not distinguish between them at the end of the experiment then the machine is thought to have acted humanly and therefore show signs of intelligence.

Rational Agent Approach:
"An agent is anything that perceives its environment through sensors and acting upon that environment through actuators" [Winston-84]. The word "Agent" comes from the Latin *Agre*, which means "to do". A rational agent is one that "acts so as to achieve the best outcome or, when there is uncertainty the best expected outcome" [Winston-84].

Figure 3.1. Definitions of artificial intelligence

Intelligence is the ability to problem-solve, plan, reason, learn and adapt by applying knowledge or logic in certain domains. According to Husserl Heidegger and Merleau-Ponty in 1962, "intelligence was not knowing what was true, but rather knowing how to cope in a world that is constantly changing and evolving" [Luger-98]. A computer is thought to have achieved intelligence when its performance can be compared to that of an actual human expert when applied to a specific problem solving-application. This stemmed from the Turing Test [Russell-03] described in Figure 3.1.

The study of AI has led to the existence of a variety of techniques that allow computers to act intelligently [Russell-03], making them capable of solving problems that would have initially involved extensive and time-consuming expertise. One field that draws on AI is machine learning, where a computer program is said to learn from experience [Mitchell-97]. Machine learning algorithms can be useful in a variety of application domains, for example: in domains where a lack of human knowledge is available to develop effective algorithms; domains that are constantly changing and where the program must dynamically adapt to account for these changes; or to discover valuable knowledge from large volumes of data through a method known as data mining. Data mining allows the automatic discovery of patterns in data and can also provide a first step towards classification, and thereby diagnostics, for example through clustering techniques. Examples of other machine learning algorithms that can be used to "search a hypothesis space" [Mitchell-97] and learn to classify specific situations include neural networks, support vector machines and decision trees.

It is not the intention of this thesis to discuss the merits of different AI techniques or to enter into philosophical debate regarding the definition of AI. However, these AI techniques can be used for the diagnosis of PD sources within high voltage equipment insulation [Hucker-95][Krivda-95][Kemp-95][Sahoo-05][Grimmelius-99] and this chapter is concerned with discussing a variety of these PD diagnostic techniques.

3.1 Artificial Intelligence Techniques Used for PD Diagnosis

AI techniques can be used to extract useful information from large amounts of data, which would otherwise be laborious to analyse, offering a fast means of classification of insulation defects. The data presented to these types of systems must have a time trend correlating to the state of the system under evaluation, along with threshold values associated with the correct operation of the equipment [Montanari-07]. As previously explained in chapter 2, PD data provides such information.

It should be noted that there are a large number of AI techniques that have been researched in the area of PD diagnostics, and describing every diagnostic application would be too onerous for the scope of this thesis. Therefore, this section will focus on a selection of AI techniques that are successful in the area of automated PD diagnostics, along with their advantages and disadvantages.

3.1.1 Neural Networks

A neural network (NN) [Winston-94] is a problem solving AI system modelled on the biology of the human brain. A NN involves a number of interconnecting processors (neurons) operating in parallel to solve specific problems. To achieve this, a large set of training data is presented to the NN allowing it to learn by example. Once trained NN are able to predict outputs based on new observations and its previous learning.

Within the area of PD diagnostics, much research effort has been expended on the utilisation of NNs, applying them in various pattern classification forms to a variety of PD fingerprints generated by the defects [Satish-94][Krivda-95][Grimmelius-99][Sahoo-05][McArthur-04][James-95][Danikas-03]. All of these examples of NN use pattern recognition techniques to gain a diagnosis. Danikas et al [Danikas-03] discovered that supplying the NN with the PD pulse and phase patterns sometimes resulted in misclassification, where similar patterns could belong to different categories and a particular category could be made up of very different patterns. However, it was proposed by [Hoof-97] that PD parameters, such as PD inception and PD extinction, should be included as the input to a NN to provide meaningful input about the PD source, which can then lead to an enhanced classification.

Cachin et al [Cachin-95] exposed that the intrinsic problem of classifying defects from PRPD patterns resulted in a very large NN. Therefore, Cachin et al proposed that using pre-processing knowledge, which examines the related parameters to the physical process of PD, before involving a NN for classification, can lead to a smaller NN and so an advanced classification. It can also reduce the training time and reduce the number of examples needed. The knowledge base associated with this system consists of knowledge regarding the appropriate features of the PRPD pattern, which relate to the physical PD process and therefore the condition of the equipment. This generates normalised distributions of useful parameters that can decipher between different defect classes. While this output classification still lacks justification, like many NN applications, it does have the benefit of requiring less training time and providing a more accurate classification.

When training a NN, feature vectors, which hold the PD parameters associated with a PRPD patterns are used as the inputs. This feature vector comprises of a number of attributes that describe the PD pattern in such a way that can lead to the classification of various defects. Gulski [Gulski-91] determined that this feature vector should comprise of 101 statistical features characterising the PRPD pattern that would lead to the unique representation of a PD source. This feature vector can then be presented to the NN input [McArthur-04] for training, testing and ultimately classification. Once trained the NNs are presented with previously unseen new data and are then capable of diagnosing defects that show similar traits to the originals, and thus forming a conclusion as to the type of PD source creating the newly presented feature vector.

One major disadvantage of using a NN with a feature vector that examines the phase-resolved pattern per half cycle exists when calculating various statistics, such as the kurtosis and skew, as found in Gulski's statistics [Gulski-91]. Comprising the feature vector of statistical features characterising the separate positive and negative half cycles of the PRPD pattern can pose an issue for pattern recognition techniques. The actual discharge activity can occur across the two half cycles, i.e. across the zero crossings, which can be difficult to characterise by statistical features, and can distort the calculation of the positive and negative half cycle statistics [Berg-02] leading to misclassification.

The advantage of NNs are their ability to deal with noisy data or incomplete information to reach a result. However, NNs require a large and comprehensive data set for training, which may not always be available, and are considered 'black box' techniques. This means that when presented with a set of inputs, patterns are matched within the concealed system to produce an unexplained output. The disadvantage of such a system is the lack of justification presented with the result. Another disadvantage of NN is its inability to identify defects that it has not been trained on [Hucker-95]. This need for comprehensive data poses a problem when trying to identify new defects [Grimmelius-99]. A further disadvantage which may occur is the issue of 'over training' the NN. In this case the general characteristics of the data sets would be lost and result in misclassification of new data.

3.1.2 Fuzzy Logic

In the 1960s Dr. Lotfi Zadeh of the University of California at Berkeley proposed his theory of fuzzy logic [Luger-98]. Fuzzy logic is an approximate reasoning process based on the degrees of truth, indicating the extent to which something is true. It is a problem solving methodology designed to determine the distinctions among imprecise data, in unpredictable conditions, to reach a result.

In the case of PD diagnosis, fuzzy classification predicts the conditional probability that a measurement belongs to a PD type [Cavallini-05][Salama-00][Phyng-98]. The system created by Contin et all [Contin-02] uses fuzzy classification to separate multiple PD sources and then classify them from a 3D plot, which represents the number of pulses as a function of their amplitude and phase. To perform the separation of multiple PD sources and noise, the fuzzy classifier is split into two functions: a PD-pulse feature extractor, where meaning is mapped to the pulses; and a feature classifier, which can be defined as a set consisting of a parameter vector (θ) and by a rule [Contin-00]. θ represents the points in the data space and the rule decides if a pattern (x_k) belongs to class i or some alternative class. The separation side of the fuzzy classification relies on clustering algorithms to match the similarities of two patterns. Fuzzy logic is then applied to the features of the extracted pattern to identify which of three main PD categories the pattern belongs to [Cavallini-04], which in turn can be sub-categorised further depending on the apparatus type.

Salama et al [Salama-00] exploit fuzzy logic to classify the size of cavities or voids from PD data. They perform this type of classification "in view of the foregoing pulse discharge pattern recognition difficulties" [Salama-00], where it could be beneficial to describe the PD pattern more vaguely. Here, an approximate range of the apparent charge transfer is used to infer the cavity size, translating the pulse amplitude classification into cavity size classification. The reason Salama et al apply fuzzy logic to the PD process is due to the lack of precise information of cavity sizes and their respected PD behaviour.

The main advantage of fuzzy classification is the ability to classify defects from imprecise data. It also provides the opportunity to identify and classify the presence of multiple PD sources, as well as filter out external noise [Contin-02]. However, fuzzy classification can fail when different PD phenomena produce similar signal shapes. This type of classification also possesses a lack of justification for the derived classification, although it can provide a description of the parts of the PD pattern that were examined to produce a classification.

3.1.3 Clustering

Clustering [Russell-03] is not technically an AI technique; however, it is included here as a method that can be used for PD diagnostics. Clustering can be applied to PD data to identify various parameters that could describe a specific PD source. Clustering is an unsupervised learning method to problem solving, which tries to determine how the data is organised through the learning of unlabelled data. K-means is one of the simplest clustering algorithms available and is often used for diagnostics [McArthur-04]. To achieve this, K-means groups the data into a number of (K) clusters by combining together objects with similar characteristics.

The first step of the K-means algorithm is to define K centroids (cluster centres) that represent each cluster. The distance between each point, belonging to a given data set, and each cluster centre is then calculated using L2-Distance (otherwise known as Euclidean distance [Hucker-95]) to assign the point to the closest cluster. A new cluster centre is then calculated prior to assigning the next point. The Euclidean calculation is used to measure the similarity of two vectors, which can be used in diagnostic applications to decide which pattern best matches the one to be diagnosed. In terms of PD diagnosis, clustering can therefore be used to decide which PD source a certain pattern belongs to [Meijer-05][Hucker-95][Sahoo-05][McArthur-04].

Although the clustering technique can correctly identify a defect type within the insulation, it offers no reasoning for this classification, and therefore a lack of confidence could be associated with this method. Another issue with K-means is that the number of initial nodes, K, must be predefined. A wrong choice in the number of chosen clusters can lead to the misclassification of PD sources, since different locations of these initial clusters can cause very different results.

3.1.4 Support Vector Machine

Another form of defect classification from PD data is through the use of a support vector machine (SVM). Otherwise known as kernel machines, SVMs, first proposed by V.N. Vapnik in 1995, offer a method that "use an efficient training algorithm and can represent complex, nonlinear functions" [Russell-03]. SVMs are similar to the NN described above; however, the input feature vector dimensions are increased to achieve an enhanced classification.

SVMs use machine learning based on statistical learning theory to find either classical or regression functions from a set of labelled training data [Hao-06]. To do this, a subset of the training data is used to construct the solution to the problem. As with NNs, feature extraction is an important stage in development of a SVM. Hao et al use features from phase-based information, frequency spectrum and wavelet decomposition coefficients. During training a kernel is chosen to map the input vector to a 3D space [Hao-06]. A hyperplane is then placed between the clustered data to separate the PD sources. When presented with new data the SVM can then classify the PD source by identifying which side of the hyperplane best matches the new features.

Although the SVM can correctly identify the PD defect behind a pattern [Hao-05][Catterson-06], again they suffer the same disadvantage as the NN, i.e. needing a large volume of training data, along with a lack of explanation of the classification.

3.1.5 Decision Trees

Decision trees [Winston-84] are a data mining method that graphically represent all of the alternatives in a decision making process. They take an input, described by a set of attributes, and return a "decision" (predicted output). The decision is achieved by executing a sequence of tests, represented by nodes in a tree. Each adjacent branch represents possible values for the test depicted by the node.

Ross Quinlan developed C4.5 and later C5.0 as algorithms to extract informative patterns from data [Strachan-05]. C5.0 is a commercial decision tree and rule induction product. It is a "sophisticated data mining tool for discovering patterns that delineate categories, assembling them into classifiers, and using them to make predictions" [RuleQuest]. One of the main advantages of the decision trees is their immunity to noise.

Due to their ability to discover patterns within sets of data, decision trees have been used in the field of PD diagnostics to classify defects based on the patterns that reside in PD data [Strachan-05][Abdel-Galil-05]. In the case of [Strachan-05], the C5.0 rule induction algorithm is presented with the PD feature vector of the 101 Gulski statistics that was also presented to the NN described above [McArthur-04]. From this feature vector a decision tree and a production rule set was automatically derived, identifying the various statistical thresholds pertaining to the associated defect classes.

The system described by Abdel-Galil et al [Abdel-Galil-05] is used for the classification of void sizes from time dependent PD pulse patterns. Rather than utilising the 3D phase-resolved plot, the data associated with this method considers features describing the shape of the PD pulses. The extracted information used to construct the decision tree consists of peak apparent charge transfer, rise time, fall time, area under the PD current pulse and the pulse width. This algorithm has the advantage of explaining the result via a self-created rule base, identifying the thresholds of the above attributes, which can be utilised in a fuzzy expert system for void size classification.

[Abdel-Galil-05] states that "this strategy combines the advantage of a rule-based system and minimises the expense and time associated with building such systems" by inferring the identification rules directly from the data. However, as a result only the required threshold values can be explained using this self-generated rule base to identify the attributes that describe the pulses associated with cavity size. Although a decision tree can provide some degree of explanation regarding the threshold statistics chosen, it does not inform the operator of the actual PD behaviour or defect characteristics that are occurring within the insulation. This knowledge cannot be automated and must therefore be elicited from experts within the field of PD diagnostics, using conventional knowledge engineering techniques, which will be described in chapter 4, and will lead to the creation of the knowledge-based expert system described in this thesis.

3.1.6 Expert System

Expert systems are computer programs that use heuristic problem solving methods for interpretation, prediction, diagnosis, design, planning, monitoring, debugging and repair, instruction and control [Luger-98]. The term expert system has been used loosely in diagnostic systems that have been created in the past in the area of PD diagnostics [Huecker-98][Hucker-95]. In this thesis however, expert systems are defined as AI applications that draw upon a combination of raw data and a knowledge base of human expertise for problem solving. This section will describe the three subcategories of expert systems; case-based reasoning, model-based reasoning and knowledge-based system, and show how they have been, and also in the case of the knowledge-based system, could be, utilised in PD diagnostics.

3.1.6.1 Case-Based Reasoning

Case-based reasoning (CBR) is a problem solving AI technique originating from the work of Schank and Abelson in 1977 [Luger-98]. The earliest CBR system, CYRUS [Watson-94], was developed in the early eighties by Janet Kolodner from Roger Schank's group at Yale University, which involved a question-answering system with knowledge of the various travels and meetings of former US Secretary of State, Cyrus Vance.

To perform the problem-solving task, CBR uses the solutions of similar past problems to solve new ones. To achieve this, a four-stage process [Luger-98] is adopted. CBR begins with a set of cases with descriptive indexes consisting of features. Case matching between the numerous sample cases and target case is carried out until the 'most similar' sample case in the case base is found. The main advantage of CBR is the ability to solve problems without the need for detailed knowledge of the domain, allowing solutions to be found where domain knowledge is limited or incomplete.

CBR has been utilised for transformer fault diagnosis by using DGA data [Qian-06]. Qian et al discuss the use of CBR to classify the inception fault within the transformer. Using a case base with defined diagnosed faults and retrieving the base case that most matches the symptoms of the target case achieves this. Although this system uses gas ratios as its parameters to identify the faults that are occurring within the transformer, this still takes into account the identification of PD sources that could be occurring (since, from chapter 2 it was discussed that DGA is used to detect certain gases that occur within the insulation as a result of the by products of the PD source).

This cyclic problem solving approach retains new experience as new problems are solved, therefore forming a constantly evolving knowledge base that can be used to solve future problems [Aamodt-94]. This ability to update the case base after a problem is solved denotes that CBR is a subset of machine learning, where failures and correct classifications are maintained to avoid mistakes and correctly identify solutions in the future.

A case retrieved by the system may, in certain situations, prove to "be close to the required solution, but not close enough" [Watson-97]. Here, case adaption rules can be created from generalised knowledge to fit the case to a particular solution [Maher-95]. Rather than extensively analysing the domain knowledge, as in the case of a rule-based system, CBR "allows a simple additive model for knowledge acquisition" [Luger-02]. Here, expert knowledge is inserted to the system to alter the case for a particular solution. The expert will decide if the output of the system is correct, and if it is thought to be incorrect the expert will insert, delete, substitute or transform components of the solution to fix the discrepancies. This new/improved solution is then placed back in the system for future use. However, case adaption is a knowledge intensive task, and since CBR is often applied to problems where the domain is not well understood, adaption may not always be possible.

3.1.6.2 Model-Based Reasoning

Model-based reasoning (MBR) [Luger-98] is another well-established problem solving technique. There are two approaches to MBR. The first uses causal rules to represent a model of the physical world. These physical models are used to describe the components, behaviour and internal structure of a system. This enables the models to simulate how a system should behave in certain situations.

An alternative approach to MBR is a technique widely used in diagnostic systems [Davidson-03]. The diagnosis of a fault is achieved by examining discrepancies in predicted and observed behaviour of the system to be diagnosed. This is achieved by letting the user of the system know what to expect from the system, or when a difference in behaviour occurs, how the discrepancies led to identifying a fault.

Aschwanden et al [Aschwanden-98] utilises this model-based approach to allow monitoring of the condition within power transformers. It considers adaptive thresholds, which can be altered depending on the working conditions of the transformer. This is achieved by using mathematical models which examine the past output values of various sensors, including PD, along with the operator's decision. However, as suggested in [Aschwanden-98] "the transformer problem is not well defined and has some non-linear components". Therefore, the model-based approach described in [Aschwanden-98] produces a message or signal indicating that a fault condition exists within the transformer. It is not capable on its own to then qualify what this fault is. In this case a further diagnostic layer is required to locate and identify the fault.

Aschwanden et al [Aschwanden-98] then go onto discuss the diagnostic layer, required to identify the fault. Here two possible methods are identified, which are later dismissed. The first is a case-based approached, as described above. The main disadvantage of this technique is the onerous amount of data required to model every operating condition of the transformer. And as stated in [Aschwanden-98], "at present, the on-line monitoring experience of transformers is rather limited and there are only few failure data available." The second type of classification system identified in [Aschwanden-98] is a knowledge-based expert diagnostic system, however this is also dismissed, due to the lack of data available about faulty conditions and the lack of knowledge known by human experts.

Therefore, Aschwanden et al use NNs to diagnose the defects. However, since publication of [Aschwanden-98], human expert knowledge regarding the diagnosis of defects has been augmented by a limited number of domain experts and the use of this knowledge, within a knowledge-based system, to diagnose PD defects is now more viable, and has subsequently directed the research reported in this thesis.

3.1.6.3 Knowledge-Based Systems

Sir Francis Bacon once said, "Knowledge is power." [Luger-98].

A knowledge-based expert system is a system where human creativity can be expressed in a computer program [Luger-98] to solve problems in a specific domain. Due to their ability to provide explanations and justification of their results, knowledge-based expert systems have maintained a permanent role in industry, winning the acceptance and trust of the end user [Hayes-Roth-94]. The construction of these systems is achieved by capturing the expert knowledge in a domain and then invoking this knowledge as needed in response to a particular problem, allowing the computer to draw on the expert's knowledge to mimic the expert's reasoning process.

This leads on to the question *what is knowledge?* Knowledge is information about information, where a concise presentation of structured data with contextual meaning is known about a particular domain. Expert knowledge about a particular domain is one that is gained with years of experience, through a combination of theoretical understanding of a problem and a collection of problem solving rules that are obtained over time.

Knowledge-based expert systems, especially in the area of diagnostic reasoning, have reached conclusions unanticipated by their designers [Luger-98]. In the mid 1960s Joshua Lederberg and Feigenbaum began the development of one of the earliest knowledge-based expert system called DENDRAL [Buchanan-85]. DENDRAL was designed to deduce the structure of organic molecules by employing expert knowledge regarding the chemical formulas of the organic molecules and mass spectrographic information about their chemical bonds. The major issue with the creation of this system was how to represent the expert knowledge so that it could be utilised by a computer.

Many of the lessons learned in constructing DENDRAL led to the development of another expert system called MYCIN [Buchanan-85]. This first generation rule-based system was engineered at Stanford in the mid-1970s. MYCIN "established the methodology of contemporary expert systems" [Luger-98]. It was created to diagnose and prescribe treatment for spinal meningitis and bacterial infections in the blood, by the use of expert medical knowledge. Since then, a variety of knowledge-based systems have been constructed in various domains [Hayes-Roth-94], and today, the largest knowledge-based system is Lenat's CYC system [Lenat-95], which incorporates common sense facts about the world.

A rule-based system is a knowledge-based expert system that comprises of a number of heuristic rules to analyse information [Buchanan-85]. Production rules, written using first order logic [JBoss-08], are used in rule-based systems to represent the knowledge of an expert in a domain, in an IF *condition* THEN *action* format. Rule-based systems are not only used to solve difficult problems, but also to provide an explanation to justify the decisions made. This explanation offers the user of the system more confidence in the result [Hayes-Roth-94], with the rules leading to reasoning that can be understood and criticised.

A rule-based system is made up of the parts identified in Figure 3.2 [Buchanan-85]. The knowledge base of the expert system consists of "a collection of symbols intended to reflect the state of the world" [Buchanan-85]. These symbols represent the knowledge in the domain and these, along with the inference engine, are at the heart of a rule-based expert system. To determine which rules should be fired, the reasoning part of the inference engine is accomplished by one of two fundamental strategies, forward chaining (data-driven) or backward chaining (goal-directed).

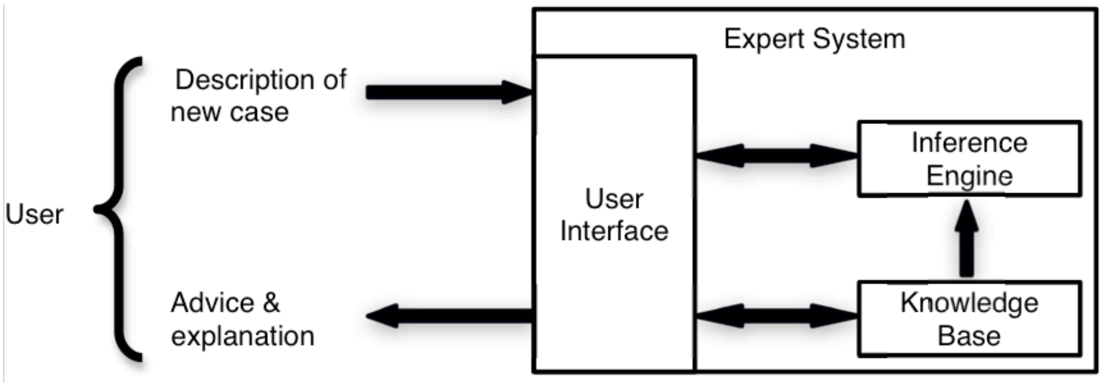


Figure 3.2. Major parts of an expert system (arrows indicate information flow) [Buchanan-85]

Forward chaining is otherwise known as a data-driven method for problem solving and should be employed when all the preliminary facts are known, and these are used to determine what the conclusion might be. This method starts with the initial facts and applies the knowledge rules to draw new conclusions or take certain actions. The facts are represented in the working memory of the system, which is continually updated. The interpreter controls the application of the rules, and examples of this include Drools [JBoss-08], Clips (programmed in C) and Jess (CLIPS' java clone) [Friedman-Hill-97]. One of the main pattern matching algorithms used within these interpreters, to match the conditions (left-hand side) of the rules, is the RETE algorithm [Jackson-99]. Dr. Charles Forgy invented this algorithm in 1982 to improve the efficiency of condition matching. Rather than testing every rule, the RETE algorithm reduces unnecessary iteration through the sorting of the rules into a tree structure, where each node represents a certain pattern occurring in the condition.

An alternative inference method to control the invoking of rules within the rule-based system is backward chaining. It provides a goal-driven approach, which is achieved by starting with the hypothesis/goal. These goals are proved by looking for rules to confirm it with the aid of newly created sub goals. Prolog [Bratko-01] is an example of a backward chaining engine, and

PUFF and MYCIN are well known examples of systems that use backward chaining [Buchanan-85].

Independent of the type of inference engine used, invoked rules are placed in the working memory of the system and can therefore be used to show the route taken to reach a conclusion. This ability of a rule-based system to provide reasoning behind a diagnosis sets it apart from the machine learning techniques. Other advantages of rule-based expert systems are that they are always available to perform their task. This can free up the expert's time if they wish to retire or are under constant demand or, in the context of this thesis, limited in numbers. Another advantage of an expert system is its flexible use of the knowledge. This allows an expert system to perform as well or better than an actual expert. As new knowledge is introduced by additional experts, or through further understanding of the domain, additional knowledge can easily be added to the system, which offers an extensible system. The importance of this flexibility and transparency is crucial, since the system will spend most of its life being changed, updated and improved [Davis-82].

The limitations of expert systems are their lack of ability to solve problems that are unsolvable by humans. Other limitations of knowledge-based systems are their inability to perform commonsense reasoning or identify how situations may change over time [Luger-98]. It is also difficult to develop an expert system where graphical information cannot be described verbally. Therefore an expert system can only be successful if there exists problem solving knowledge within the domain, as well as a suitable way of representing the data.

Knowledge-based systems have been used in the power industry [McDonald-97][Newbould-98], and in particular for predictive maintenance in power transformers by applying expert knowledge to diagnose defects from DGA data [Lin-93][Ahfaz Khan-06][Baroni-95][Ward-01][Xu-97][Tomsovic-98][Wang-00]. Wang et al [Wang-00] developed a system that consists of a NN and expert system that diagnose faults from DGA data. This expert system integrates IEEE and IEC guidelines, as well as human expert knowledge, which is utilised when there is insufficient data to train the NN.

An example of a knowledge-based system that is used for state assessment, preventive diagnosis and intervention planning of power transformers is ASTRA [Baroni-94]. ASTRA supports operators of power transformers by clearly presenting data, assessing the state of the transformer and providing preventive diagnosis complete with an explanation of its conclusion and definition of appropriate interventions. To achieve this, ASTRA holds human expertise regarding a number of different domains, from the physical structure of the transformer, its historical data, its internal physical phenomenon, along with relationships between physical quantities and the internal physical phenomenon. Therefore, specialist in the areas of oil and DGA are required along with numerous others. A traffic light system is displayed to the operator to indicate the state of various parts of the transformer.

Within the area of PD diagnosis, there is an offline expert system for acoustic diagnostics [Lungaard-92], where the operator is asked questions regarding the characteristics of an osillographic representation of the voltage associated with the acoustic consequences of PD activity. These user inputs are fed to a rule-based system, which classifies the PD source using a knowledge base of expertise. Although expert knowledge is utilised to classify the source from the user input, it does not identify the underlying physical PD phenomena associated with the PD activity. Another example of a knowledge-based system for PD classification has been published by Gulski et al [Gulski-05], where knowledge rules are used to determine which of three condition classes the condition of a cable is. This decision is made after utilising statistics on the PRPD fingerprint to determine the condition of the insulation. The knowledge rules "support the decision process of the asset managers in making distinctions between cable networks with different insulation conditions" [Gulski-05].

Although these systems use expert knowledge as part of their diagnosis, they do not utilise the expert knowledge to classify the defect by regarding the PD's physical behaviour and defect characteristics that can be inferred from the phase-resolved patterns. Abdel-Galil et al [Abdel-Galil-05] did suggest that knowledge-based systems in the area of PD diagnosis were too costly and time consuming, and perhaps impossible to clearly identify features of the phase-resolved pattern that would enable the expert to diagnose the defect. However, this was when identifying specific sizes of cavities in capacitors.

It was also expressed by Satish et al [Satish-94] that "manual identification and coding of rules required to build these systems was often found very difficult, if not impossible". However, expert knowledge within the area of PD diagnostics has since improved and the potential of knowledge rules, pertaining to PD diagnosis, has been recognised by CIGRE [CIGRE226-03], which specialises in condition monitoring of critical plant items and PD, and sharing diagnostic knowledge and experience. The potential of a knowledge-based system has also been recognised by Gulski, an expert in the field of PD diagnosis. Originally in 1993, Gulski wrote that there was no need to have knowledge about the underlying physics to diagnose a fault from within the equipment [Kreuger-93]. However, Gulski recently collaborated with Strachan [Strachan-08] and recognised that understanding the physical aspects of the insulation can lead to advanced diagnosis for decision support.

Displaying the PD data in phase-resolved patterns has led to an augmentation of knowledge about these phase-resolved patterns. This has led to experts being able to extract useful information from this data format and therefore diagnosing defects. The engineering of relevant domain knowledge to be used in the subsequent implementation of a knowledge-based system for PD diagnosis represents the core of this thesis and will be described in chapter 5.

3.2 Conclusion

Although machine learning diagnostic techniques can correctly identify defects occurring within high voltage equipment insulation, they offer no justification of their classification. Some applications of these types of techniques have been described in this chapter. These AI techniques also require an extensive dataset of previous defects to be able to train the algorithms prior to being able to classify the defect. This can lead to the inability to identify new defects where there is a lack of historical data. In addition, networks must first be trained before they can recognise defects. Another disadvantage of these machine learning techniques is that once trained, the classifier is then specific to the equipment and sensory data type it was trained on.

To overcome the need for network training (on data that may not always exist) before a new defect can be identified, the equipment specific nature of machine learning techniques and the lack of output explanation, this thesis proposes a knowledge-based expert system approach when diagnosing defects from PD data. The introduction of this knowledge-based approach will offer the explanation behind why a certain defect was chosen, by referring to the underlying PD behaviours and defect characteristics that may be present in the high voltage equipment, which can lead to the final classification. The knowledge-based approach also does not require constant re-training to accommodate new defect types but simply the addition of new rules.

Another issue of the described pattern recognition techniques is their misclassification of defects, where the discharges occur across the zero crossings of the phase-resolved pattern [Berg-02]. Incorporating this knowledge into a knowledge-based system can lead to a classification where the actual discharges are grouped per activity, rather than per half cycle. This will prevent incorrect calculation of statistics, such as kurtosis and skew, which could lead to a misclassification. This will be further discussed in chapter 5.

A limited number of experts posses this knowledge about PD behaviours, phase-resolved patterns and defect characteristics. A major challenge encountered during the research detailed in this thesis was the task of acquiring, representing and organising expert knowledge for PD diagnosis. Knowledge engineering techniques can be utilised to elicit and model this knowledge to assist in the implementation of this expert knowledge within a rule-based system, and these techniques and their application in the development of the knowledge-based system detailed in this thesis will be discussed in chapters 4 and 5.

3.3 References

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Chapter 4

Knowledge Engineering

4.0 Introduction to Knowledge Engineering

> "Knowledge engineering is traditionally concerned with the development of information systems in which knowledge and reasoning play pivotal roles." [Schreiber-00]

As highlighted in the previous chapter, the pattern recognition techniques presently employed to diagnose PD defects from phase-resolved patterns possess a number of disadvantages. The main disadvantages imposed by these machine learning techniques include that the trained classifiers remain specific to the equipment they were trained on, and they do not provide a justification of their classification. It was also identified in the previous chapter that the introduction of a knowledge-based system to diagnose defects from phase-resolved PD patterns could provide this explanation and justification. Along with this justification, the introduction of this knowledge-based approach would also provide further benefits described in chapter 1, including the potential of a generic system, which would not be specific to the equipment it was trained on. However, before the knowledge-based system can be created, the knowledge pertaining to phase-resolved patterns, PD phenomena and defect characteristics must first be identified, captured, and modelled. To achieve this identification and management of knowledge, a process of knowledge engineering [Struder-98] must be conducted.

Edward A. Feigenbaum (1977) defines the activity of knowledge engineering as "the art of building complex computer programs that represent and reason with knowledge of the world" [Angele-98]. It is a process that involves identifying and implementing knowledge that would, after years of experience, reside in a human's mind. The elicitation of this knowledge would be beneficial to implement into a knowledge-based system, to create automated systems that could provide diagnosis, assessment or advice based on the expert's knowledge, saving the human expert the labour intensive task.

Although originally believed to be a process of simply acquiring and implementing this knowledge, it was found that this in fact involved a long and time consuming exercise, where the acquisition of knowledge became more difficult than was originally supposed [Angele-98]. To assist in the acquisition of this knowledge, over the years the knowledge engineering process has migrated through two stages; the knowledge *transfer approach* and the *modelling approach* [Struder-98].

During the *transfer approach,* knowledge was directly transferred from the human into an implemented system. This direct transfer of knowledge identified the knowledge elicitation bottleneck [Forsythe-89]. This bottleneck recognised that the actual acquisition of expert knowledge was difficult to articulate. It was identified that this bottleneck arose from two assumptions; firstly, that production rule systems were adequate for representing the knowledge and secondly, that the required knowledge only needed to be collected since it already existed.

During the knowledge *transfer approach* it was identified [Struder-98] that knowledge acquisition was not a direct transfer of already available knowledge as previously assumed, but that a process for creating a knowledge model was required. To try to overcome the knowledge elicitation bottleneck the knowledge *modelling approach* was recognised, where knowledge models were created to illustrate the functionality of knowledge-based systems, as well as the expert knowledge that is required to achieve this functionality.

Modern knowledge engineering is therefore a technique that can be utilised to model the knowledge and the system, which are required when creating a knowledge-based system. This chapter will discuss different ways of conducting knowledge engineering, through the use of tools and models. The advantages and disadvantages of these methods will be highlighted and the route taken to create the knowledge-based system described in this thesis will be identified and justified in this chapter.

4.1 Knowledge Engineering Tools

The "knowledge level" was introduced by A. Newell [Newell-82] in the 1980s, as a means of providing a conceptual representation of an expert's knowledge, as part of knowledge-based system design. The knowledge level separates different kinds of knowledge into different models, as well as completely separating the symbol level (functionality of the system) from this knowledge. It describes the goals to be achieved, the actions needed to achieve these goals and the knowledge required to perform these actions [Struder-98]. The idea of a knowledge-level inspired two ESPRIT research projects to develop a structured methodology supporting the representation of expertise. The outcome of this research was the Knowledge Analysis and Design Support (KADS) methodology, which later evolved into KADS II and most recently CommonKADS [Schreiber-00].

The use of a modelling framework for knowledge engineering assists in eliciting, representing and storing important knowledge in a domain for utilisation in a knowledge-based system, as well as avoiding the knowledge bottleneck associated with that domain [Freiling-85]. Although attempts have been made to automate the process of knowledge engineering [Freiling-85], it is still a manual and labour intensive task involving knowledge capture, transcribing knowledge documents and developing prototypes. However, the assistance of modelling frameworks provide guidance and support, and this section will describe the aforementioned CommonKADS, along with another modelling framework MIKE [Angele-98].

4.1.1 CommonKADS

> "The aim of CommonKADS is to fill the need for a structured methodology for knowledge-based system projects by constructing a set of engineering models built with the organisation and the application in mind." [Schreiber-94]

CommonKADS is the product of research since 1983 and is the leading methodology to support structured knowledge engineering. Within CommonKADS a collection of models exist to aid in the construction of a knowledge-based system [Schreiber-00]. These are the:

1. Organisation Model: describes the organisational structure, identifying problems and opportunities where a knowledge-based system will be installed and any impacts it may produce.
2. Task Model: describes the hierarchy of the goals within the organisation where the knowledge-based system will be installed.
3. Agent Model: specifies the characteristics of an agent (human or information system), where agents are executors carrying out a task.
4. Communication Model: highlights the various interactions required between agents.
5. Knowledge Model: also known as the Expertise Model, this model provides structure to the knowledge that is required to perform a problem-solving task, detailing the different types of knowledge required for the knowledge-based system.
6. Design Model: provides the technical system specification, highlighting how the knowledge and communication models can be implemented.

Within CommonKADS the first four models defined above are beneficial for a business or organisation that might require a knowledge-based system, by exposing the rewards, impacts and costs of the introduction of a knowledge-based system through development of these models. However, it is only the expertise model and the design model that are necessary for describing aspects required to develop the knowledge-based system itself [Struder-98].

As described above, the design model provides technical system specification for the implementation of the knowledge-based system. This includes [Schreiber-00]:

1. Designing the systems architecture: defining the general structure of the software, identifying the subsystems, control and software modules.
2. Identifying the target implementation platform: deciding upon the hardware and software that will be utilised for the system.
3. Specifying the architectural components: where the subsystems identified in 1 are designed in detail.
4. Specifying the application within the architecture: mapping the tasks, inferences, knowledge bases and transactions onto the architecture.

The other model from CommonKADS, which is important when creating a knowledge-based system, is the expertise model. [Struder-98] indicated that "a major contribution of the KADS approach is its proposal for structuring the Expertise Model, which distinguishes three different types of knowledge required to solve a particular task". This model can be viewed as the specification of the problem solving requirements, which is achieved by splitting the knowledge into three categories:

1. *Task knowledge:* describes the goals and how they can be accomplished through the use of subtasks and inferences.
2. *Inference knowledge:* describes the steps that are required to reach a goal. This is achieved by making use of the domain knowledge.
3. *Domain knowledge:* is knowledge about the overall topic in an application.

These three types of knowledge models identify the expert's knowledge within a domain, which is required for the successful creation of the knowledge-based system. Each of the three categories is modelled using Unified Modelling Language (UML) diagrams [Booch-98], creating abstract models of expertise. Representing the knowledge in this way provides easy validation by the human expert, as well as an uncomplicated transition for implementation into a knowledge-based system.

4.1.1.1 Construction of Expertise Model

The construction of the expertise model is one of the major tasks of the CommonKADS knowledge engineering process. With the expertise model being the most useful in developing a functional specification for knowledge-based system prototype development, as described above, it will be further detailed in this section.

As shown above, the expertise model is split into three categories, with the knowledge in each of these categories requiring acquisition and modelling. To perform these tasks, the CommonKADS knowledge engineering process is split into four stages; knowledge elicitation, knowledge representation, knowledge validation and knowledge utilisation. Each of these categories will be described in more detail in this section.

4.1.1.1.1 Knowledge Elicitation

> "Expert knowledge is a combination of a theoretical understanding of the problem and a collection of heuristic problem solving rules" [Luger-98].

The above definition of expert knowledge implies that knowledge can either be *explicit*, where the knowledge is well defined and understood, or *tacit*, where the knowledge has become second nature to the expert. It is this tacit knowledge that often sets experts apart from non-experts and similarly distinguishes expert systems from traditional information systems. In either case, knowledge is a valuable entity, especially in situations where an expert may be retiring or overworked due to being the only expert in a certain field.

Tacit knowledge is the most important form of knowledge and the most difficult to capture. It is knowledge that is learned through experience rather than something that is taught and often becomes 'second nature' to the expert, which makes it difficult to articulate. An example of tacit knowledge is the ability to ride a bike. This is learnt through personal experimentation rather than by reading a textbook. Extracting this type of knowledge from an expert can be difficult due to the expert having difficulty articulating this knowledge.

Different elicitation techniques can be applied to assist in the articulation of the varying types of knowledge, fundamentally helping the expert to unearth his/her tacit knowledge. There are five types of techniques [Schreiber-00] that the CommonKADS methodology promotes, these are:

1. *Interviewing*: Interviews are meetings where the expert discusses his/her domain. These meetings should be kept to a minimum length so as not to overexert the expert. It is beneficial to record these meetings and create a transcript for further use in the modelling stage of the knowledge engineering task. Interviews are the most common form of elicitation technique and take many forms, from unstructured to structured:
    a. Unstructured interviews have no agenda and should only be applied in the initial stages of the modelling process. The lack of constraints provides considerable scope for the meeting and the outcome supplies a broad view of the domain. However, the lack of structure can lead to the expert digressing.
    b. On the other hand structured interviews are formally planned interviews. Structuring the meetings leads to refining the knowledge gained from the unstructured interview. However, care must be taken to not over structure a meeting, and so lose vital knowledge that would be outside the scope of the interview.
2. *Protocol Analysis:* Otherwise known as shadowing, this technique allows the knowledge engineer (person who is constructing the expert system) to observe and record the expert as he/she works.
3. *Laddering*: This technique is mainly used in the early stages of knowledge engineering to construct initial informal hierarchies. This is accomplished by constructing a two-dimensional graph, of nodes (objects of key terms in the domain) and labelled arcs (depicting relations between objects), forming a hierarchy of trees. Both the expert and the knowledge engineer agree on key terms in the domain

(objects), any associations, and attributes describing the object prior to representing them in a structured manner.

4. *Concept Sorting:* Also known as card sorting, this technique uncovers relationships between concepts (a set of objects/instances in the domain sharing similar characteristics) as seen by the expert. This is achieved by presenting the expert with cards of concepts and requesting that he/she sorts the cards into categories. Sorting concepts this way can lead to the expert also discovering how he/she interprets his/her domain.
5. *Repertory grids:* Repertory grid is seen as a statistical counterpart to card sorting. It is designed to reveal a conceptual map of the domain. The expert is presented with a range of similar domain elements and asked to choose those elements that are different from the others and explain why. Discriminating between different elements results in a matrix of similarity ratings. These are then analysed using clustering analysis, which can reveal additional clusters of concepts and elements, which may not have been articulated in an interview.

There are many pitfalls that could influence the success of the knowledge capture, these include; the knowledge engineer directing the questions in such a way to either over or under influence the expert, having a fear of silence, failing to listen to the expert, interviewing without a recording device, or a lack of planning [Forsythe-89]. To overcome some of the pitfalls associated with elicitation, the CommonKADS approach encourages the audio recording of each meeting to ensure that valuable knowledge is not lost and the expert is not interrupted while notes are taken. This establishes a smooth meeting, where the expert could talk freely about his/her domain.

From the knowledge engineer's point of view, the use of a recording device allows greater focus on the questioning strategy rather than taking notes. Also, since 75% of the time we are distracted or forgetful and only 20% of the time we remember what we hear [ETSU-03], recording the knowledge elicitation meetings ensures that valuable information is retained. Once knowledge meetings have taken place the elicited knowledge then needs to be represented.

A further pitfall that could influence successful knowledge elicitation is when multiple domain experts are involved. Issues can be encountered if the experts disagree, either at the initial knowledge elicitation stage or from the employment of further experts at later stages of the knowledge engineering process. If the conflict of opinion is mild then the experts should be left to discuss the domain and hopefully agree on a final outcome. However, if the disagreement cannot be resolved then two or more alternative approaches could be incorporated into the knowledge-based system, providing different ways to reach the overall system's goal. Within this research, no significant differences of opinion were encountered.

4.1.1.1.2 Knowledge Representation

Knowledge representation is probably the most important stage of knowledge engineering, since representing the knowledge in one way may make the solution simple, while an unfortunate choice of representation may make the solution more difficult to identify. During this stage, the knowledge ascertained during knowledge elicitation meetings are transcribed and modelled to expose the key knowledge, which could latterly be utilised in the knowledge-based system.

First, a transcript of the meeting is documented from the recordings of the elicited knowledge. These transcripts are textual documents that represent the knowledge acquired during the knowledge elicitation meetings. It is important to ensure that these documents are well structured to provide understanding of the transcribed knowledge and allow the expert to easily validate the content of the document. Validation will highlight any incompleteness, contradiction or uncertainty, which could be improved with further elicitation meetings.

Once the expert has validated these documents, displaying the knowledge graphically exposes any areas where the knowledge may be limited. CommonKADS "encourages the use of object-oriented development and the notations from UML" [Abullah-05] for its representation of the knowledge and system design. UML diagrams are used to construct the task and inference models of the expertise model, which will be shown in chapter 5. The task model highlights all the individual objectives needed to complete the overall goal. The inference models are constructed to describe individual reasoning steps required to reach a goal, detailing the input and output of each inference. Both the inference and task models map out the agenda for eliciting the domain knowledge by highlighting knowledge areas required to accomplish the goals and inferences.

One such approach of displaying the expert's domain knowledge, in a way that makes it easier to understand and validate, are semantic network models. Semantic network models are causal diagrams that represent the knowledge using nodes (the objects or concepts) and links (relationships between the nodes). The links that connect each node add meaning to the models. An example of a semantic network model is shown in Figure 4.1.

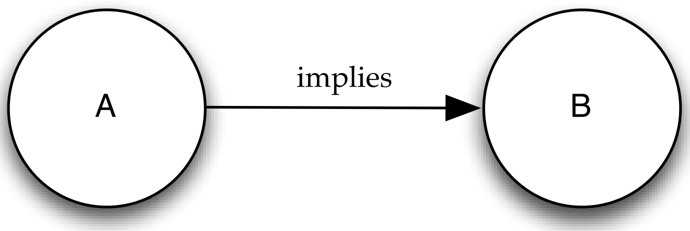

Figure 4.1. Example of a semantic network model

Graphically representing the knowledge in this way can help both experts and non-experts (i.e. knowledge engineers) understand the structure of the elicited knowledge, which can assist in the validation process. These semantic network diagrams can also assist in the implementation stage, where the semantic models created during the representation stage are converted to rules within the knowledge-based system.

4.1.1.1.3 Knowledge Validation and Utilisation

Knowledge validation is an important stage of knowledge engineering due to its exposure of misinterpreted or missing knowledge. It occurs after both forms of knowledge representation: the knowledge transcripts and the UML models. The validation of the knowledge after the creation of the transcripts would expose any areas where the transcribed knowledge had been misunderstood or misrepresented by the knowledge engineer. Validation after the graphical representation of the knowledge would expose any areas that require further knowledge elicitation. Therefore, each validation meeting would lead to either redrafting a transcript, remodelling semantic models or creating an agenda for further knowledge elicitation meetings.

After the knowledge has been validated, any changes to the knowledge are incorporated and the knowledge is finally converted into rules to be used in a knowledge-based system. A cyclic process is followed to validate and alter the expert's knowledge prior to being implemented into a programming environment. This ensures that all the facts about a domain are known before utilisation.

4.1.2 MIKE

> "MIKE puts emphasis on a formal and executable specification of the Expertise Model". [Struder-98]

During the 1980s an alternative tool to support the knowledge engineering process was developed. Model-based and Incremental Knowledge Engineering (MIKE) [Angele-98] covers the entire development process from acquisition and design right through to implementation. This full featured, portable software environment offers a low cost method to knowledge engineering by utilising the expertise model from CommonKADS.

MIKE's process model, see Figure 4.2 [Struder-98], follows a spiral model, with each stage of the cycle producing a prototype. This diagram shows the smooth transition from the semiformal model, where graphical diagrams are used to represent a high level of the knowledge, to a formal model, KARL, which is an executable language that enables validation of the models by prototyping. Finally, the process leads to the creation of a design model, which captures all functional and non-functional requirements of the knowledge-based system [Angele-98] prior to implementation. The design model not only incorporates all the knowledge already in the MIKE process but also adds information required to implement the knowledge-based system, such as defining algorithms, data structures and goals.

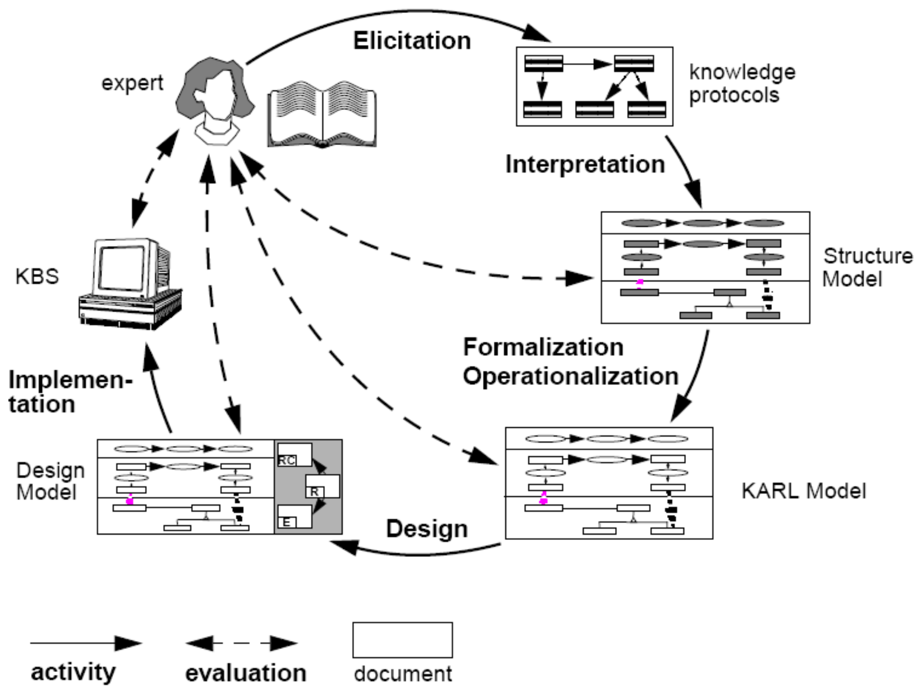

Figure 4.2. Steps and documents in MIKE development process from [Struder-98]

The main advantage of MIKE is the facility to validate each stage of the process by prototyping. Prototypes cannot only be used to depict progress [Freiling-85], but also provide the ability to test within a real target environment, leading to the correction, modification or extension of the prototype during the succeeding stage of the cycle. Further benefits are achieved through the ability to reuse parts of the model for developing multiple knowledge-based systems to tackle similar problems. However, MIKE only assists in the creation of the knowledge-based system itself. This means that if the knowledge-based system was to be embedded within a business environment, additional models would be required, for example the organisation, task, agent and communication models of CommonKADS.

4.2 Choosing a Framework

There are limited criteria to follow when deciding on a knowledge engineering framework. The knowledge-based system described in this thesis requires the knowledge engineering process to identify, capture, document, model and implement knowledge relating to diagnosing defects from phase-resolved PD patterns. From the two modelling frameworks described previously, CommonKADS offers a range of models and techniques to articulate the tacit knowledge associated with a domain.

A number of the elicitation methods from the CommonKADS methodology were chosen to assist in the acquisition of valuable expert knowledge regarding PD diagnostics. The mix of techniques assisted in eliciting the tacit knowledge. Protocol analysis along with the unstructured and structured interviews were employed to gain an initial insight into the expertise, following which card sorting techniques were deployed to categorise the knowledge into groups of similar traits allowing conclusions to be assigned to each group. The CommonKADS approach encourages audio recording and transcription of these meetings, which then required a decision to be made on how best to represent the elicited knowledge.

With the expertise model offering a means of structuring both the system functionality and the domain knowledge, it offers the best representation of knowledge within a domain [Struder-98] and has been constructed in this thesis. CommonKADS encourages the use of UML models to represent the different types of knowledge acquired. Using semantic network models to display the domain knowledge, along with other UML models to represent the task and inference models provides a graphical notation, which is easy for the expert to understand and validate. The elicitation and implementation of the knowledge into the rules, which hold the domain knowledge, will be described in the next chapter.

The spiral process, adopted in MIKE offers many benefits in terms of validation, reuse and prototyping, and for these reasons the process, but not the actual language, has been used in this thesis. The main benefits of using prototypes are to provide a physical system for the expert to validate.

4.3 Conclusion

Knowledge engineering is a technique used to capture and utilise expert knowledge within a knowledge-based system. It has been identified that the transfer of this knowledge is not a simple task, but must involve a knowledge representation process to aid the elicitation of tacit knowledge. This tacit knowledge is the key when creating a knowledge-based expert system and there exist different tools to assist in the activity of knowledge engineering, with CommonKADS being a leading methodology.

The expertise model in CommonKADS is the most beneficial of the available models and was chosen to represent the knowledge implemented in the knowledge-based system described in this thesis, due to its ability to model different types of knowledge for validation and implementation. A spiral approach was followed, similar but not identical to that used in MIKE, to model, implement and prototype the different stages of the knowledge-based system. The design and implementation of the knowledge-based system for PD diagnosis will be discussed in the next chapter.

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Chapter 5

Knowledge-Based Approach to Partial Discharge Diagnosis

5.0 Introduction

Understanding the type of defect present within the insulation of an electrical plant item, through the interpretation of PD data, has the potential to offer equipment health information to the engineer, assisting in the possible identification of an appropriate maintenance strategy for the particular plant item. For example, certain defects could indicate the requirement for an outage to repair the problem, while others could potentially lead to replacement of parts or the asset.

Although originally PD data was thought to be stochastic [Hucker-95], with the present defect exhibiting no constant PD behaviour, it was shown that displaying more than one cycle of a PD event could lead to the identification of the physical phenomena occurring at the discharge site [Patsch-01][Hoof-95]. Plotting the PD data on a phase-resolved PD pattern that displays multiple cycles of data, provides experts with a useful insight into the PD phenomena, space charge affects (discussed in section 5.1.1.2), and other characteristics, which could help identify the type of defect present. Therefore, when examined by an expert in the field of PD, meaning can be sought from the phase-resolved pattern regarding the PD source. To prove the novelty of this technique this thesis focuses on phase-resolved patterns for one PD source at a time. However, ongoing research is focusing on extracting independent signatures from phase-resolved patterns holding multiple PD sources [Judd-04][Yang-03] and in the future these pre-processed signatures could be input to the knowledge-based system for diagnosis.

Through previous research at the University of Strathclyde it was identified that six different defect classes produced different PD signatures [Cleary-05] on phase-resolved patterns due to the variation in PD activity behaviour occurring within the insulation. The phase-resolved patterns [Pearson-95] utilised in this research display the relative pulse amplitude as a function of the voltage cycle and cycle number, similar to those discussed in chapter 2. These physical experiments led experts to gain a greater understanding of the various features of PD activity behaviour evident in the phase-resolved pattern, creating a knowledge base in the mind of the experts concerning the various meaningful distinguishing features (descriptors) of the phase-resolved pattern and how they correlate with the physical behaviour of the PD activity.

Automation of PD diagnosis from these phase-resolved patterns was achieved through machine learning techniques applied at the University of Strathclyde [McArthur-04][Catterson-06][Strachan-05]. These techniques, discussed in chapter 3, assisted the experts in increasing their knowledge base, linking the cause and effect of PD phenomenon, and providing the opportunity to retain and embed this knowledge within a knowledge-based system for PD diagnosis [Strachan-08].

Before the creation of such a knowledge-based system, first it must be ascertained as to whether the knowledge held by these experts could be utilised to classify defects. This thesis uses knowledge engineering techniques (described in chapter 4) with experts to identify PD defects from phase-resolved patterns (where the relative pulse amplitude is displayed as a function of the voltage cycle and cycle number), captured through UHF sensors on gas insulated substations (GIS). This is the first time that knowledge relating phase-resolved patterns to PD phenomena in GIS has been captured from experts. It exposed a step-by-step approach to diagnosis that the expert was not consciously aware of following when classifying the defect behind the pattern.

The knowledge engineering process highlighted that the experts could identify descriptors from the phase-resolved pattern, by simply looking for certain features created by the pulses (descriptors). The experts could also identify the PD behaviour depicted by the identified descriptor, a combination of which inferred defect characteristics and defect classification. The introduction of a knowledge-based system, which utilises this expert knowledge, has the potential to provide the following benefits:

- Classification of defects from a three-dimensional phase-resolved pattern, consisting of the *pulse's amplitude*, the *cycle number* on which the pulse appears and the *phase position* of the pulse on the voltage cycle.
- Explanation of diagnosis from expert knowledge providing confidence in the result.
- Storage of valuable expert knowledge regarding phase-resolved patterns, PD phenomena, defect characteristics and PD diagnosis.
- Scalability by allowing room for expansion as knowledge regarding PD diagnosis grows.
- Reduction of the miscalculation of features that lead to a classification by splitting the phase-resolved pattern by PD activity rather than per half cycle.
- Flexibility by providing a varying degree of explanation suitable for engineers with different levels of understanding and experience, due to an incremental approach, providing knowledge regarding the PD physical phenomena, along with the defect characteristics and classification.
- The potential for a generic approach to classify defects from phase-resolved patterns created through data from either UHF or IEC60270 data, due to the common physical nature of PD within high voltage equipment [Fuhr-91] and taking the phase-resolved PD pattern as input.

- The potential for a generic, flexible approach to PD diagnosis in a variety of equipment, including transformers and GIS, offering flexible support for condition monitoring, due to the consistent physical nature of PD across different high-voltage equipment [Fuhr-91] .

From chapter 4 it was identified that the development of a knowledge-based system requires knowledge engineering to capture the valuable expert knowledge. The acquisition and utilisation of this knowledge is required in order to automate the problem-solving task that an expert already has the ability to perform. As previously discussed, this elicitation involves a variety of the knowledge engineering techniques, described in chapter 4, to articulate the experts' expertise through the use of interviews, experiment observations and case studies. Using appropriate representation and modelling techniques to model the knowledge (tasks, inferences and domain knowledge) is necessary before implementing it within the knowledge-based system.

This chapter describes the construction of this knowledge-based system, outlining the functionality of the system, which is based on the experts' methodology of PD diagnosis. The knowledge engineering techniques, which were performed throughout this research, are described along with the UML diagrams, which were constructed from the experts' knowledge.

5.1 Capturing Diagnostic Knowledge Rules

The construction of a knowledge-based system starts with designing the software architecture, which describes the system in terms of subsystems and modules. This is achieved by using the CommonKADS design process, discussed in chapter 4. In previous research [Strachan-05] it was thought that a five-stage process to PD diagnosis would not only provide correct classification of the defect, but also provide the operator with varying levels of explanation regarding the classification. The rudimentary idea of this stage process was adopted, validated and developed in this research. The actual knowledge applied in each of the five stages required elicitation from the experts, along with appropriate knowledge representation (through transcripts and models) that would ease the validation process and assist in the design, development and testing of the knowledge-based system.

As previously explained in chapter 4, knowledge engineering techniques are required to identify and capture tacit knowledge from the expert, which is achieved by splitting the process into four tasks. First the knowledge requires elicitation from the experts. Following elicitation, the knowledge is transcribed and represented in model form to assist the expert in validation. Once validated, the knowledge is implemented in a rule-based system for further validation and utilisation.

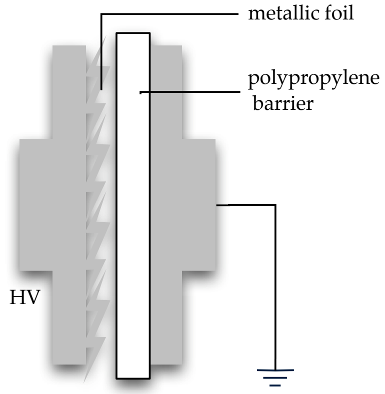
Interviews were undertaken to capture the appropriate knowledge from experts in the field of PD diagnosis within the high voltage group at the University of Strathclyde. Each meeting scheduled with the experts involved an agenda to steer the meeting, was recorded using a voice recorder so as not to interrupt the experts' trains of thought or lose valuable information, and transcribed immediately after completion of the meeting. Throughout this research, 15 meetings, ranging from one to three hours in duration were held over 30 months. These meetings consisted of interviews, case studies, protocol analysis and card sorting techniques. Expertise was also included from the publications of Gulski [Gulski-91] and led to collaboration with Gulski and Meijer, through the joint writing of an IEEE journal paper [Strachan-08].

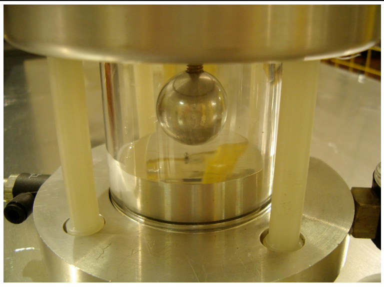
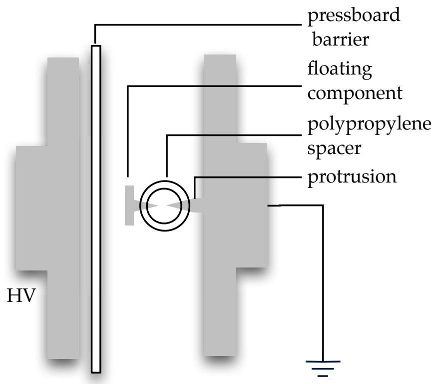
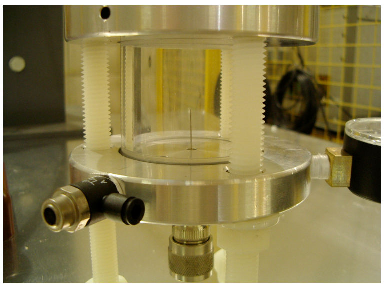
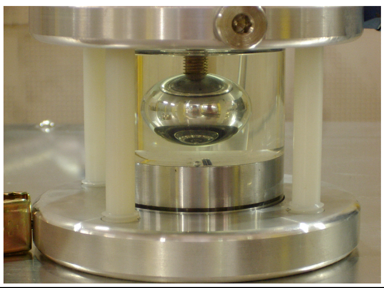
The representation aspect of the knowledge engineering process resulted in 15 meeting transcripts, the outcome of which was a master transcript of 40 pages of PD diagnosis knowledge. After validation, this led to the construction of 148 semantic knowledge models and 5 knowledge bases. These knowledge models were then constructed as 148 production rules within these knowledge bases, resulting in 5 prototypes and 1 final system. The construction of these knowledge bases and the overall diagnostic system will be discussed in this section, the application of which will be shown in chapter 6.

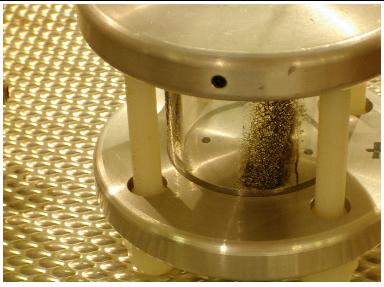
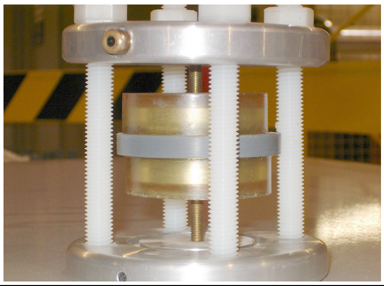
5.1.1 Initial Stages of Knowledge Engineering and System Specification

The initial interview with the experts was unstructured, allowing the experts to speak freely about their domain. The outcomes from this interview consisted of background knowledge regarding PD and insulation materials utilised within high voltage equipment. The initial meeting was a "scoping" meeting designed to set the agenda for subsequent knowledge capture, i.e. defining defect types for diagnosis, which can be seen in Table 5.1. These defects differ slightly to the defects defined in previous research [Cleary-05], as further experiments resulted in the omission of the suspended particle due to the expert believing this defect type would not exist in the field. Three further defects have been added to the list of defects (the void, the floating electrode and the bouncing particle) since further experiments allowed the expert to gain a knowledge base of these additional defect types and are so included in the knowledge-based system described in this thesis.

Table 5.1. Definition of defects

Defect	Definition	Experiment Diagram
Bad Contact	Caused by sparking, e.g. between the threads of loose nuts and bolts.	 [Cleary-02]

Bouncing Particle	Caused by free particles in motion due to electrostatic forces.	
Floating Component	Smaller conducting objects that have become isolated and acquire a floating potential.	 [Cleary-02]
Floating Electrode	Capacitive sparking at components such as stress shields that have become partially detached resulting in ineffective bonding.	
Protrusion	Fixed, sharp metallic protrusions on conductors.	
Rolling Particle	Caused by free particles resting on a conductive surface until influenced by the electric field causing them to roll without bouncing.	

Surface Discharge	Caused by moisture ingress causing pressboard to become semi-conducting.	
Void	Gas filled cavity in solid or liquid insulation, e.g. a bubble or a crack, or a void in epoxy resin.	

5.1.1.1 Types of Insulation

SF_6 and oil are the two types of insulating material considered within this thesis. Although these two types of insulation materials possess different properties, the knowledge-based system was designed to contain generic rules that could extract the descriptors from the phase-resolved PD pattern regardless of the insulating material.

5.1.1.2 Space Charge

Further background knowledge gained from the initial interview concerned the presence of space charge within the insulation. This physical phenomenon exists at the time of PD and may be considered as a charge that is relatively immobile or trapped in the insulation. Depending on the conditions, space charge can influence subsequent pulses.

Space charge is generated once ionisation has occurred. For example, in the case of a protrusion defect, there exist metal conductors and insulation that initially contain no charge. Prior to discharge within the insulation, there is an electric field that is directed from positive to negative, where the geometrical field before the discharge is directed from plate to tip of the protrusion, as shown in Figure 5.1. During the discharge, the electrons leaving the tip will cause the tip to become more positively charged than before, creating a counteracting field that tends to terminate on the negative charges, see Figure 5.2.

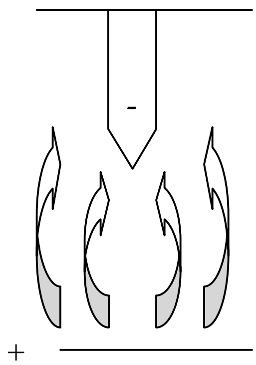


Figure 5.1. Electric field before discharge

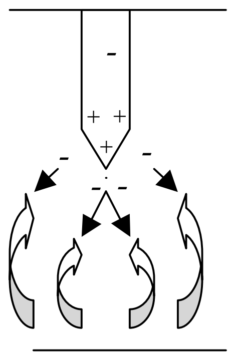


Figure 5.2. Electric field after discharge

Therefore, space charge is created when there is a negative discharge from the tip causing the electrons that have been extracted from the tip to be accelerated through the insulation. In the case of SF_6, which has a high attachment coefficient, free electrons are rapidly removed with the formation of negative ions (quenching the discharge). Charge is now present within the insulation as opposed to only in the metal. Due to the free electrons captured by the SF_6 molecules, the SF_6 molecules are now negatively charged, repelling it from the tip towards the plate. This occurs due to the negative charge on the tip and the positive charge on the plate, as shown in Figure 5.3.

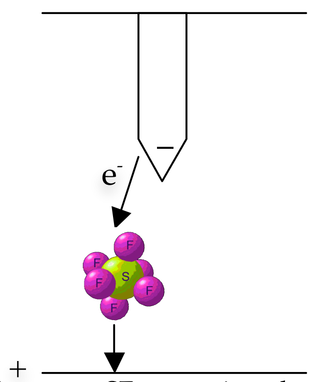


Figure 5.3 SF_6 capturing electron

The different levels of mobility in the different types of insulation material govern whether the space charge affects the pulses in the next cycle or if it changes all subsequent pulses encapsulated in the phase-resolved PD pattern. SF_6 is unusual since it is an electronegative gas, which readily forms negative ions. This property of SF_6, along with the relatively large molecules present within the gas allows free electrons to be absorbed very quickly. These SF_6 molecules are mobile and readily disperse, reducing the memory effect between cycles.

However, in oil the space charge becomes trapped and can "leave an 'imprint' in the region surrounding the PD" [Cleary-05]. This is due to the immobile property of oil, which tends to act more as a solid, trapping the space charge at the PD site. The trapping of this charge permanently affects subsequent pulses, as will be apparent in the resulting phase-resolved PD pattern.

5.1.1.3 Identification of Diagnostic Process

Once this background knowledge was gained, it was possible to construct case studies of possible defects and perform structured meetings with the experts. A well thought-out agenda led to the meetings being highly focused, which aided in the elicitation of meaningful knowledge. The use of case studies (phase-resolved PD patterns of various defects provided by the experts, see Figure 5.4) to enable the experts to demonstrate the process they followed, highlighted the step-by-step process followed in the experts' classification of the PD defect responsible for generating the phase-resolved PD pattern.

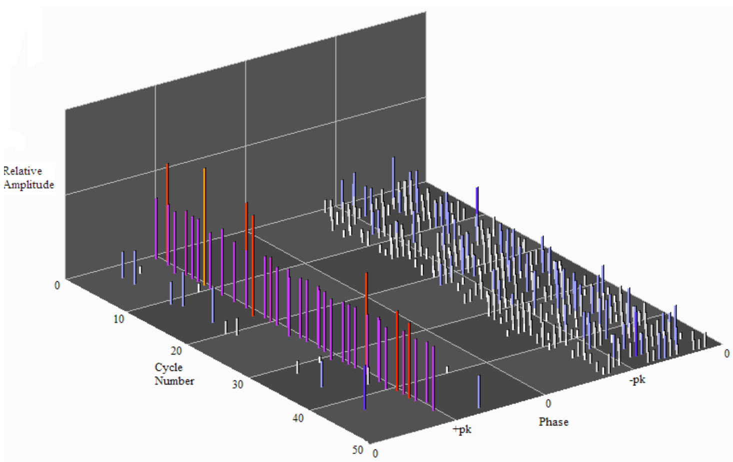


Figure 5.4 Phase-resolved PD plot of a protrusion defect

The experts were asked to explain the initial steps in their examination of a phase-resolved pattern. This was the first time that the experts had attempted to articulate the generic process associated with their examination of phase-resolved patterns for PD defect classification. Capturing and representing this tacit knowledge resulted in the formulation of a novel step-by-step process for PD defect diagnosis. It was clearly evident that the experts followed an incremental process, where the level of diagnosis evolved from an understanding of PD behaviour through the defect characterisation and ultimately classification. From this information, a UML activity diagram (Figure 5.5) was constructed to represent the system specification, mimicking this step-by-step process. This diagram highlights the breakdown of the diagnostic process into five high level steps each supported by detailed expert knowledge of the domain.

From Figure 5.5, it is shown that to achieve classification the expert first extracts features from the phase-resolved pattern that not only describes the signal, but may also be used to discriminate between various defect classes. This identification of descriptors (key features) highlights the underlying physics occurring at the site of the discharge. The nature of PD phenomena will depend upon certain characteristics pertaining to the defect site, and so allow the expert to classify the type of defect responsible for generating the PD activity. By utilising the knowledge within the first four stages it might also be possible for the expert to identify the site of the defect. This identification is dependent on the type of defect classified and discriminating descriptors of the phase-resolved pattern, further discussion and examples of which will be shown in chapter 6.

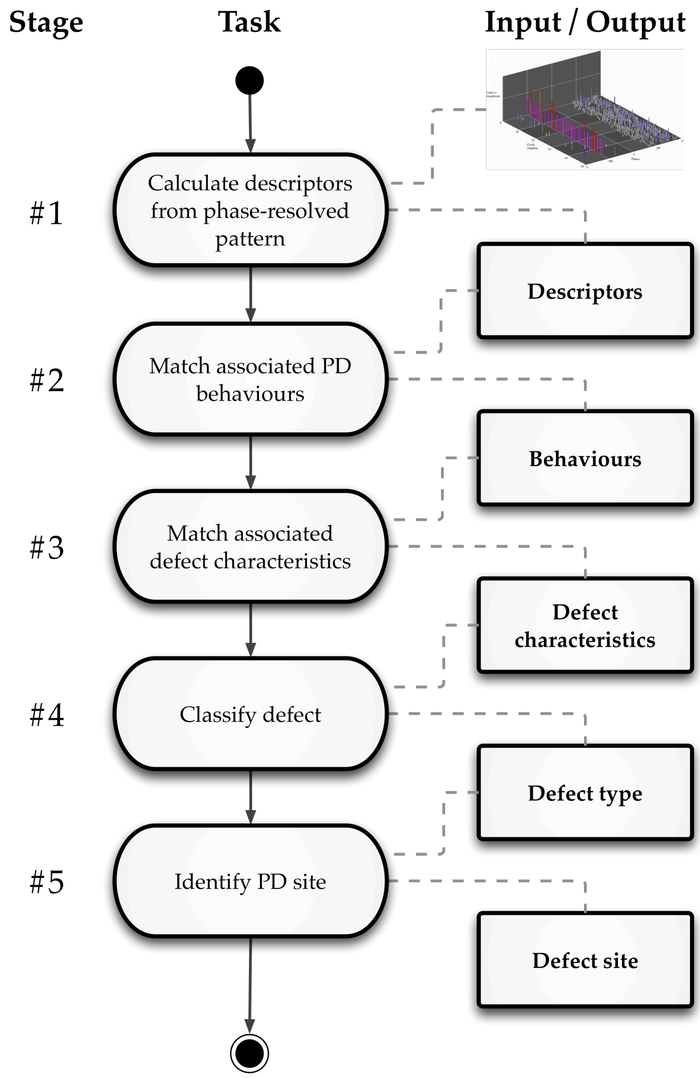


Figure 5.5 Activity diagram of the system

5.1.1.4 Initial CommonKADS Models

In order to ascertain and validate the knowledge possessed by the experts, the knowledge engineering approach from chapter 4 was applied. As previously stated in chapter 4, the expertise model from the CommonKADS methodology [Schreiber-05] is the most beneficial when modelling the knowledge required for a knowledge-based system. This model splits the knowledge into three categories, and is modelled using UML diagrams.

From the structured meetings with the expert it was possible to construct the task model (Figure 5.6), which highlights all the 'goals' needed to complete the diagnosis. This is an alternative representation to the activity diagram (Figure 5.5), which also displays how a diagnosis can be achieved.

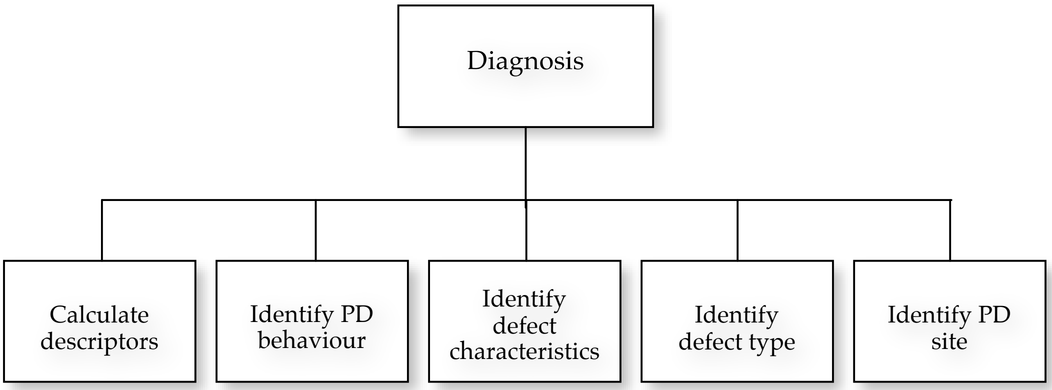


Figure 5.6. Task model of the system

The second type of knowledge model identified in CommonKADS is the inference model. CommonKADS contains a library of a standard set of inferences to describe the individual steps required to reach a goal. The first stage (calculate descriptors), see Figure 5.7, requires the 'abstract' inference, where a data set (the phase-resolved pattern) is output in an abstracted form (descriptors). Stages 2 and 3 involve the 'match' inference (see Figure 5.8-5.9), where given a set of inputs, specific combinations of inputs may lead to particular outputs. Each further stage involved in the knowledge-based system requires the 'classify' inference (see Figure 5.10-5.11), where the output is associated with the input. The identification of the type of inference informs the computational method required. CommonKADS suggests a forward chaining method for the 'abstract' and 'match' inferences, along with pattern matching for 'classify'. Both of these can be accomplished in a forward-chaining rule-based system.

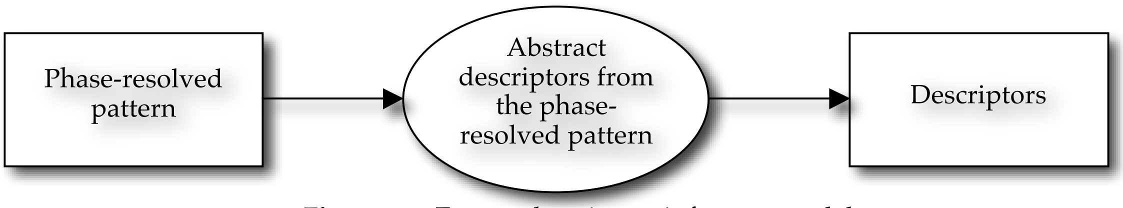


Figure 5.7. Extract descriptors inference model

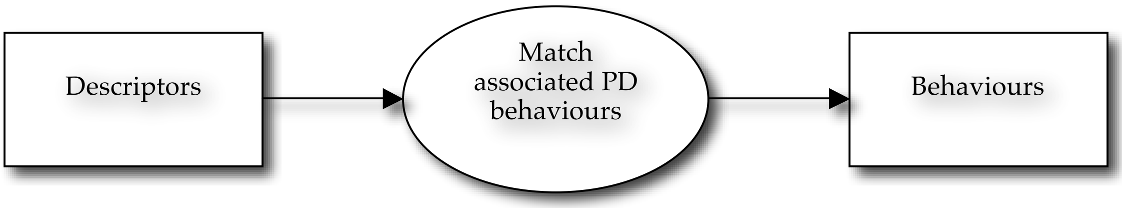


Figure 5.8. Behaviour matching inference model

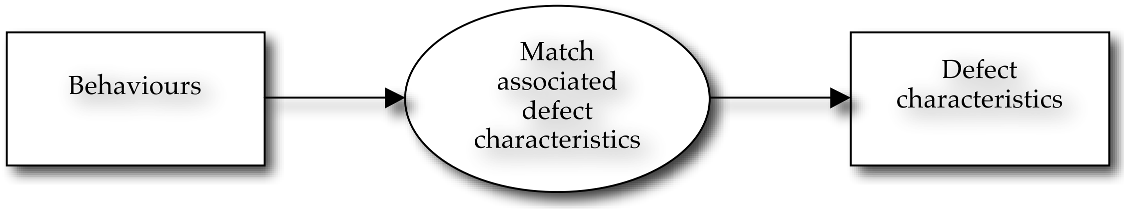


Figure 5.9. Defect characteristics matching inference model

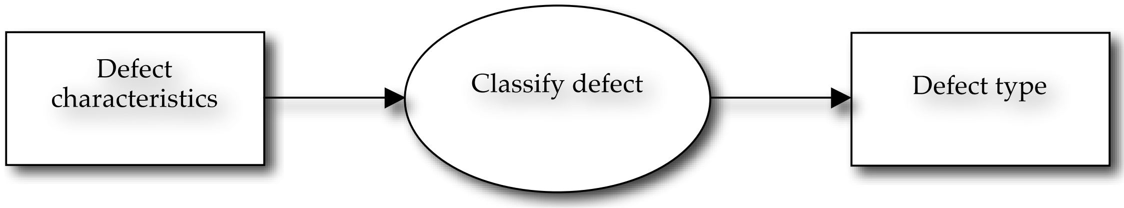


Figure 5.10. Classify defect inference model

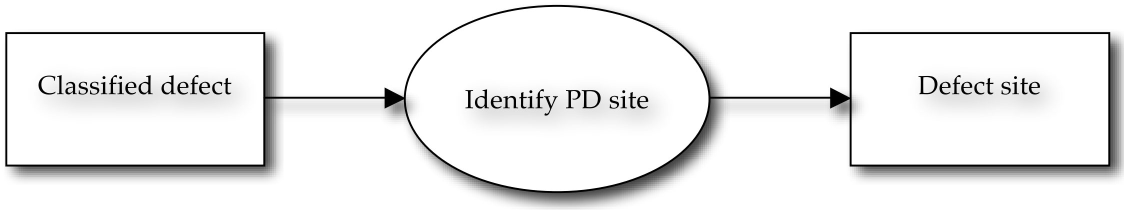


Figure 5.11. Classify PD site inference model

5.1.2 Acquisition, Validation and Creation of the Five Stages of the Knowledge-Based System

After the task and inference models had been validated by the experts and finalised, it became necessary to elicit the domain knowledge for each of the five stages. Meetings were held with the experts to identify this knowledge, and each of the individual stages were captured, modelled and validated separately, leading to a cyclic process similar to that of MIKE [Struger-98], described in chapter 4. This led to a staged process where each of the five stages were constructed into a prototype to be tested and verified by the experts. However, the elicitation of the later stages led to necessary alterations in earlier ones. The alteration of the knowledge followed a cyclic iteration changing the different stages as new knowledge arose. The construction of these individual stages will be explained in this section.

5.1.2.1 Stage #1: Calculate Descriptors from Phase-resolved Pattern

In order to identify useful information from the PD data, it is necessary to represent the data in a suitable format. As previously explained in chapter 2, a phase-resolved pattern represents the PD activity in a way that can provide meaning to the data through expert interpretation. The phase-resolved pattern was chosen for its meaningful representation and its ability to be constructed using data derived from many types of sensors across different apparatus. The pattern utilised in this thesis is created by plotting the amplitude of each pulse captured by the UHF sensor, or in the case of the IEC data the apparent charge, on a three-dimensional axis consisting of the *pulse's relative amplitude*, the *cycle number* on which the pulse appears and the *phase position* of the pulse on the voltage cycle [Pearson-95] (see Figure 5.12). It should be noted that this phase-resolved pattern is not the same format as the PRPD pattern [Vaillancourt-89], which is examined in other PD diagnostic research [Kranz-05][Satish-94][Sahoo-05].

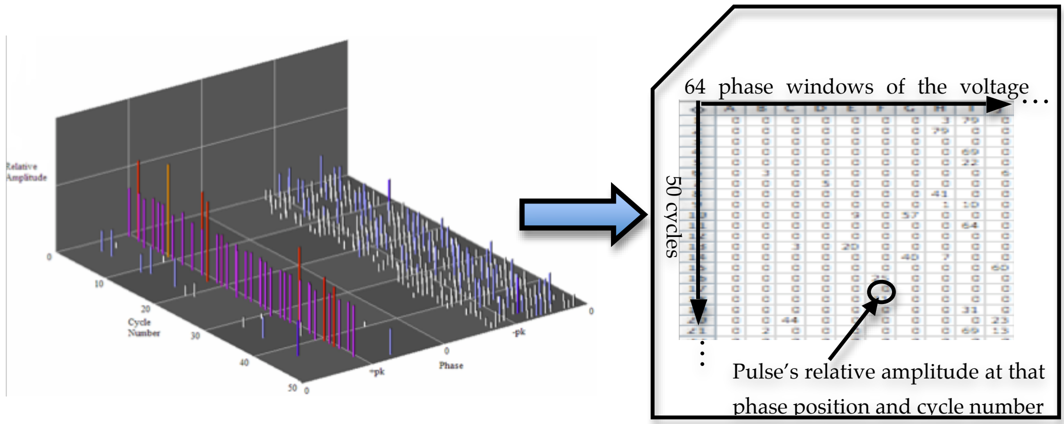


Figure 5.12. Phase-resolved pattern represented in 50*64 matrix form

The input to Stage #1 of the knowledge-based system is this phase-resolved pattern, representing a one second (50 cycle at 50Hz) snapshot of PD activity. The input is in the form of a 50*64 matrix of floating points that represent the PD activity in 50 cycle bursts across 64 evenly spaced phase windows (buckets) of the voltage cycle, see Figure 5.12. This format of the phase-resolved pattern was chosen due to the experts' knowledge base of these patterns. To gain a classification, the descriptors of the phase-resolved pattern required identification and defining from the experts, as well as interpreting the statistics that could lead to these descriptors.

To assist in the elicitation of this knowledge, case studies of the phase-resolved pattern representing defects captured though UHF sensors in GIS were utilised to focus the meeting. Working through these case studies demonstrated that the experts could identify twelve descriptors that they always acknowledged when seeking a diagnosis. Each identified descriptor informs the expert about the behaviour of the PD activity within the insulation, which is indicative of the defect characteristics and subsequently the PD defect type. The descriptors, identified and defined by the experts during the preliminary interviews, are:

1. *Name:* Phase position

   Description: The knowledge elicitation meetings identified that the most important and first descriptor of the phase-resolved pattern examined by the experts is the position of the pulses on the voltage cycle. This is because the position of the pulses is dependent on the PD behaviour that is occurring at the defect site. Different phase positions are indicative of different defect types, meaning that the phase position should always be included when seeking a diagnosis. The knowledge-based system should also check the phase position first because in the case of the PD activity occurring across the zero crossings, the pattern must be shifted prior to calculating the rest of the descriptors (as explained at the end of this section).

   In order to calculate the phase position, the pattern is split into two half cycles, positive and negative. Then within a single half cycle there exist different regions, see Figure 5.13.

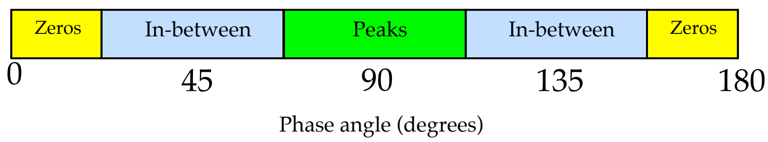


Figure 5.13. Phase positions in a half cycle of a phase-resolved pattern

Values: The expert highlighted that there are four main areas where the pulses can occur that infers and discriminates between particular PD behaviour; these are:

- On the voltage peaks, where the main window of pulses lies around the 90° phase angle.
- On the zero crossings, where the discharges are occurring across the two half cycles and would be grouped in terms of discharge activity, as opposed to half cycle (this will be explained at the end of this section).
- In-between the zero and peaks, in the first and third quadrant, where the discharge activity is occurring between 0° and 45° and 180° to 225°.
- Spread randomly across the phase-resolved pattern.

2. *Name:* Magnitude

Description: The magnitude descriptor can prove problematic in the classification of the PD behaviour due to signal attenuation, where the distance of the sensor from the PD source can affect the magnitude of the signal. Therefore magnitude should be used with caution when trying to determine how stressed the discharge is. However, a podium (the characteristic shape that the pulses embody, see Figure 5.17), would imply that it is close to breakdown no matter where the sensor is positioned. When identifying the magnitude it is important to consider the relative magnitude across the two half cycles rather than on an absolute basis. Magnitude is therefore a useful descriptor when assessing symmetry between half cycles.

Values: Due to the format of the phase-resolved pattern displaying the relative magnitude, rather than actual magnitude of the PD pulse, the magnitude descriptor can offer some indication of PD behaviour rather than the severity of the discharge. In this case the mean pulse height in one half cycle is calculated and is categorised by arbitrary levels; as three levels:

- Small: 0-20% of relative amplitude,
- Medium: 20%-50% of relative amplitude,
- Large: 50%-100% of relative amplitude.

3. *Name:* Shape

   Description: Apparent shapes identified from the maximum magnitudes of the pulses in each half cycle.

   Values: Shapes that can be identified from the phase-resolved pattern and inform the expert about the PD behaviour occurring at the source are:

   - The chopped sine wave (Figure 5.14), where the amplitude of the pulses follow the sine wave but it appears chopped since the pulses follow the voltage cycle waveform but will not necessarily be at the same amplitude or phase position as the voltage cycle.

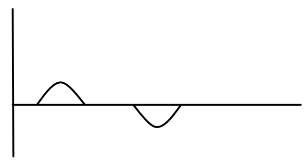


Figure 5.14. Chopped Sine Wave

   - A rectangular shape, see Figure 5.15.

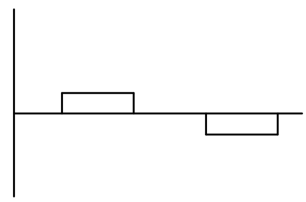


Figure 5.15. Rectangular Box

   - The knife blade (or an extremely narrow rectangle), shown in Figure 5.16, is a row of discharges in a very narrow phase window. It may consist of a single row of discharges, where one may occur per half cycle.

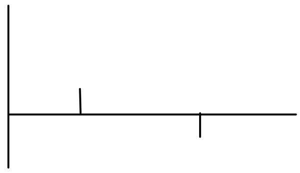


Figure 5.16. Knife Blade

- A podium shape, see Figure 5.17.

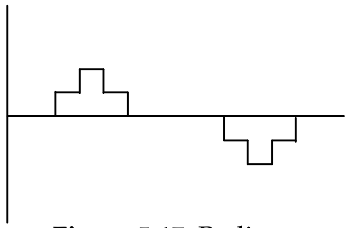


Figure 5.17. Podium

4. *Name:* Phase inception symmetry

   Description: The initial pulse of PD activity in each half cycle infers the phase inception. Therefore, phase inception symmetry compares the position of the initial PD pulses between half cycles.

   Values: There are two states of phase inception symmetry:
   - Symmetrical.
   - Asymmetrical.

5. *Name:* Magnitude symmetry

   Description: Magnitude symmetry examines the magnitude variation over the two phases and checks which of the two half cycles is experiencing the greater magnitude.

   Values: Magnitude symmetry is threefold:
   - Magnitude in positive half cycle is greater than the negative half cycle.
   - Magnitude in the positive half cycle is less than the negative half cycle.
   - Equality between the magnitudes across the half cycles.

6. *Name:* Shape symmetry

   Description: Shape symmetry compares the shapes that the maximum PD pulses create between half cycles.

Values: Shape symmetry is twofold:

- Symmetrical.
- Asymmetrical.

7. *Name:* Density symmetry

Description: Density symmetry compares the frequency of PD pulses in each half cycle. Calculating the number of PD pulses in each half cycle and then comparing the two half cycles achieves this.

Values: Density symmetry is threefold:

- Positive half cycle more sparse.
- Positive half cycle less sparse.
- Same density.

8. *Name:* Pulse distribution

Description: The pulse distribution examines where the pulses of greatest magnitude lie within the PD activity within a half cycle. This is calculated by taking the area of activity (in one half) and comparing the right hand side of the activity with the left hand side, identifying where the greatest magnitude (bias) lies.

Values: Pulse distribution is categorised as follows:

- Biased to an earlier phase position (Figure 5.18).
- Biased to a later phase position (Figure 5.19).
- Unbiased, three examples shown in Figure 5.20.

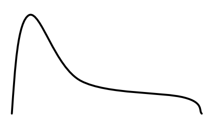


Figure 5.18. Biased to an earlier phase position

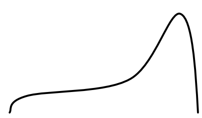


Figure 5.19. Biased to a later phase position

Figure 5.20. Unbiased

9. *Name:* Phase range

Description: The phase range is the width of the window of PD activity in the half cycle; this is calculated by subtracting the pulse extinction (final pulse) from the pulse inception (initial pulse).

Values: The phase range is broken into two categories:

- Broad.
- Narrow.

10. *Name:* Phase density

Description: Phase density refers to the frequency of PD pulses within a region of PD activity occurring within one half cycle. Since this relates to some extent on how individual pulses affect subsequent pulses, it will have physical meaning and therefore should be taken into account as a descriptor.

Values: The phase density is broken into two categories:

- Dense.
- Sparse.

11. *Name:* Magnitude consistency

Description: The consistency of pulse heights across the discharge activity in one half cycle.

Values: Magnitude consistency is twofold:

- Constant pulse magnitude.
- Not constant magnitude, showing a broad distribution of pulse magnitudes.

12. *Name:* Cycle to cycle activity

Description: Examining the PD activity over successive cycles to identify if there are a number of cycles of inactivity between a row of PD pulses across a half cycle.

Values: Cycle to cycle activity is twofold:

- A number of cycles between PD activity.
- No cycles between PD activity.

With the exception of the symmetry descriptors, each of the other descriptors are examined on a per half cycle basis. Individually these infer the physical PD phenomena occurring within the insulation. The symmetry descriptors can then be used to compare the half cycles and identify further PD behaviours within the insulation, examples of which are shown in Table 5.3 in section 5.1.2.2.

Figure 5.21 shows a hierarchical domain model identifying the descriptors of the phase-resolved pattern for diagnosis. This type of model includes all the possible descriptors, which have been highlighted by the experts as important features of the phase-resolved pattern, along with their subcategories (descriptor values). In order to use these descriptors to identify the PD type, they must first be extracted from the phase-resolved pattern. Performing various mathematical calculations, as well as using some of Gulski's statistical features [Gulksi-91], led to the extraction of these descriptors. This statistical extraction of the descriptors proved to be an intricate task, since although the expert could describe them, creating a computer algorithm to exactly identify these descriptors was complex.

Table 5.2 identifies how applying statistics to the PD data finally captured the various descriptors. The experts provided the preliminary limits associated with each calculation. The initial values of these limits would be changed over time as further knowledge was gained from the experts, and further case studies were invoked to test these limits and validated them through expert judgement.

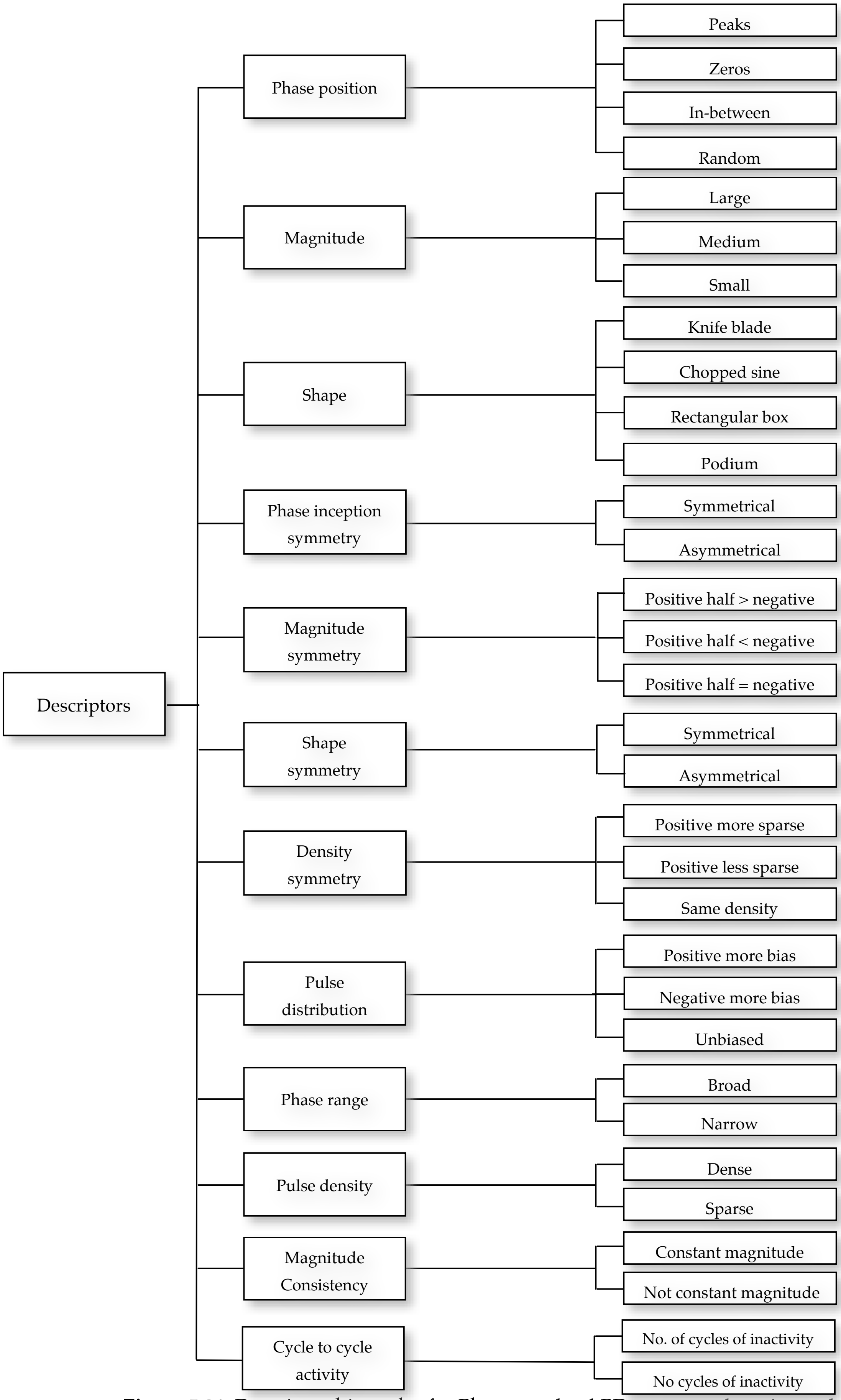


Figure 5.21. Descriptor hierarchy for Phase-resolved PD patterns, domain model

Table 5.2. Calculation of descriptors (*Gulski statistics)

Descriptor Name	Statistics	Descriptor Value	How to calculate?
1.Phase position	• Split phase into 4 windows and see where the most pulses occur. • Biasness (b)	a. peaks	*If most pulses at peaks and b < 258.*
		b. zeros	*If most pulses at zeros.*
		c. in between	*If most pulses are in-between peaks and zeros OR on peaks and b >= 258.*
	• Average space between pulses • Range • Average number of discharges per bucket (an)	d. random	*In a phase if the space between pulses >= 11 and range >= 19 and an < 50*
2. Magnitude	• *Mean (μ)= Sum of magnitudes/number of discharges	a. large	μ=50-100% = 127.5→255 (since scale is 0-255)
		b. medium	μ =20-50% = 53→127.5
		c. small	μ = 0-20% = 0→53
3. Shape	• *Kurtosis of max (ku) • *Number of peaks (pe) • Range • *Standard deviation of max (msd)	a. knife	*IF ku >3, pe= 1 and range <20 and msd>=5.5 OR If range > 0 and <=3.*
	• *Kurtosis of max (ku) • Range • *Standard deviation of max (msd)	b. chopped sine	*IF ku <= 3 and range > 3 and msd >=5.5.*
	• *Standard deviation of max (msd) • Range • *Number of discharges (n)	c. rectangular box	*IF msd < 5.5 and n >=10 and range > 3.*
	• *Number of Peaks (pe) • *Standard deviation of max (msd) • Range • *Kurtosis of max (ku)	d. podium	*IF pe != 1 and range > 3 and ku > 5 and msd >= 5.5.*

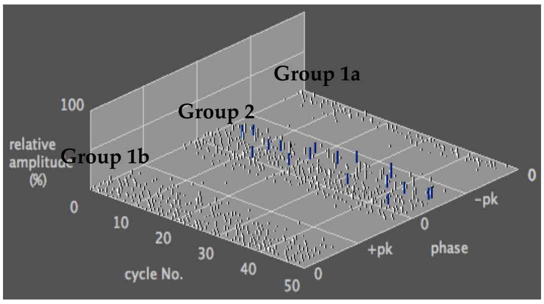
Descriptor Name	Statistics	Descriptor Value	How to calculate?
4. Symmetry	• *Phase inceptions (i)	a. phase	*IF (i in positive – i in negative) is ±=2* *ELSE position asymmetry*
5. Magnitude symmetry	• *Asymmetry operator (Q)	b. magnitude	*IF Q>=0.9 && Q<=1.1 THEN symmetrical* *IF Q <0.9 THEN positive > negative* *IF Q >1.1 THEN positive < negative*
6. Shape symmetry	• Compare the shapes found previously between half cycles	c. shape	*IF same THEN symmetrical* *ELSE shape asymmetry*
7. Density symmetry	• Compare no. of discharges per half cycle	d. density	*IF (pos – neg)>40 THEN neg more sparse* *ELSE IF(neg-pos) >40 THEN pos more sparse* *ELSE IF (pos – neg) or (neg – pos) <=40 THEN same density*
8. Pulse distribution	• Biasness (b)	a. unbias	*IF b > -370 && b < 258*
		b. bias to an earlier phase	*IF b >= 258*
		c. bias to a later phase	*IF b <= -370*
9. Pulse range	• Range = *extinction - *inception	a. broad	*IF range > 8*
		b. narrow	*IF range <= 8*
10. Pulse density	• *Number of discharges (n) • Range	a. dense	*IF n/range >= 11*
		b. sparse	*IF n/range < 11*
11. Magnitude consistency	• Standard deviation (sd), where variance looks at mean pulses and count, only taking into account actual pulses	a. Constant	IF sd < 8
		b. Not Constant	IF sd >= 8
12. Cycle to cycle activity	• Examine the no. of cycles between PD activity, looking at the average space and no. of pulses per cycle	a. A number of cycles	*IF cycles of inactivity between PD activity*
		b. No cycles	*If no cycles of inactivity between PD activity*

Gulski originally stated that three main groups of quantities could be used to characterise the PD activity [Gulski-91]. These are basic quantities, deduced quantities and statistical operators:

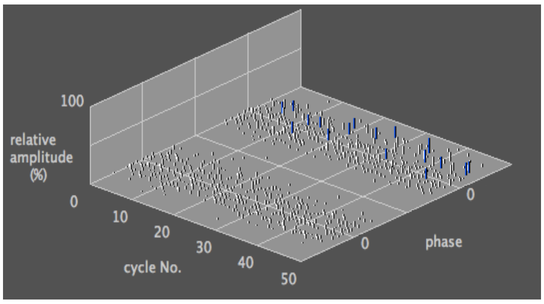
1. The basic quantities identify the magnitude and position of the discharge pulse along a single voltage cycle.
2. The deduced quantities characterise the PD over a number of voltage cycles.
3. The statistical features create an input feature vector describing the PD activity over a number of cycles and across the voltage cycle, which could be utilised by a pattern recognition method for defect diagnosis [McArthur-04][Catterson-06][Strachan-05].

Using a feature vector containing 101 of Gulski's statistics to identify the specific defect behind a phase-resolved pattern not only examines the pattern as a whole but also examines the positive and negative half cycles individually. A range of statistics, including kurtosis and skew, are used to determine the type of defect present. This statistical approach can pose a problem when the discharges occur on the zero crossings relative to the voltage cycle [Berg-02]. This problem arises due to the statistical features of skew and kurtosis being calculated on a per half cycle basis. When the discharges occur across the zero crossings then the PD activity is in fact occurring between the half cycles. Conventional statistical algorithms do not recognise this effect and therefore feed erroneous parameter values into pattern recognition techniques. This is resolved in the knowledge-based system by implementing the approach an expert utilises when the pulses are mainly occurring on the zero crossings. This is used to reproduce the way in which an expert views the pattern as being continuous over the zero-crossing points of the ac waveform.

When the experts look at the pattern, the main phase bands in which discharges occur are first identified. In the case of pulses occurring around the zero crossings (e.g. as shown in Figure 5.14(a)), the expert views the pulses as two groups spanning the boundaries of the positive and negative half cycles. By taking Figure 5.22(a) as an example, the pulses in Group 1a would be viewed as being in front of the pulses in Group 1b and would become the new positive half in the system, with Group 2 becoming the new negative half. This regrouping results in the phase-resolved pattern of Figure 5.22(b), which is then used to calculate the remaining descriptors, excluding the phase position, which remain as on the zeros. Incorporating this functionality into the knowledge-based system, and automatically adjusting the calculations accordingly leads to the descriptors being correctly computed and an enhanced classification capability.



(a) Phase-resolved pattern displaying discharges occurring on the zero crossing



(b) Phase-resolved pattern after grouping the PD activity

Figure 5.22. Grouping the PD activity in a phase-resolved pattern when across the zero crossings

5.1.2.2 Stage #2: Match Associated PD Behaviour

The second stage of this novel diagnostic approach, as shown in Figure 5.5, is concerned with recognising the underlying PD physical phenomena associated with the meaningful descriptors identified in the first stage. This stage determines the physical process that occurs within the insulation at the time of a PD, which is characterised by the different descriptors apparent within the phase-resolved pattern.

Before the statistics were created for stage #1 of the process, these PD behaviours were sought after from the experts. This allowed validation of whether the experts could indeed infer PD phenomena from the descriptors that were identified in stage #1. Once the PD behaviours had been elicited and validated by the expert, prior to automating the statistics to identify the descriptors within the phase-resolved pattern, a prototype was created. This prototype consisted of drop down menus of the descriptors and their values, allowing the expert to manually choose the descriptors apparent in the phase-resolved pattern to be diagnosed. This was created to test the validity of the PD behaviours that will be described in this section. Statistics for identifying the descriptors were then automated by performing various mathematical calculations and feature extraction, shown in Table 5.2 and described in the last section.

Interviews with the experts were performed to establish the PD behaviours associated with the descriptors. Again a structured meeting centred on the use of case studies was used to establish how experts can infer PD behaviour from phase-resolved pattern descriptors. Relevant knowledge from the transcripts produced was selected to create semantic network models of domain knowledge. This was achieved by identifying 'indicative' relationships within the domain knowledge, which highlighted specific PD behaviours and how they can be described using distinguishing descriptors of the phase-resolved pattern. Representing this knowledge as semantic network models, see Appendix 1, provides graphical diagrams of how the descriptors match to the associated PD behaviours. This comprehensible representation makes it easier for the experts to understand and subsequently validate.

An example transcript is displayed in Figure 5.23. It should be noted that this transcript is taken from the final knowledge document and is included here to highlight how the various descriptors and PD behaviours could be "extracted" from a transcript and modelled for validation.

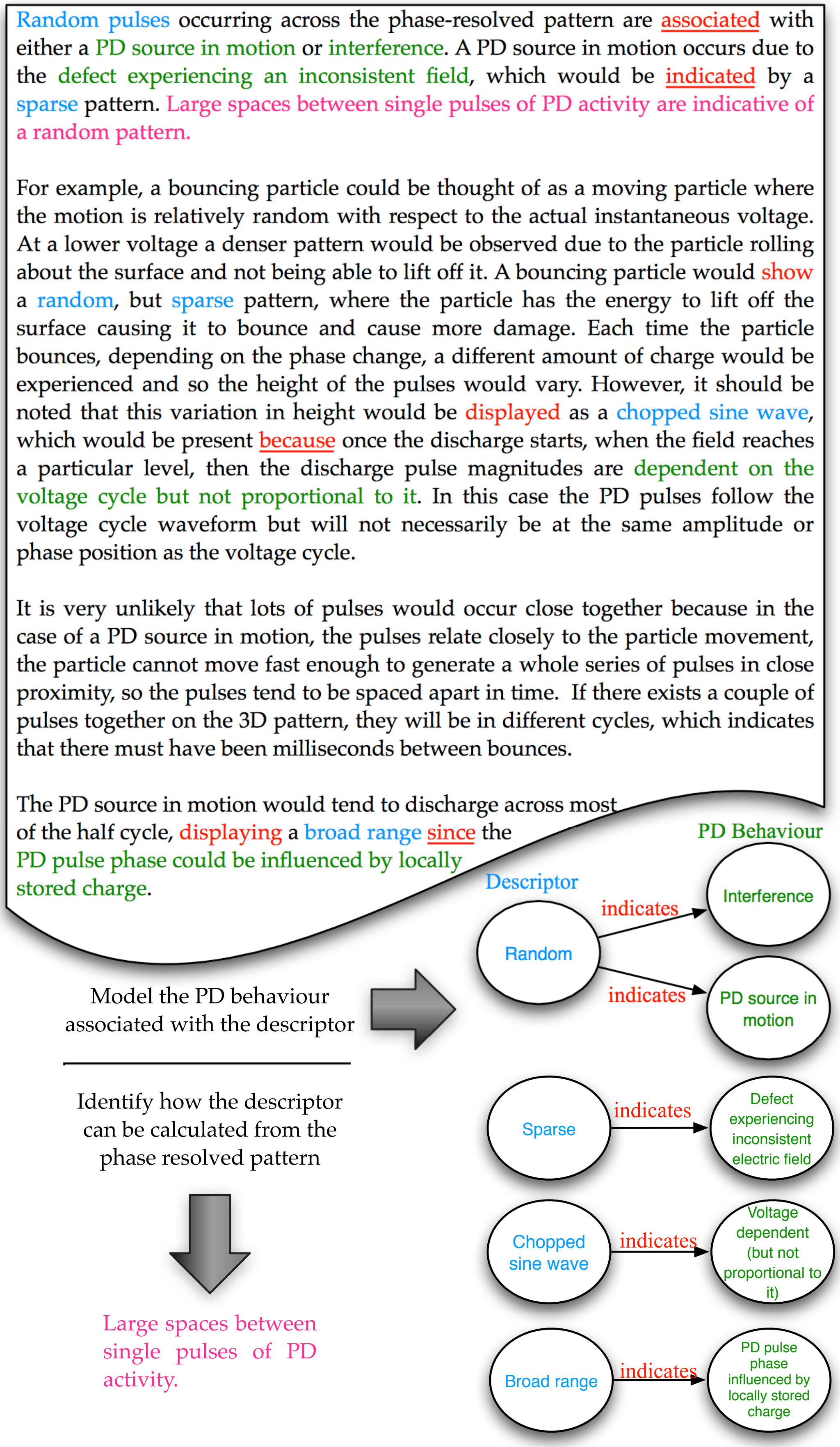


Figure 5.23. Extraction of descriptors and their inferred PD behaviours from a transcript

In Figure 5.23 the words that highlighted the presence of certain descriptors were sought and highlighted in red, which included "displayed", "displaying" and "show". This led to the areas in the transcript that discussed certain descriptors, which were highlighted in blue. Then words that highlighted relationships between descriptors and PD behaviours were identified, and in this case included "associated", indicated", "because" and "since", which are highlight in red and underlined. From the identification of these relationships the PD behaviours could be identified and highlighted in green. From the highlighted sections, the various semantic network models could be created and are shown in Figure 5.23. The remainder of the transcript holds further details of the identified models or clues as to how to extract the descriptor from the phase-resolved pattern (highlighted in pink). This transcript abstract also holds knowledge regarding how the characteristics are identified from the PD behaviours, which will be demonstrated in section 5.1.2.3.

As further transcripts are modelled, additional PD behaviours could be inferred from the same descriptor. Table 5.3 shows the list of descriptors with their inferred PD behaviours (it should be noted that this is the expert knowledge and it is not the intention of this thesis to discuss PD phenomena). This table was created from the validated models, see Appendix 1, and implemented into the original prototype to create a prototype that could validate stages 1 and 2. This prototype enabled the experts to validate the usefulness of the descriptors identified in classifying PD behaviour from phase-resolved patterns and the correctness of their statistical thresholds.

Table 5.3. List of descriptors and their PD behaviours

Descriptor Name	Descriptor Value	Behaviour
Position	Peaks	• Minimal space charge present i.e. no memory effect beyond half cycle
	Zero	• Discharge dependent on rate of change of voltage • Issue of Space charge
	In-between	• Shift Between absolute and rate of change of voltage • Issue of Space charge
	Random	• PD Source in motion • Interference
Magnitude	Large	• Arcing
	Medium	• Pulses initiated in insulation
	Small	• Pulses at a very sharp tip • Pulses at a small site
Shape	Knife blade	• Energetic Discharge
	Chopped sine	• Voltage dependent (but not proportional to it)
	Rectangular box	• Not voltage dependent
	Podium	• No space charge • Discharge capable of going through two mechanisms
Phase Inception Symmetry	Symmetrical	• Conditions for PD inception are the same for both polarities
	Asymmetrical	• Conditions for PD inception are different for both polarities
Magnitude Symmetry	Positive more than negative	• Extraction of electrons requires comparatively more energy in positive half cycle
	Positive less than negative	• Extraction of electrons requires comparatively more energy in negative half cycle
	Positive equals negative	• Defect is geometrically symmetrical
Shape Symmetry	Symmetrical	• Defect is geometrically symmetrical
	Asymmetrical	• Defect is geometrically asymmetrical
Density Symmetry	Positive more sparse	• Ease of discharging is greater in negative half cycle
	Negative more sparse	• Ease of discharging is greater in positive half cycle
Pulse Distribution	Biased to earlier phase	• Discharge retains memory from previous cycle
	Biased to later phase	• Not possible
	Unbiased	• No space charge
Range	Broad	• PD pulse influenced by local stored charge • Many small discharge sites acting simultaneously • Charge can disperse easily
	Narrow	• Sufficient charge released to suppress further pulses
Density	Dense	• Pulses at a conducting surface • No space charge
	Sparse	• Defect experiencing inconsistent electric field • Interference • Space charge with a long time constant
Magnitude Consistency	Constant magnitude	• Constant geometry and capacitance • Certain amount of energy to ionise the insulation
	Not constant magnitude	• Locally stored charge • PD site is not confined to one region
Cycle to cycle activity	Number of cycles of between PD activity	• Significant quantity of locally stored charge

5.1.2.3 Stage 3: Match Associated Defect Characteristics

The creation of the new prototype led to the scheduling of further knowledge elicitation meetings to capture expert knowledge used to classify defect characteristics from "observed" PD behaviour. A knowledge elicitation technique called 'card sorting' was utilised to facilitate this acquisition.

The card sorting technique involved creating cards describing different PD behaviours highlighted and validated during the previous knowledge elicitation and prototype development. These PD behaviours were presented to the expert and the expert was asked to group them into similar traits. An example of this can be seen in Figure 5.24, where the grouped PD behaviours are all signs of the presence of a metal part within the insulation. The expert was then able to identify which PD behaviours could lead to the creation of particular defect characteristics. An example of this is shown in Figure 5.25, where the left-hand side represents the PD behaviours and the right-hand side their combined defect characteristic.

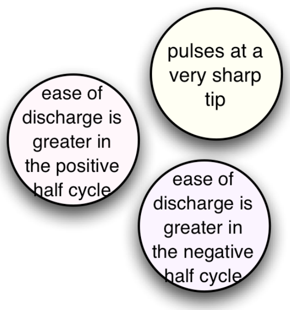


Figure 5.24. A group of PD behaviours indicating the presence of a metal part

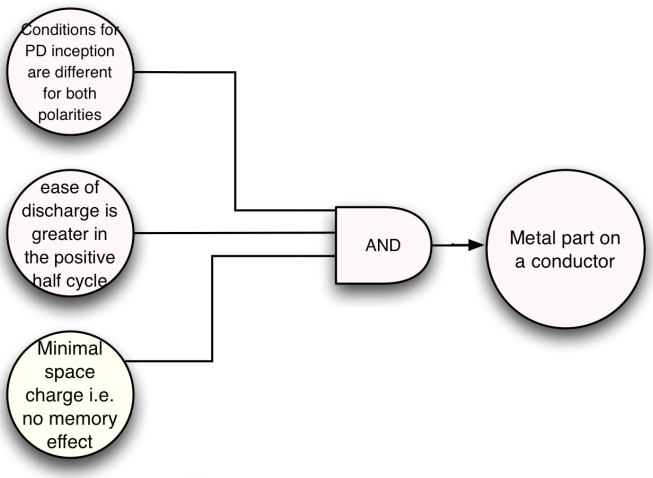
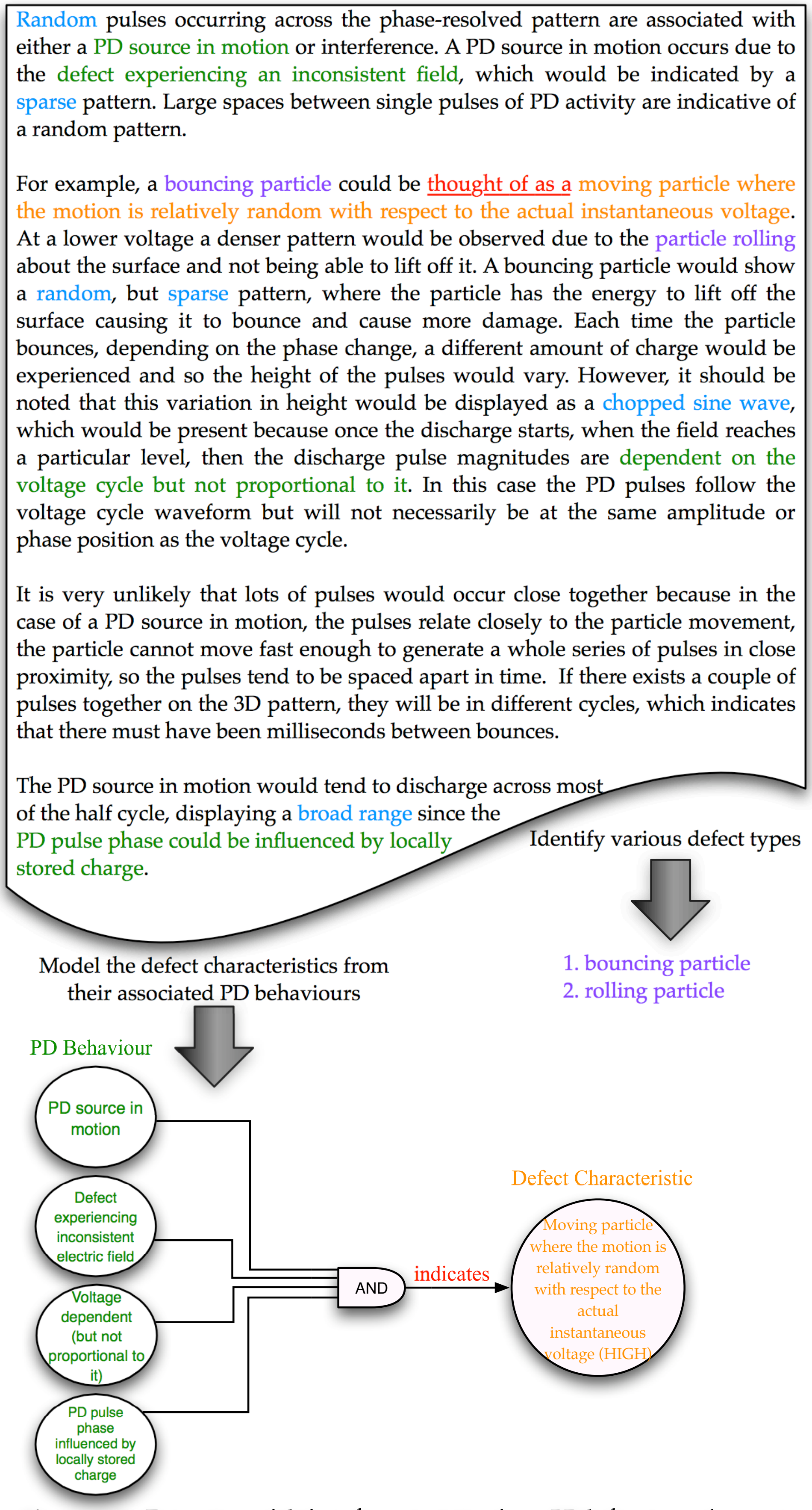


Figure 5.25. Combination of PD behaviours leading to a defect characteristic

Stage #3 of the diagnostic process invokes the knowledge of how to match these defect characteristics to their associated PD behaviours, already identified in stage #2. These defect characteristics inform the expert about the physical nature and make-up of the defect source e.g. presence of metal parts, or between which types of material the discharge is occurring. The identification of specific defect characteristics would allow the expert to subsequently infer the existence of actual defect types (stage #4).

From previous elicitation meetings, it was discovered that the phase position of the pulses within a half cycle was an important descriptor of the phase-resolved pattern. The experts highlighted that each of the identified defect characteristics were tied to the phase position of the pulses. Therefore, as seen in the knowledge models in Appendix 2, each defect characteristic is inferred by multiple PD behaviours including a behaviour that is indicative of the phase position. Also, when the expert was examining the activity within one half cycle, it became apparent that the half cycle that was being examined should be an attribute of each defect characteristic.

The semantic network models that were created for this stage of the process can be found in Appendix 2. These models were created as a result of the transcripts that were constructed after the card sorting technique. Using the same example abstract of transcript from section 5.2.2.2 (shown in Figure 5.26) key words were identified that could lead to the area in the transcript that described defect characteristics. In this case the key words "thought of as a" were highlighted in red and underlined leading to the identification of the description of the defect characteristics, which is highlighted in orange. The PD behaviours, which could be grouped to imply this defect characteristic, were identified in stage #2 and are highlighted in green, along with their descriptors, which are highlighted in blue. Other information apparent in this transcript are the description of defect types, these are highlighted in purple and are used in stage #4.



Random pulses occurring across the phase-resolved pattern are associated with either a PD source in motion or interference. A PD source in motion occurs due to the defect experiencing an inconsistent field, which would be indicated by a sparse pattern. Large spaces between single pulses of PD activity are indicative of a random pattern.

For example, a bouncing particle could be thought of as a moving particle where the motion is relatively random with respect to the actual instantaneous voltage. At a lower voltage a denser pattern would be observed due to the particle rolling about the surface and not being able to lift off it. A bouncing particle would show a random, but sparse pattern, where the particle has the energy to lift off the surface causing it to bounce and cause more damage. Each time the particle bounces, depending on the phase change, a different amount of charge would be experienced and so the height of the pulses would vary. However, it should be noted that this variation in height would be displayed as a chopped sine wave, which would be present because once the discharge starts, when the field reaches a particular level, then the discharge pulse magnitudes are dependent on the voltage cycle but not proportional to it. In this case the PD pulses follow the voltage cycle waveform but will not necessarily be at the same amplitude or phase position as the voltage cycle.

It is very unlikely that lots of pulses would occur close together because in the case of a PD source in motion, the pulses relate closely to the particle movement, the particle cannot move fast enough to generate a whole series of pulses in close proximity, so the pulses tend to be spaced apart in time. If there exists a couple of pulses together on the 3D pattern, they will be in different cycles, which indicates that there must have been milliseconds between bounces.

The PD source in motion would tend to discharge across most of the half cycle, displaying a broad range since the PD pulse phase could be influenced by locally stored charge.

Figure 5.26. Extraction of defect characteristics from PD behaviours from a transcript

Again after validation, a prototype demonstrating this stage of the diagnosis was implemented from these semantic network models, which extended the creation of the first two stages for validation. Further testing of this new prototype and presentation of the results to the expert led to identifying issues with the statistic thresholds in stage #1, and the terminology associated with the original models from stage #2. The expert disagreed with some of the automated descriptors, highlighting that the thresholds required altering to capture the correct descriptor values. These were not identified earlier, due to the automated statistics being implemented in parallel to the knowledge base of stage #3.

Presenting the results to the expert also led to discrepancies in the terminology of stage #2. This was highlighted when certain PD behaviours no longer made sense to the expert in the context of a certain defect characteristic. Here, further tacit knowledge was discovered regarding the PD behaviours, which were then remodelled and re-implemented, before being revalidated by the experts.

5.1.2.4 Stage #4: Classify Defect

All defect characteristics modelled in stage #3 were presented to the expert again in card sorting format. From the card sorting technique the experts were instructed to assign specific defect characteristics to the defect types that were defined in the initial knowledge elicitation meetings (Table 5.1). Again the assignment of defect characteristics to defect types is not included to provoke discussion about the individual types, but to show how the experts placed each defect characteristic into the defined defect types (Figure 5.27). The expert was then asked if the characteristics in each of the defect classes could be combined to create the implied PD source. Semantic models (Appendix 3) were created from these decisions, and implemented in the prototype system. The models in Appendix 3 show the whole diagnostic flow through the different stages, indicating which conditions and actions are utilised in each stage.

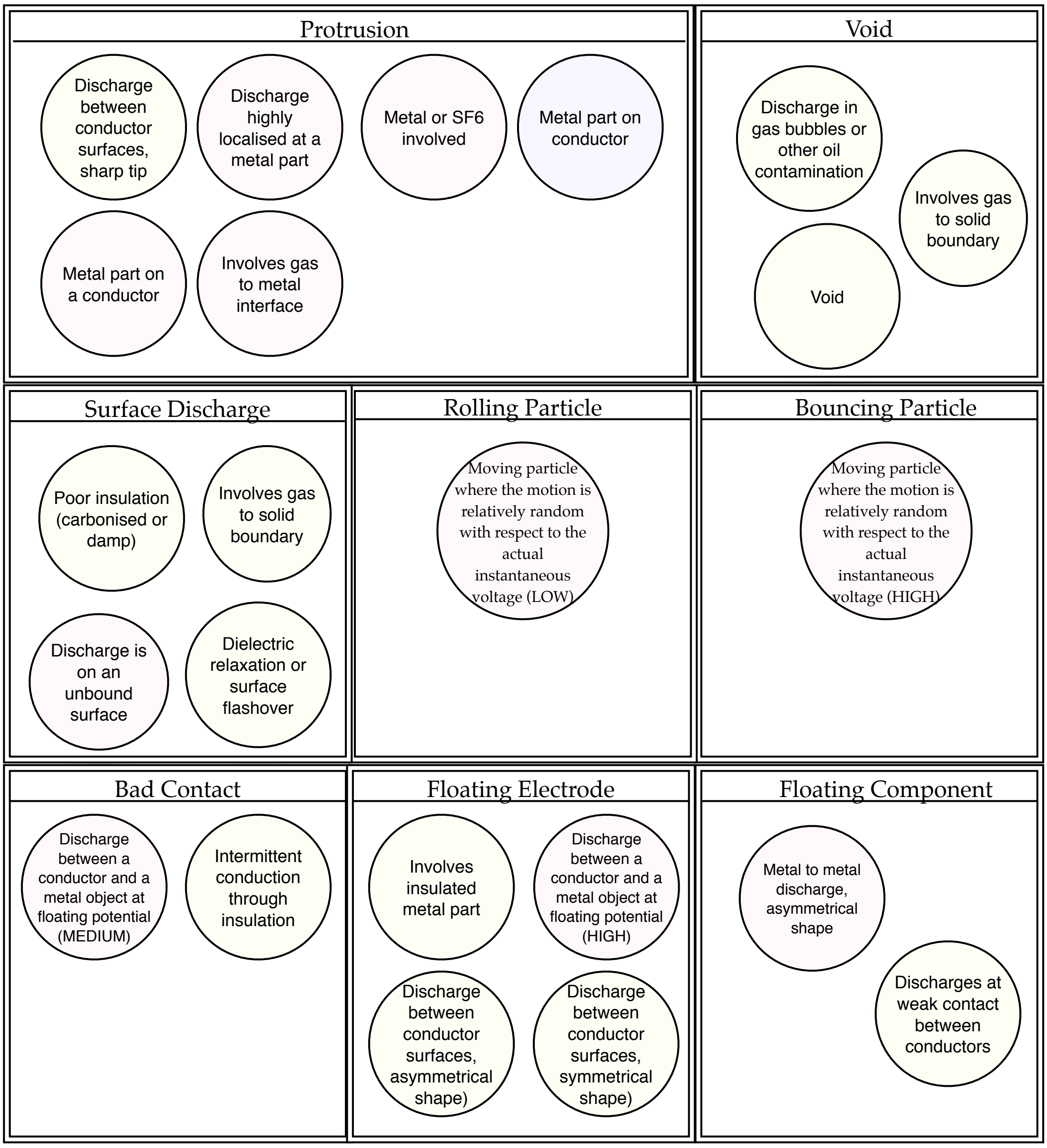


Figure 5.27. Assignment of defect characteristics to defect classes

A checklist of the various defects and descriptors was created to show the experts which descriptor values were utilised, in various ways, to describe each of the defects. This was created to allow verification that the correct descriptors were being used. This table is shown in Table 5.4.

Table 5.4. Descriptors used for defect classification

	Floating Component	Floating Electrode	Protrusion	Void	Surface Discharge	Bad Contact	Rolling Particle	Bouncing Particle
Phase Positon								
Peaks			X					
Zeros	X	X		X	X	X		
Inbetween	X	X		X	X			
Random							X	X
Magnitude								
Small			X	X	X			
Megium	X	X		X	X			
Large		X						
Shape								
Knide Blade			X			X		
Chopped Sine	X			X	X		X	X
Podium			X					
Rectangle		X		X	X			
Phase Inception Symmetry								
Symmetrical		X				X		
Asymmetrical			X					
Magnitude Symmetry								
Positive more than negative			X					
Positive less than negative			X					
Positive equals negative	X	X		X	X	X		
Shape Symmetry								
Symmetrical	X	X		X	X	X		
Asymmetrical	X	X	X			X		
Density Symmetry								
Positive more sparse			X					
Negative more sparse			X					
Same density								
Pulse Distribution								
Biased to later phase								
Biased to earlier phase			X	X	X			
Unbiased			X					
Phase Range								
Broad	X	X	X		X	X	X	X
Narrow				X	X			
Density								
Dense		X	X		X	X	X	
Sparse	X		X	X	X			X
Magnitude Consistency								
Constant		X	X					
Not Constant				X	X			
Cycle to Cycle Activity								
No. of cycles of inactivity	X							

5.1.2.5 Stage #5: Identify PD Site

The location of the defect is important when diagnosing defects so that the defect can be found quickly and repaired. Previous research identified the PD location from various techniques including "time-of-flight" [Judd-04]. This technique provides valuable location information, however, it is thought that the knowledge-based system could support this more accurate PD location technique by adding confidence to (or corroborating) the output of the PD location algorithm. Therefore, stage #5 deploys the experts' knowledge to inform the user about the subsystem within the equipment where the defect identified in stage #4 may exist. It should be noted that the PD site is identified from the phase-resolved pattern alone, utilising the experts' knowledge regarding the PD site from certain descriptors in the pattern. This type of information is usually not sought from a phase-resolved pattern but rather through the positioning of multiple sensors and calculations using the "time-of-flight" algorithm [Judd-04].

The identification of this knowledge was gained through further structured meetings with the experts. From these meetings it became clear that only the protrusion defect could be categorised into two sub categories, by using the descriptors from the phase-resolved pattern; on the high voltage or earth conductors. Therefore, it is only the protrusion that presents a site of the PD source to the operator of the system. This knowledge was modelled, validated and implemented within the prototype.

It was hoped that the insulation type would be transparent when trying to decipher the site of the protrusion defect, however, during the knowledge ascertain meetings it was discovered that the insulation type was required prior to concluding the PD site. Originally it was thought that other descriptors of the phase-resolved pattern could be utilised to identify the type of insulation prior to automatically identifying the PD site, without user input. However, as far as an expert is concerned there is ambiguity between these situations. Automatically identifying (from the PD activity represented in the phase-resolved pattern) the insulation type, as well as the site of the protrusion (high voltage or earth conductor) can therefore not be performed without manual intervention.

5.1.3 Knowledge Validation and Utilisation

As shown in the sections above, each of the stages involved a cyclic process of elicitation, representation, validation and implementation within a prototype for further validation. As the knowledge was captured in each stage, it was presented back to the experts in the transcripts, models and the prototype, allowing the experts to gain a picture of how the knowledge would be applied. These feedback sessions identified various misinterpretations and discrepancies that existed in the modelled knowledge, along with any areas of missing knowledge, which led to the alterations of various terminologies and the addition of certain descriptors.

An example of a descriptor that was added after validation was the magnitude consistency descriptor. Having not been discovered in the original knowledge elicitation meetings, running further case studies through the prototype of the knowledge-based system identified trouble in discriminating between certain defect types. Further meetings were arranged presenting these case studies to the experts, where it became apparent that the expert examined the consistency of the magnitude of the pulses in the phase-resolved pattern. The addition of this descriptor would aid in the classification of defect types, which the knowledge-based system was having trouble discriminating between. This was missed in previous meetings due to this descriptor being overshadowed by more important ones in the original case studies presented to the experts. The discovery of this new descriptor led to further elicitation meetings to capture the PD behaviour associated with magnitude consistency, along with assigning these new behaviours to the appropriate defect characteristics to aid in the diagnosis.

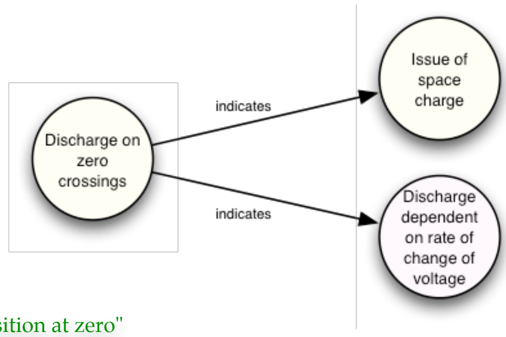
The models of the individual stages in Figure 5.5 were implemented as rules to create the prototype systems prior to development of the final system. To implement these rules, a software environment that allows the creation of a forward-chaining rule-based system was identified; 'Drools' [JBoss-08]. Data-driven reasoning was chosen due to the inference models identified in the elicitation process, and because the descriptors of the phase-resolved pattern were already known and could be calculated in a way that could lead to the identification of certain defect classes.

Drools [JBoss-08] is an example of a forward-chaining inference engine and has been used to construct the knowledge-based system described in this thesis. Drools was chosen because of its implementation in java and therefore its ability to be integrated into existing work by the University of Strathclyde, which will be described in the future work section of chapter 7. Drools' data-driven reasoning provides a result by matching the condition of the rules, where a rule follows the structure IF *condition* THEN *action*. To achieve this data-driven approach, Drools uses the RETE algorithm (described in section 3.1.6.3) to traverse through the data until it results in fewer matches and a conclusion can be reached. The rules are stored in the five knowledge bases in production memory, while the facts (java objects) that the inference engine matches are placed into the working memory, where they can be further used to describe the conditions of new rules.

There is no strict algorithm to follow when converting the knowledge captured in the CommonKADS models into a rule-based system. When constructing the prototype of the system the different stages of the activity diagram became the different stages of the system, which were required to complete the classification of a defect. Within these tasks, knowledge rules are needed. These rules within Drools follow a *WHEN condition THEN action* structure and are constructed by the use of the semantic network models gathered during the knowledge elicitation stage. An example of how a model is converted to the Drools rules can be seen in Figure 5.28.

Figure 5.28 shows how the left-hand side of the model becomes the *when* part of the rule and the right-hand side becomes the *then*. For example, in stage #2 of the system, the *when* part of the rule examines the identified descriptor from the phase-resolved pattern and distinguishes its name and value. In this example the conclusion inserts two new PD behaviour facts into the working memory; this allows them to be used in the next stage for identifying defect characteristics (Figure 5.29), which in turn are used to classify the PD source.

Semantic Network Model

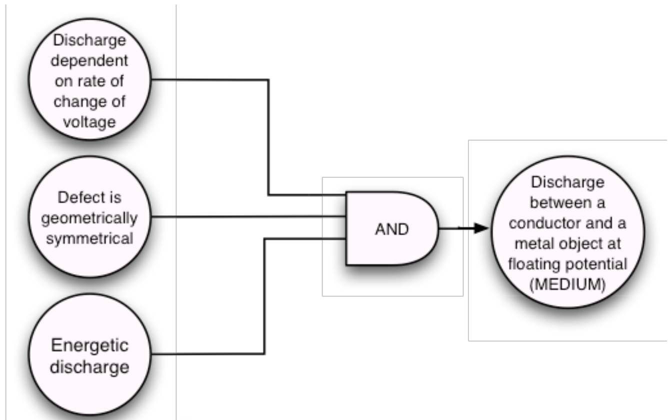


Drools Rule

```
rule "Phase Position at zero"
no-loop true
salience 1
 when
     d: Descriptor(eval(name.equals(Messages.getString("descriptor.position"))),
     eval(value.equals(Messages.getString("descriptor.zero"))))
  then
     insert(new Behaviours(Messages.getString("behaviour.rateOfChangeVoltage"), d));
     insert(new Behaviours(Messages.getString("behaviour.spaceCharge"), d));
end
```

Figure 5.28. Conversion of semantic network model to Drools rule – stage #2

Semantic Network Model



Drools Rule

```
rule "floating components, Medium severity"
no-loop true
 when
     b: Behaviours(eval(behaviour == Messages.getString("behaviour.rateOfChangeVoltage")))
          and b2: Behaviours(eval(behaviour == Messages.getString("behaviour.energetic")))
          and b3: Behaviours(eval(behaviour == Messages.getString("behaviour.sym")))
 then
     String phase1 = b.getPhase();
     String phase2 = b2.getPhase();
     if(phase1 == phase2){
       insert(new Characteristics(Messages.getString("characteristic.medConductor"), b, b2, b3));
     }
end
```

Figure 5.29. Conversion of semantic network model to Drools rule – stage #3

The rules are constructed initially with a unique name beside the attribute “rule”. Within the rule the keyword “insert” means that the output is placed in working memory where it can be further utilised. The “no-loop true” means that once this rule has been fired it cannot be fired again, eliminating recursion. The “salience” of a rule depicts the priority of that rule, with a rule exhibiting a higher salience being fired before other rules with relatively lower salience levels. The expert decided on the recursion and salience associated with each rule and test cases were run to validate the ordering. The salience was more important during the initial stages of diagnosis due to certain descriptors e.g. phase positions, having an influence on later rules within the same rule base. For example, within stage #1, a salience from 1 to 7, with 7 representing the highest priority, was implemented for the calculation of the various descriptors.

5.2 Generic Nature of System

The incremental knowledge-based approach, described above, to the analysis of PD data was originally created using knowledge pertaining to UHF sensor data from GIS. However, due to the common physical nature of PD within high voltage equipment [Fuhr-91] the knowledge-based system offers the potential of a generic approach to classifying defects from phase-resolved patterns created from IEC60270 or UHF sensors. The generic application is achieved by providing a diagnosis from IEC60270 data, performed using the knowledge already captured and implemented from UHF phase-resolved patterns. Due to the consistent physical nature of PD across different high voltage apparatus [Fuhr-91] this knowledge-based system also has the potential to diagnose defects in different high voltage equipment, including power transformers and GIS.

The generic nature of the knowledge-based system created during this research, was realised when diagnosing defects from transformer data received in IEC60270 format from the University of Southampton. This generic nature, along with the results of the original UHF diagnostics, will be examined in chapter 6 of this thesis.

5.3 Conclusion

This chapter has shown that, using knowledge engineering techniques, the diagnostic process of experts in the field of PD diagnostics can be identified, modelled, validated and implemented within a knowledge-based system to automate diagnosis. Knowledge engineering techniques played an important role in this research. It helped clarify the experts' understanding of how they examined phase-resolved patterns and identify their structured diagnostic process. It provided elicitation techniques to discover expert knowledge in the identification of meaningful descriptors of the phase-resolved pattern, their associated PD behaviours, defect characteristics, classification and PD site. Knowledge representation approaches formed a major part ensuring that the knowledge was constructed in a suitable format for validation and implementation into the knowledge-based system.

A knowledge-based approach to the diagnosis of PD data, not only provides a classification of the PD source, but it also provides explanation of how the classification was derived. Capturing the tacit knowledge of experts in the area of PD phenomena, phase-resolved patterns and defect classification underpins this explanation. The main benefit of this knowledge-based system is the explanation provided as to why a certain defect was identified. This justification of the classification will provide the user with more confidence in the final output. This is a novel approach to phase-resolved defect diagnosis, as the systems created and researched in the past, see section 3.1, applied machine learning techniques offering no explanation of how a defect is classified. These systems present the user with the diagnosed defect for a certain input, without informing the user as to how it reached its diagnosis. A further disadvantage of the previous types of techniques is their requirement to be trained on previous data sets, which are not always available. Unlike these techniques, the knowledge-based system does not have the requirement to be trained, or retrained as new defect samples arise.

During the knowledge engineering stage specific issues were highlighted with regard to the examination of the phase-resolved pattern. When the discharges occur across the zero crossings the PD activity is occurring between the half cycles. Previous classifiers/machine learning techniques do not recognise this effect causing the miscalculation of certain statistics resulting in misclassification. Therefore when the discharges occur across the zero crossings the expert knowledge is reproduced in the knowledge-based system by examining the pattern as being continuous over the zero-crossing points of the ac waveform. The grouping of the discharges on a per activity basis, along with the construction of algorithms to calculate different descriptors of the phase-resolved pattern forms the first stage of the diagnostic process in the knowledge-based system.

The knowledge for the various stages has been captured from the literature of Gulski and through elicitation meetings with Judd and Reid at the University of Strathclyde. It has been modelled using CommonKADS, validated, and implemented in a Drools knowledge-based expert system shell. The experts' knowledge is implemented in individual stages of the diagnostic process shown in Figure 5.5. Therefore, this knowledge-based approach provides storage of valuable expert knowledge in this domain. As new knowledge of PD behaviour, defect characteristics or defect classification are introduced by additional experts, or through further understanding of the phase-resolved pattern and PD phenomena, additional knowledge can easily be added to the corresponding stage of the knowledge-based system. This offers an extensible system for automated PD diagnostics.

Using the phase-resolved PD pattern as the input, the knowledge-based system has the potential to classify defects from either IEC60270 or UHF sensor data. The knowledge associated with PD behaviours is independent of the type of equipment; this knowledge can be employed immediately on various apparatus, including transformers and GIS. Consequently, this knowledge-based approach could form the basis of a generic system for the diagnosis of defects from a variety of sensory data across several types of high voltage equipment. The application and results identified by this approach are provided in the next chapter.

5.4 References

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Chapter 6

Application of Knowledge-Based System for PD Analysis

6.0 Introduction

As shown in the last chapter, an incremental knowledge-based approach was adopted to diagnose PD sources within high voltage equipment. To quantify the application of the knowledge-based system, the knowledge was constructed in the Drools programming language, as previously described. Once the final prototype of the system was created it was tested with a variety of defects in various high voltage apparatus, examples of which will be demonstrated through assorted case studies presented in this chapter.

As explained in chapter 5, the generic workable format input to the knowledge-based system is a phase-resolved PD pattern consisting of the *pulse's amplitude*, the *cycle number* on which the pulse appears and the *phase position* of the pulse on the voltage cycle, where the PD pulses are captured by a measurement system with phase-resolved capability. This research concentrates on the classification of phase-resolved patterns created from either UHF or IEC60270 PD data. These patterns are in the form of a 50*64 matrix of floating points that represent the PD pulse amplitude in 50 consecutive cycles across 64 phase windows (buckets) of the voltage cycle; with the positive half cycle appearing first, between 0° and 180° and then the negative half cycle between 180° and 360°.

In the following case studies, the phase-resolved pattern representing the PD source is input to the knowledge-based system, which increments through the five stages of knowledge-based diagnosis to reach its conclusion, as described in chapter 5. A graphical user interface (GUI) was designed to provide a staged diagnosis to the expert, and potentially the engineer. The GUI (for example Figure 6.1) is included in the following cases studies to display the phase-resolved pattern and the automatically calculated descriptors used in the diagnostic process.

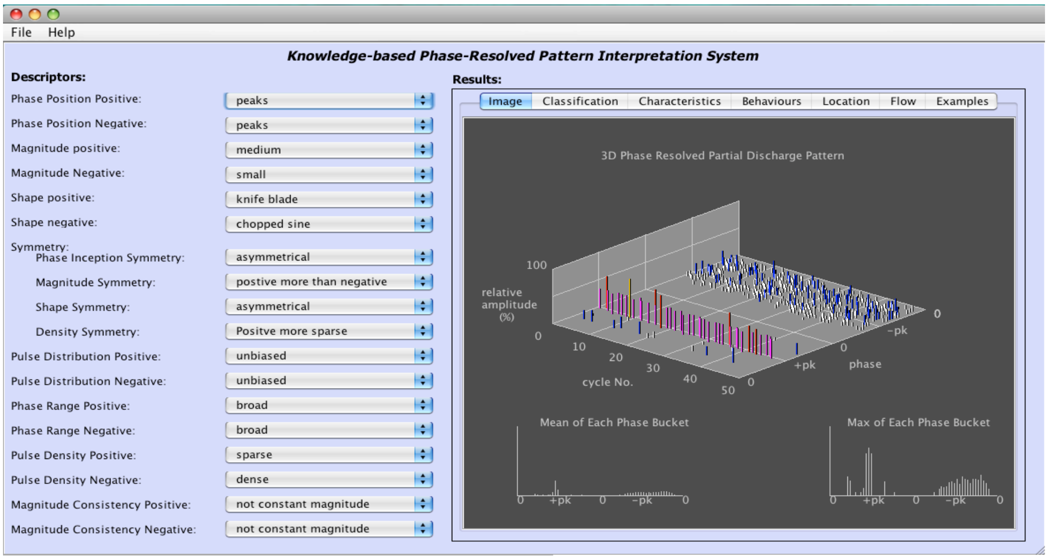


Figure 6.1. GUI display of a protrusion defect in GIS captured through a UHF sensor

Although the knowledge-based system was initially intended to diagnose the PD source following noise removal, it was subsequently decided that some noise should also be removed by the system. Prior to identifying the descriptors of the phase-resolved pattern, the system removes small random pulses that lie outside the main phase regions in which discharges are present. However, if the pattern being analysed is considered to be random, this process is not carried out; otherwise valid data might be lost. The motivation for this approach to noise removal was from a visibility point of view, where small noise pulses might obscure certain descriptors. This process is performed to mimic the way an expert would remove noise by eye from the pattern. Alternatively, pulses below a certain noise threshold can be manually remove from the pattern by choosing an option in the system's GUI.

To achieve the explanation associated with the classification, the GUI is split into sections. The right-hand side of the GUI displays the 3D phase-resolved pattern of the discharge pulses, along with 2D mean and maximum graphs calculated from the 3D pattern. All three of these graphs assist the expert (and the knowledge-based system) when diagnosing a defect. The left-hand side of the GUI shows the descriptors that have been calculated from the phase-resolved pattern using the statistical operators described in chapter 5. These descriptors describe the different aspects of the pattern that inform the expert about the PD behaviours occurring in the insulation.

The inferred PD behaviours are then deployed to highlight the defect characteristics and classify the defect that is present in the insulation, along with its possible site within the equipment. A varying level of explanation regarding the diagnosis is conveyed through tables of knowledge (within the various tabs on the right-hand side of the GUI and in the following case studies) to justify the classification and provide the user with confidence in the result. It should be noted that the knowledge-based system assumes that an insulation defect exists within the apparatus and was created for diagnosis after an anomalous event [Brown-08] was flagged.

This chapter will demonstrate through the use of suitable case studies the application of the knowledge-based system created in this research and show how the incremental approach to PD diagnosis justifies the final classification of the PD defect source. Various case studies from PD data monitored by UHF sensors or measured by conventional IEC60270 techniques are included, representing PD sources from a variety of high voltage equipment, to demonstrate the potential generic nature of the knowledge-based system.

6.1 UHF Diagnosis

Utilising the outcomes of previous research at the University of Strathclyde, UHF sensors were employed to capture the PD activity within a short section of 400kV GIS busbar energised using a metalclad transformer in laboratory conditions [Pearson-95]. The experimental setup deployed in this process is shown in Figure 6.2(a), along with the layout of UHF sensors on the section of GIS, Figure 6.2(b). The PD activity captured by this method was used as input to the knowledge-based system and represents the various SF_6 case studies used in the following subsection to demonstrate the use of the knowledge-based system.

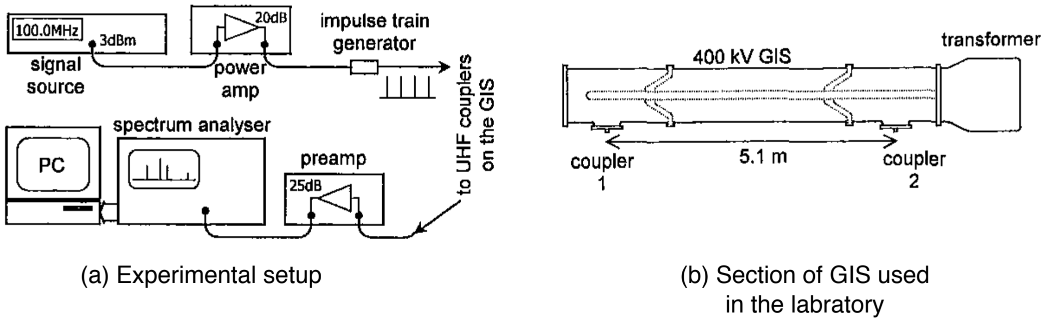


Figure 6.2. Experimental setup and section of GIS used to monitor PD activity [Judd-99]

Other research at the University of Strathclyde recorded PD activity under high voltage ac conditions [Cleary-02][Cleary-06] using a broadband current transformer to measure the PD current pulses, and a pair of sensors mounted inside a metal tank to detect the UHF signals. This experimental setup can be seen in Figure 6.3 [Cleary-06] and was conducted to show the PD activity similar to that in an oil insulated transformer. The oil used in these experiments was reclaimed light-grade transformer oil, as commonly used in power transformers in the UK. The PD data captured from these experiments were previously used to test various diagnostic methods, constructed through previous research at the University of Strathclyde [McArthur-04][Catterson-06][Strachan-05]. The following subsections will demonstrate the knowledge-based diagnosis based on this data obtained from experiments synthesising defects in oil-insulated transformer.

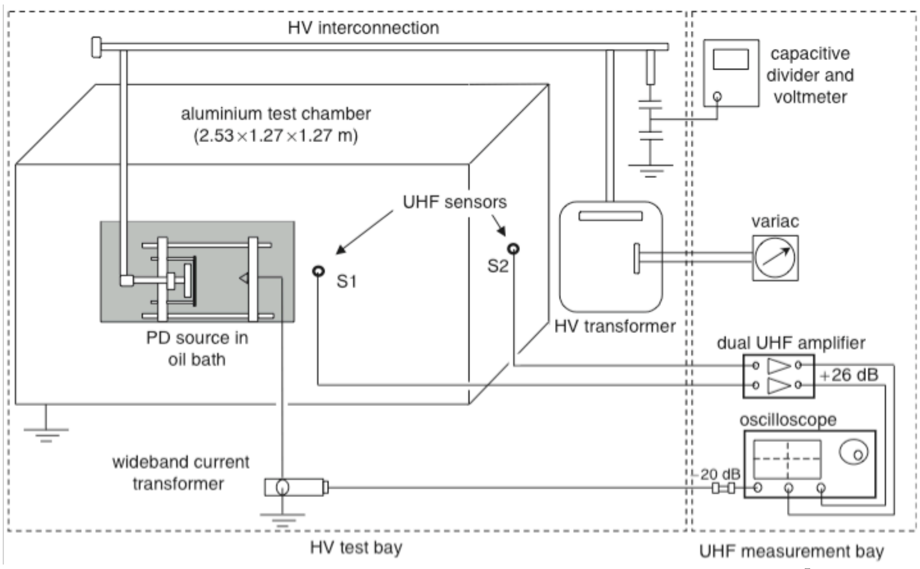


Figure 6.3. Experimental setup to capture PD activity in transformer oil [Cleary-06]

This section will show, through the use of various case studies, the ability of the knowledge-based system to diagnose previously captured UHF activity that represent a variety of PD sources in both the GIS and transformer laboratory experiments.

6.1.1 Protrusion Defect

Fixed, sharp metallic objects on conductors.

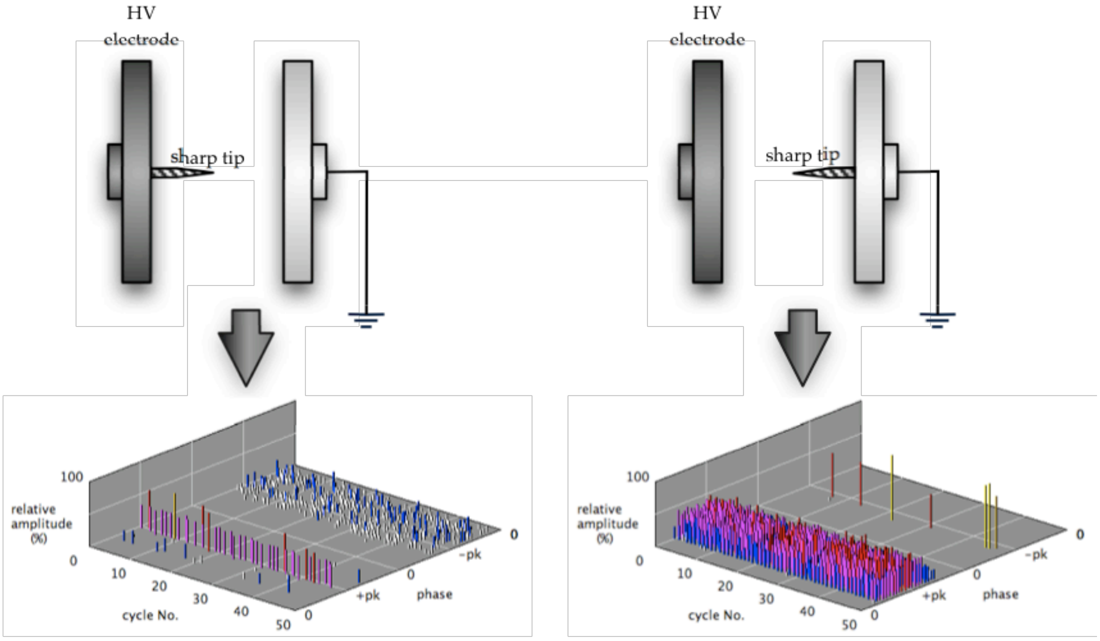
In this section, various case studies will be presented of a protrusion defect. Most types of discharge tend to exhibit some characteristic phase correlation with the 50Hz voltage cycle, and the protrusion, which is strictly a point to plane geometry, is the classic example of this. When a high voltage (at 50Hz) is applied across the test cell that holds the protrusion, it results in a geometrical field pattern that is greatest at the sharp tip. Since the field at the tip is proportional to the instantaneous ac voltage, PD will tend to occur around the voltage peaks at phase positions of 90° and 270°, as can be seen in Figure 6.1.

When examining a phase-resolved pattern of a protrusion defect, the peaks of the voltage cycle tend to be the most interesting reference points. This is because, in a given geometry, the electric field within the insulation is proportional to the voltage, implying that the stress on the insulation is greatest in magnitude at the peaks. The force on charges is governed by the electric field, so when ionisation occurs, depending on the polarity of the voltage and the position on the ac waveform, the way in which the ionised electrons or ions try to move under the influence of the field controls the current pulses, which are the PD.

The protrusion can potentially exist either on the high voltage or earth conductor; see Figure 6.4. If the protrusion occurs on the high voltage side there are two mechanisms that can cause a PD, depending on whether the protrusion is at a positive polarity or a negative polarity. Due to the different polarities, the different direction in which the electric field is exerting a force on charges, and the fact that it is primarily the electrons that are mobile (i.e. easily accelerated because of their small mass), an electron source (free electron) will initiate the discharge. Depending on the polarity, the electrons that form the conducting channel must be either extracted from the metal or liberated from the insulation by ionisation.

When the tip is negative and the plane opposite is positive, electrons are emitted from the metal tip. This is as a result of the high field strength and comparatively lower force required to liberate electrons from the metal surface, meaning that the discharges are likely to start first on the negative polarity, when increasing the voltage from zero [Nattrass-88]. At a higher voltage, once the point is reached where there are discharges on both polarities, they would be expected to occur earlier on in the negative part of the cycle with a greater density of pulses, because of the comparative ease with which electrons can be extracted from the metal tip at that time. These descriptors can be seen in the phase-resolved pattern in Figure 6.4(a).

When the point is positive and the plane is negative the electrons must be liberated though ionisation of the insulation material. In the case of a protrusion on the high voltage conductor, this would occur during the positive half cycle. This requires a stronger electric field (higher voltage) and the resulting pulse tends to be more energetic. Within the phase-resolved pattern, a larger magnitude is observed when extracting the electrons from the insulation due to the overstressed insulation during the migration of the electrons to the positively charged metal tip. These descriptors can also be seen in the phase-resolved pattern in Figure 6.4(a).



(a) Protrusion on high voltage conductor

(b) Protrusion on earth conductor

Figure 6.4. Protrusion defect on (a) high voltage and (b) earth conductor

If the sharp point is earthed and the plane opposite is at high voltage then the discharge physics are the same but the above explanation would be reversed in relation to the polarity of the ac cycle. This means that during the first (positive) half cycle the sharp point will be negative and during the second (negative) half cycle the sharp point will be positive, permitting the electrons to be removed from the metal tip in the positive half cycle and the insulation during the negative half. This would therefore show the reverse descriptors in the phase-resolved pattern, with the greater density of pulses in the positive half cycle and pulses with a larger magnitude in the negative half cycle, as shown in the phase-resolved pattern of Figure 6.4(b).

The actual field at the metal tip is a combination of the geometrical field plus the local space charge field, described in section 5.1.1.2. Although different insulations hold different properties when it comes to the space charge effect, the phase-resolved patterns still show similar descriptors, which can be used for diagnosis. The following case studies will show diagnoses from a protrusion defect, as shown in Table 5.1, in SF_6 (from the experiment in Figure 6.2) and in oil (from the experiment in Figure 6.3), where the protrusion occurs on either the high voltage and earth conductors.

6.1.1.1 Protrusion in SF_6 Case Study 1

Figure 6.1 shows the phase-resolved pattern of a PD source input to the knowledge-based system for diagnosis. The descriptors calculated from the pattern are also displayed in Figure 6.1, with the explanation from the GUI (representing the remaining stages of diagnosis) displayed in Table 6.1 to Table 6.4 respectively. This varying explanation supports the user by providing a build up of knowledge that leads to the classification. Parts of the phase-resolved pattern examined are highlighted to the user, along with their inferred PD behaviours, defect characteristics, classification and PD site, allowing the user of the system to investigate the diagnosis. This will also be apparent in the other case studies.

Table 6.1 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Asymmetrical	1. Conditions for PD inception are different for both polarities
Whole cycle	Magnitude symmetry	Positive more than negative	1. Extraction of electrons requires comparatively more energy in the positive half cycle
Whole cycle	Density symmetry	Positive more sparse	1. Ease of discharging is greater in negative half cycle
Whole cycle	Shape symmetry	Asymmetrical	1. Defect is geometrically asymmetrical
Positive half	Position	Peaks	1. Minimal space charge present i.e. no memory effect beyond half cycle
Positive half	Density	Sparse	1. Defect experiencing inconsistent electric field 2. Interference 3. Space charge with a long time constant
Positive half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Knife blade	1. Energetic discharge
Positive half	Magnitude	Medium	1. Pulses initiated in insulation
Positive half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region
Negative half	Position	Peaks	1. Minimal space charge present i.e. no memory effect beyond half cycle
Negative half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Negative half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Negative half	Distribution	Unbiased	1. No space charge
Negative half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Negative half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Negative half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region

Table 6.2 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Whole cycle	Conditions for PD inception are different for both polarities AND minimal space charge present i.e. no memory effect beyond half cycle AND ease of discharging is greater in negative half cycle	Metal part on conductor
Whole cycle	Conditions for PD inception are different for both polarities AND pulses at a conducting surface AND defect is geometrically asymmetrical AND pulses at a very sharp tip AND Minimal space charge present i.e. no memory effect beyond half cycle AND PD pulse phase influenced by local stored charge	Discharge between conductor surfaces, sharp tip
Positive half	No space charge AND minimal space charge present i.e. no memory effect beyond half cycle	Metal or SF6 involved
Positive half	Minimal space charge present i.e. no memory effect beyond half cycle AND space charge with a long time constant AND conditions for PD inception are different for both polarities	Involves gas to metal interface
Positive half	Minimal space charge present i.e. no memory effect beyond half cycle AND space charge with a long time constant AND defect is geometrically asymmetrical	Involves gas to metal interface
Negative half	No space charge AND minimal space charge present i.e. no memory effect beyond half cycle	Metal or SF6 involved

Table 6.3 Classification of PD Source

Characteristics	Behaviours	Classification
Metal or SF_6 involved		PROTRUSION
Involves gas to metal interface		PROTRUSION
Metal part on conductor		PROTRUSION
Metal part on conductor	Extraction of electrons requires comparatively more energy in the positive half cycle AND energetic discharge	SEVERE PROTRUSION
Discharge between conductor surfaces, sharp tip		PROTRUSION

Table 6.4 Site of PD Source

Classification	Characteristics	Contributing Descriptors	Site
PROTRUSION	Metal part on conductor	Positive half more sparse	On high voltage conductor
SEVERE PROTRUSION	Metal part on conductor	Positive half more sparse	On high voltage conductor

Inputting the 50*64 matrix, represented by the protrusion phase-resolved pattern in the GUI of Figure 6.1, the knowledge-based system produces the classification shown in Table 6.3. As seen in the table, the system reached five conclusions that suggest the defect is a protrusion. As the knowledge-based system incrementally progresses through its diagnostic process, the actions of the rules in each stage are placed in working memory where they can be utilised as conditions for further rules. In this case study five results, along with the evidence associated with each classification, are displayed to justify the final diagnosis of the PD source. The site of the protrusion has also been identified as existing on the high voltage conductor, by examining and comparing the different activity in each half cycle.

As shown in row four of Table 6.3, the severity of the protrusion can also be recognised by the expert's knowledge. In this case, the severity of the protrusion was identified from the physical PD process where the extraction of electrons requires comparatively more energy in the positive half cycle, along with an energetic discharge. This was apparent from the magnitude (descriptor) in the positive half of the voltage cycle being greater than the negative half, in addition to the knife blade shape in the positive half cycle. The final decision regarding the intensity of the protrusion is left to the user, which can be achieved by the decision support provided through the build up of evidential knowledge associated with the diagnosis.

6.1.1.2 Protrusion in SF_6 Case Study 2

Figure 6.5 displays the GUI associated with an alternative phase-resolved pattern, which represents the same defect in case study 1, captured by the same method. This case study was included because on first inspection Figure 6.5 shows different activity on the positive half cycle to that of Figure 6.1. However, as highlighted by the explanation displayed in Table 6.5 to Table 6.8, the knowledge-based system is still able to correctly classify the protrusion defect with the expert knowledge held in its knowledge bases. This is due to the generic nature of the knowledge rules captured during the knowledge engineering process. Again the system classifies the PD source as a protrusion defect on the high voltage conductor.

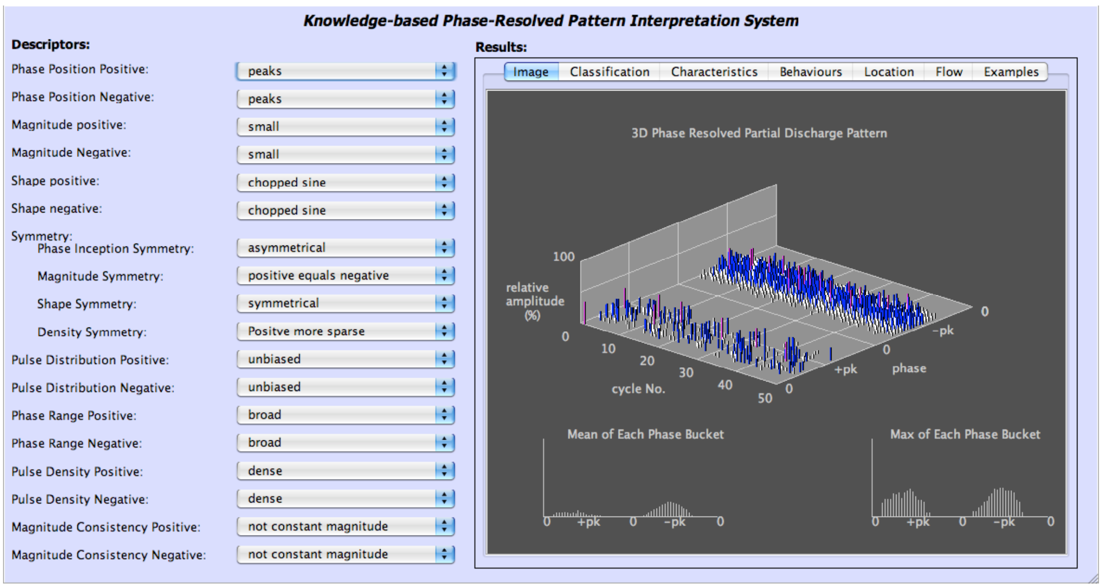


Figure 6.5. GUI display of a protrusion defect in GIS captured through a UHF sensor

Table 6.5 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Asymmetrical	1. Conditions for PD inception are different for both polarities
Whole cycle	Magnitude symmetry	Positive equals negative	1. Defect is geometrically symmetrical
Whole cycle	Density symmetry	Positive more sparse	1. Ease of discharging is greater in negative half cycle
Whole cycle	Shape symmetry	Symmetrical	1. Defect is geometrically symmetrical
Positive half	Position	Peaks	1. Minimal space charge present i.e. no memory effect beyond half cycle
Positive half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Positive half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Chopped sine	1. Energetic discharge
Positive half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Positive half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region
Negative half	Position	Peaks	1. Minimal space charge present i.e. no memory effect beyond half cycle
Negative half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Negative half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Negative half	Distribution	Unbiased	1. No space charge
Negative half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Negative half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Negative half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region

Table 6.6 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Whole cycle	Conditions for PD inception are different for both polarities AND minimal space charge present i.e. no memory effect beyond half cycle AND ease of discharging is greater in negative half cycle	Metal part on conductor

Table 6.7 Classification of PD Source

Characteristics	Classification
Metal part on conductor	PROTRUSION

Table 6.8 Site of PD Source

Classification	Characteristics	Contributing Descriptors	Site
PROTRUSION	Metal part on conductor	Positive half more sparse	On high voltage conductor

6.1.1.3 Protrusion in SF_6 Case Study 3

Figure 6.6 shows an example of the initial stages of a protrusion defect. Within the phase-resolved pattern the negative half cycle displays signs that a protrusion is present, through the shape and location of the pulses. As highlighted in the descriptors in the figure, the system cannot identify the phase position, distribution, range or density of the positive half cycle, due to the small number of pulses, believed by the system to be noise. However, identifying the possible characteristics of a protrusion in the negative half cycle, along with examining the pattern as a whole, the system reached the same conclusion as case study 6.1.1.2. The explanation associated with this classification can be seen in Table 6.9 to Table 6.12.

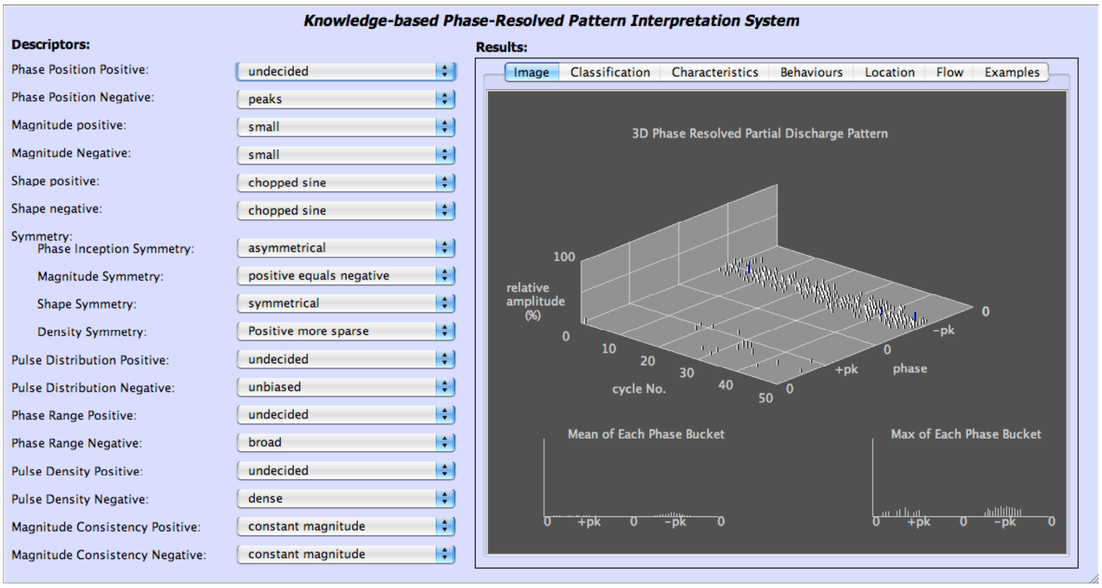


Figure 6.6. GUI of protrusion defect in GIS

Table 6.9 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Asymmetrical	1. Conditions for PD inception are different for both polarities
Whole cycle	Magnitude symmetry	Positive equals negative	1. Defect is geometrically symmetrical
Whole cycle	Density symmetry	Positive more sparse	1. Ease of discharging is greater in negative half cycle
Whole cycle	Shape symmetry	Symmetrical	1. Defect is geometrically symmetrical
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Chopped sine	1. Energetic discharge
Positive half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Positive half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region

Phase Range	Descriptor Name	Descriptor	Behaviours
Negative half	Position	Peaks	1. Minimal space charge present i.e. no memory effect beyond half cycle
Negative half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Negative half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Negative half	Distribution	Unbiased	1. No space charge
Negative half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Negative half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Negative half	Magnitude consistency	Constant magnitude	1. Constant geometry and capacitance 2. Certain amount of energy to ionise the insulation

Table 6.10 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Whole cycle	Conditions for PD inception are different for both polarities AND minimal space charge present i.e. no memory effect beyond half cycle AND ease of discharging is greater in negative half cycle	Metal part on conductor

Table 6.11 Classification of PD Source

Characteristics	Classification
Metal part on conductor	PROTRUSION

Table 6.12 Site of PD Source

Classification	Characteristics	Contributing Descriptors	Site
PROTRUSION	Metal part on conductor	Positive half more sparse	On high voltage conductor

6.1.1.4 Protrusion in SF_6 Case Study 4

A lack of data from a protrusion defect on the earth conductor in SF_6 led to further experiments in the laboratory using the experimental setup in [Reid-06], with a 15mm needle on the earth conductor and a gap between the plates of 34mm. An example of the PD activity just after inception can be seen in the phase-resolved pattern of Figure 6.7. Inputting this phase-resolved pattern to the knowledge-based system correctly classified the defect as a protrusion. The explanation associated with this classification can be seen in Table 6.13 to Table 6.16. The system also concluded that the protrusion resided on the earth conductor by comparing of the pulse density in each half cycle (identified in Table 6.16).

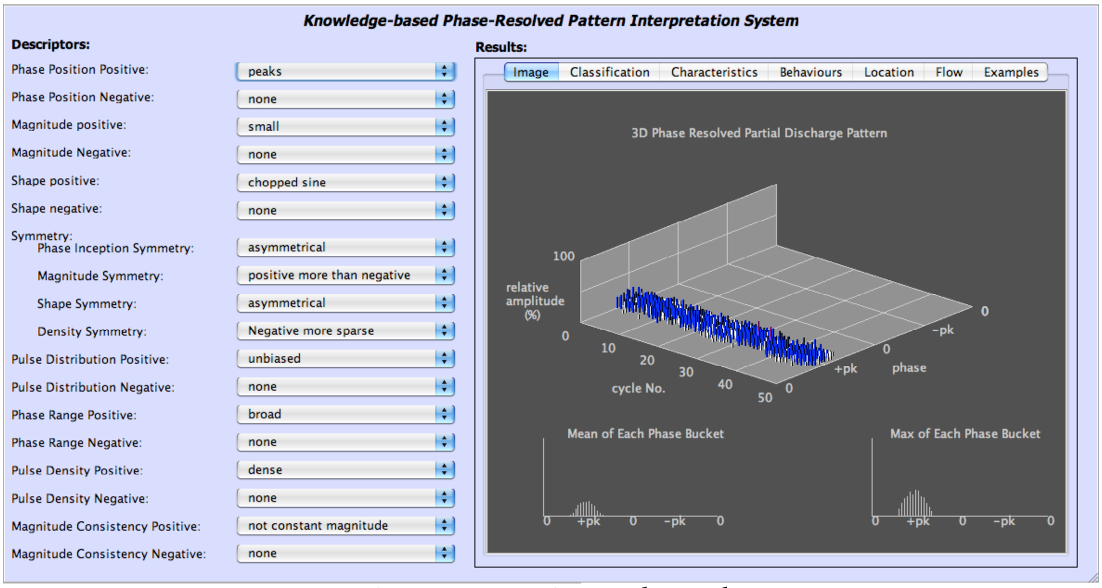


Figure 6.7. GUI of protrusion defect on the earth conductor in SF_6

Table 6.13 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Asymmetrical	1. Conditions for PD inception are different for both polarities
Whole cycle	Magnitude symmetry	Positive more than negative	1. Extraction of electrons requires comparatively more energy in positive half cycle
Whole cycle	Density symmetry	Negative more sparse	1. Ease of discharging is greater in positive half cycle
Whole cycle	Shape symmetry	Asymmetrical	1. Defect is geometrically asymmetrical
Positive half	Position	Peaks	1. Minimal space charge present i.e. no memory effect beyond half cycle
Positive half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Positive half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Positive half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Positive half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region
Negative half	Number of pulses	Too few	1. Too few pulses to diagnose

Table 6.14 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Whole cycle	Conditions for PD inception are different for both polarities AND minimal space charge present i.e. no memory effect beyond half cycle AND ease of discharging is greater in positive half cycle	Metal part on conductor
Whole cycle	Conditions for PD inception are different for both polarities AND pulses at a conducting surface AND defect is geometrically asymmetrical AND pulses at a very sharp tip AND Minimal space charge present i.e. no memory effect beyond half cycle AND PD pulse phase influenced by local stored charge	Discharge between conductor surfaces, sharp tip
Positive half	No space charge AND minimal space charge present i.e. no memory effect beyond half cycle	Metal or SF6 involved
Negative half	Too few pulses to diagnose	Too few pulses to diagnose

Table 6.15 Classification of PD Source

Characteristics	Classification
Metal part on conductor	PROTRUSION
Discharge between conductor surfaces, sharp tip	PROTRUSION
Metal or SF6 involved	PROTRUSION

Table 6.16 Site of PD Source

Classification	Characteristics	Contributing Descriptors	Site
PROTRUSION	Metal part on a conductor	Negative half more sparse	On earth conductor

6.1.1.5 Protrusion in SF_6 Case Study 5

The experimental setup in [Reid-06] was used to examine a severe case of PD activity of a protrusion on the earth conductor. This was achieved by increasing the voltage level to simulate a severe protrusion, the results of which can be seen in the phase-resolved pattern of Figure 6.8. Inputting this into the knowledge-based system resulted in correct classification of a protrusion on the earth conductor; the explanation associated with the classification can be seen in Table 6.17 to Table 6.20.

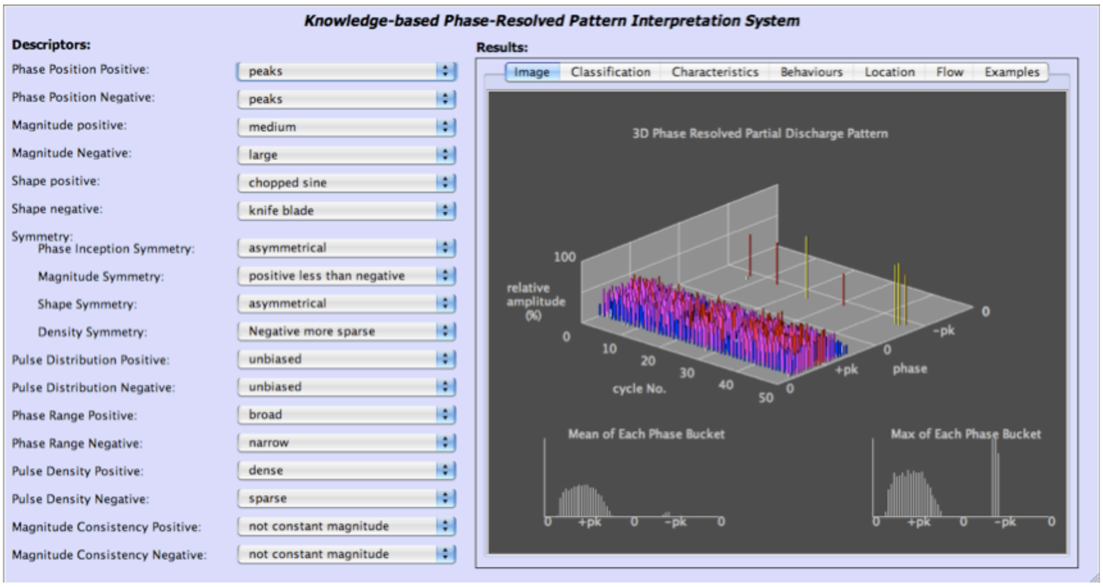


Figure 6.8. GUI of protrusion defect on the earth conductor in SF_6

Table 6.17 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Asymmetrical	1. Conditions for PD inception are different for both polarities
Whole cycle	Magnitude symmetry	Positive less than negative	1. Extraction of electrons requires comparatively more energy in the negative half cycle
Whole cycle	Density symmetry	Negative more sparse	1. Ease of discharging is greater in positive half cycle
Whole cycle	Shape symmetry	Asymmetrical	1. Defect is geometrically asymmetrical
Positive half	Position	Peaks	1. Minimal space charge present i.e. no memory effect beyond half cycle
Positive half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Positive half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Positive half	Magnitude	Medium	1. Pulses initiated in insulation
Positive half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region
Negative half	Position	Peaks	1. Minimal space charge present i.e. no memory effect beyond half cycle
Negative half	Density	Sparse	1. Defect experiencing inconsistent electric field 2. Interference 3. Space charge with a long time constant
Negative half	Range	Narrow	1. Sufficient charge released to suppress further pulses
Negative half	Distribution	Unbiased	1. No space charge
Negative half	Shape	Knife blade	1. Energetic discharge
Negative half	Magnitude	Large	1. Arcing
Negative half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region

Table 6.18 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Whole cycle	Conditions for PD inception are different for both polarities AND minimal space charge present i.e. no memory effect beyond half cycle AND ease of discharging is greater in positive half cycle	Metal part on a conductor
Positive half	No space charge AND minimal space charge present i.e. no memory effect beyond half cycle	Metal or SF6 involved
Negative half	Minimal space charge present i.e. no memory effect beyond half cycle AND space charge with a long time constant AND conditions for PD inception are different for both polarities	Involves gas to metal interface
Negative half	No space charge AND minimal space charge present i.e. no memory effect beyond half cycle	Metal or SF6 involved
Negative half	Minimal space charge present i.e. no memory effect beyond half cycle AND space charge with a long time constant AND defect is geometrically asymmetrical	Involves gas to metal interface

Table 6.19 Classification of PD Source

Characteristics	Behaviours	Classification
Metal or SF_6 involved		PROTRUSION
Involves gas to metal interface		PROTRUSION
Metal part on a conductor		PROTRUSION
Metal part on a conductor	Extraction of electrons requires comparatively more energy in the negative half cycle AND energetic discharge	SEVERE PROTRUSION

Table 6.20 Site of PD Source

Classification	Characteristics	Contributing Descriptors	Site
PROTRUSION	Metal part on a conductor	Negative half more sparse	On earth conductor
SEVERE PROTRUSION	Metal part on a conductor	Negative half more sparse	On earth conductor

6.1.1.6 Protrusion in Oil-insulated Transformer Case Study

Figure 6.9 shows a typical phase-resolved pattern from a protrusion placed within the transformer oil laboratory experiment (Figure 6.3). PD activity in oil (Figure 6.9) still demonstrates similar characteristics to that of a protrusion within SF_6 (Figure 6.8).

In the case of Figure 6.9 the protrusion resides on the high voltage conductor. The automatic identification of the site of the protrusion defect in oil is not as straight forward as its classification. When the protrusion resides on the high voltage conductor, the PD activity in oil behaves differently to that in SF_6. Depending on the polarity, a different pattern (indicating the PD site) is observed depending on the insulation in which the protrusion defect exists

[Cleary-05]. The main descriptors of the phase-resolved pattern used to identify the site of the protrusion are the comparison of the density between half cycles. When the protrusion resides on the high voltage conductor in oil these features are shown in the reverse half cycle to the protrusion in SF_6, for example see Figure 6.1.

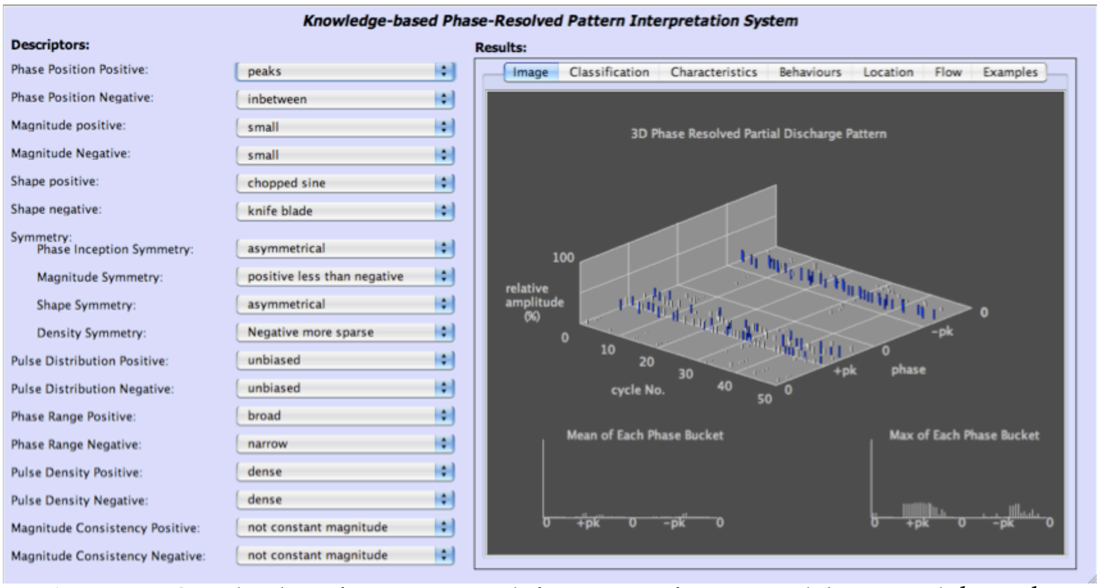


Figure 6.9. GUI display of a protrusion defect in transformer model captured through a UHF sensor

As discussed in section 5.1.2.5, the identification of the PD site requires user intervention regarding the type of insulation prior to diagnosis. For this case study, the protrusion resides on the high voltage conductor in oil. According to the expert, the difference in pattern to that obtained for a defect in SF_6 could be due to the oil containing carbon, which is semi conducting. When large discharges occur carbonisation is caused in the oil, eventually turning the oil brown. Therefore, when a discharge occurs, fractures could appear within the liquid, and possible carbonisation within the gas channels could create a source of electrons and therefore a greater number of small discharges in the positive half cycle.

Inputting this phase-resolved pattern to the knowledge-based system resulted in the diagnosis shown in Table 6.21 to Table 6.24, correctly identifying the defect as a protrusion. A clearer classification regarding the site of the PD could be achieved with further investigation, experiments and an increase in knowledge base. However at present, due to the defect being in oil, the knowledge-based system is unsure of the site of the protrusion, since in oil this pattern is also indicative of a protrusion on the earth conductor.

Table 6.21 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Asymmetrical	1. Conditions for PD inception are different for both polarities
Whole cycle	Magnitude symmetry	Positive less than negative	1. Extraction of electrons requires comparatively more energy in negative half cycle
Whole cycle	Density symmetry	Negative more sparse	1. Ease of discharging is greater in positive half cycle
Whole cycle	Shape symmetry	Asymmetrical	1. Defect is geometrically asymmetrical
Positive half	Position	Peaks	1. Minimal space charge present i.e. no memory effect beyond half cycle
Positive half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Positive half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Positive half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Positive half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region
Negative half	Position	Inbetween	1. Shift between absolute and rate of change of voltage 2. Issue of space charge
Negative half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Negative half	Range	Narrow	1. Sufficient charge released to suppress further pulses
Negative half	Distribution	Unbiased	1. No space charge
Negative half	Shape	Knife blade	1. Energetic discharge
Negative half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Negative half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region

Table 6.22 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Whole cycle	Conditions for PD inception are different for both polarities AND minimal space charge present i.e. no memory effect beyond half cycle AND ease of discharging is greater in positive half cycle	Metal part on a conductor
Whole cycle	Conditions for PD inception are different for both polarities AND pulses at a conducting surface AND defect is geometrically asymmetrical AND pulses at a very sharp tip AND Minimal space charge present i.e. no memory effect beyond half cycle AND PD pulse phase influenced by local stored charge	Discharge between conductor surfaces, sharp tip
Positive half	No space charge AND minimal space charge present i.e. no memory effect beyond half cycle	Metal or SF6 involved
Negative half	Sufficient charge released to suppress further pulses AND issue of space charge	Discharge on an unbounded surface

Table 6.23 Classification of PD Source

Characteristics	Behaviours	Classification
Metal or SF_6 involved		PROTRUSION
Metal part on a conductor		PROTRUSION
Metal part on a conductor	Extract electrons required comparatively more energy in negative half AND energetic discharge	SEVERE PROTRUSION
Discharge between conductor surfaces, sharp tip		PROTRUSION

Table 6.24 Site of PD Source

Classification	Insulation	Site
PROTRUSION	Oil	Either on the earth or high voltage conductor

6.1.2 Surface Discharge Defect

Caused by moisture ingress causing pressboard to become semi-conducting.

Surface discharges occur as a result of dielectric relaxation or surface flashover, with the possibility of arcing in a severe case. Within the phase-resolved pattern the PD activity would show a broad distribution of pulses. The main activity would occur over the zero crossings, or between the zero crossings and the peaks, due to the accumulation of space charge creating "enough residual electric field at the zero-crossing positions to maintain PD activity" [Cleary-05]. This section will demonstrate how the system diagnoses the surface discharge defect, as shown in Table 5.1, in SF_6 (from the experiment in Figure 6.2) and transformer oil (from the experiment in Figure 6.3).

6.1.2.1 Surface Discharge in SF_6 Case Study

The phase-resolved pattern in Figure 6.10 represents PD from a solid dielectric sample captured by UHF sensors in GIS. This data was input to the knowledge-based system for diagnosis. As shown in the two 2D plots at the bottom of Figure 6.10, the half cycles have been shifted before the classification occurs. This case study shows an example of when the discharges are occurring on the zero crossings relative to the voltage cycle. Here, as explained in section 5.1.2.1, the discharges are grouped on a per activity basis over the zero crossings, rather than per a half cycle basis, as with other pattern recognition approaches to PD diagnostics. Grouping the activity in this way ensures that the statistics applied to the discharges are correctly calculated for the PD activity and in this case the system correctly classified the defect as a surface discharge.

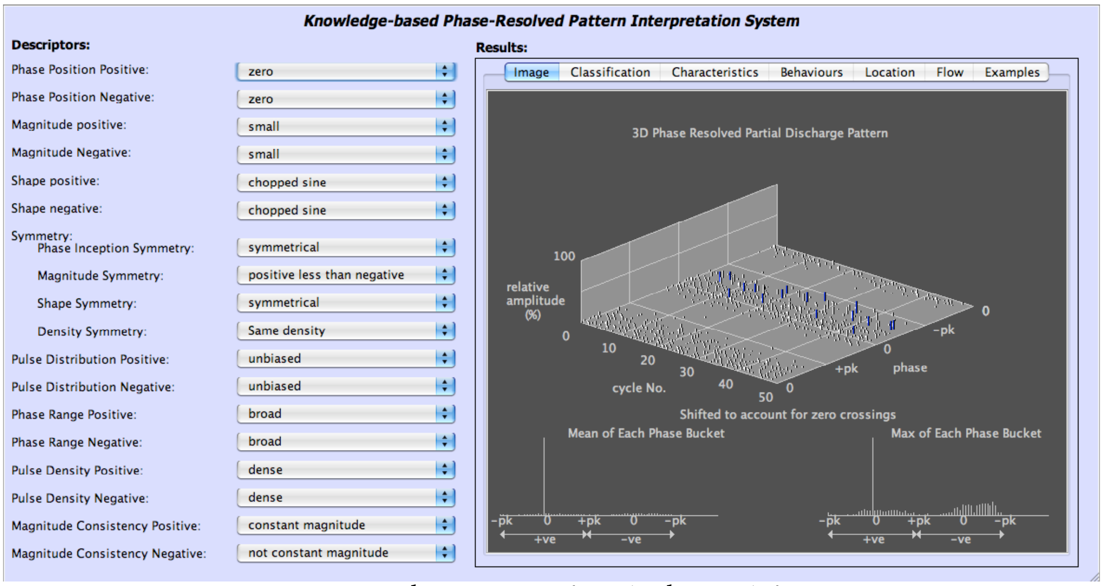


Figure 6.10. GUI showing a surface discharge defect in GIS

The explanation for this classification is shown in Table 6.25 to Table 6.27. As apparent in Table 6.26, after the phase position has been identified as around the zero crossings, the PD behaviour associated with the range, density, shape and size of the pulses inform the expert of the possibility that surface discharge is occurring.

Table 6.25 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Symmetrical	1. Conditions for PD inception are the same for both polarities
Whole cycle	Magnitude symmetry	Positive less than negative	1. Extraction of electrons requires comparatively more energy in the negative half cycle
Whole cycle	Shape symmetry	Symmetrical	1. Defect is geometrically symmetrical
Positive half	Position	Zero	1. Discharge dependent on rate of change of voltage 2. Issue of space charge
Positive half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Positive half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Positive half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Positive half	Magnitude consistency	Constant magnitude	1. Constant geometry and capacitance 2. Certain amount of energy to ionise the insulation
Negative half	Position	Zero	1. Discharge dependent on rate of change of voltage 2. Issue of space charge
Negative half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Negative half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Negative half	Distribution	Unbiased	1. No space charge
Negative half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Negative half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Negative half	Magnitude consistency	Not constant magnitude	1. Voltage dependent (but not proportional to it)

Table 6.26 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Positive half	Charge can disperse easily AND issue of space charge AND pulses act at a conducting surface AND voltage dependent (but not proportional to it) AND pulses at a small site	Poor insulation (carbonised or damp)
Negative half	Charge can disperse easily AND issue of space charge AND pulses act at a conducting surface AND voltage dependent (but not proportional to it) AND pulses at a small site	Poor insulation (carbonised or damp)

Table 6.27 Classification of PD Source

Characteristics	Classification
Poor insulation (carbonised or damp)	SURFACE DISCHARGE

6.1.2.2 Surface Discharge in Oil-insulated Transformer Case Study 1

Surface discharge was reproduced in the laboratory by soaking a pressboard sample for 24 hours prior to testing to mimic the moisture contamination [Cleary-06]. The phase-resolved pattern in Figure 6.11 represents this PD source, showing the distribution of pulses in-between the zero crossings and the peaks due to the accumulation of space charge within the insulation (explained in section 5.1.1.2). The diagnosis performed in this case study can be seen in Tables 6.28 to 6.30.

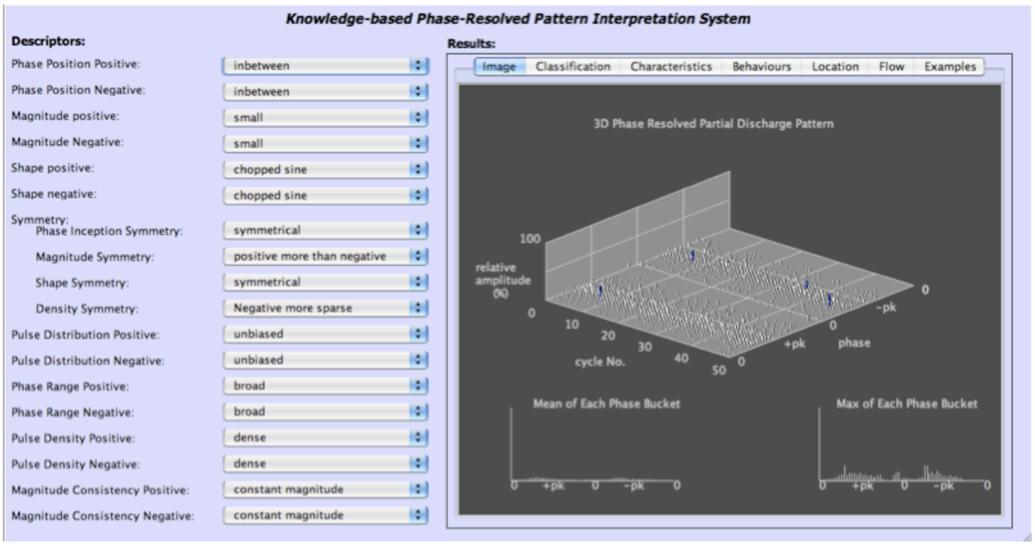


Figure 6.11. GUI of surface discharge in oil-filled transformer model

As shown in the following tables, the system correctly classified the PD source as surface discharge. In the case of a surface discharge, the experts' knowledge regarding the phase-resolved pattern cannot be used to identify the site of this PD source. This is due to the expert not being able to distinguish unique descriptors for this PD source that would inform the PD site.

Table 6.28 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Symmetrical	1. Conditions for PD inception are the same for both polarities
Whole cycle	Magnitude symmetry	Positive more than negative	1. Extraction of electrons requires comparatively more energy in the positive half cycle
Whole cycle	Density symmetry	Negative more sparse	1. Ease of discharging is greater in positive half cycle
Whole cycle	Shape symmetry	Symmetrical	1. Defect is geometrically symmetrical
Positive half	Position	Inbetween	1. Shift between absolute and rate of change of voltage 2. Issue of space charge
Positive half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Positive half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Positive half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Positive half	Magnitude consistency	Constant magnitude	1. Constant geometry and capacitance 2. Certain amount of energy to ionise the insulation
Negative half	Position	Inbetween	1. Shift between absolute and rate of change of voltage 2. Issue of space charge
Negative half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Negative half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Negative half	Distribution	Unbiased	1. No space charge
Negative half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Negative half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Negative half	Magnitude consistency	Constant magnitude	1. Constant geometry and capacitance 2. Certain amount of energy to ionise the insulation

Table 6.29 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Positive half	Charge can disperse easily AND issue of space charge AND pulses act at a conducting surface AND voltage dependent (but not proportional to it) AND pulses at a small site	Poor insulation (carbonised or damp)
Negative half	Charge can disperse easily AND issue of space charge AND pulses act at a conducting surface AND voltage dependent (but not proportional to it) AND pulses at a small site	Poor insulation (carbonised or damp)

Table 6.30 Classification of PD Source

Characteristics	Classification
Poor insulation (carbonised or damp)	SURFACE DISCHARGE

6.1.2.3 Surface Discharge in Oil-insulated Transformer Case Study 2

Figure 6.12 shows a phase-resolved pattern captured from a surface discharge in oil. This pattern is similar to that of a surface discharge in GIS (Figure 6.10). In this case the discharges also occur across the zero crossings of the ac waveform and the pattern is also examined on an activity, rather than phase, basis (as explained in section 5.1.2.1). The similarity of these two patterns, in different insulation types, shows the similar behaviour of PD activity occurring in different items of equipment [Fuhr-91]. In this case the knowledge-based system also identified the defect as a surface discharge, where the electrons were readily supplied from ionised water molecules on the moist pressboard [Cleary-06]. Tables 6.31 to 6.33 show the explanation for this classification.

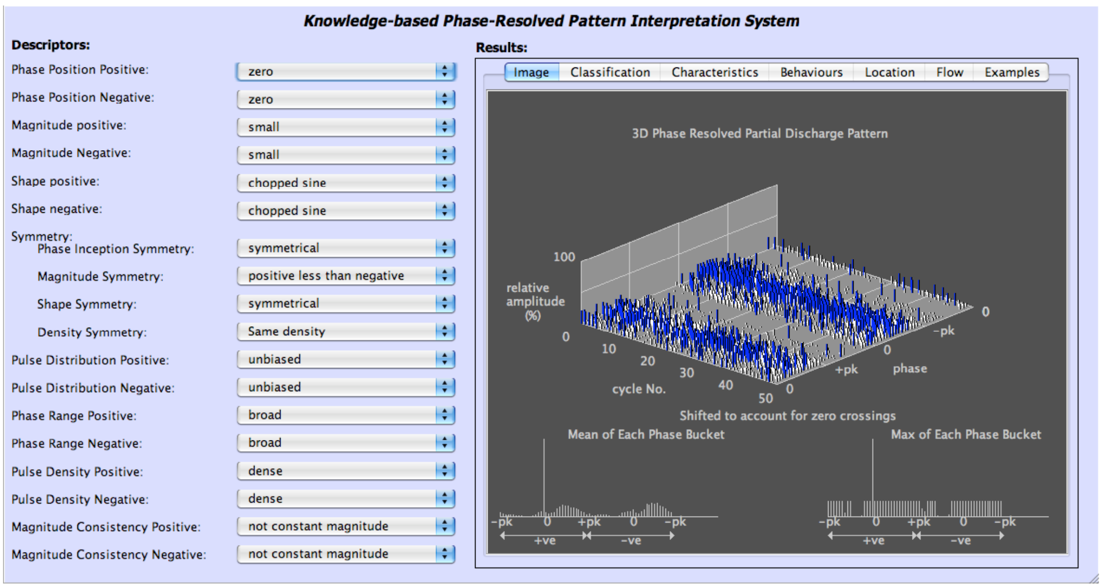


Figure 6.12. GUI of surface discharge defect in oil-filled transformer model

Table 6.31 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Symmetrical	1. Conditions for PD inception are the same for both polarities
Whole cycle	Magnitude symmetry	Positive less than negative	1. Extraction of electrons requires comparatively more energy in the negative half cycle
Whole cycle	Shape symmetry	Symmetrical	1. Defect is geometrically symmetrical
Positive half	Position	Zero	1. Discharge dependent on rate of change of voltage 2. Issue of space charge
Positive half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Positive half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Positive half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Positive half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region
Negative half	Position	Zero	1. Discharge dependent on rate of change of voltage 2. Issue of space charge
Negative half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Negative half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Negative half	Distribution	Unbiased	1. No space charge
Negative half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Negative half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Negative half	Magnitude consistency	Not constant magnitude	11. Locally stored charge 2. PD site is not confined to one region

Table 6.32 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Positive half	Charge can disperse easily AND issue of space charge AND pulses act at a conducting surface AND voltage dependent (but not proportional to it) AND pulses at a small site	Poor insulation (carbonised or damp)
Negative half	Charge can disperse easily AND issue of space charge AND pulses act at a conducting surface AND voltage dependent (but not proportional to it) AND pulses at a small site	Poor insulation (carbonised or damp)

Table 6.33 Classification of PD Source

Characteristics	Classification
Poor insulation (carbonised or damp)	SURFACE DISCHARGE

6.1.3 Void Defect

Gas filled cavity in solid or liquid insulation, e.g. a bubble or a crack, or a void in epoxy resin.

Phase-resolved data that represents a void defect, as shown in Table 5.1, will be diagnosed in this section from the GIS experiment (as shown in Figure 6.2). Voids can form as a result of differential thermal expansion between the epoxy and the metallic electrodes or due to epoxy shrinkage during the curing process [CIGRE- 92].

The void defect was not researched in [Cleary-06] and therefore, UHF sensor data from the oil-insulated transformer model of a void defect is unavailable for diagnosis through the knowledge-based system. However, this defect was the focus of research at the University of Southampton and an example of IEC60270 data from oil filled transformers are provided in section 6.2.

6.1.3.1 Void in SF_6 Case Study

The PD activity in phase-resolved patterns for a void (e.g. Figure 6.13) and surface discharge defect (e.g. Figure 6.11) exhibit similar characteristics, making it more difficult for experts (and the knowledge-based system) to distinguish between them. In both cases the PD activity tends to occur on the zero crossings or in the first and third quadrants of the phase-resolved pattern, due to the accumulation of space charge in both instances. The main distinguishing descriptor is the density of the pattern, with a void tending to show a more sparse distribution of pulses, than is the case for a surface discharge.

Typically a void pattern (Figure 6.13) tends to show the pulses occurring in the rising signal, as the voltage is increased. The pattern in Figure 6.13 was input to the knowledge-based system for diagnosis, the results of which can be seen in the instantiation of the descriptors in Figure 6.13, which led to the diagnosis in Tables 6.34 to 6.36.

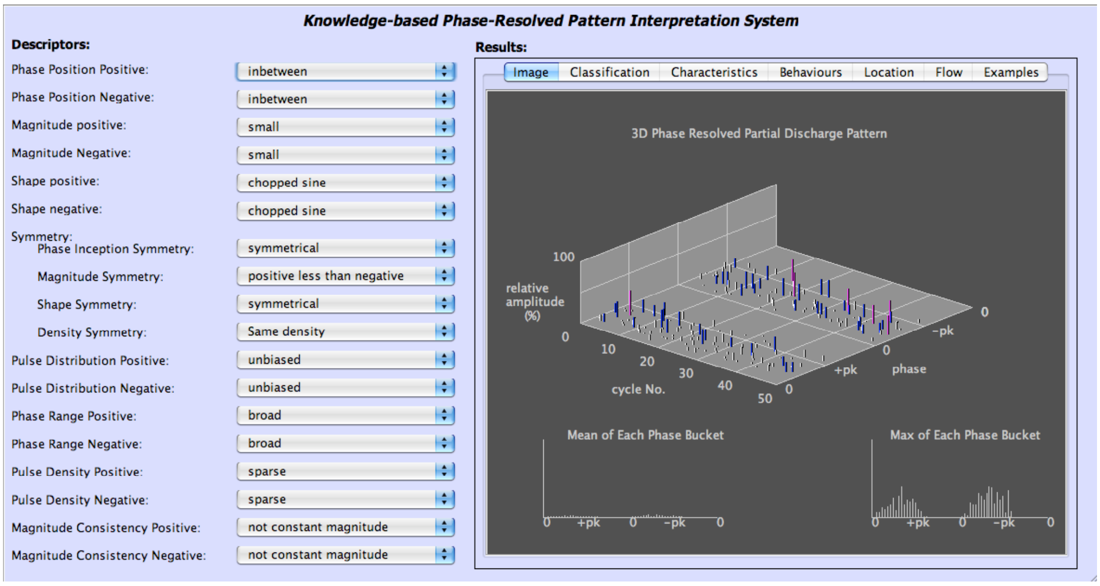


Figure 6.13. GUI of void in GIS

Table 6.34 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Symmetrical	1. Conditions for PD inception are the same for both polarities
Whole cycle	Magnitude symmetry	Positive less than negative	1. Extraction of electrons requires comparatively more energy in positive half cycle
Whole cycle	Shape symmetry	Symmetrical	1. Defect is geometrically symmetrical
Positive half	Position	Inbetween	1. Shift between absolute and rate of change of voltage 2. Issue of space charge
Positive half	Density	Sparse	1. Defect experiencing inconsistent electric field 2. Interference 3. Space charge with a long time constant
Positive half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Positive half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Positive half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region
Negative half	Position	Inbetween	1. Shift between absolute and rate of change of voltage 2. Issue of space charge
Negative half	Density	Sparse	1. Defect experiencing inconsistent electric field 2. Interference 3. Space charge with a long time constant
Negative half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Negative half	Distribution	Unbiased	1. No space charge
Negative half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Negative half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Negative half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region

Table 6.35 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Positive half	Issue of space charge AND space charge with a long time constant AND locally stored charge AND defect is geometrically symmetrical AND pulses at a small site AND voltage dependent (but not proportional to it)	Involves a gas to solid boundary
Negative half	Issue of space charge AND space charge with a long time constant AND locally stored charge AND defect is geometrically symmetrical AND pulses at a small site AND voltage dependent (but not proportional to it)	Involves a gas to solid boundary

Table 6.36 Classification of PD Source

Characteristics	Classification
Involves a gas to solid boundary	VOID

As shown in Table 6.35, three different conclusions of the presence of space charge, the identification of a geometrically symmetrical defect and the PD being dependent on the voltage has led to the conclusion of the PD source involving a gas to solid boundary, which is the characteristic of a void defect (Figure 6.13).

6.1.4 Metallic Particles

Rolling Particles: Caused by free particles resting on a conductive surface until influenced by the electric field causing them to roll without bouncing.
Bouncing Particles: Caused by free particles in motion due to electrostatic forces.

Metallic particles resulting as a by-product of the manufacturing or assembly process, is the most common defect found in gas-insulated equipment [CIGRE23-01-92]. Particles have the ability to acquire charge and move under the influence of the electric field in two different ways, bouncing and rolling. Both types of particle show similar characteristics in the phase-resolved pattern, where random pulses occur across the pattern due to a PD source in motion. The random occurrence of the pulses implies that the discharges are relatively random with respect to the actual instantaneous voltage.

A particle is an example of a PD source in motion and occurs due to the defect experiencing an inconsistent electric field. Each time it bounces, depending on the phase change, it could carry a different amount of charge. At lower voltage, a denser pattern would be observed due to the particle rolling about the surface and not being able to lift off the conductor. Another example of a random, but sparse, phase-resolved pattern is a bouncing particle, where the particle has the energy to lift off the surface causing it to bounce, resulting in more damage. This section will show examples of how the knowledge-based system diagnoses the particle defect, as shown in Table 5.1, in SF_6 (from the experiment in Figure 6.2) and transformer oil (from the experiment in Figure 6.3).

6.1.4.1 Metallic Particle in SF_6 Case Study

As shown in the 2D plot of the maximum pulses of Figure 6.14, each phase bucket shows the amplitude of the pulses following a similar sine wave to the ac voltage. This suggests that the voltage has an influence on the extent to which the pulse moves, when plotted over 50 cycles. When viewing the 3D pattern, the discharges appear to occur randomly across the phase-resolved pattern. Examining both types of pattern offers a clearer insight into the PD activity. When the activity in Figure 6.14 was input to the knowledge-based system the diagnosis in Table 6.37 to Table 6.39 were concluded.

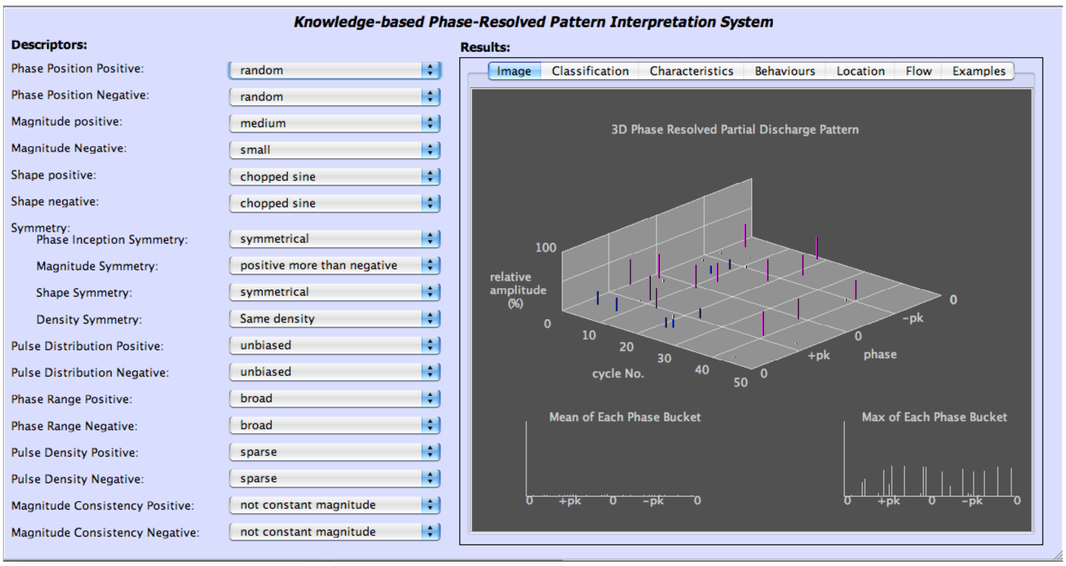


Figure 6.14. GUI of particle in GIS

Table 6.37 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Symmetrical	1. Conditions for PD inception are the same for both polarities
Whole cycle	Magnitude symmetry	Positive more than negative	1. Extraction of electrons requires comparatively more energy in the positive half cycle
Whole cycle	Shape symmetry	Symmetrical	1. Defect is geometrically symmetrical
Positive half	Position	Random	1. PD source in motion 2. Interference
Positive half	Density	Sparse	1. Defect experiencing inconsistent electric field 2. Interference 3. Space charge with a long time constant
Positive half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Positive half	Magnitude	Medium	1. Pulses initiated in insulation
Positive half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region
Negative half	Position	Random	1. PD source in motion 2. Interference
Negative half	Density	Sparse	1. Defect experiencing inconsistent electric field 2. Interference 3. Space charge with a long time constant
Negative half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Negative half	Distribution	Unbiased	1. No space charge
Negative half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Negative half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Negative half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region

Table 6.38 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Positive half	Voltage dependent (but not proportional to it) AND PD pulse phase influenced by locally stored charge AND defect experiencing inconsistent electric field AND PD source in motion	Motion is relatively random with respect to the instantaneous voltage (HIGH SEVERITY)
Negative half	Voltage dependent (but not proportional to it) AND PD pulse phase influenced by locally stored charge AND defect experiencing inconsistent electric field AND PD source in motion	Motion is relatively random with respect to the instantaneous voltage (HIGH SEVERITY)

Table 6.39 Classification of PD Source

Characteristics	Classification
Motion is relatively random with respect to the instantaneous voltage (HIGH SEVERITY)	BOUNCING PARTICLE

From Table 6.38 it can been seen that the system has identified that the PD source is voltage dependent (but not proportional to it); is experiencing inconsistent electric field; is influenced by locally stored charge; and is in motion. These behaviours led the system to define the defect motion as relatively random with respect to the instantaneous voltage. This combined with the severity of the discharge, resulted in the knowledge-based system concluding that the PD source is a bouncing particle.

6.1.4.2 Metallic Particle in Oil-insulated Transformer Case Study

A free metallic particle in the oil-insulated transformer was reconstructed by placing a 2.5mm stainless steel particle on a concave earth electrode. During the experiment the voltage applied to the test cell was increased. At 33.4kV and 35.9kV the particle was seen to lift off and fall back to the earth electrode [Cleary-05]. A phase-resolved pattern depicting this activity was input to the knowledge-based system and the results can be seen in Figure 6.15, along with the explanation output in Tables 6.40 to 6.42.

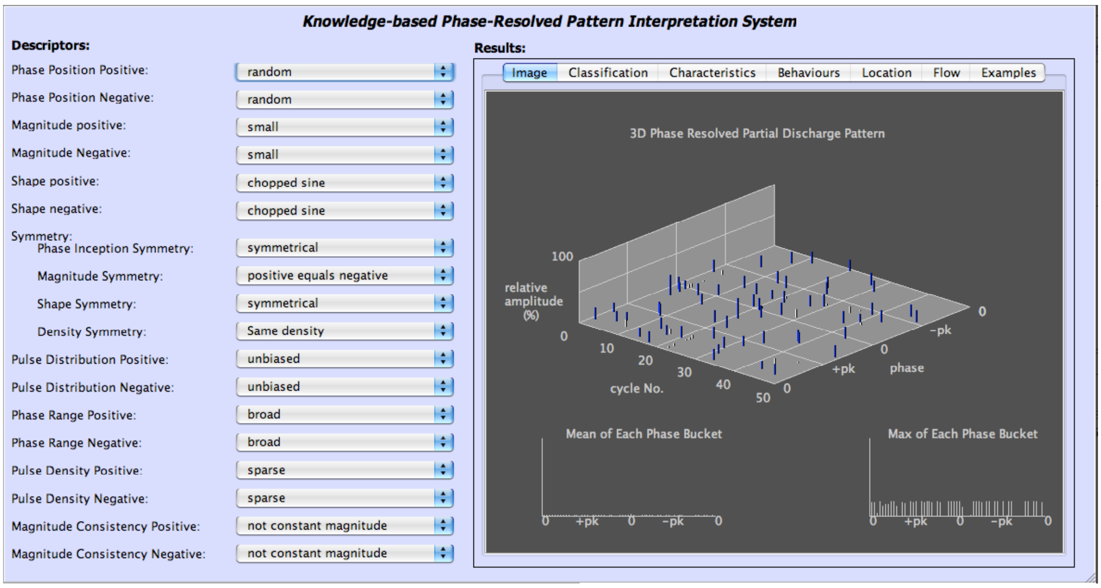


Figure 6.15. GUI of a metallic particle in oil-insulated transformer

Table 6.40 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Symmetrical	1. Conditions for PD inception are the same for both polarities
Whole cycle	Magnitude symmetry	Positive equals negative	1. Defect is geometrically symmetrical
Whole cycle	Shape symmetry	Symmetrical	1. Defect is geometrically symmetrical
Positive half	Position	Random	1. PD source in motion 2. Interference
Positive half	Density	Sparse	1. Defect experiencing inconsistent electric field 2. Interference 3. Space charge with a long time constant
Positive half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Positive half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Positive half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region
Negative half	Position	Random	1. PD source in motion 2. Interference
Negative half	Density	Sparse	1. Defect experiencing inconsistent electric field 2. Interference 3. Space charge with a long time constant
Negative half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Negative half	Distribution	Unbiased	1. No space charge
Negative half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Negative half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Negative half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region

Table 6.41 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Positive half	Voltage dependent (but not proportional to it) AND PD pulse phase influenced by locally stored charge AND defect experiencing inconsistent electric field AND PD source in motion	Motion is relatively random with respect to the instantaneous voltage (HIGH SEVERITY)
Negative half	Voltage dependent (but not proportional to it) AND PD pulse phase influenced by locally stored charge AND defect experiencing inconsistent electric field AND PD source in motion	Motion is relatively random with respect to the instantaneous voltage (HIGH SEVERITY)

Table 6.42 Classification of PD Source

Characteristics	Classification
Motion is relatively random with respect to the instantaneous voltage (HIGH SEVERITY)	BOUNCING PARTICLE

6.1.5 Bad Contact Defect

Caused by sparking, e.g. between the threads of loose nuts and bolts.

Bad contacts can exist due to poor or loose electrical or mechanical contacts between conducting parts [CIGRE23-01-92]. Bad connections are an unusual source of PD, however the consequences can be very significant [James-08]. An example of a bad contact is a stress shield that has become disconnected causing discharges to occur across the break. This type of defect would tend to discharge at the zero crossings of the phase-resolved pattern due to the maximum rate of change in voltage amplitude occurring at this point. This section will demonstrate a variety of PD data (in SF_6, using the experiment in Figure 6.2 and in oil, using the experiment in Figure 6.3) associated with a bad contact, as shown in Table 5.1, and their associated diagnoses from the knowledge-based system.

6.1.5.1 Bad Contact in SF_6 Case Study

Figure 6.16 illustrates the discharge activity of a bad contact in GIS. As shown in the figure, the activity occurring over the zero crossing caused the system to split the pattern per activity rather than per half cycle (see section 5.1.2.1). The high current sparking at the site of a bad contact would cause a spark near the zero crossings, along with only one discharge per cycle or less, depicted by the knife blade shape across the zero crossings. These descriptors can be seen in the pattern of Figure 6.16. Inputting this phase-resolved pattern to the knowledge-based system resulted in the diagnosis shown in Table 6.43 to Table 6.45.

As shown in Table 6.45, the PD source in this experiment can be identified as a bad contact. Table 6.44 and Table 6.45 show that the "discharge is on an unbounded surface" characteristic is not utilised to classify the final defect. This is due to the requirement of an additional condition part of the rule (identified characteristic) for classification, which has not been achieved in this situation.

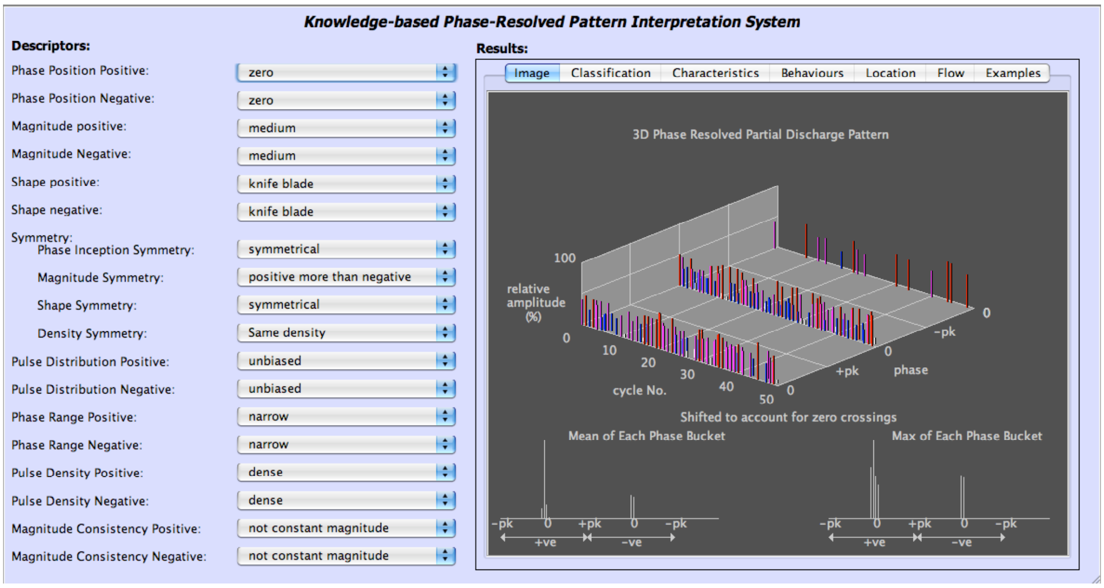


Figure 6.16. GUI of bad contact in GIS

Table 6.43 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Symmetrical	1. Conditions for PD inception are the same for both polarities
Whole cycle	Magnitude symmetry	Positive more than negative	1. Extraction of electrons requires comparatively more energy in the positive half cycle
Whole cycle	Shape symmetry	Symmetrical	1. Defect is geometrically symmetrical
Positive half	Position	Zero	1. Discharge dependent on rate of change of voltage 2. Issue of space charge
Positive half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Positive half	Range	Narrow	1. Sufficient charge released to suppress further pulses
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Knife blade	1. Energetic discharge
Positive half	Magnitude	Medium	1. Pulses initiated in insulation
Positive half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region
Negative half	Position	Zero	1. Discharge dependent on rate of change of voltage 2. Issue of space charge
Negative half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Negative half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Negative half	Distribution	Unbiased	1. No space charge
Negative half	Shape	Knife blade	1. Energetic discharge
Negative half	Magnitude	Medium	1. Pulses initiated in insulation
Negative half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region

Table 6.44 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Positive half	Sufficient charge released to suppress further pulses AND issue of space charge	Discharge is on an unbound surface
Positive half	Discharge dependent on rate of change of voltage AND energetic discharge AND defect is geometrically symmetrical	Discharge between a conductor and a metal object at floating potential (Medium severity)
Negative half	Sufficient charge released to suppress further pulses AND issue of space charge	Discharge is on an unbound surface
Negative half	Discharge dependent on rate of change of voltage AND energetic discharge AND defect is geometrically symmetrical	Discharge between a conductor and a metal object at floating potential (Medium severity)

Table 6.45 Classification of PD Source

Characteristics	Classification
Discharge between a conductor and a metal object at floating potential (Medium severity)	BAD CONTACT

6.1.5.2 Bad Contact in Oil-insulated Transformer Case Study 1

A piece of aluminium foil was placed between the polypropylene barrier and the high voltage electrode to simulate a bad contact on the high voltage electrode within the transformer test cell [Cleary-05]. One of the phase-resolved patterns captured during these previous experiments (Figure 6.3) can be seen in Figure 6.17.

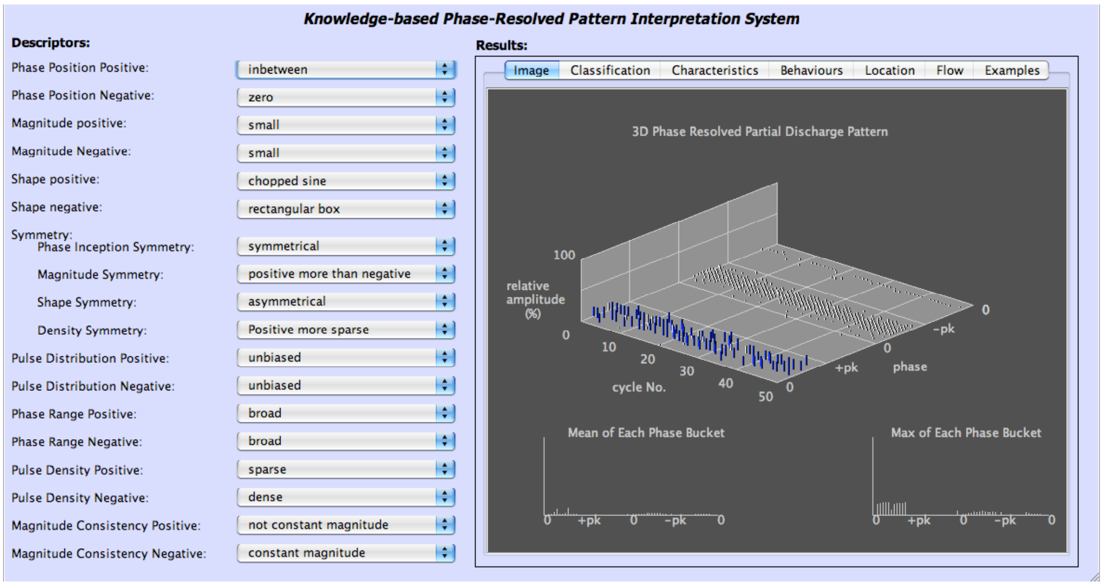


Figure 6.17 GUI of bad contact in oil-insulated transformer

Two different defects have been classified by the knowledge-based system for this pattern, the correct classification of a bad contact and the misclassification of a floating component. The diagnosis can be seen in Table 6.46 to Table 6.48. The reason that a floating component and a bad contact has been classified could be due to aluminium foil acquiring charge from the high voltage electrode, with the electric field between the foil and the high voltage electrode not being high enough to cause a localised breakdown [Cleary-05], exhibiting PD behaviour associated with a floating component.

The presentation of the explanation of the diagnosis to the user would aid in resolving the conflict of classification by highlighting the parts of the pattern used for diagnosis, as well as the identification of the present PD behaviours and defect characteristics, which resulted in the classifications. An expert could be hired to make the final decision about these more complex patterns and conflicts in classification. By offering the expert the explanation associated with classifying these more difficult patterns, they are provided with evidence and descriptions to assist the start of their diagnostic process.

Table 6.46 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Symmetrical	1. Conditions for PD inception are the same for both polarities
Whole cycle	Magnitude symmetry	Positive more than negative	1. Extraction of electrons requires comparatively more energy in the positive half cycle
Whole cycle	Density Symmetry	Positive more sparse	1. Ease of discharging is greater in the negative half cycle
Whole cycle	Shape symmetry	Asymmetrical	1. Defect is geometrically asymmetrical
Positive half	Position	Inbetween	1. Shift between absolute and rate of change of voltage. 2. Issue of space charge
Positive half	Density	Sparse	1. Defect experiencing inconsistent electric field 2. Interference 3. Space charge with a long time constant
Positive half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Positive half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Positive half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region
Negative half	Position	Zero	1. Discharge dependent on rate of change of voltage 2. Issue of space charge
Negative half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Negative half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Negative half	Distribution	Unbiased	1. No space charge
Negative half	Shape	Rectangular box	1. Not voltage dependent
Negative half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Negative half	Magnitude consistency	Constant magnitude	1. Constant geometry and capacitance 2. Certain amount of energy to ionise insulation

Table 6.47 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Whole cycle	Conditions for PD inception are the same for both polarities AND pulses at a conducting surface AND defect is geometrically asymmetrical AND discharge dependent on rate of change of voltage AND PD pulse phase influenced by local stored charge	Intermittent conduction through insulation
Positive half	Voltage dependent (but not proportional to it) AND defect is geometrically asymmetrical AND issue of space charge AND space charge with a long time constant AND defect experiencing inconsistent electric field	Metal to metal discharge, asymmetrical shape

Table 6.48 Classification of PD Source

Characteristics	Classification
Intermittent conduction through insulation	BAD CONTACT
Metal to metal discharge, asymmetrical shape	FLOATING COMPONENT (Asymmetrical shape)

6.1.5.3 Bad Contact in Oil-insulated Transformer Case Study 2

When the electric field between the foil and the high voltage electrode is sufficiently high, the PD would be expected to be seen around the zero crossings, like that presented in Figure 6.18. This pattern also shows a knife blade shape of pulses in the positive half cycle, which is more indicative of a bad contact and not a floating component. The floating component would more likely exhibit a chopped sine shape, shown in Figure 6.17, which aided in the previous classification of the floating component. The classification of Figure 6.18 pattern is solely the bad contact, the diagnosis of which is shown in Tables 6.49 to 6.51. As displayed in Table 6.51, a different characteristic is highlighted to that in section 6.5.2.1 and used to classify the bad contact. This is due to the varying characteristics created by a bad contact.

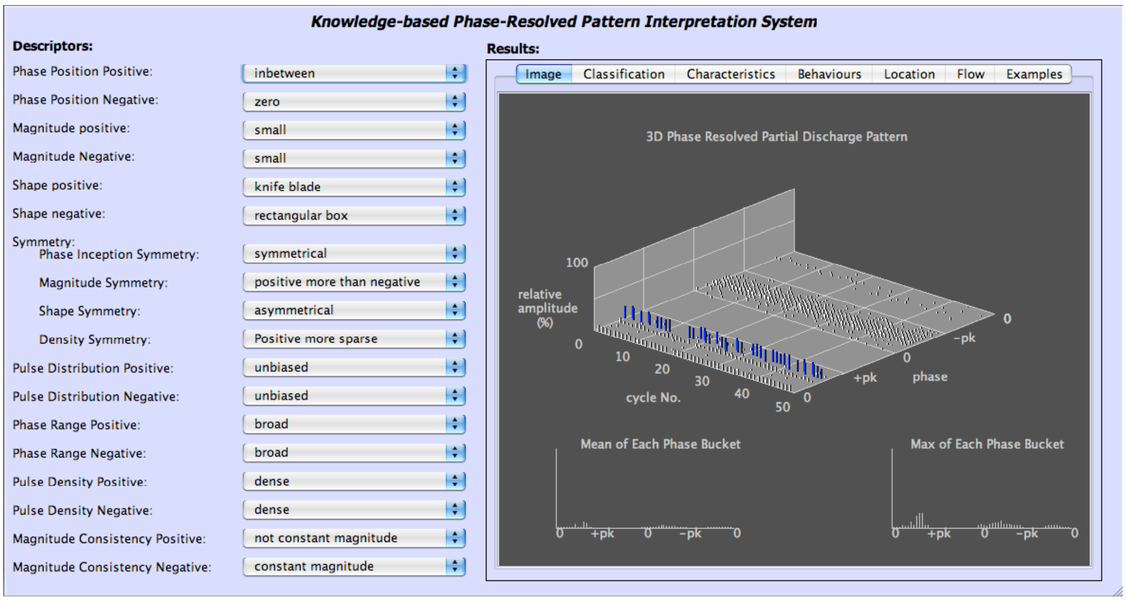


Figure 6.18. GUI of bad contact in oil-insulated transformer

Table 6.49 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Symmetrical	1. Conditions for PD inception are the same for both polarities
Whole cycle	Magnitude symmetry	Positive more than negative	1. Extraction of electrons requires comparatively more energy in the positive half cycle
Whole cycle	Density Symmetry	Positive more sparse	1. Ease of discharging is greater in the negative half cycle
Whole cycle	Shape symmetry	Asymmetrical	1. Defect is geometrically asymmetrical
Positive half	Position	Inbetween	1. Shift between absolute and rate of change of voltage. 2. Issue of space charge
Positive half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Positive half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Knife blade	1. Energetic discharge
Positive half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Positive half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site is not confined to one region
Negative half	Position	Zero	1. Discharge dependent on rate of change of voltage 2. Issue of space charge
Negative half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Negative half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Negative half	Distribution	Unbiased	1. No space charge
Negative half	Shape	Rectangular box	1. Not voltage dependent
Negative half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Negative half	Magnitude consistency	Constant magnitude	1. Constant geometry and capacitance 2. Certain amount of energy to ionise insulation

Table 6.50 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Whole cycle	Conditions for PD inception are the same for both polarities AND pulses at a conducting surface AND defect is geometrically asymmetrical AND discharge dependent on rate of change of voltage AND PD pulse phase influenced by local stored charge	Intermittent conduction through insulation

Table 6.51 Classification of PD Source

Characteristics	Classification
Intermittent conduction through insulation	BAD CONTACT

6.1.5.4 Bad Contact in Oil-insulated Transformer Case Study 3

As the voltage in the experiments [Cleary-05] was increased to 2.0kV and 2.3kV, the experimental observations reported that the connection between the metallic foil and the high voltage electrode was poorer. Therefore, it is likely that multiple sites existed at the surface of the metallic foil, creating a more complex pattern [Cleary-05]. A pattern depicting this activity can be seen in Figure 6.19. Here, the knowledge-based system classified the defect as a bad contact, void and surface discharge.

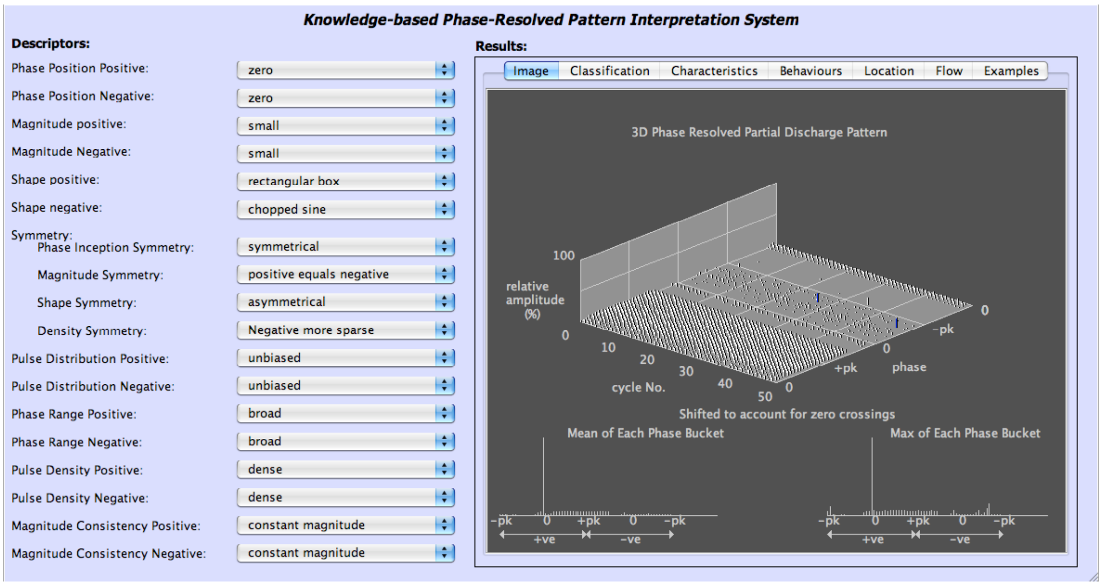


Figure 6.19. GUI of bad contact in oil-insulated transformer

At first glance the classification of three different PD sources may look like a misinterpretation by the system. However, examining the explanation offered by the knowledge associated with each knowledge base, shown in Table 6.52 to Table 6.54, identifies that many small sites could be acting simultaneously, there could be intermittent conduction through the insulation, the insulation is carbonised or damp and there are issues of space charge, which can all be possible conditions during this experiment. Although the interpretation of the pattern is not precisely the PD source, the knowledge-based system offers insight into the activity occurring within the insulation. A more detailed classification could be achieved latterly when the PD activity becomes more stable.

Table 6.52 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Symmetrical	1. Conditions for PD inception are the same for both polarities
Whole cycle	Magnitude symmetry	Positive equals negative	1. Defect is geometrically symmetrical
Whole cycle	Density Symmetry	Negative more sparse	1. Ease of discharging is greater in positive half cycle
Whole cycle	Shape symmetry	Asymmetrical	1. Defect is geometrically asymmetrical
Positive half	Position	Zero	1. Discharge dependent on rate of change of voltage 2. Issue of space charge
Positive half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Positive half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Rectangular box	1. Not voltage dependent
Positive half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Positive half	Magnitude consistency	Constant magnitude	1. Constant geometry and capacitance 2. Certain amount of energy to ionise insulation
Negative half	Position	Zero	1. Discharge dependent on rate of change of voltage 2. Issue of space charge
Negative half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Negative half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Negative half	Distribution	Unbiased	1. No space charge
Negative half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Negative half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Negative half	Magnitude consistency	Constant magnitude	1. Constant geometry and capacitance 2. Certain amount of energy to ionise insulation

Table 6.53 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Whole cycle	Conditions for PD inception are the same for both polarities AND pulses at a conducting surface AND defect is geometrically asymmetrical AND discharge dependent on rate of change of voltage AND PD pulse phase influenced by local stored charge	Intermittent conduction through insulation
Positive half	Not voltage dependent AND issue of space charge AND defect is geometrically symmetrical AND pulses at a small site	Discharge in gas bubbles or other oil contamination
Negative half	charge can disperse easily AND issue of space charge AND pulses at a conducting surface AND voltage dependent (but not proportional to it) AND pulses at a small site	Poor insulation (carbonised or damp)

Table 6.54 Classification of PD Source

Characteristics	Classification
Intermittent conduction through insulation	BAD CONTACT
Discharge in gas bubbles or other oil contamination	VOID
Poor insulation (carbonised or damp)	SURFACE DISCHARGE

6.1.6 Floating Objects in the Insulation

Floating Electrode: Capacitive sparking at components such as stress shields that have become partially detached resulting in ineffective bonding.
Floating Component: Smaller conducting objects that have become isolated and acquire a floating potential.

A floating electrode is a further example of a capacitive defect where the capacitive current causes sparking across a gap. Similar in characteristic to the bad contact, a floating electrode shows its maximum discharges in the first and third quadrants of the phase-resolved pattern, where the current is changing maximally. A floating electrode has a capacitance (sparking) across a gap, which tends to be quite a consistent discharge over time. The main descriptor of the floating electrode is the gull wing shape of pulses when viewed top down, see Figure 6.20. Difficulty in representing this shape with statistics led to an alternative way to describe these pulses, examining its rectangular box shape of constant magnitude. Usually displaying a broad range of discharges within the first and third quadrants of the phase-resolved pattern, the PD pulse is influenced by local stored charge and in this case the charge is being stored in the capacitance of the electrode. This section will show an example of this PD source, along with a floating component (both shown in Table 5.1), in SF_6 (using the experiment in Figure 6.2) and oil-insulated transformer (using the experiment in Figure 6.3).

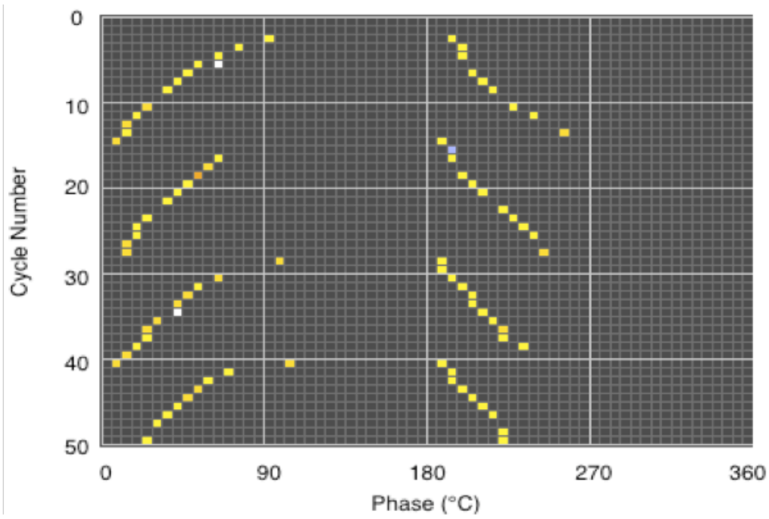


Figure 6.20. Top down view of gull wings of floating electrode, courtesy of DMS

6.1.6.1 Floating Electrode in SF_6 Case Study

Figure 6.21 displays the PD activity in the GIS section. As apparent in the phase-resolved pattern the gull wing pulses are displayed in the first and third quadrants of the pattern. The descriptors the knowledge-based system calculated are displayed on the left hand side of the GUI. As shown in Figure 6.21, a rectangular box shape and constant magnitude has been calculated to describe the present gull wing shape. Both these descriptors contribute to the knowledge-based system's conclusion of a floating electrode (Table 6.55 to Table 6.57).

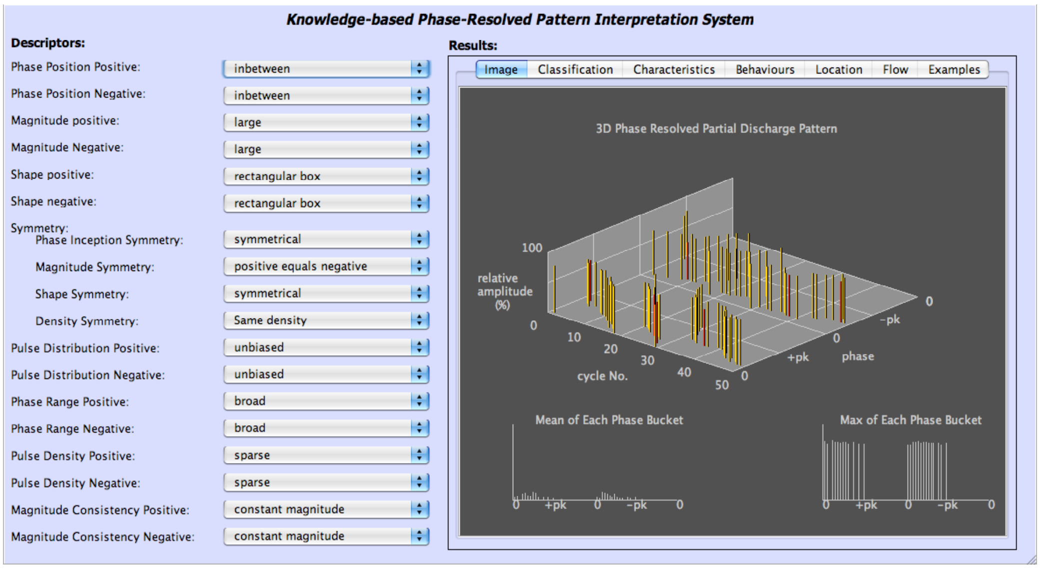


Figure 6.21. GUI of floating electrode in GIS

Table 6.57 highlights that the knowledge-based system identified two decisions of the PD source being a floating electrode. Firstly, the system concluded that an insulated metal part was present, which could indicate a floating electrode. Secondly, a discharge between a conductor and a metal object at floating potential was concluded, leading the knowledge-based system to decide on the severity of the floating electrode as high.

Table 6.55 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Symmetrical	1. Conditions for PD inception are the same for both polarities
Whole cycle	Magnitude symmetry	Positive equals negative	1. Defect is geometrically symmetrical
Whole cycle	Shape symmetry	Symmetrical	1. Defect is geometrically symmetrical
Positive half	Position	Inbetween	1. Shift between absolute and rate of change of voltage 2. Issue of space charge
Positive half	Density	Sparse	1. Defect experiencing inconsistent electric field 2. Interference 3. Space charge with a long time constant
Positive half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Rectangular box	1. Not voltage dependent
Positive half	Magnitude	Large	1. Arcing
Positive half	Magnitude consistency	Constant magnitude	1. Constant geometry and capacitance 2. Certain amount of energy to ionise insulation
Negative half	Position	Inbetween	1. Shift between absolute and rate of change of voltage 2. Issue of space charge
Negative half	Density	Sparse	1. Defect experiencing inconsistent electric field 2. Interference 3. Space charge with a long time constant
Negative half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Negative half	Distribution	Unbiased	1. No space charge
Negative half	Shape	Rectangular box	1. Not voltage dependent
Negative half	Magnitude	Large	1. Arcing
Negative half	Magnitude consistency	Constant magnitude	1. Constant geometry and capacitance 2. Certain amount of energy to ionise insulation

Table 6.56 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Positive half	Arcing AND not voltage dependent AND issue of space charge	Discharge between a conductor and a metal object at floating potential (High severity)
Positive half	Constant geometry and capacitance AND shift between absolute and rate of change of voltage AND PD pulse influenced by local stored charge AND arcing	Involves insulated metal part
Negative half	Arcing AND not voltage dependent AND issue of space charge	Discharge between a conductor and a metal object at floating potential (High severity)
Negative half	Constant geometry and capacitance AND shift between absolute and rate of change of voltage AND PD pulse influenced by local stored charge AND arcing	Involves insulated metal part

Table 6.57 Classification of PD Source

Characteristics	Classification
Discharge between a conductor and a metal object at floating potential (High severity)	FLOATING ELECTRODE (High Severity)
Involves insulated metal part	FLOATING ELECTRODE

6.1.6.2 Floating Component in Oil-insulated Transformer Case Study

A floating component was simulated in an oil-insulated transformer model in the laboratory (using the setup in Figure 6.3) by suspending a small metal part between the high voltage electrode and an earthed electrode protrusion using a polypropylene spacer [Cleary-05]. Arcing was heard during these experiments, introducing space charge into the liquid dielectric. Figure 6.22 shows an example of the phase-resolved PD pattern obtained from PD activity occurring during these experiments. As apparent in the phase-resolved pattern in the GUI, PD events do not occur on every half cycle. This is due to space charge affecting subsequent pulses (see section 5.1.1.2). The results of the diagnosis, which would be displayed in the various tabs of the GUI, can be seen in Table 6.58 to Table 6.60.

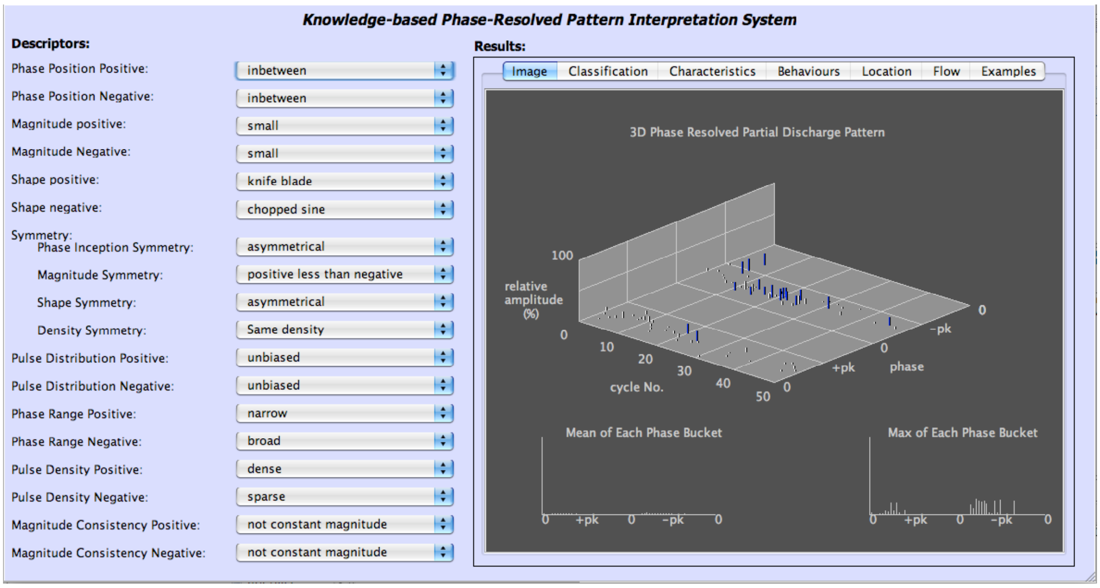


Figure 6.22. GUI of floating component in an oil-insulated transformer

Table 6.58 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Asymmetrical	1. Conditions for PD inception are different for both polarities
Whole cycle	Magnitude symmetry	Positive less than negative	1. Extraction of electrons requires ns requires comparatively more energy in the positive half cycle
Whole cycle	Shape symmetry	Asymmetrical	1. Defect is geometrically asymmetrical
Positive half	Position	Inbetween	1. Shift between absolute and rate of change of voltage 2. Issue of space charge
Positive half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Positive half	Range	Narrow	1. Sufficient charge released to suppress further pulses
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Knife blade	1. Energetic discharge
Positive half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Positive half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site not confined to one region
Negative half	Position	Inbetween	1. Shift between absolute and rate of change of voltage 2. Issue of space charge
Negative half	Density	Sparse	1. Defect experiencing inconsistent electric field 2. Interference 3. Space charge with a long time constant
Negative half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Negative half	Distribution	Unbiased	1. No space charge
Negative half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Negative half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Negative half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site not confined to one region

Table 6.59 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Positive half	Sufficient charge released to suppress further pulses AND issue of space charge	Discharge is on an unbound surface
Negative half	Voltage dependent (but not proportional to it) AND defect is geometrically asymmetrical AND issue of space charge AND space charge with a long time constant AND defect experiencing inconsistent electric field	Metal to metal discharge, asymmetrical shape

Table 6.60 Classification of PD Source

Characteristics	Classification
Metal to metal discharge, asymmetrical shape	FLOATING COMPONENT (Asymmetrical shape)

6.1.7 Multiple PD Sources

Displaying PD activity from multiple PD sources on a single phase-resolved pattern creates a chaotic and complex pattern. This would be more prevalent in transformers, where it is quite common to have several PD sources active simultaneously due to the equipment's relatively more complex structure with several potential PD activity locations, when compared to GIS busbars. Figure 6.23 shows an example of this, where there are different parts of the phase-resolved pattern covered by activity from multiple sources. When this type of pattern is presented to the knowledge-based system it recognises that it cannot identify the defect and informs the engineer of this fact. For example in Figure 6.23 the knowledge-based system could not work out the phase positions of the PD activity and could therefore not match any knowledge to identify the defect. When diagnosing defect types it is more beneficial to not classify a PD source than to misclassify. This is not possible in black box AI techniques, which when presented with a pattern will always try to match a PD source [Catterson-06].

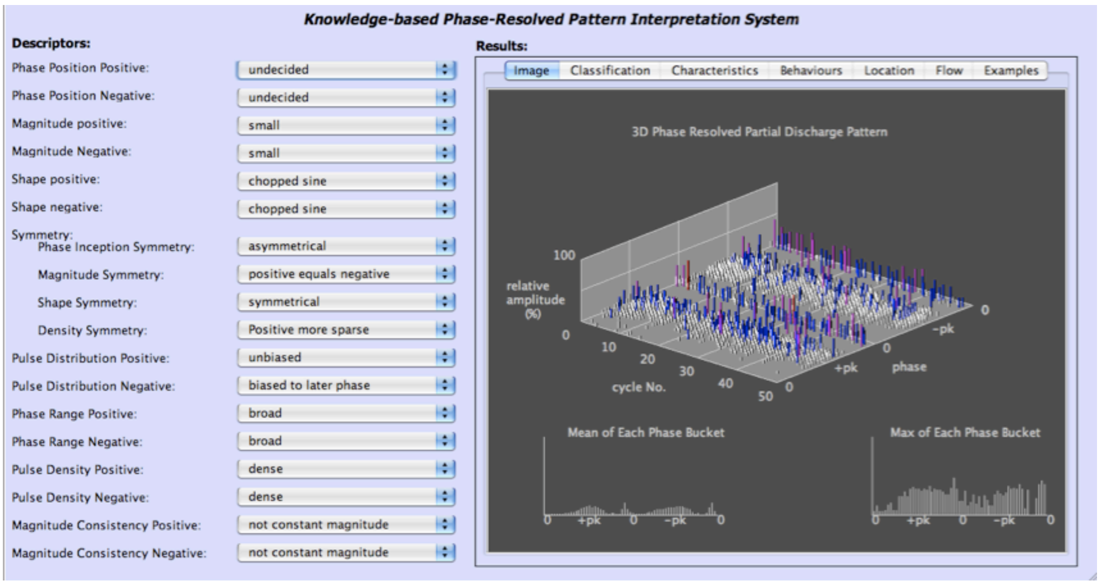


Figure 6.23. GUI of multiple PD sources in an oil-filled transformer in the field (Courtesy of DMS)

Another situation where the knowledge-based system also has trouble identifying the defect is where multiple PD sources exist, creating multiple regions of activity on one phase-resolved pattern. In this situation the knowledge-based system holds no knowledge to match the behaviours and therefore is not able to classify the defect. An example of this can be seen in Figure 6.24, where there are four rows of PD activity implying that activity from multiple PD sources have been captured. It should be noted that there is ongoing research to separate multiple PD sources into their constituent parts [Judd-04][Yang-03], which would then pre-process the data for input into the knowledge-based system for diagnosis.

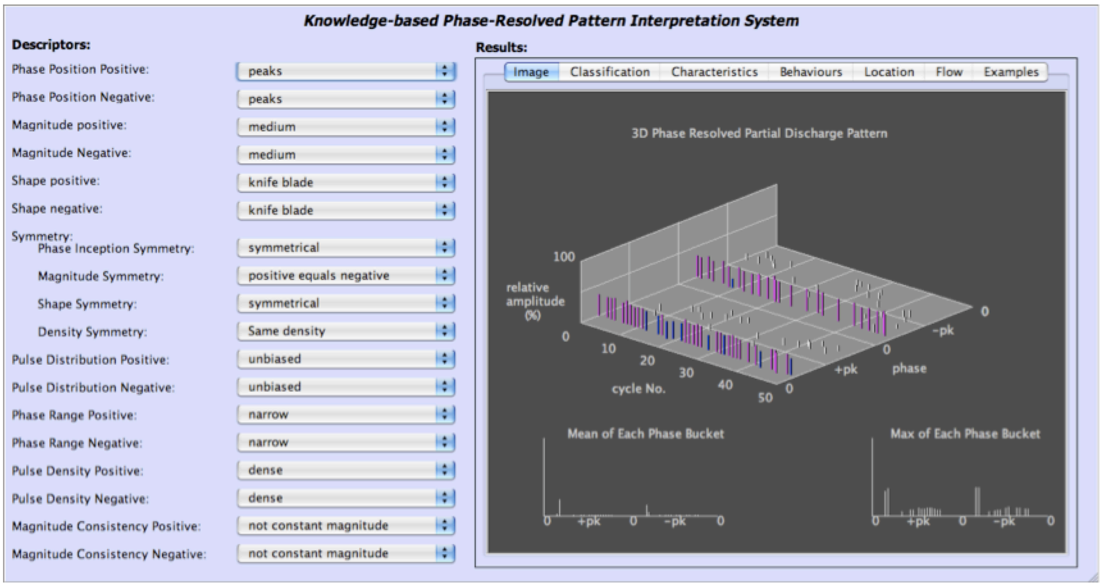


Figure 6.24. GUI of multiple PD sources in an oil-filled transformer in the field (Courtesy of DMS)

6.2 IEC60270 Data

The previous section demonstrated the generic nature of the knowledge-based system across different equipment using UHF sensor data. To further demonstrate the generic nature of the knowledge-based system, this section will concentrate on the diagnosis of PD sources captured through the IEC60270 measurements in oil-filled transformer insulation, while utilising the knowledge originally pertaining to UHF diagnosis of GIS. Although the PD signals were captured using a different measurement technique, after plotting the signal on the generic phase-resolved pattern (relative amplitude, cycle number and phase position), it became evident that the PD activity and the knowledge retained by the expert are not specific to the measurement system.

Dr. Liwei Hao at the University of Southampton performed laboratory experiments to capture PD data from defects within power transformer models, see Figure 6.25 [Hao-08]. To capture this data, radio frequency current transducer sensors are used with a bandwidth of 10kHz – 200MHz, along with a conventional IEC60270 PD detector. To test the potential of the generic nature of the knowledge-based system, the data captured through this technique was obtained. Not only is this data captured through a different PD measurement system, it is also on different apparatus to the GIS.

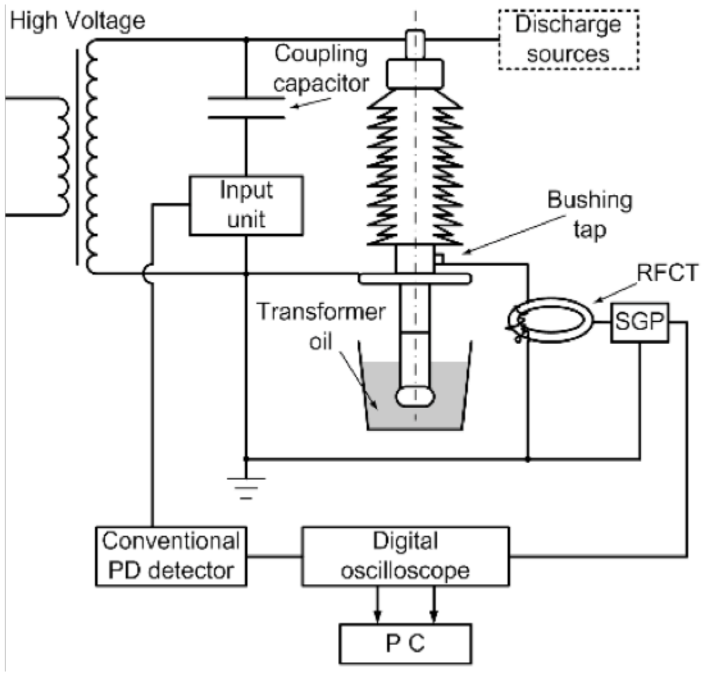


Figure 6.25. University of Southampton's experimental setup [Hao-08]

Dr. Hao provided raw PD data where the defect type was already known prior to diagnosis, as well as raw PD data of undisclosed defect types for "blind" diagnosis. These data sets consisted of voids, surface discharges, protrusions and floating components. Prior to inputting these data sets to the knowledge-based system it was first necessary to convert it into the specific data format required by the system, a phase-resolved pattern of 50*64 matrix (as described in section 5.1.2.1). This was achieved by plotting consecutive pulses generated by the defect on the 3D phase-resolved pattern. The creation of the phase-resolved pattern from the raw Southampton data was constructed using the Java programming language, implementing the following process:

1. **Split the raw data into 50 cycles**

   The raw file, consisting of 50 power cycles of PD data, contained 500,000 points, therefore, each cycle consisted of 10,000 points (500,000 points / 50 cycles).

2. **Remove noise and negative values**

   Due to the oscillating nature of the signal the negative values were removed from the data. A noise level was then chosen to remove any noise from the signal. Displaying the raw data in the programming environment Matlab identified the appropriate noise level.

3. **Construct the phase buckets**

   The 10,000 points per cycle were split into 64 segments to represent the 64 phase buckets. The value used in these buckets was the peak value (in volts) that occurred in each consecutive 156 values i.e. 1 segment (10,000/64).

4. **Change the peak value from volts to pC**

   Since the calibration factor was 600mV = 500pC, the peak value was transformed to pC by performing the following calculation:

   $$SegmentAmplitude = PeakValue/0.6V * 500pC \qquad \text{(Eq 6.1)}$$

5. **Find the relative amplitude**

   The relative amplitude was plotted as a percentage and in terms of the Southampton data, 5V (or 4167pC by using Eq 6.1) corresponds to 100% amplitude. In the knowledge-based system, the 100% corresponds to a numerical value of 255 (8-bit resolution). Therefore, the relative amplitude of the value calculated in step 4 was found by:

   $$RelativeAmplitude = (SegmentAmplitude/4167) * 255 \qquad \text{(Eq 6.2)}$$

6. **Plot the relative amplitude against phase and cycle number to form a 50*64 matrix**

   Inserting the relative amplitude at the phase and cycle number of the matrix formed the phase-resolved matrix.

Once the data had been transformed into the 50*64 phase-resolved matrix format, it was input to the knowledge-based system for classification. The appropriate descriptors were automatically extracted from the pattern by the knowledge-based system, resulting in a classification of the PD source. Although the Southampton data was captured using the conventional IEC60270 technique, the knowledge-based system showed positive signs of being able to classify correctly the defect type within the transformer model. These classifications were presented to the University of Southampton; staff confirmed the results as being correct. The correct classifications were derived using knowledge that originally related to UHF diagnosis in GIS. Validation of the classifications demonstrated the potential generic nature of the knowledge-based system. Further case studies were sent from the University of Southampton, the results of which are demonstrated below in the various case studies.

6.2.1 Void Defect

To simulate the void defect, a 5mm (diameter) x 1 mm (depth) void was embedded between two pieces of perspex and two symmetrical planar electrodes [Hao-08]. The constructed 50*64 phase-resolved matrix of the raw PD data was input to the knowledge-based system for diagnosis. This section will show an example of the void defect.

6.2.1.1 Void Defect in Transformer Oil Case Study

The raw PD signal captured through IEC60270 standard PD detector can be seen in Figure 6.26. From this raw PD signal the phase-resolved pattern, shown in the right hand side of the GUI in Figure 6.27, was constructed by following the algorithm outlined in section 6.2. This phase-resolved pattern was input to the knowledge-based system and the various descriptors, behaviours, defect characteristics and classification were generated. The results, shown in Table 6.61 to Table 6.63, were sent back to Dr. Hao for verification, and were subsequently confirmed as resulting from an internal void defect.

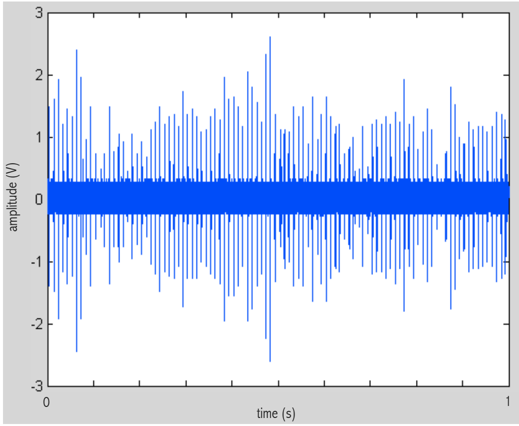


Figure 6.26. Raw PD signal of void

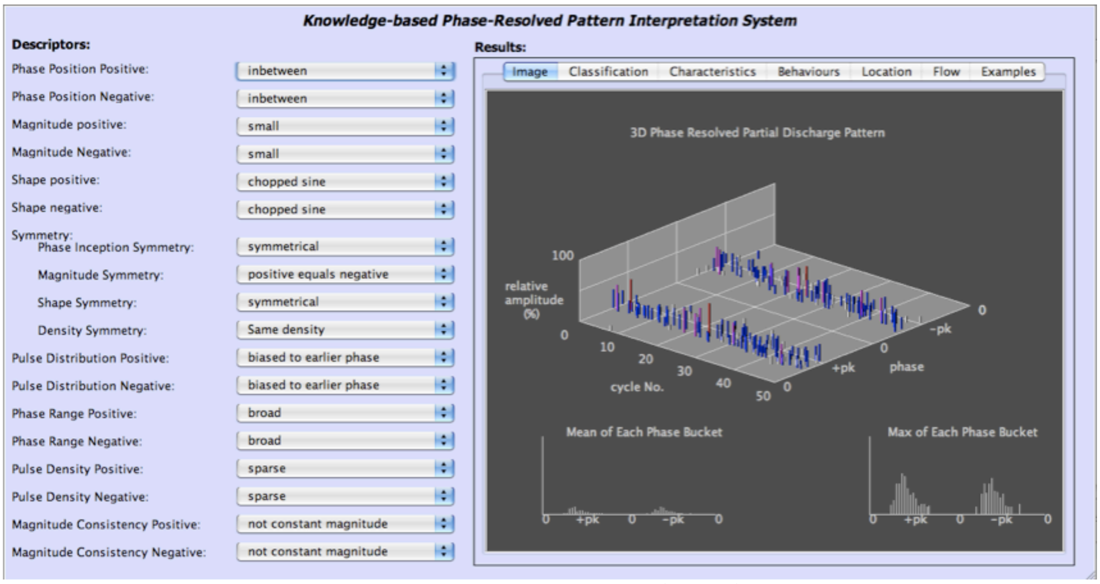


Figure 6.27. GUI of void captured through IEC60270

No adjustments were made to the knowledge in the knowledge bases, which had been captured pertaining to UHF GIS phase-resolved patterns, prior to analysing the IEC60270 data. As is evident in Table 6.61 to Table 6.63 and the phase-resolved pattern of Figure 6.27, the knowledge-based system applied this same knowledge and descriptors to correctly classify the void defect.

Table 6.61 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Symmetrical	1. Conditions for PD inception are the same for both polarities
Whole cycle	Magnitude symmetry	Positive equals negative	1. Defect is geometrically symmetrical
Whole cycle	Shape symmetry	Symmetrical	1. Defect is geometrically symmetrical
Positive half	Position	Inbetween	1. Shift between absolute and rate of change of voltage 2. Issue of space charge
Positive half	Density	Sparse	1. Defect experiencing inconsistent electric field 2. Interference 3. Space charge with a long time constant
Positive half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Positive half	Distribution	Biased to earlier phase	1. Charge retains memory from previous cycle
Positive half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Positive half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Positive half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site not confined to one region
Negative half	Position	Inbetween	1. Shift between absolute and rate of change of voltage 2. Issue of space charge
Negative half	Density	Sparse	1. Defect experiencing inconsistent electric field 2. Interference 3. Space charge with a long time constant
Negative half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Negative half	Distribution	Biased to earlier phase	1. Charge retains memory from previous cycle
Negative half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Negative half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Negative half	Magnitude consistency	Not constant magnitude	1. Locally stored charge 2. PD site not confined to one region

Table 6.62 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Positive half	Issue of space charge AND discharge retains memory from previous cycle AND locally stored charge AND defect is geometrically symmetrical AND pulses at a small site AND voltage dependent (but not proportional to it)	Involves a gas to solid boundary
Positive half	Issue of space charge AND space charge with a long time constant AND locally stored charge AND defect is geometrically symmetrical AND pulses at a small site AND voltage dependent (but not proportional to it)	Involves a gas to solid boundary
Negative half	Issue of space charge AND discharge retains memory from previous cycle AND locally stored charge AND defect is geometrically symmetrical AND pulses at a small site AND voltage dependent (but not proportional to it)	Involves a gas to solid boundary
Negative half	Issue of space charge AND space charge with a long time constant AND locally stored charge AND defect is geometrically symmetrical AND pulses at a small site AND voltage dependent (but not proportional to it)	Involves a gas to solid boundary

Table 6.63 Classification of PD Source

Characteristics	Classification
Involves a gas to solid boundary	VOID

6.2.2 Surface Discharge Defect

The surface discharge defect was simulated in the University of Southampton by using a needle as the upper (high voltage) electrode, and a plane lower (earth) electrode, with a piece of perspex as the insulation between the two electrodes [Hao-08]. The PD signals captured through the IEC60270 measurements and constructed as the phase-resolved pattern expected by the knowledge-based system can be seen in the following case study.

6.2.2.1 Surface Discharge in Air Case Study

The constructed phase-resolved pattern from the raw IEC60270 signal (Figure 6.28) is shown in Figure 6.29. As apparent in Figure 6.29, the discharge pulses occur in a similar distribution to that of section 6.1.2. Although the pulses have been captured with a different measurement system, the PD source still experiences similar PD activity that leads the pulses to occur in the first and third quadrant of the phase-resolved pattern. The same knowledge utilised in the original case study of 6.1.2 is also applicable to this captured activity and the explanation is shown in Table 6.64 to Table 6.66.

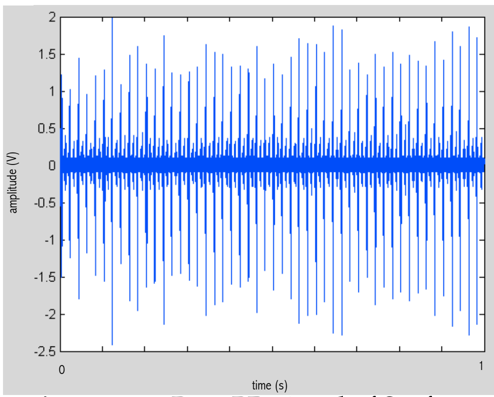


Figure 6.28. Raw PD signal of Surface Discharge

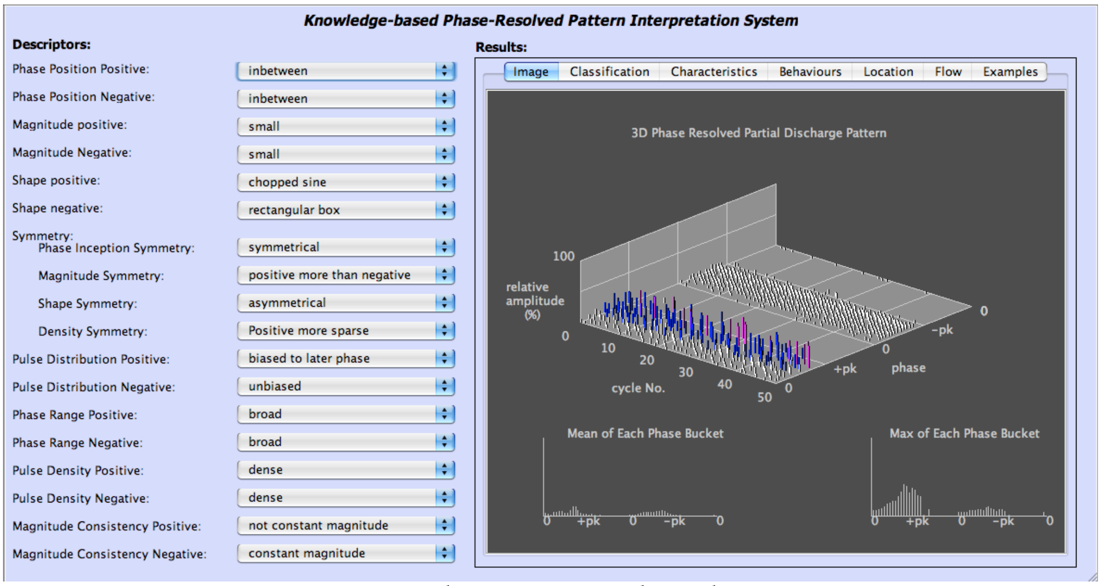


Figure 6.29. GUI of surface discharge captured through IEC60270 measurements

Table 6.64 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Symmetrical	1. Conditions for PD inception are the same for both polarities
Whole cycle	Magnitude symmetry	Positive more than negative	1. Extraction of electrons requires comparatively more energy in the positive half cycle
Whole cycle	Density symmetry	Negative more sparse	1. Ease of discharging is greater in positive half cycle
Whole cycle	Shape symmetry	Symmetrical	1. Defect is geometrically symmetrical
Positive half	Position	Inbetween	1. Shift between absolute and rate of change of voltage 2. Issue of space charge
Positive half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Positive half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Positive half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Positive half	Magnitude consistency	Constant magnitude	1. Constant geometry and capacitance 2. Certain amount of energy to ionise the insulation
Negative half	Position	Inbetween	1. Shift between absolute and rate of change of voltage 2. Issue of space charge
Negative half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Negative half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Negative half	Distribution	Unbiased	1. No space charge
Negative half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Negative half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Negative half	Magnitude consistency	Constant magnitude	1. Constant geometry and capacitance 2. Certain amount of energy to ionise the insulation

Table 6.65 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Positive half	Charge can disperse easily AND issue of space charge AND pulses act at a conducting surface AND voltage dependent (but not proportional to it) AND pulses at a small site	Poor insulation (carbonised or damp)
Negative half	Charge can disperse easily AND issue of space charge AND pulses act at a conducting surface AND voltage dependent (but not proportional to it) AND pulses at a small site	Poor insulation (carbonised or damp)

Table 6.66 Classification of PD Source

Characteristics	Classification
Poor insulation (carbonised or damp)	SURFACE DISCHARGE

6.2.3 Protrusion Defect

Using the same PD measurement system, described previously in section 6.2, PD activity was also captured from a protrusion in oil [Hao-08]. This section will show how the knowledge-based system used this raw PD signal to identify the defect type.

6.2.3.1 Protrusion in Transformer Oil Case Study

Inputting a raw data set of a protrusion defect to the knowledge-based system resulted in the phase-resolved pattern and deciphered descriptors in Figure 6.30. The results of each stage of explanation can be seen in Table 6.67 to Table 6.70. Since the insulation is oil, the knowledge-based system was unable to identify the site of the PD, similar to the case of section 6.1.1.4.

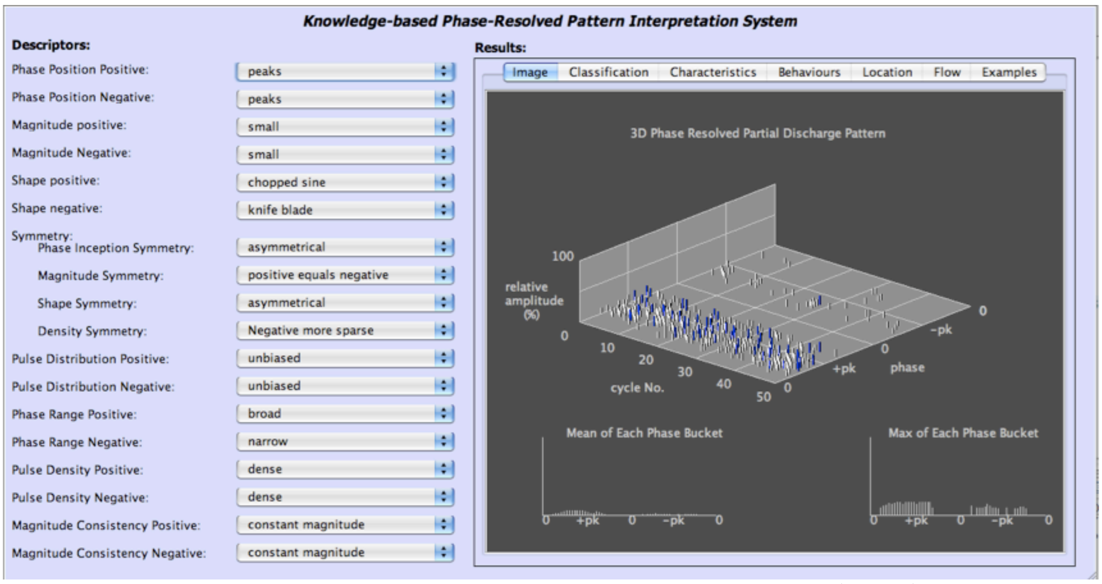


Figure 6.30. GUI of protrusion defect in transformer oil captured through IEC60270 measurement

Table 6.67 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Asymmetrical	1. Conditions for PD inception are different for both polarities
Whole cycle	Magnitude symmetry	Positive equals negative	1. Defect is geometrically symmetrical
Whole cycle	Density symmetry	Negative more sparse	1. Ease of discharging is greater in positive half cycle
Whole cycle	Shape symmetry	Asymmetrical	1. Defect is geometrically asymmetrical
Positive half	Position	Peaks	1. Minimal space charge present i.e. no memory effect beyond half cycle
Positive half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Positive half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Chopped sine wave	1. Voltage dependent (but not proportional to it)
Positive half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Positive half	Magnitude consistency	Constant magnitude	1. Constant geometry and capacitance 2. Certain amount of energy required to ionise the insulation
Negative half	Position	Peaks	1. Minimal space charge present i.e. no memory effect beyond half cycle
Negative half	Density	Dense	1. Pulses at a conducting surface 2. No space charge
Negative half	Range	Narrow	1. Sufficient charge released to suppress further pulses
Negative half	Distribution	Unbiased	1. No space charge
Negative half	Shape	Knife blade	1. Energetic discharge
Negative half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Negative half	Magnitude consistency	Constant magnitude	1. Constant geometry and capacitance 2. Certain amount of energy required to ionise the insulation

Table 6.68 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Whole cycle	Conditions for PD inception are different for both polarities AND minimal space charge present i.e. no memory effect beyond half cycle AND ease of discharging is greater in positive half cycle	Metal part on a conductor
Whole cycle	Conditions for PD inception are different fro both polarities AND pulses at a conducting surface AND defect is geometrically asymmetrical AND pulses at a very sharp tip AND minimal space charge present i.e. no memory effect beyond half cycle AND PD pulse phase influenced by local stored charge	Discharge between conductor surfaces, sharp tip
Negative half	Energetic discharge AND certain amount of energy to ionise the insulation AND minimal space charge present i.e. no memory effect beyond half cycle AND defect is geometrically asymmetrical	Discharge highly localised at a metal part

Table 6.69 Classification of PD Source

Characteristics	Classification
Metal part on a conductor	PROTRUSION
Discharge between conductor surfaces, sharp tip	PROTRUSION
Discharge highly localised at a metal part	PROTRUSION

Table 6.70 Site of PD Source

Classification	Insulation	Site
PROTRUSION	Oil	Either on the earth or high voltage conductor

6.2.4 Floating Component

The final defect type provided by the University of Southampton is a floating metallic discharge in oil (floating component).

6.2.4.1 Floating Component in Transformer Oil Case Study

After transformation into the 50*64 matrix, the phase-resolved pattern was input to the knowledge-based system. Figure 6.31 shows the phase-resolved pattern and the resulting descriptors. The explanation associated with the classification can be seen in Table 6.71 to Table 6.73. In this instance the knowledge-based system could not decide on the phase positions of the PD activity. Usually in this case, the defect type could not be classified due to the rules requiring the identification of the phase position. However, a floating component differs in its classification by also examining the cycle to cycle activity; identifying a number of cycles of inactivity between bursts of PD activity. This identifies a significant quantity of locally stored charge, which along with the other identified PD behaviours has led to the identification of the floating component.

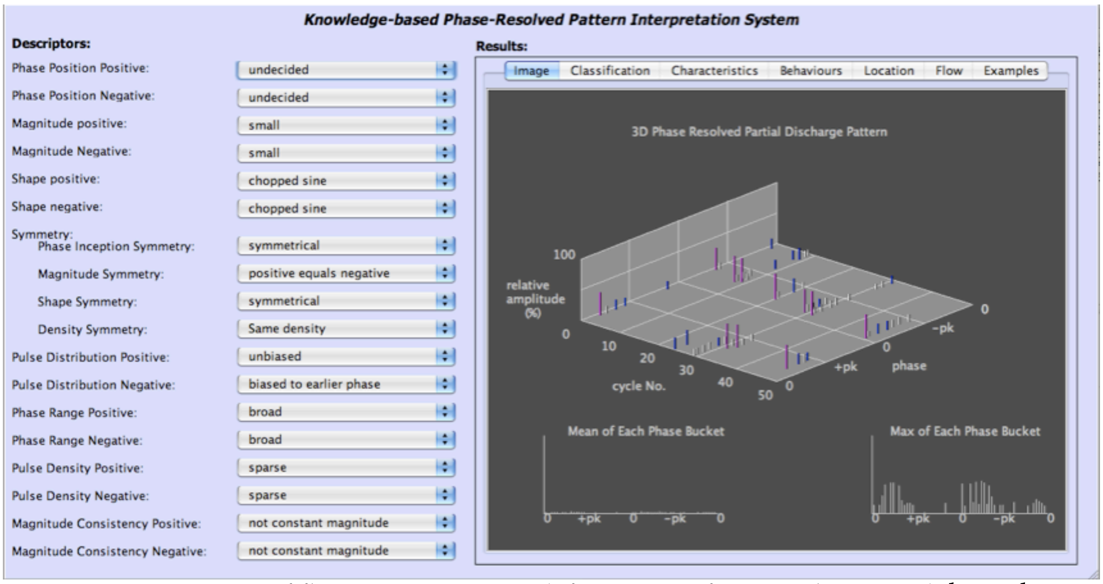


Figure 6.31. GUI of floating component defect in transformer oil captured through IEC60270 measurement

Table 6.71 Descriptors to PD Behaviours

Phase Range	Descriptor Name	Descriptor	Behaviours
Whole cycle	Phase inception symmetry	Symmetrical	1. Conditions for PD inception are the same for both polarities
Whole cycle	Magnitude symmetry	Positive equals negative	1.Defect is geometrically symmetrical
Whole cycle	Shape symmetry	Symmetrical	1. Defect is geometrically symmetrical
Positive half	Density	Sparse	1. Defect experiencing inconsistent electric field 2. Interference 3. Space charge with a long time constant
Positive half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Positive half	Distribution	Unbiased	1. No space charge
Positive half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Positive half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Positive half	Magnitude consistency	Constant magnitude	1. Constant geometry and capacitance 2. Certain amount of energy to ionise the insulation
Positive half	Cycle to cycle activity	Number of cycles between PD activity	1. Significant quantity of locally stored charge
Negative half	Density	Sparse	1. Defect experiencing inconsistent electric field 2. Interference 3. Space charge with a long time constant
Negative half	Range	Broad	1. PD pulse phase influenced by local stored charge 2. Many small discharge sites acting simultaneously 3. Charge can disperse easily
Negative half	Distribution	Biased to earlier phase	1. Discharge retains memory from previous cycle
Negative half	Shape	Chopped sine	1. Voltage dependent (but not proportional to it)
Negative half	Magnitude	Small	1. Pulses at a very sharp tip 2. Pulses at a small site
Negative half	Magnitude consistency	Constant magnitude	1. Constant geometry and capacitance 2. Certain amount of energy to ionise the insulation
Negative half	Cycle to cycle activity	Number of cycles between PD activity	1. Significant quantity of locally stored charge

Table 6.72 PD Behaviours Relation to Defect Characteristics

Phase Range	Behaviours	Characteristics
Positive half	Significant quantity of locally stored charge AND locally stored charge AND space charge with a long time constant AND defect is geometrically symmetrical	Metal part suspended between conductors
Negative half	Significant quantity of locally stored charge AND locally stored charge AND space charge with a long time constant AND defect is geometrically symmetrical	Metal part suspended between conductors

Table 6.73 Classification of PD Source

Characteristics	Classification
Metal part suspended between conductors	FLOATING COMPONENT

6.3 Further Testing of the Knowledge-Based System

The previous sections of this chapter have shown the correct classification and discussion of certain PD sources as input to the knowledge-based system for diagnosis. Table 6.74 shows a comprehensive range of tests by displaying the results of the diagnosis of a variety of PD sources captured in oil and SF_6, through both the UHF and IEC60270 techniques (as described in the experimental setups in section 6.1 and 6.2). This provides an overview and enables assessment of the knowledge-based system's performance.

The columns in Table 6.74 display the different PD sources presented to the knowledge-based system for classification. These are split by insulation type, where the defect was either placed in an oil or SF_6 test cell, as shown in Table 5.1. By taking the protrusion defect as an example (column 1), the rows of Table 6.47 will be explained. The first row highlights the total number of samples input to the knowledge-based system for the protrusion defect; in this case there are 60 samples. The next row, "break down of number of samples", displays the three sample sets input to the knowledge-based system for diagnosis:

- Defect in oil using IEC60270 measurements.
- Defect in oil using UHF sensors.
- Defect in SF_6 using UHF sensors.

In this example, 10 samples from a protrusion in oil were measured using the IEC60270 technique, 12 samples from a protrusion in oil were measured with UHF sensors and 38 samples from a protrusion in SF_6 were measured with UHF sensors, totalling 60 samples.

Table 6.74 Table of test results

		PD source													
		Protrusion (PRO)		Surface discharge (SD)		Void (V)		Metallic particle (MP)		Bad Contact (BC)		Floating component (FC)		Floating electrode (FE)	
		Oil	SF_6	Oil	SF_6	Oil	SF_6	Oil	SF_6	Oil	SF_6	Oil	SF_6	Oil	SF_6
Total number of samples		60		50		16		50		5		50		10	
Breakdown of the number of samples	IEC	10	-	10	-	12	-	-	-	-	-	20	-	-	-
	UHF	12	38	38	2	-	4	40	10	4	1	30	-	-	10
Total number of correct classifications	IEC	9	-	10	-	4	-	-	-	-	-	17	-	-	-
	UHF	7	38	31	2	-	2	37	9	3	1	9	-	-	6
Number of diagnoses correctly classifying only the PD source	IEC	7	-	10	-	3	-	-	-	-	-	16	-	-	-
	UHF	5	38	27	2	-	1	37	9	1	0	7	-	-	3
Number of diagnoses correctly classifying the PD source but also classifying other PD sources	IEC	2	-	0	-	1	-	-	-	-	-	1	-	-	-
	UHF	2	0	4	0	-	1	0	0	2	0	2	-	-	3
Other types classified	IEC	2x V	-	-	-	1x SD	-	-	-	-	-	1x V	-	-	-
	UHF	2x SD	-	4x V	-	-	1x FC	-	-	1x FC 1x SD 1x V	-	3x V 1x SD	-	-	1x SD 3x FC 1x V
Number of diagnoses that do not know what the PD source is	IEC	1	-	0	-	6	-	-	-	-	-	3	-	-	-
	UHF	5	0	7	0	-	2	3	1	1	0	20	-	-	3
Number of wrong diagnosis	IEC	0	-	0	-	2	-	-	-	-	-	0	-	-	-
	UHF	0	0	0	0	-	0	0	0	0	0	1	-	-	1
PD source classified	IEC	-	-	-	-	2x P	-	-	-	-	-	-	-	-	-
	UHF	-	-	-	-	-	-	-	-	-	-	1x V	-	-	1x V

The knowledge-based system's output could result in multiple defect classifications, as highlighted in section 6.1.5.4. It was therefore felt that the table should highlight the number of correct classifications inclusive of additional types and also split these into classifications relating to a single defect type, and classifications that resulted in additional defect types (displaying these additions). The row entitled "total number of correct classifications" covers the diagnoses that resulted in the protrusion defect type; this could also include the classification of other PD sources. In this example the knowledge-based system resulted in the correct classification of the protrusion in:

- 9 out of the 10 samples in oil through the IEC60270 technique,
- 7 out of the 12 samples in oil through UHF sensors,
- and 38 out of the 38 samples in SF_6 through UHF sensors.

By taking the IEC60720 technique in oil, in this protrusion column, as a more detailed example, the next row, “number of diagnoses correctly classifying only the PD source”, means that 7 out of the original 9 (from the row above) classifications related specifically to the protrusion defect. The next row, “number of diagnoses correctly classifying the PD source but also classifying other PD sources”, in this case resulted in 2 out of the original 9 classifying alternative PD sources along with the protrusion defect. These additions are shown in the row below (“other types classified”), which in this example resulted in the system classifying the protrusion along with a void defect in two cases.

The next row, “number of diagnoses that do not know what the PD source is”, displays the number of samples for which the knowledge-based system could not distinguish any defect type from the PD activity using the knowledge within its knowledge bases. In this example, out of the 10 samples taken from a protrusion defect in oil using the IEC60270 technique, the knowledge-based system could not classify 1 sample. Finally, Table 6.74 displays the number of samples that the knowledge-based system presented as a wrong diagnosis. In the protrusion example, this was zero in each of the three sample sets. However, if the knowledge-based system wrongly classified the defect type, then the next row (“PD source classified”) would display the defect type classified by the system.

As apparent from the table, the knowledge-based system is more accurate in diagnosing certain PD sources, which can also be said of machine learning techniques [Catterson-06]. However, unlike machine learning techniques, the knowledge-based system provides a justification for its classification, which can assist the engineer in making a final decision. Highlighting the parts of the phase-resolved pattern examined, along with their inferred PD behaviours, defect characteristics, classification and PD site portrays this. Therefore, the user of the system is provided with a build up of knowledge that led to the classification and this provides enhanced visibility of the diagnostic process. It should also be noted that these machine learning techniques, once trained, become specific to the equipment they were trained on. This is not the case with the knowledge-based approach, where generic knowledge rules were elicited and implemented to offer the potential of diagnosing the same defect independent of the equipment, insulation type or measuring technique. This can be seen in Table 6.47, where, for example, the knowledge-based system identifies the protrusion defect:

- 90% of the time in transformer oil from the IEC measurements,
- 58% of the time in transformer oil from the UHF sensors,
- and 100% of the time in SF_6 from the UHF sensors.

Furthermore, as evident in the table, the knowledge-based system has more difficulty in identifying the defect types in oil from the UHF sensors. It should be noted that the expert also found these phase-resolved patterns difficult to classify, highlighting that it was harder to categorise PD sources in oil. Additionally, the test data for this sample set was from previous experiments [Cleary-05] where the oil bath was open to air. The expert suggested that this could have an effect on the PD activity, with the oil rapidly becoming saturated, with a possible strong influence of polarised water molecules affecting the PD activity at the defect site. This questions the replicability of this data within a real transformer. Therefore, further testing of the knowledge-based system using UHF sensors on oil insulated defects with proper oil conditioning should be the focus of future work.

As highlighted in section 6.1.5.4, the diagnosis of a phase-resolved pattern could result in a conflict of classification. This is also noticeable in Table 6.47, where the diagnosis results in the addition of alternative defect types along with the correct classification; for example the surface discharge in oil using UHF sensors also classifies the void defect in four samples. In these cases an engineer would be assisted in resolving this conflict by being presented with the different stages of the knowledge-based approach, which resulted in the classifications. Although the diagnosis presents multiple PD sources, the knowledge-based system offers insight into the activity occurring within the insulation. In the case of these more complex patterns and conflicting classifications, an expert could be brought in to resolve the conflict with the assistance of the evidence and descriptions offered by the knowledge-based system's diagnosis.

Also as shown in the table, the knowledge-based system can decide that it cannot classify the PD source. In this instance the engineer is informed regarding this troubled diagnosis and has the option to manually choose descriptors for an improved classification. It is felt that this unknown classification is more beneficial than a wrong diagnosis, with the potential of the knowledge-based system diagnosing the PD source as the PD activity evolves and possibly stabilises.

An example of where the knowledge-based system does not know what the result is 50% of the time is when diagnosing the void defect through IEC60270 compliant sensors in the oil filled transformer. This lack of diagnosis is due to the knowledge-based system calculating the position of the PD pulses as being on the peaks of the voltage waveform, which is not indicative of a void defect and so has not been classified as one. During the calculation the difference between peaks and in-between position on the voltage waveform can be minute and in these cases the position have been wrongly categorised. This wrong calculation of the phase position of PD pulses could be resolved in the future with more accurate statistics to calculate the position or through other pattern recognition techniques that are discussed in the future work section of this thesis. At present the knowledge-based system allows the engineer to resolve this miscalculation by manually changing the descriptor to the preferred choice and rerunning the diagnosis. For these test case the void defect was achieved after manually changing the discrepancies in the descriptors and rerunning the diagnosis.

The construction of Table 6.74 provides a useful aid for the validation of the expert knowledge and was utilised in the knowledge engineering process. Highlighting any cases of wrong diagnosis provides this assistance; along with identifying the type of PD source that appear incorrectly. Through further testing, knowledge and future experiments it may be possible to add additional descriptors to further distinguish these defects.

6.4 Conclusion

This chapter was included to prove that human expert knowledge in the area of PD diagnostics can be captured effectively and efficiently, and implemented into a knowledge-based system to provide generic diagnosis of the PD source behind phase-resolved patterns. The phase-resolved pattern was taken as input to the knowledge-based system because of its ability to highlight the PD behaviour inside the equipment and its ability to be constructed from PD data from different measurement systems. The variety of experimental data has illustrated the application of the knowledge-based approach to oil-insulated transformers, where the signals were captured through UHF and IEC60270 measurements, as well as UHF signals in GIS. This ability to diagnose the phase-resolved pattern, independent of the equipment, insulation and measurement system demonstrated the generic applicability of the experts' knowledge and the knowledge-based system. Although the discharges show variations within the insulation materials (SF_6 and oil), the knowledge-based system was proven to have generic rules that could be applied to either type of insulation.

The creation of the knowledge-based system to diagnose PD signals in a variety of equipment, has not only shown that the expert knowledge in this area of research has increased over the years to be able to diagnose a pattern by eye, but also that this knowledge can be captured, transcribed, modelled and implemented in to a rule-based system for automated PD diagnosis. However, it should be noted that expert knowledge regarding the site of the PD source is still not sufficient for all defect types, with the site of the PD source only applying to the protrusion defect in SF_6, due to the other PD sources not showing distinguishing descriptors regarding their site within the phase-resolved pattern. Other techniques, for example time-of-flight [Judd-04], are being investigated to overcome this, albeit in a different way from capturing more knowledge.

It has also been demonstrated that phase-resolved patterns can become complex and in these cases so can the classification. As shown in the above case studies, the final result may not always identify a unique PD source as the source of the data. This is apparent in section 6.1.5.2 and 6.1.5.4. In these cases, more than one classification is offered to the engineer, whose decision should form the last part of the diagnostic process. From the justification of the classification through the use of the expert knowledge in the incremental stages of diagnosis, the engineer would be able to make the final classification through this decision support. PD experts also found difficulty in classifying defects that the knowledge-based system struggled to classify. In this case the knowledge-based system is expected to only work as well as an expert when presented with a complex phase-resolved pattern.

Another time where the patterns can become complex is when activity from multiple PD sources are captured and displayed on a single phase-resolved pattern. In these cases the knowledge-based system has an advantage that it informs the user that it cannot classify a PD source. This could be because the pattern displays multiple regions of PD activity within the one pattern or because a noisy pattern is observed. In the case of multiple PD sources it would be necessary to strip out a single PD source [Yang-03] prior to diagnosis through the knowledge-based system. With the knowledge-based system taking the phase-resolved pattern as its input, after pre-processing a phase-resolved pattern of a single PD source, it can be input to the knowledge-based system for diagnosis.

Due to the knowledge-based system containing expert PD diagnostic knowledge, the nature of a knowledge-based system implies that it will not be able to diagnose something that an expert would not have been able to diagnose. Although a limitation of the knowledge-based approach, it still provides decision support to the engineer and a classification in under two seconds, removing the need for valuable expert’s time.

One feature offered by the GUI of the knowledge-based system is the ability to correct the automatically calculated descriptors of the phase-resolved pattern. This feature is useful if the engineer disagrees with, for example, the shape of the pulse distribution. After altering this descriptor value to one that describes the pattern more accurately, the knowledge-based system can be rerun and a more accurate diagnosis could be sought. At present there is no way of storing this correction of the calculation, however, this is a feature that could be implemented in the future and will therefore be discussed in chapter 7, along with additional future work and the conclusions of this thesis.

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Chapter 7

Conclusions and Future Work

7.0 Conclusions

The condition monitoring of high voltage equipment is becoming an activity of strategic importance with significant investment from industry. However, as shown in chapter 2 there are many strategic issues faced by the utilities when deciding on whether to adopt condition monitoring. If adopted, the measurement and monitoring of numerous parameters on high voltage equipment can lead to a large volume of data, which could hold useful information regarding the condition of the apparatus. The meaningful extraction and interpretation of this data has the potential to inform plant maintenance and asset management strategies.

As shown in chapter 2, PD monitoring is an industry-recognised means of identifying defects within dielectric insulation of high voltage equipment. The PD activity within the insulation not only highlights the presence of defects within the insulation but can also be harmful to the insulation if left to degrade, with potentially catastrophic consequences if undetected. The classification of defects as and when they occur within the insulation can inform suitable maintenance strategies to be implemented to avoid further degradation.

The phase-resolved pattern is one representation of PD data, resulting in defect specific patterns associated with particular PD activity. However, the manual interpretation of large volumes of data can prove an onerous task for an expert; and there are not many for this type of monitoring. Chapter 3 discussed the various automated techniques utilised in previous research to identify the type of PD source, which could be present in the insulation, primarily using data-driven AI techniques for PD defect classification of phase-resolved patterns.

Although correctly classifying the defect associated with the raw PD data, the data-driven approaches in chapter 3 possess the following disadvantages:

- No explanation of why a particular defect was chosen over another.
- No information of where the classification was derived from.
- The requirement of training the classifiers to a particular apparatus, resulting in the classifier being equipment and family specific.
- Large data set for training, which may not always be available, as well as a large data set for testing.
- Statistical analysis being carried on a per half cycle basis, which could lead to miscalculation and therefore misclassification.
- The possibility of choosing the wrong number of nodes in the case of clustering techniques.
- Limitations/hazards associated with using data-driven AI techniques e.g.
    - The possibility of overtraining in the case of a neural network, which could lead to misclassification.
    - An overall lack of explanation leading to lack of confidence in the classification.

To overcome the disadvantages of data-driven techniques, and to reduce the time consuming task of manual classification, this thesis has proposed a knowledge-based approach. This approach resulted in defect classification by replicating PD expert knowledge appertaining to the visual recognition and interpretation of phase-resolved PD patterns and its inferred PD activity. Mimicking the approach that an expert employs led to the construction of a knowledge base to diagnose PD sources from phase-resolved patterns. The phase-resolved pattern utilised in this research was a three-dimensional pattern consisting of the *pulse's amplitude*, the *cycle number* on which the pulse appears and the *phase position* of the pulse on the voltage cycle. The main benefit of this knowledge-based approach is the explanation provided as to why a certain defect is identified. This justification of the classification, through a novel incremental diagnostic process highlighting the descriptors of the phase-resolved pattern, the associated PD behaviours, the defect characteristics, defect classification and PD site, provides the user with more confidence in the final output.

Previous experiments at the University of Strathclyde [Cleary-05] increased the knowledge base of resident PD experts. It is apparent that experts associate specific phase-resolved descriptors with the PD phenomena occurring at the PD site. The accumulation of this knowledge from experts enabled its implementation in a knowledge-based expert system to automate the experts' diagnostic approach. A limited number of experts posses this knowledge about PD behaviours, phase-resolved patterns and defect characteristics. A major challenge encountered during the research detailed in this thesis was the task of acquiring, representing and organising expert knowledge for PD diagnosis. Chapter 4 discussed the various ways to capture the expert knowledge, and identify the tacit knowledge held by the experts. The extraction of this knowledge required an iterative approach identifying the steps applied by the experts and the domain knowledge invoked at each step. Acquisition, representation and validation were the three main stages involved in the knowledge engineering approach prior to implementation in the knowledge-based system.

Chapter 5 described the steps taken to capture this evolving knowledge base, along with the creation of the five separate knowledge bases; descriptors of the phase-resolved pattern, PD phenomena, defect characteristics, PD source types and the site of the PD. The modular design of the knowledge-based system allows for easy integration of new knowledge regarding PD phenomenon, defect characteristics, defect site, defect type and distinguishing descriptors of the phase resolved pattern, as the understanding of the domain improves. It should be noted that the knowledge pertaining to defect classification in this thesis was from a small number of experts and in the future it would be beneficial to validate and augment this expert knowledge with further experts in the field of PD diagnostics.

During the knowledge engineering stage specific issues were exposed when the discharges occur across the zero crossings of the phase-resolved pattern. In this case the PD activity is occurring between the half cycles, which previous classifiers/machine learning techniques do not take into account, causing the miscalculation of certain statistics resulting in misclassification. The knowledge-based approach overcomes this disadvantage of machine learning techniques by examining the pattern as being continuous over the zero-crossing points of the ac waveform, grouping the discharges on a per activity basis.

In chapter 6, various case studies were provided to highlight how the experts' knowledge could be utilised within the knowledge-based system to identify descriptors present in the phase-resolved pattern, which would infer the PD phenomena, the presence of defect characteristics and the classification of the PD source. It also showed how expert knowledge could be employed to identify the site of the protrusion defect in SF_6, through distinguishing descriptors of the phase-resolved pattern for this defect type (the expert knowledge was unable to provide the PD site of the other defect types). The defect types, which the knowledge-based system is able to classify, are:

- Protrusion.
- Surface discharge.
- Void.
- Metallic particle – rolling or bouncing.
- Bad contact.
- Floating objects – floating electrode or floating component.

To overcome a further disadvantage of machine learning techniques - that once trained, the classifier is then specific to the equipment and sensory data type it was trained on - the knowledge-based approach was designed to capture generic rules that could classify defects independent of the insulation type and measuring technique. The generic nature of the knowledge-based system was highlighted in chapter 6. By taking the phase-resolved pattern as its input, the knowledge-based system was presented with three data sets, varying the insulation and measuring technique. These sample sets were:

- Defect in oil using IEC60270 measurements.
- Defect in oil using UHF sensors.
- Defect in SF_6 using UHF sensors.

The generic nature of this knowledge-based system offers flexible decision support to engineers on a variety of equipment, captured by either sensor type (UHF or IEC60270) in different insulation types (oil or SF_6). However, it should be noted that the knowledge-based system achieved its weakest results when trying to diagnose defects from oil-insulated defects using UHF sensors. Future work should focus on testing the knowledge-based system with further laboratory experiments of known defect types in oil using UHF sensors and also with in-field data.

There are times when the phase-resolved patterns can become complex and in these cases so can the classification. Difficulty in classifying defects in these more complex cases was shown by both the knowledge-based system and the expert. In this case the knowledge-based system is expected to only work as well as an expert when presented with a complex phase-resolved pattern. As a result of these complex patterns, more than one classification is offered to the engineer by the knowledge-based system, whose decision should form the last part of the diagnostic process. The engineer is assisted in making a final decision through the support of the expert knowledge in the incremental stages of the knowledge-based approach. Other complex patterns are in the form of multiple PD sources on the one pattern. These also pose a problem for the knowledge-based approach; however, work is underway to strip out a single PD source [Yang-03], which after pre-processing could be input to the knowledge-based system for diagnosis.

It can therefore be concluded that the research has delivered novel contributions to automated PD diagnosis. Specifically:

- A new incremental approach to the analysis of PD data, in the form of a knowledge-based system, which provides an explanation suitable for engineers with different levels of understanding and experience. The explanation associated with the classification of a PD source from a phase-resolved pattern provides a description of the PD behaviour, defect characteristics, classification (defect type), PD site and descriptors of the phase-resolved pattern that led to a diagnosis, supplying confidence in the classification and decision support in the area of PD analysis.

- Translating the raw IEC60270 data into a format for the knowledge-based system, along with the algorithms to calculate the various descriptors, which assist in the classification.

- Examining the phase-resolved pattern on a per activity basis, rather than per half cycle basis, reducing the miscalculation of the statistics that represent the data and therefore the classification.

- An extensible, evolving knowledge base providing storage of valuable expert knowledge regarding PD phenomena, defect characteristics and PD diagnosis, which may evolve and expand in line with the knowledge base of expertise. This allows new categories of PD defect type to be included as the experts' understanding of these improves.

- By utilising the phase-resolved pattern, the knowledge-based approached offers a generic, flexible system due to the common physical nature of PD within high voltage equipment. This offers a generic approach to the classification of defects from data captured through either UHF or IEC60270 techniques, across a variety of equipment such as transformers and GIS and potentially cables, offering flexible online decision support for condition monitoring. This is in contrast with many other developed systems, which focus solely on one particular plant type, and even sometimes on one particular model of plant type.

7.1 Future work

This section will outline work that should be carried out in the future. Firstly, improvements to the knowledge-based system will be proposed, followed by a discussion on the integration of the knowledge-based system into an overall condition monitoring system.

7.1.1 Future Work to the Knowledge-Based System

As with all AI PD diagnostic techniques, the accuracy of the knowledge-based approach is variable according to the defect type. However, unlike other AI techniques, the knowledge-based system provides an explanation as to why a certain defect was classified. This means that although the final conclusion could be misclassified, the explanation provides an insight into the PD activity occurring within the insulation. In the future, these defect types could be better diagnosed with more understanding, through new field tests supplying new data and extra knowledge sources. For example, further testing of the protrusion defect in oil would allow more knowledge to be gained as to the different patterns associated with the site of the PD source.

It is hoped to further investigate the potential generic nature of the system with PD activity in cables. This investigation, along with further laboratory data and field-based trials would expose any defects that required more knowledge, the adjustment of thresholds or the addition of further descriptors to aid in the diagnosis of defect types. By also increasing the volume of test data, more confidence in the diagnosis and classification from the knowledge-based system could be achieved. Future work should also involve further testing of the knowledge-based system using UHF sensors on oil-insulated defects with proper oil conditioning, as described in section 6.3.

The nature of a knowledge-based system requires it to be periodically altered and updated as more knowledge or data sets become available. It is therefore necessary that future work will be required for this knowledge-based system by updating its various knowledge bases. The modular design of the knowledge-based system should make this update simple, however, it would be beneficial to create a user interface to support any future updates.

The knowledge-based system was constructed to provide a diagnosis of the PD source from a phase-resolved PD pattern. It does this by providing a classification along with a justification based on expert knowledge in each of the five stages of its diagnosis, as discussed previously. However, the issue of uncertainty has not been researched in this thesis with regard to how certain an expert is, for example when regarding the PD behaviour associated with a particular descriptor or a defect type associated with a defect characteristic. It is thought that further work would benefit the knowledge-based system by adding a weighting factor representing the certainty of an expert with respect to certain facts, associations and diagnoses. This would provide a degree of how probable it is that a certain defect is occurring within the insulation.

To improve the accuracy associated with the recognition of the descriptors, a “self-learning” technique could be deployed [Todd-07]. At present, the descriptors are automatically calculated from the phase-resolved PD pattern. If the engineer disagrees with a certain descriptor, the GUI associated with the prototype allows the manual alteration of these descriptors for a further diagnosis. However, the manual change of these descriptors is not retained for future similar cases. A beneficial functionality that could be integrated into the system could provide the learning of the statistics associated with this new descriptor for future cases. This could be achieved through the integration of machine learning by using feedback to improve similar situations, although further research would be required in this area prior to implementing this functionality. This self-learning functionality could also allow experts to define entirely new defects with new or existing descriptors.

Further improvements regarding the accuracy of descriptor identification could be applied to the identification of the shape the discharges created within a half cycle. When extracting the shape characteristics, at present statistical calculations are performed. Although this can identify the associated shape, a more accurate solution could be implemented in the future by using pattern recognition techniques e.g. template matching [McQueen-81]. It may also be possible to use this technique to identify other descriptors that are required for diagnosis, although again further research would be required before implementing this process.

7.1.2 Integration within an Overall Condition Monitoring System

Previous research at the University of Strathclyde constructed an agent-based condition monitoring system for the diagnosis of PD activity within oil filled power transformers [McArthur-04][Catterson-06][Strachan-05]. The condition monitoring multi-agent based system, COMMAS, employs autonomous modules (agents) to perform separate parts of the data management and interpretation tasks for UHF PD diagnosis. Full details of this system, along with the benefits of the agent-based architecture, have been reported previously [McArthur-04]. While it is not the intention of this thesis to discuss agent-based architectures and systems, it is thought that the integration of the knowledge-based system described in this thesis would add benefit to the COMMAS architecture, not only through an additional classification but also through the introduction of diagnostic explanation.

The agent-based architecture utilised in COMMAS provides an extensible framework to integrate different types of data interpretation, with the present interpretation agents performing data-driven approaches of defect classification from UHF phase-resolved PD patterns. These data-driven approaches included C5.0 Rule Induction, K-Means Clustering, and Back-Propagation Neural Network [Strachan-05]. The original interpretation agents within COMMAS were deployed due to limited domain knowledge in the area of PD phenomena and phase-resolved pattern interpretation. Issues associated with these data-driven approaches in PD classification/diagnosis were discussed in chapter 3.

The COMMAS' agent-based architecture provides flexibility, which allows it to accommodate various sensors and different data interpretation techniques. Work is underway to integrate the knowledge-based system described in this thesis into COMMAS, and eventually an overall condition monitoring architecture for transformer diagnosis [Catterson-09]. The addition of this knowledge-based agent, containing the experts' diagnostic knowledge, will ensure that the COMMAS system provides a diagnosis in terms of a practical engineering explanation of the classified defect type, and thereby enhance the user's confidence in the diagnosis. Also, this explanation allows enhanced visibility and verification of the reasoning process adopted by the expert in reaching a particular conclusion.

7.2 References

[Catterson-06] V. Catterson, "Engineering Robustness, Flexibility, and Accuracy into a Multi-Agent System for Transformer Condition Monitoring", Thesis, December 2006.

[Catterson-09] V. M. Catterson, S. E. Rudd, S. D. J. McArthur, and G. Moss, "On-line Transformer Condition Monitoring through Diagnostics and Anomaly Detection", The 15th International Conference on Intelligent System Application to Power Systems, Curitiba, Brazil, November 8-12, 2009.

[Cleary-05] G. P. Cleary, "Interpretation of UHF signals produced by partial discharges in oil filled power transformers", Thesis, May 2005.

[McArthur-04] S.D.J McArthur, S.M Strachan, G. Jahn, "The Design of a Multi-Agent Transformer Condition Monitoring System", IEEE Transactions on Power Systems, Vol. 19, No 4, pp.1845 - 1852, November 2004.

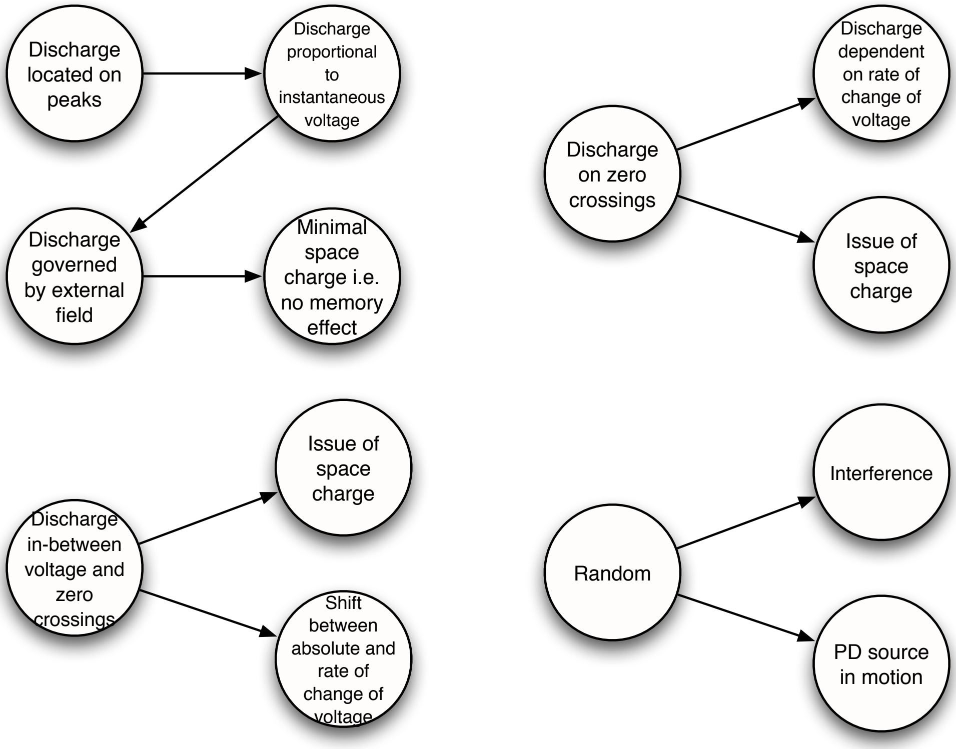
[McQueen-81] M.P.C. McQueen, "A generalization of template matching for recognition of real objects", Pattern Recognition, Volume 13, Issue 2, pp.139-145,1981.

[Strachan-05] S. M. Strachan, "Decision Support System Development for Plant Condition Monitoring and Protection Design Reuse using Structured Methods of Knowledge Engineering and Knowledge Discovery", Thesis, April 2005.

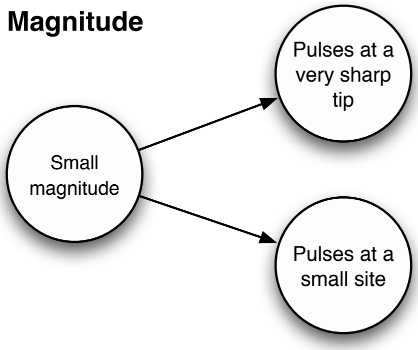
[Todd-07] M. Todd, S.D.J. McArthur, J. McDonald, S.J. Shaw, "A Semiautomatic Approach to Deriving Turbine Generator Diagnostic Knowledge," IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews, Vol. 37, No. 5, pp.979-992, September 2007.

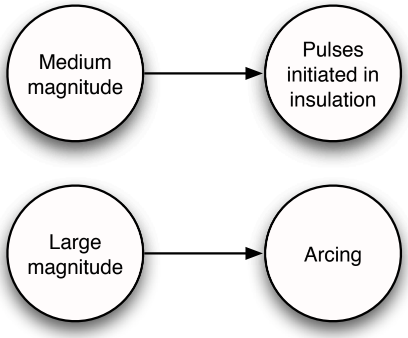
Appendix 1 - Semantic Network Models of Stage #2

Phase Position

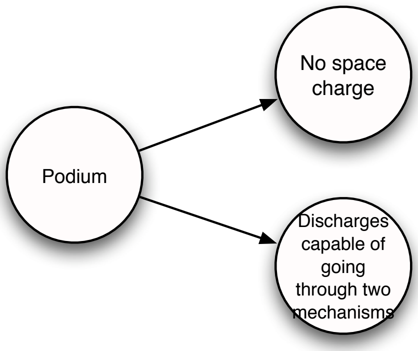


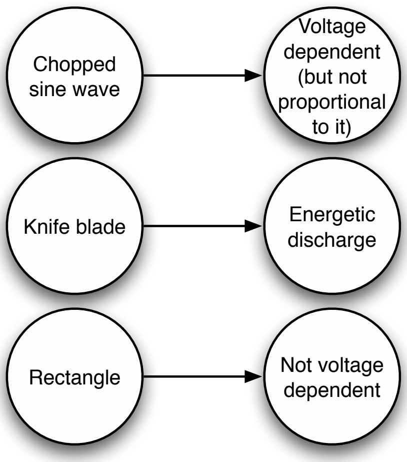
Magnitude



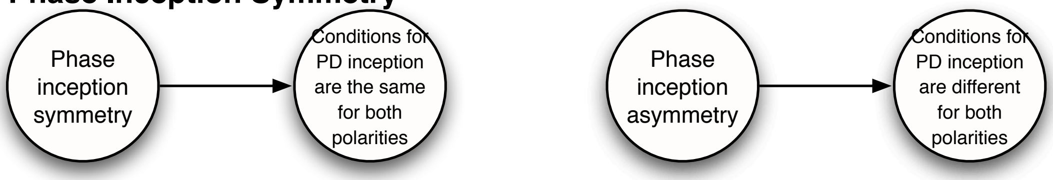


Shape

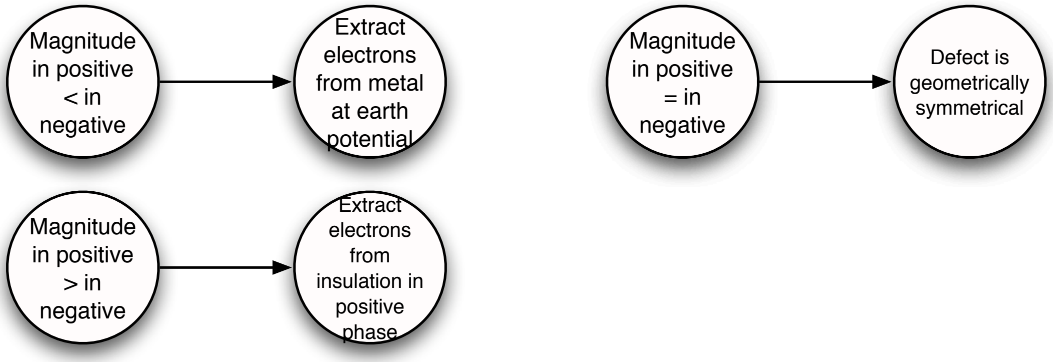




Phase Inception Symmetry

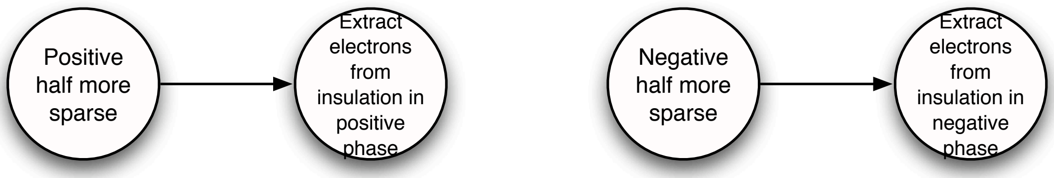


Magnitude Symmetry

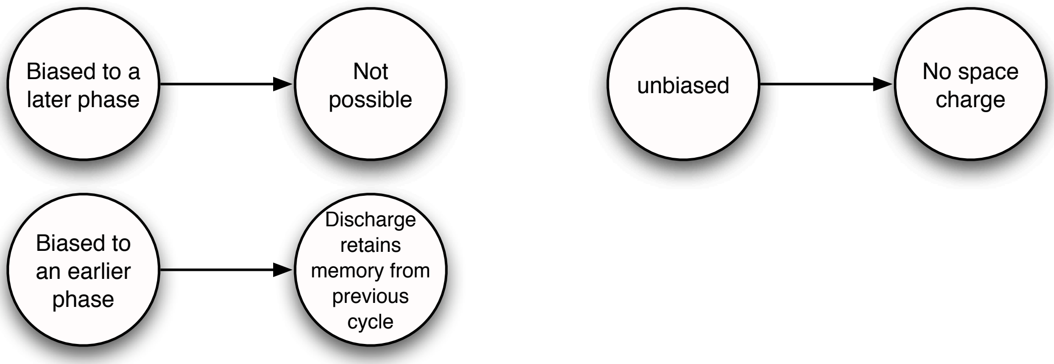


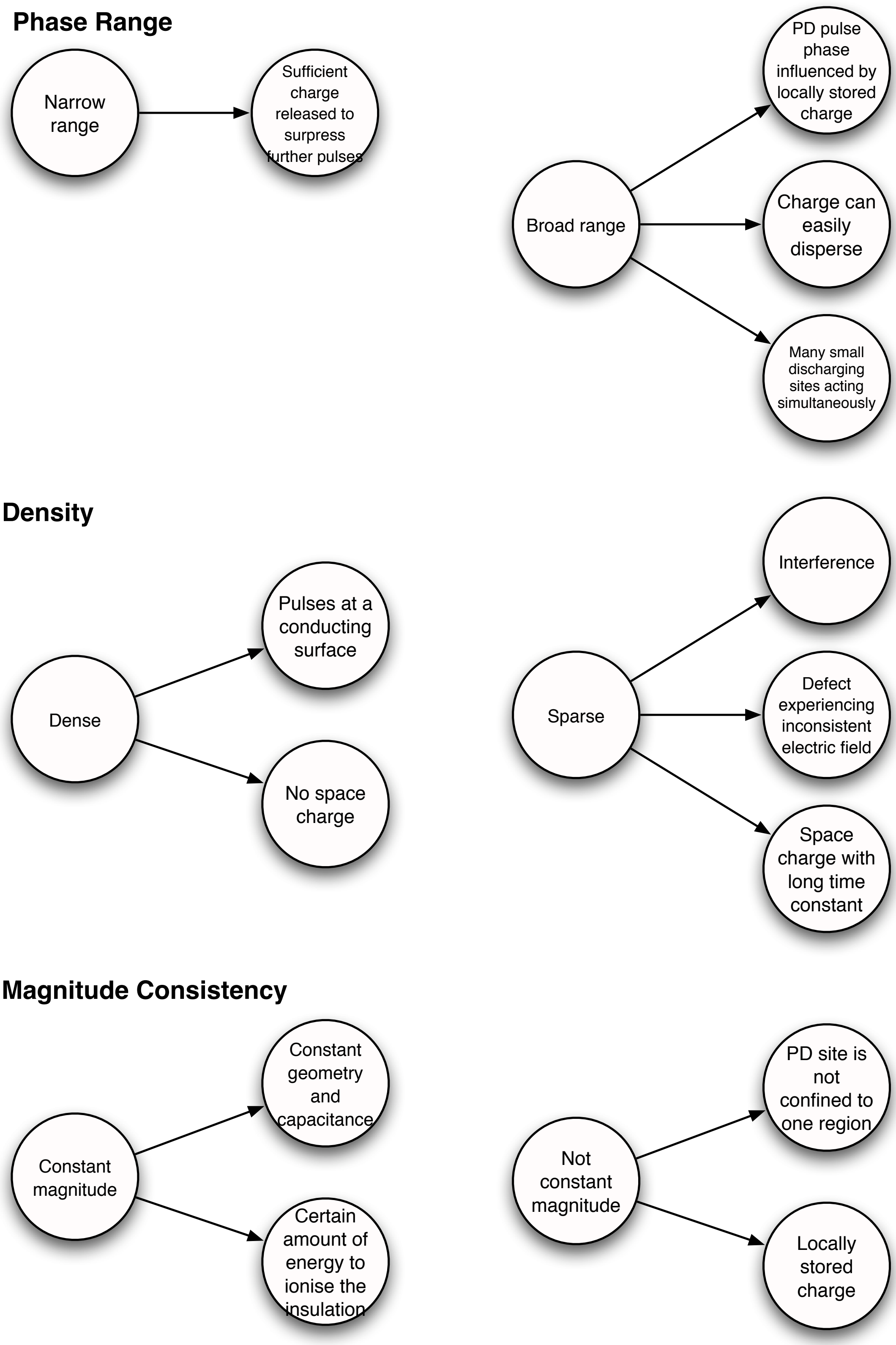
Shape Symmetry

Density Symmetry

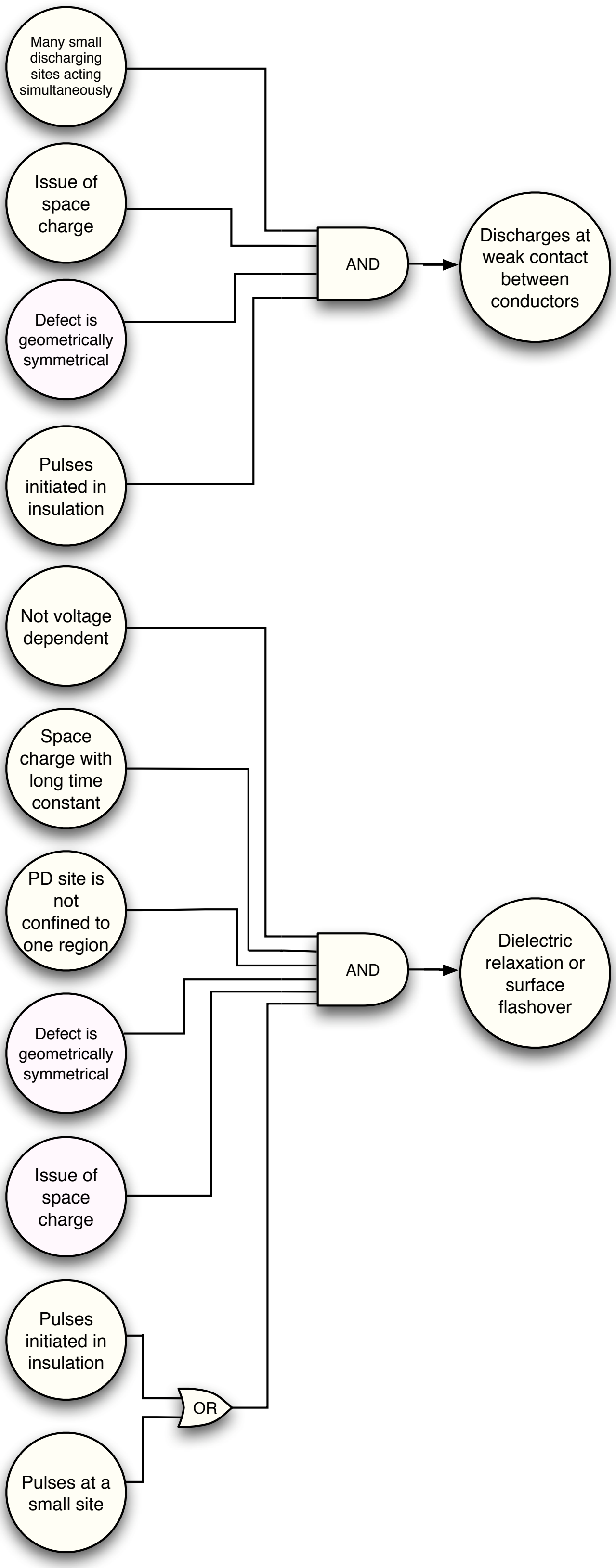


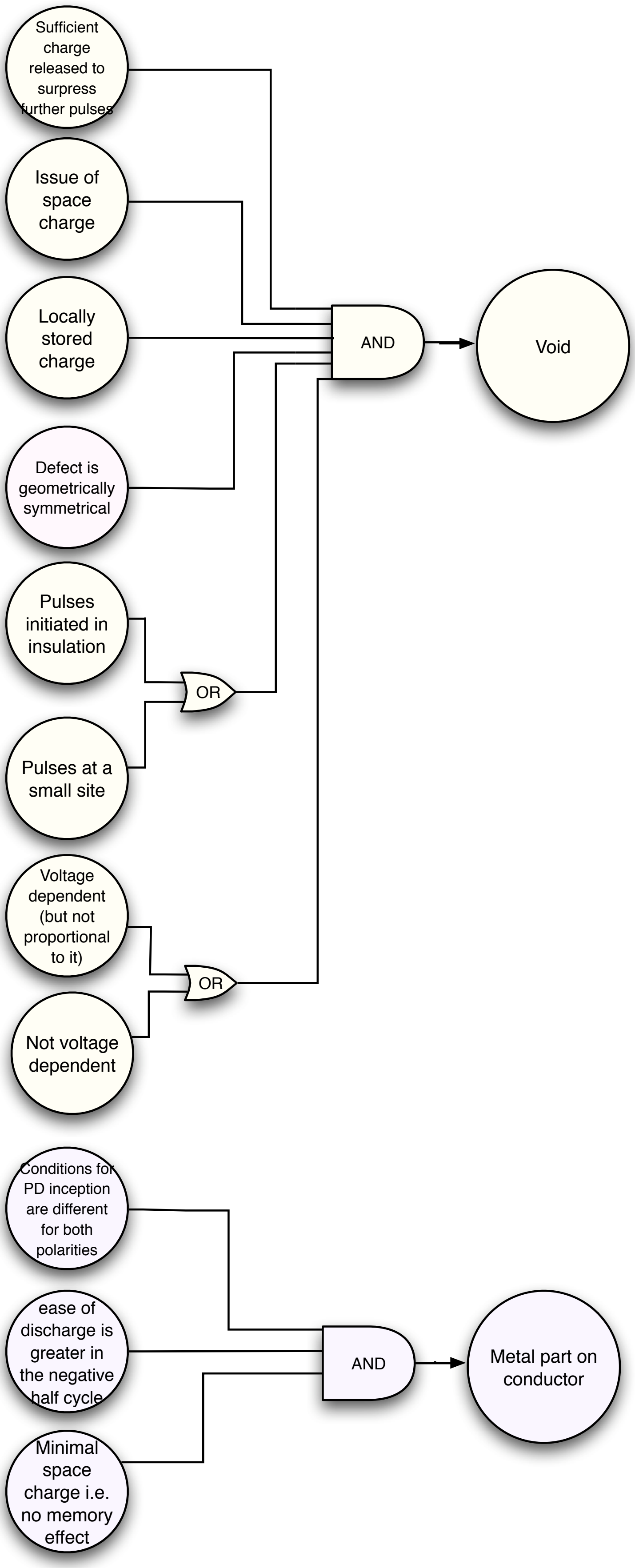
Pulse Distribution

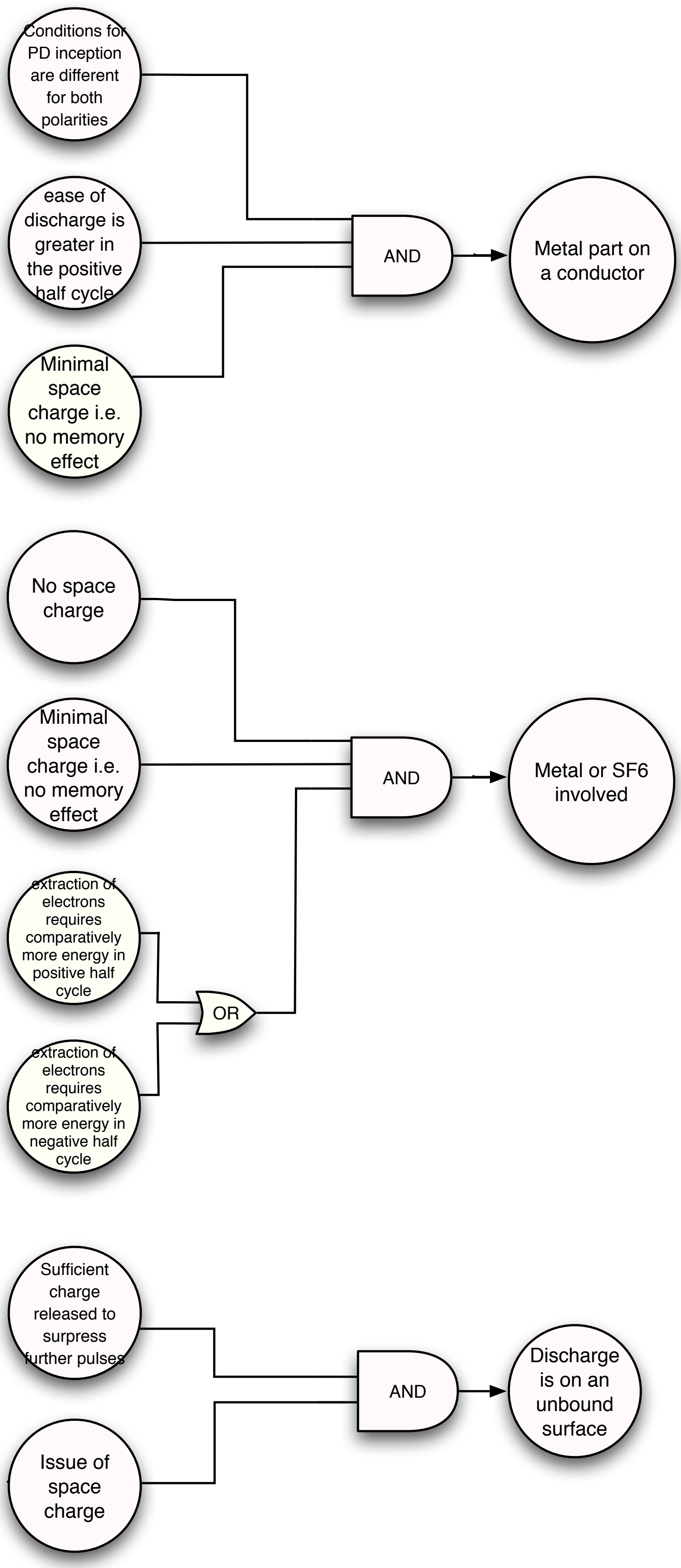


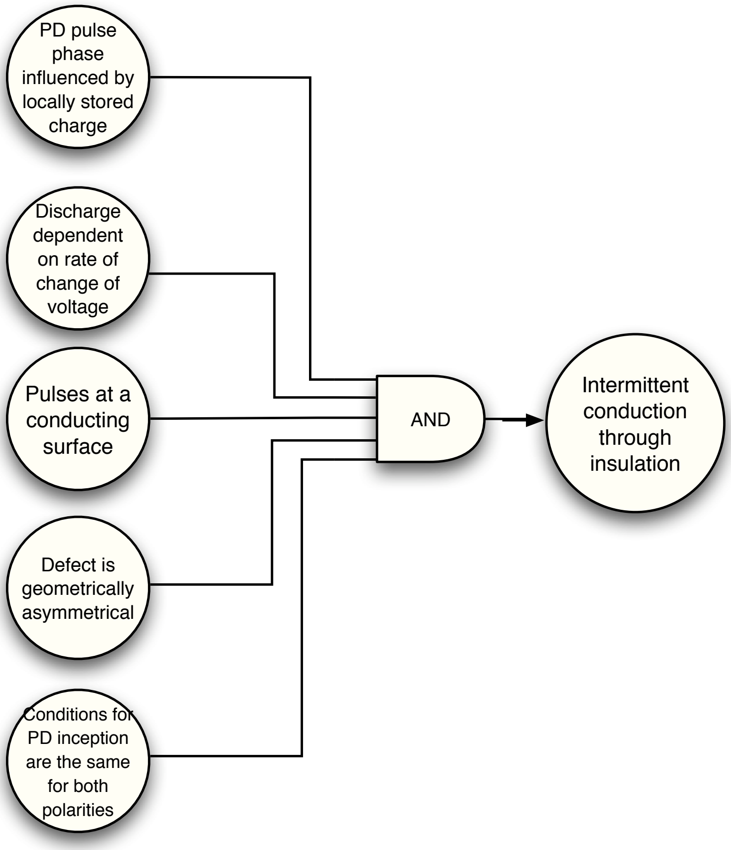

Phase Range
Narrow range
Sufficient charge released to surpress further pulses
Broad range
PD pulse phase influenced by locally stored charge
Charge can easily disperse
Many small discharging sites acting simultaneously
Density
Dense
Pulses at a conducting surface
No space charge
Sparse
Interference
Defect experiencing inconsistent electric field
Space charge with long time constant
Magnitude Consistency
Constant magnitude
Constant geometry and capacitance
Certain amount of energy to ionise the insulation
Not constant magnitude
PD site is not confined to one region
Locally stored charge

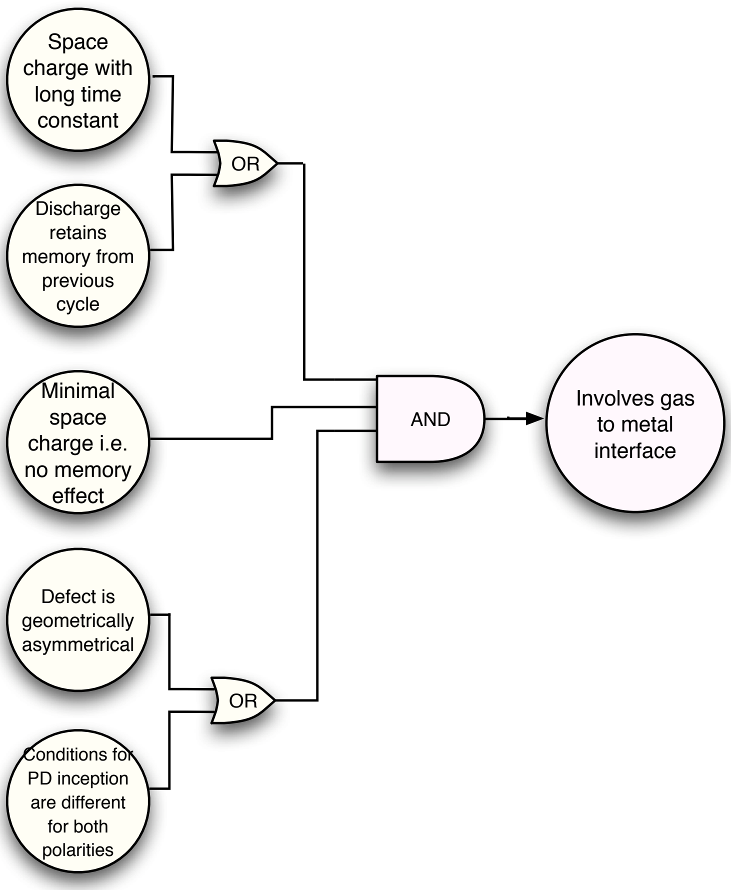
Appendix 2 - Semantic Networks Models of Stage #3

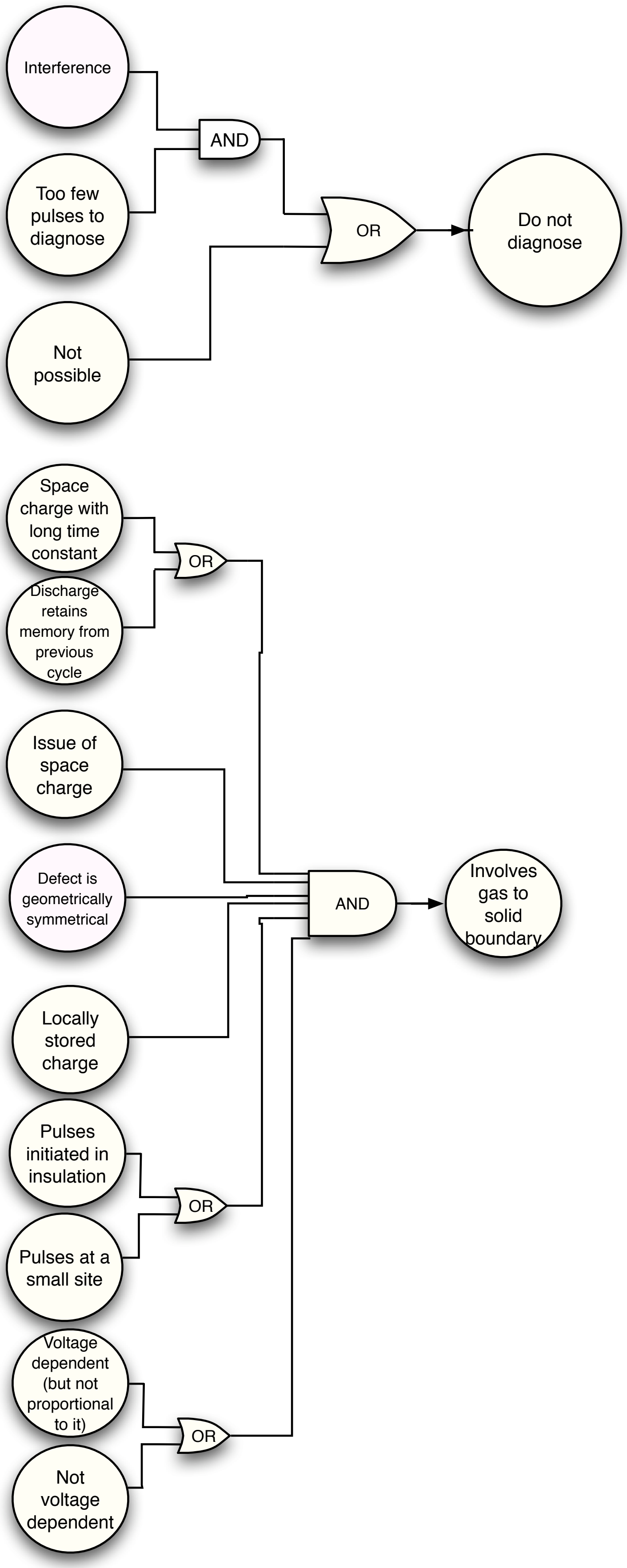


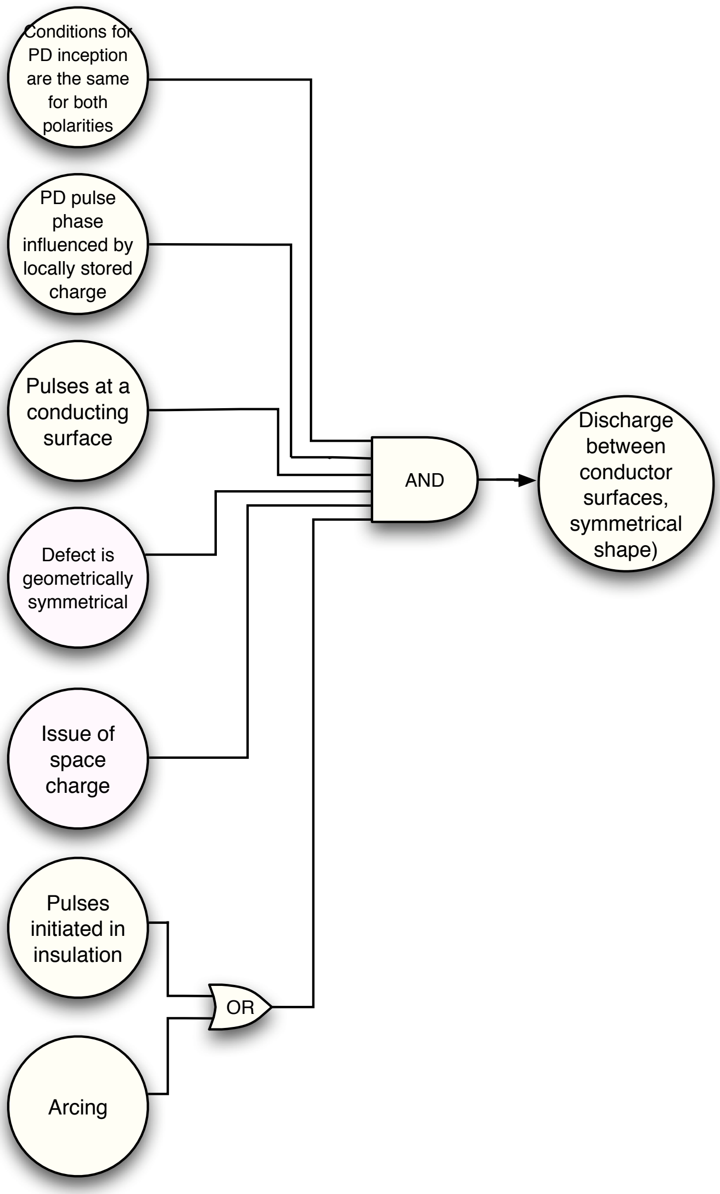

Sufficient charge released to surpress further pulses
Issue of space charge
Locally stored charge
Defect is geometrically symmetrical
Pulses initiated in insulation
Pulses at a small site
OR
Voltage dependent (but not proportional to it)
Not voltage dependent
OR
AND
Void
Conditions for PD inception are different for both polarities
ease of discharge is greater in the negative half cycle
Minimal space charge i.e. no memory effect
AND
Metal part on conductor

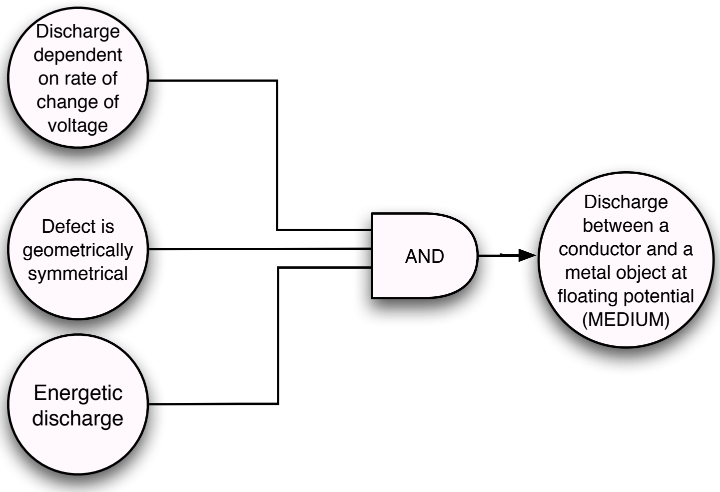

Conditions for PD inception are different for both polarities
ease of discharge is greater in the positive half cycle
Minimal space charge i.e. no memory effect
AND
Metal part on a conductor
No space charge
Minimal space charge i.e. no memory effect
extraction of electrons requires comparatively more energy in positive half cycle
extraction of electrons requires comparatively more energy in negative half cycle
OR
AND
Metal or SF6 involved
Sufficient charge released to surpress further pulses
Issue of space charge
AND
Discharge is on an unbound surface

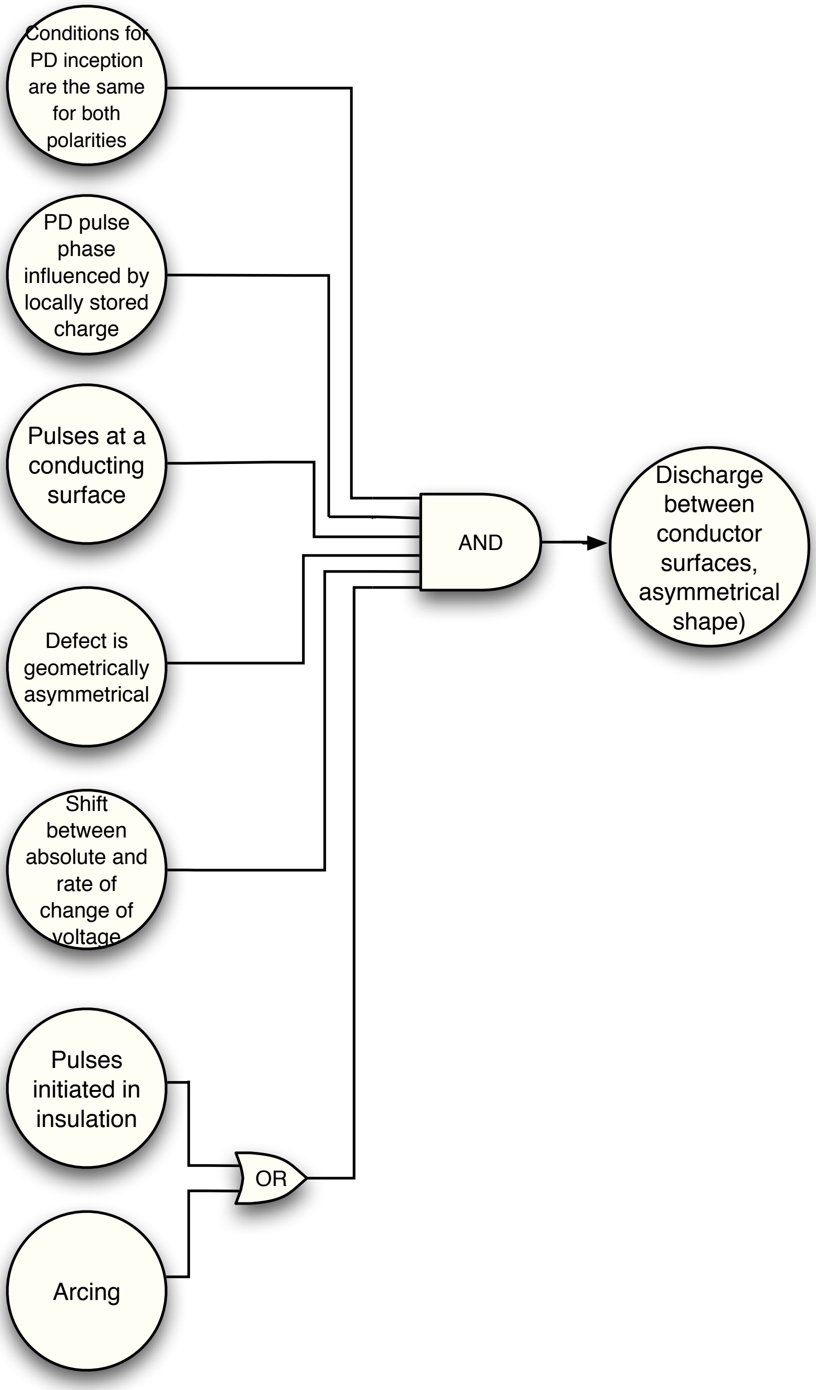

PD pulse phase influenced by locally stored charge
Discharge dependent on rate of change of voltage
Pulses at a conducting surface
Defect is geometrically asymmetrical
Conditions for PD inception are the same for both polarities
AND
Intermittent conduction through insulation

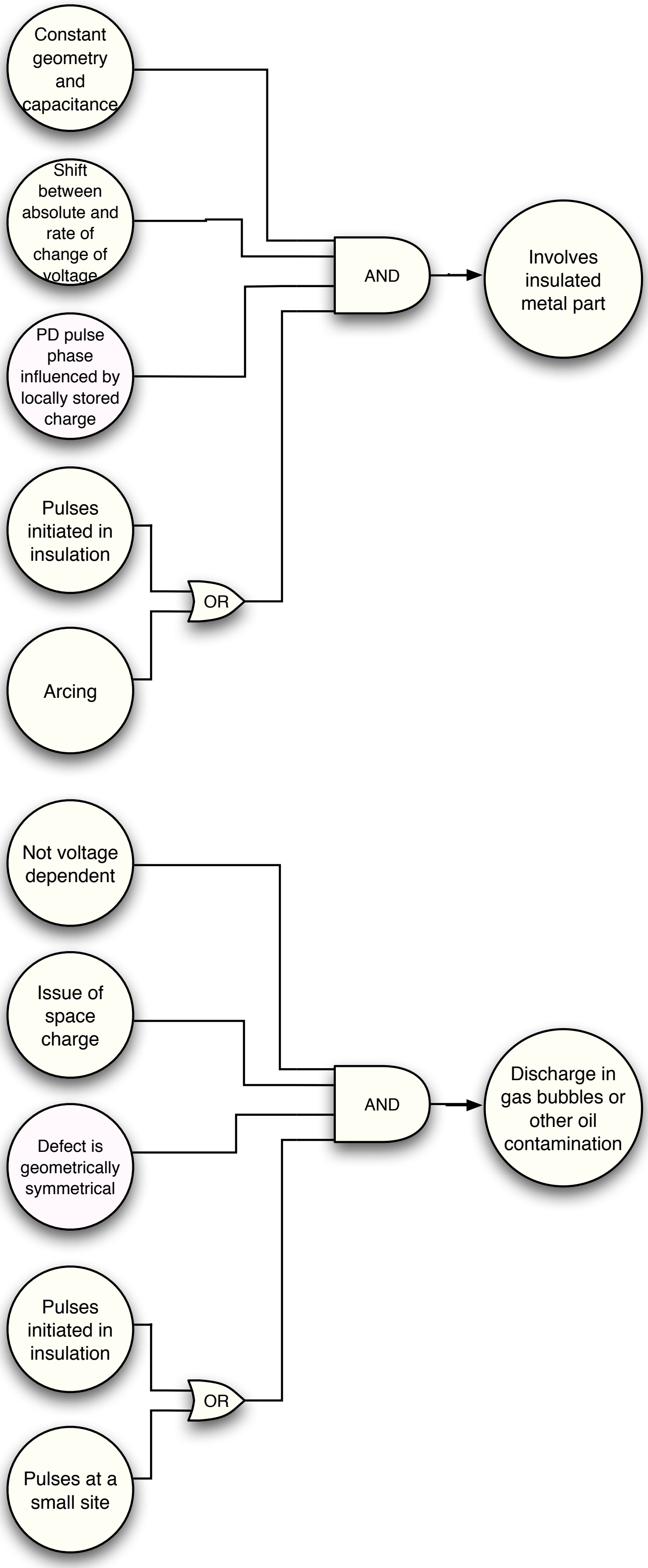

Space charge with long time constant
Discharge retains memory from previous cycle
OR
Minimal space charge i.e. no memory effect
Defect is geometrically asymmetrical
Conditions for PD inception are different for both polarities
OR
AND
Involves gas to metal interface

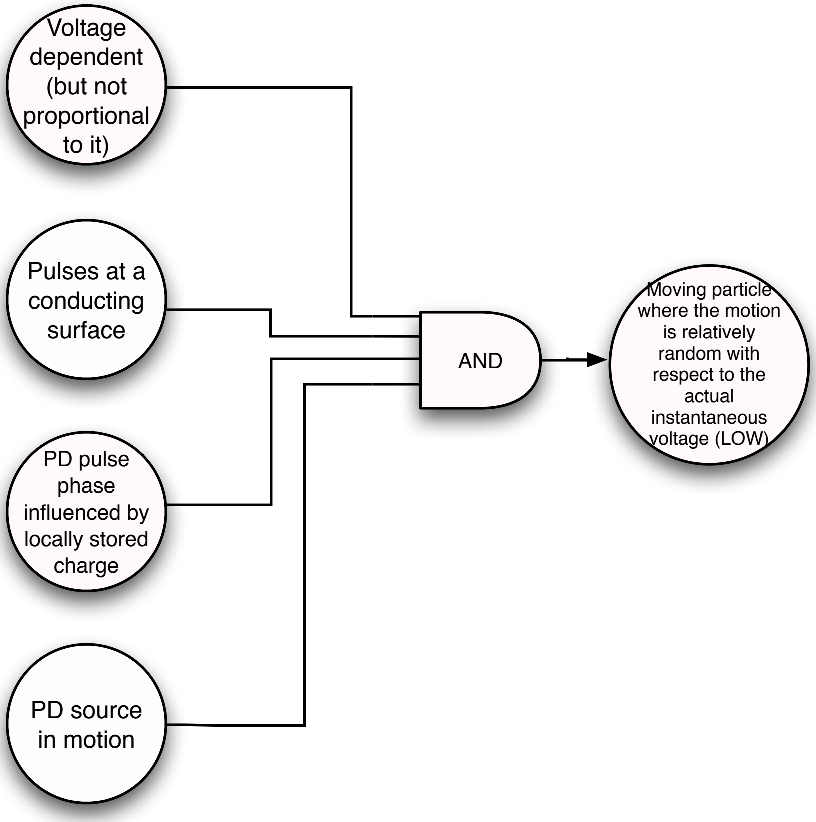

Interference
AND
Too few pulses to diagnose
OR
Do not diagnose
Not possible
Space charge with long time constant
OR
Discharge retains memory from previous cycle
Issue of space charge
Defect is geometrically symmetrical
AND
Involves gas to solid boundary
Locally stored charge
Pulses initiated in insulation
OR
Pulses at a small site
Voltage dependent (but not proportional to it)
OR
Not voltage dependent


Conditions for PD inception are the same for both polarities
PD pulse phase influenced by locally stored charge
Pulses at a conducting surface
Defect is geometrically symmetrical
Issue of space charge
Pulses initiated in insulation
Arcing
OR
AND
Discharge between conductor surfaces, symmetrical shape)

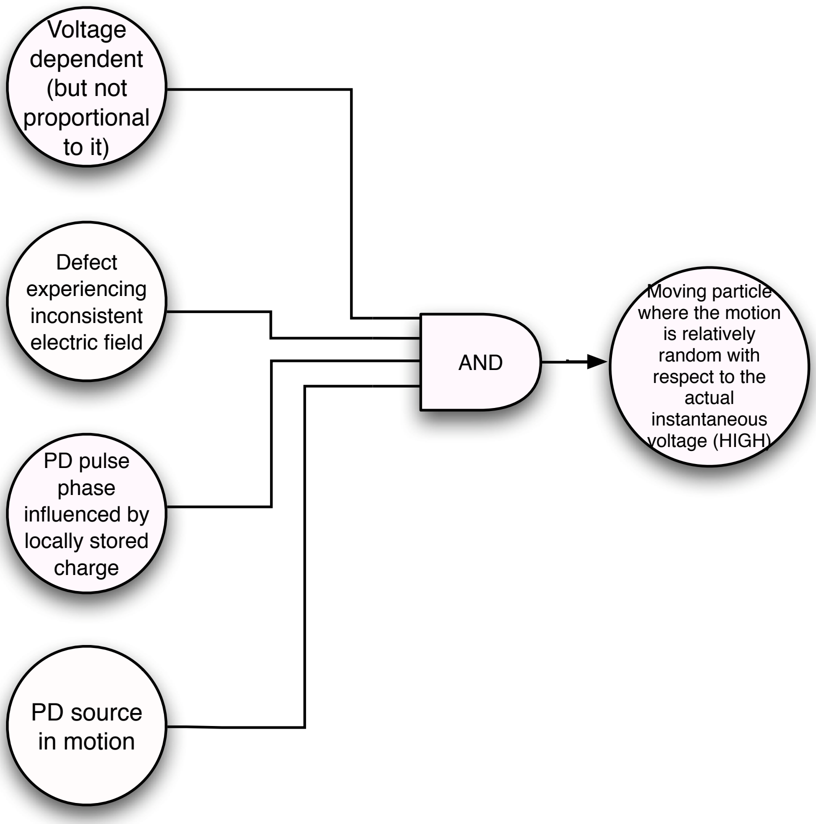

Discharge dependent on rate of change of voltage
Defect is geometrically symmetrical
Energetic discharge
AND
Discharge between a conductor and a metal object at floating potential (MEDIUM)


Conditions for PD inception are the same for both polarities
PD pulse phase influenced by locally stored charge
Pulses at a conducting surface
Defect is geometrically asymmetrical
Shift between absolute and rate of change of voltage
Pulses initiated in insulation
Arcing
OR
AND
Discharge between conductor surfaces, asymmetrical shape)

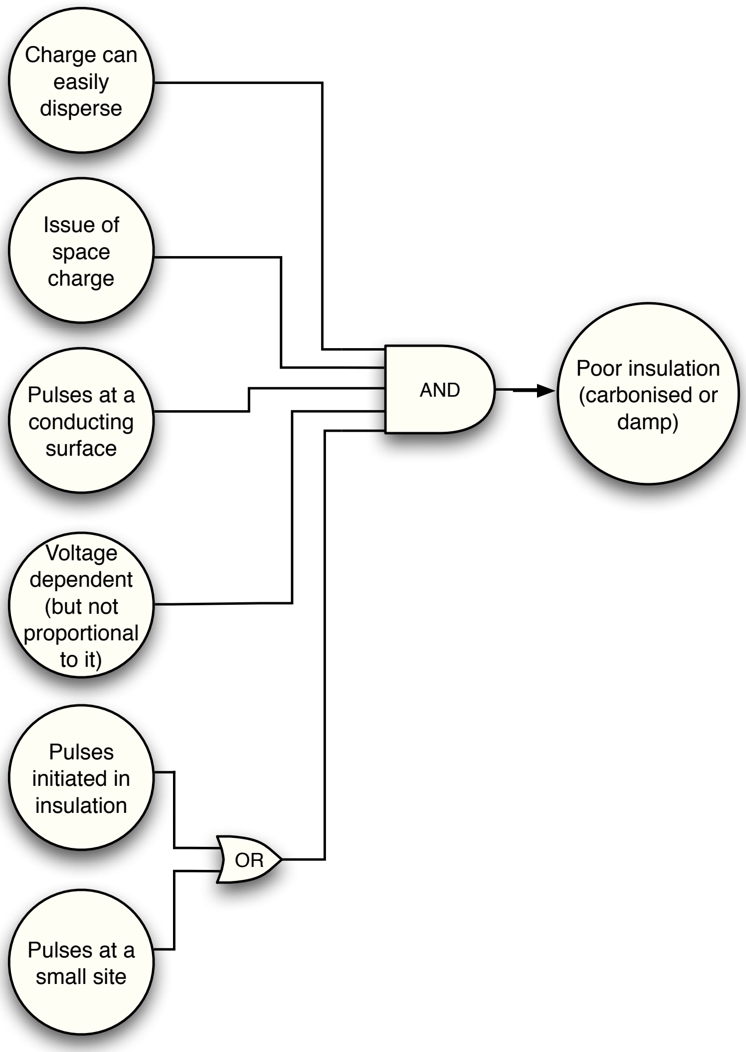

Constant geometry and capacitance
Shift between absolute and rate of change of voltage
PD pulse phase influenced by locally stored charge
Pulses initiated in insulation
Arcing
OR
AND
Involves insulated metal part
Not voltage dependent
Issue of space charge
Defect is geometrically symmetrical
Pulses initiated in insulation
Pulses at a small site
OR
AND
Discharge in gas bubbles or other oil contamination

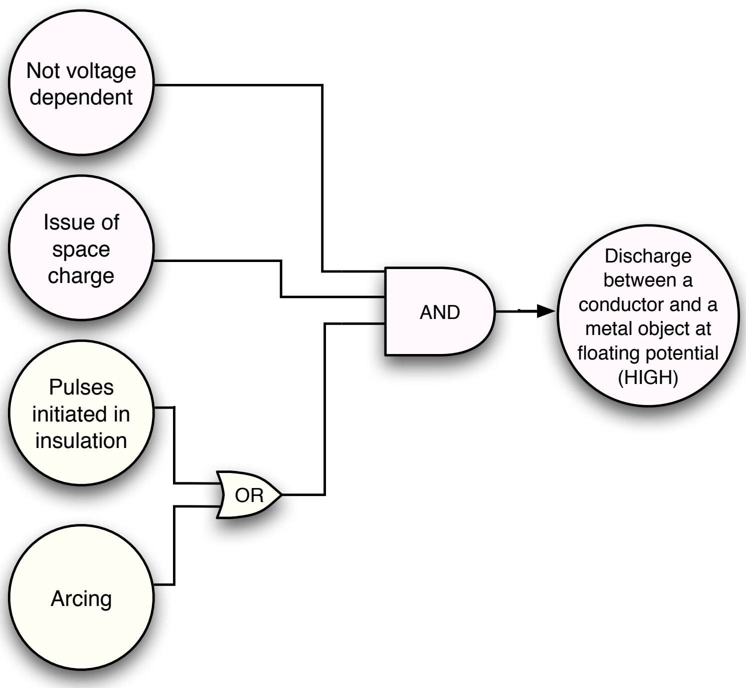


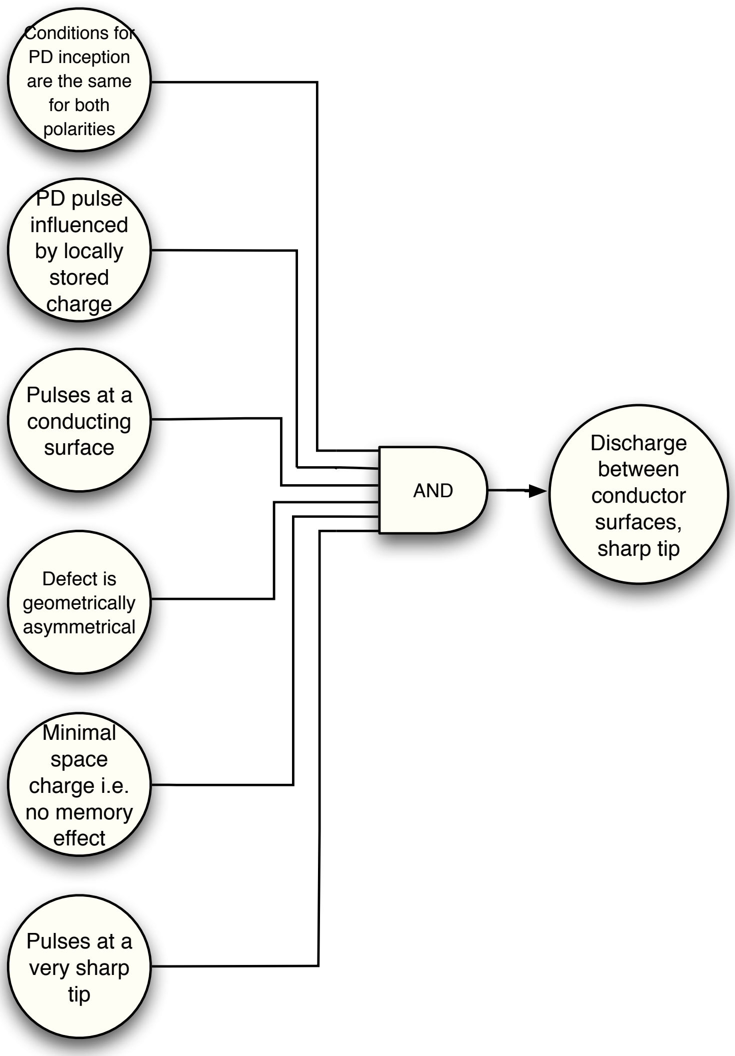
Voltage dependent (but not proportional to it)
Pulses at a conducting surface
PD pulse phase influenced by locally stored charge
PD source in motion
AND
Moving particle where the motion is relatively random with respect to the actual instantaneous voltage (LOW)

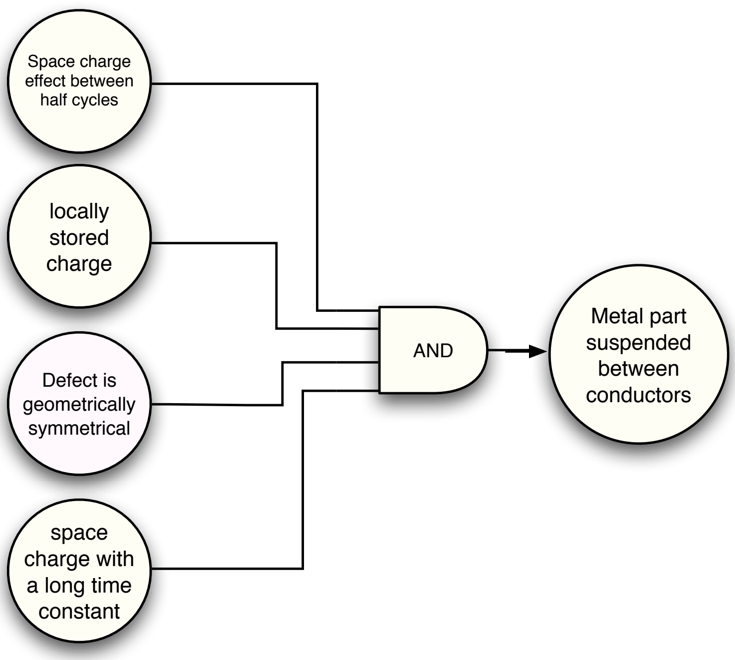


Voltage dependent (but not proportional to it)
Defect experiencing inconsistent electric field
PD pulse phase influenced by locally stored charge
PD source in motion
AND
Moving particle where the motion is relatively random with respect to the actual instantaneous voltage (HIGH)


Charge can easily disperse
Issue of space charge
Pulses at a conducting surface
Voltage dependent (but not proportional to it)
Pulses initiated in insulation
Pulses at a small site
OR
AND
Poor insulation (carbonised or damp)

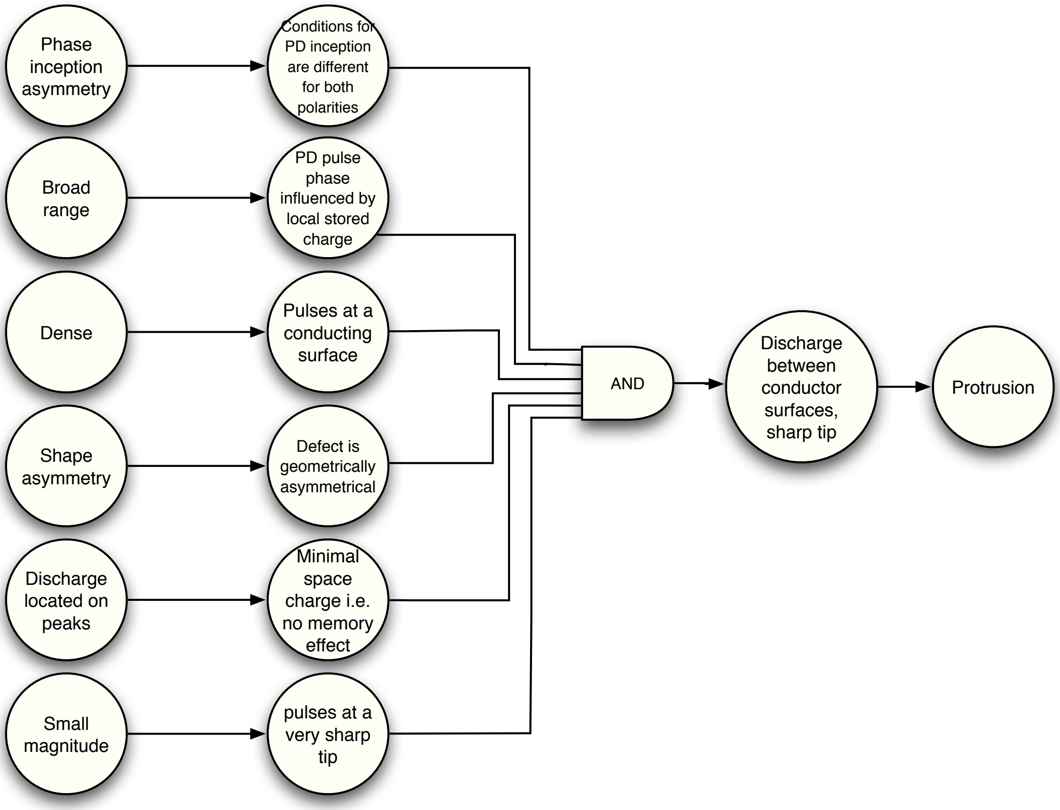

Not voltage dependent
Issue of space charge
Pulses initiated in insulation
Arcing
OR
AND
Discharge between a conductor and a metal object at floating potential (HIGH)

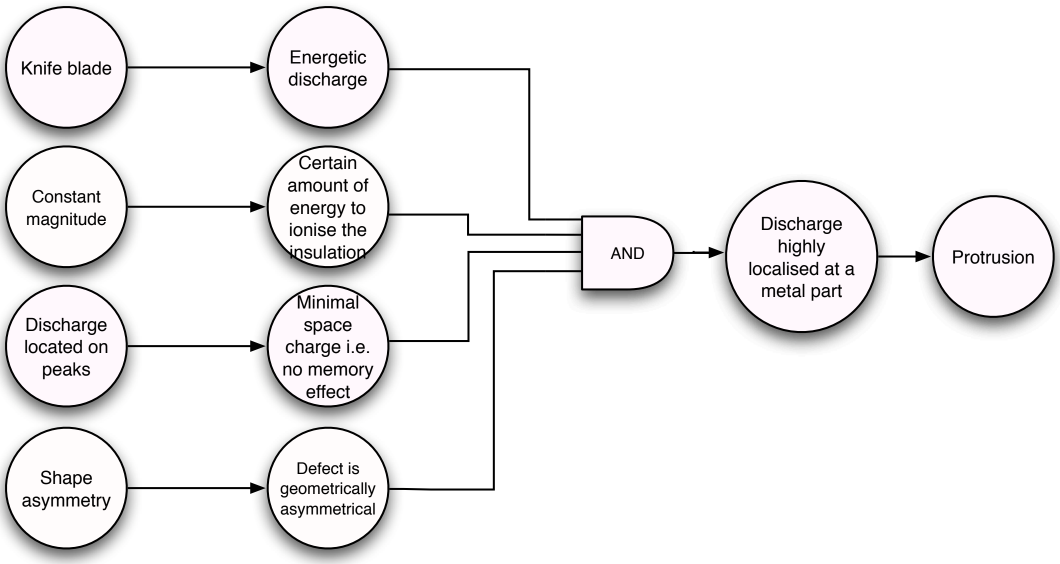

Conditions for PD inception are the same for both polarities
PD pulse influenced by locally stored charge
Pulses at a conducting surface
Defect is geometrically asymmetrical
Minimal space charge i.e. no memory effect
Pulses at a very sharp tip
AND
Discharge between conductor surfaces, sharp tip

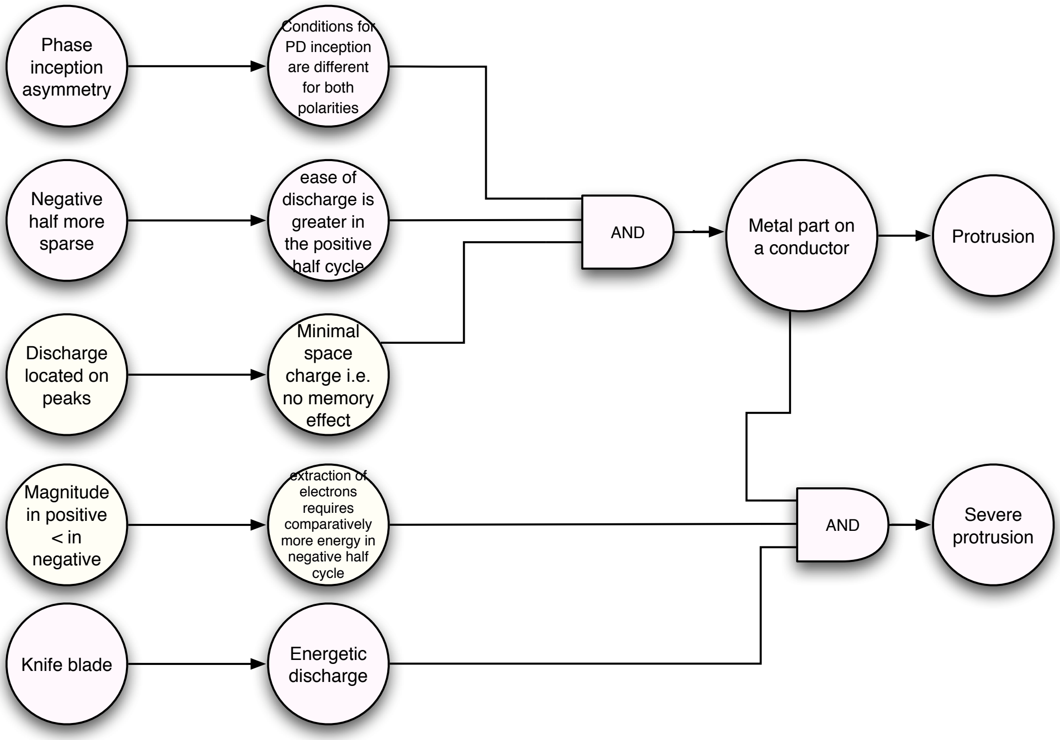

Space charge effect between half cycles
locally stored charge
Defect is geometrically symmetrical
space charge with a long time constant
AND
Metal part suspended between conductors

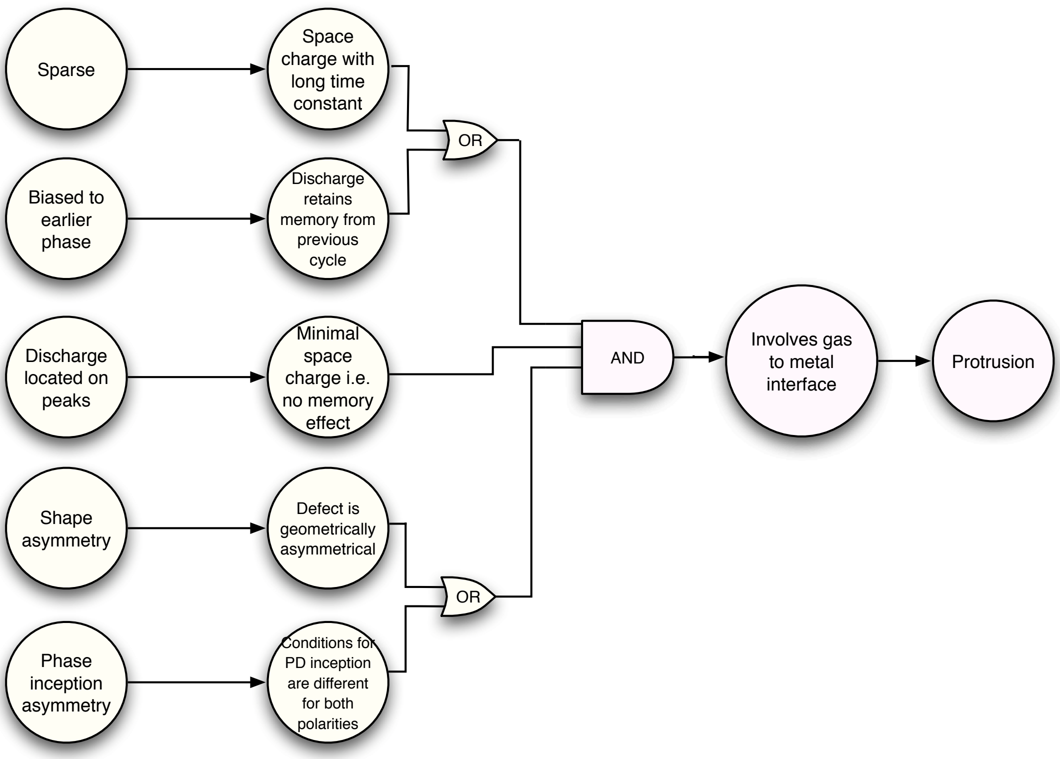
Appendix 3 - Semantic Network Models of Stage #2 to Stage #4

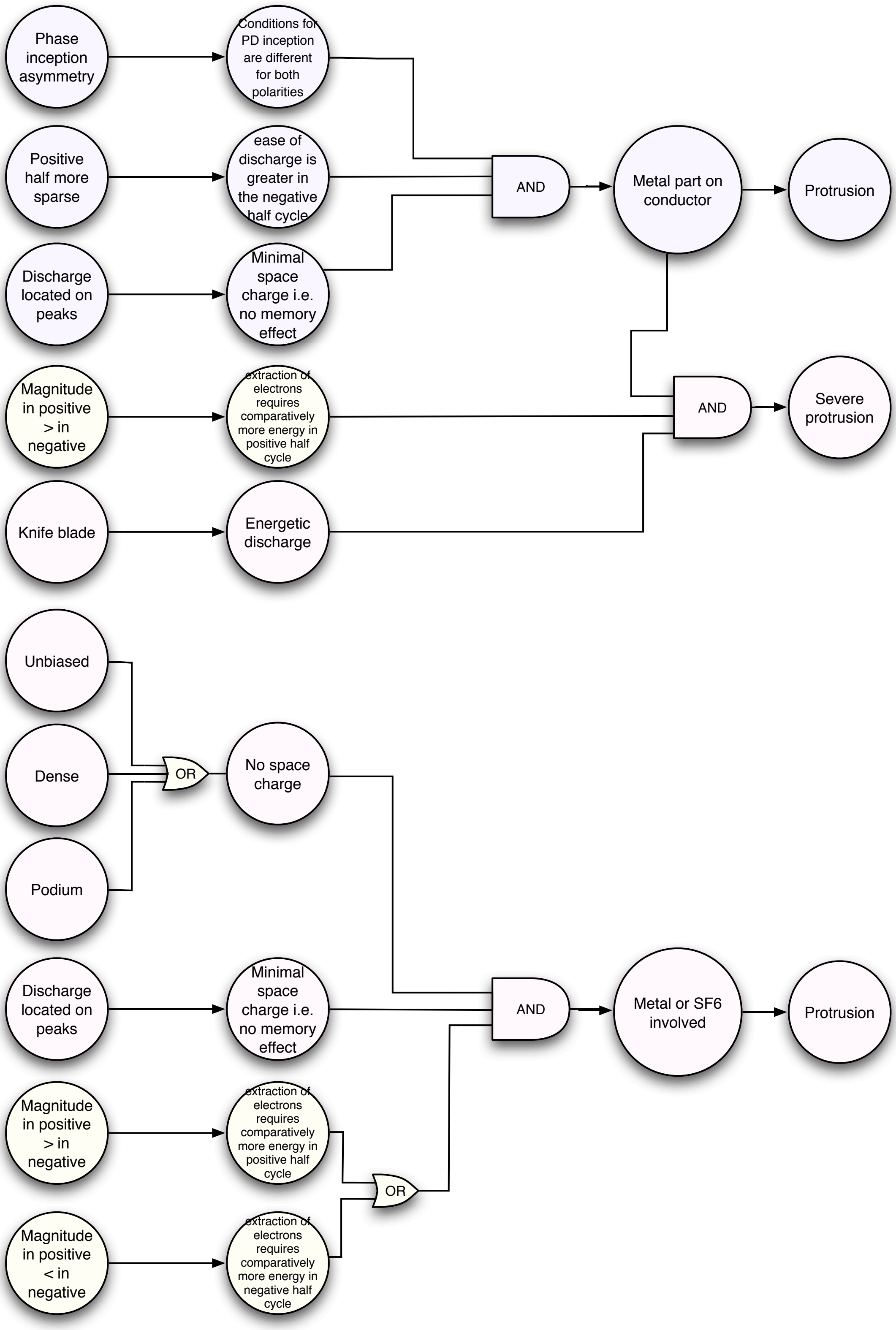
Protrusion



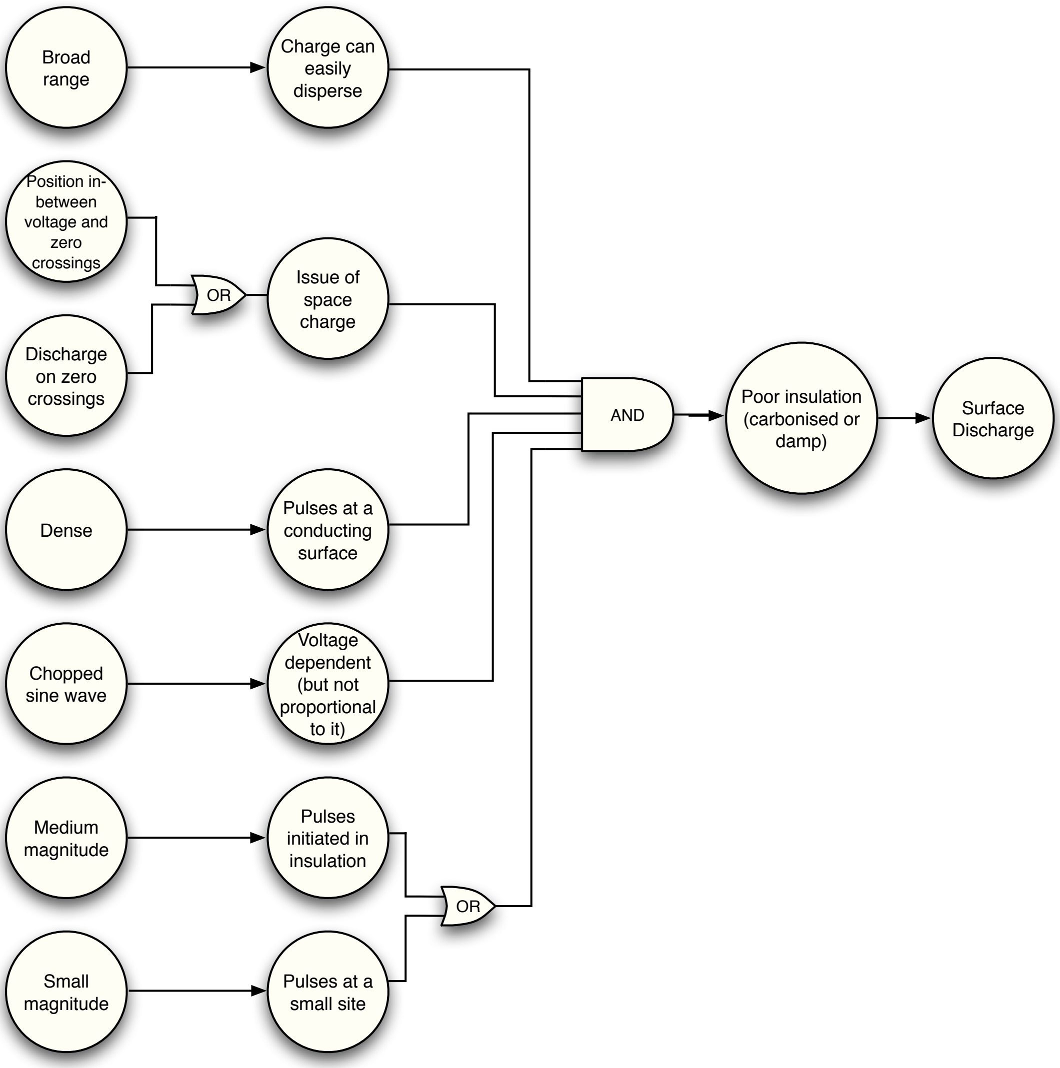


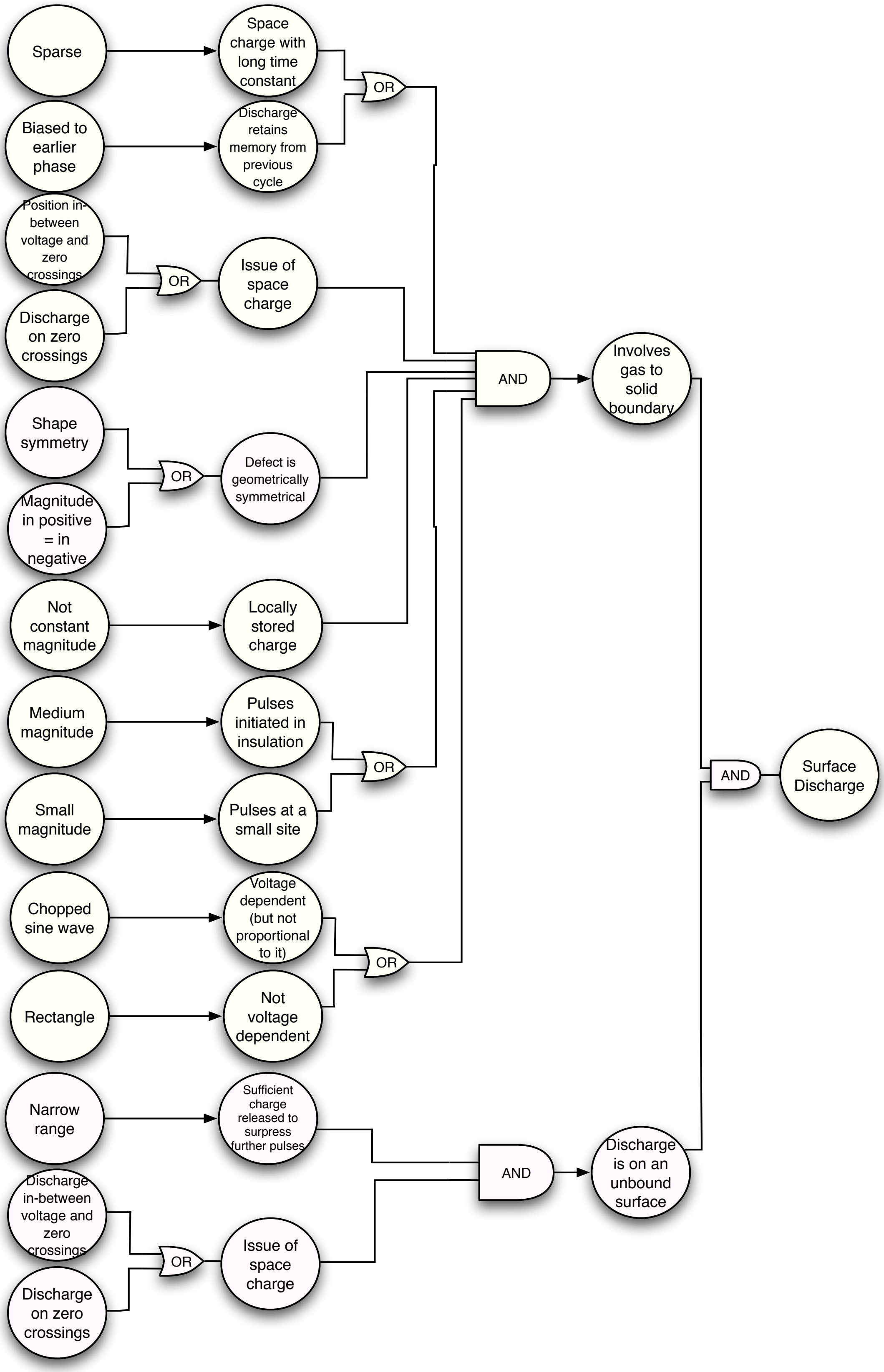

Phase inception asymmetry
Conditions for PD inception are different for both polarities
Negative half more sparse
ease of discharge is greater in the positive half cycle
Discharge located on peaks
Minimal space charge i.e. no memory effect
Magnitude in positive < in negative
extraction of electrons requires comparatively more energy in negative half cycle
Knife blade
Energetic discharge
AND
Metal part on a conductor
Protrusion
AND
Severe protrusion

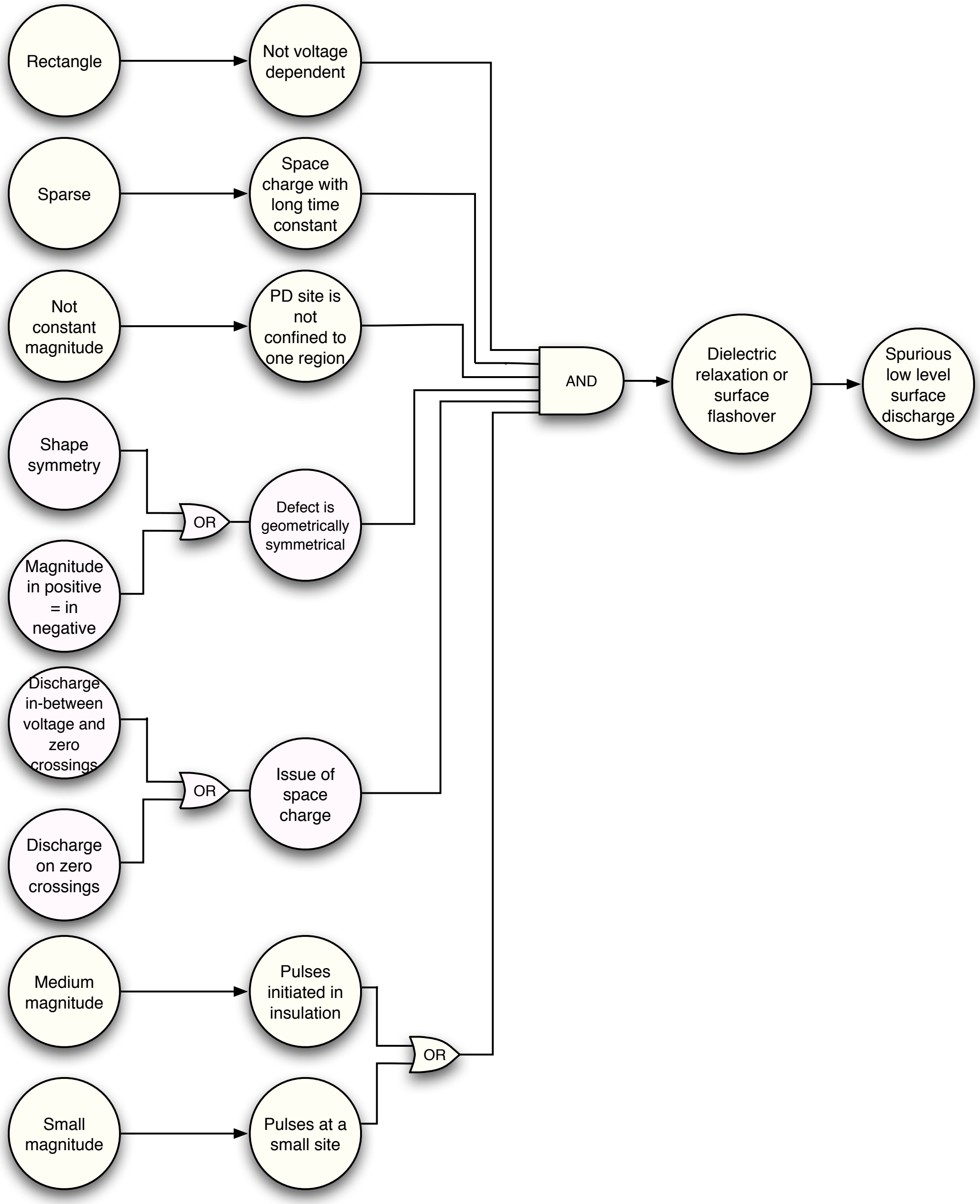

Sparse
Space charge with long time constant
Biased to earlier phase
Discharge retains memory from previous cycle
OR
Discharge located on peaks
Minimal space charge i.e. no memory effect
AND
Involves gas to metal interface
Protrusion
Shape asymmetry
Defect is geometrically asymmetrical
Phase inception asymmetry
Conditions for PD inception are different for both polarities
OR


Phase inception asymmetry
Conditions for PD inception are different for both polarities
Positive half more sparse
ease of discharge is greater in the negative half cycle
Discharge located on peaks
Minimal space charge i.e. no memory effect
AND
Metal part on conductor
Protrusion
Magnitude in positive > in negative
extraction of electrons requires comparatively more energy in positive half cycle
Knife blade
Energetic discharge
AND
Severe protrusion
Unbiased
Dense
Podium
OR
No space charge
Discharge located on peaks
Minimal space charge i.e. no memory effect
AND
Metal or SF6 involved
Protrusion
Magnitude in positive > in negative
extraction of electrons requires comparatively more energy in positive half cycle
OR
Magnitude in positive < in negative
extraction of electrons requires comparatively more energy in negative half cycle

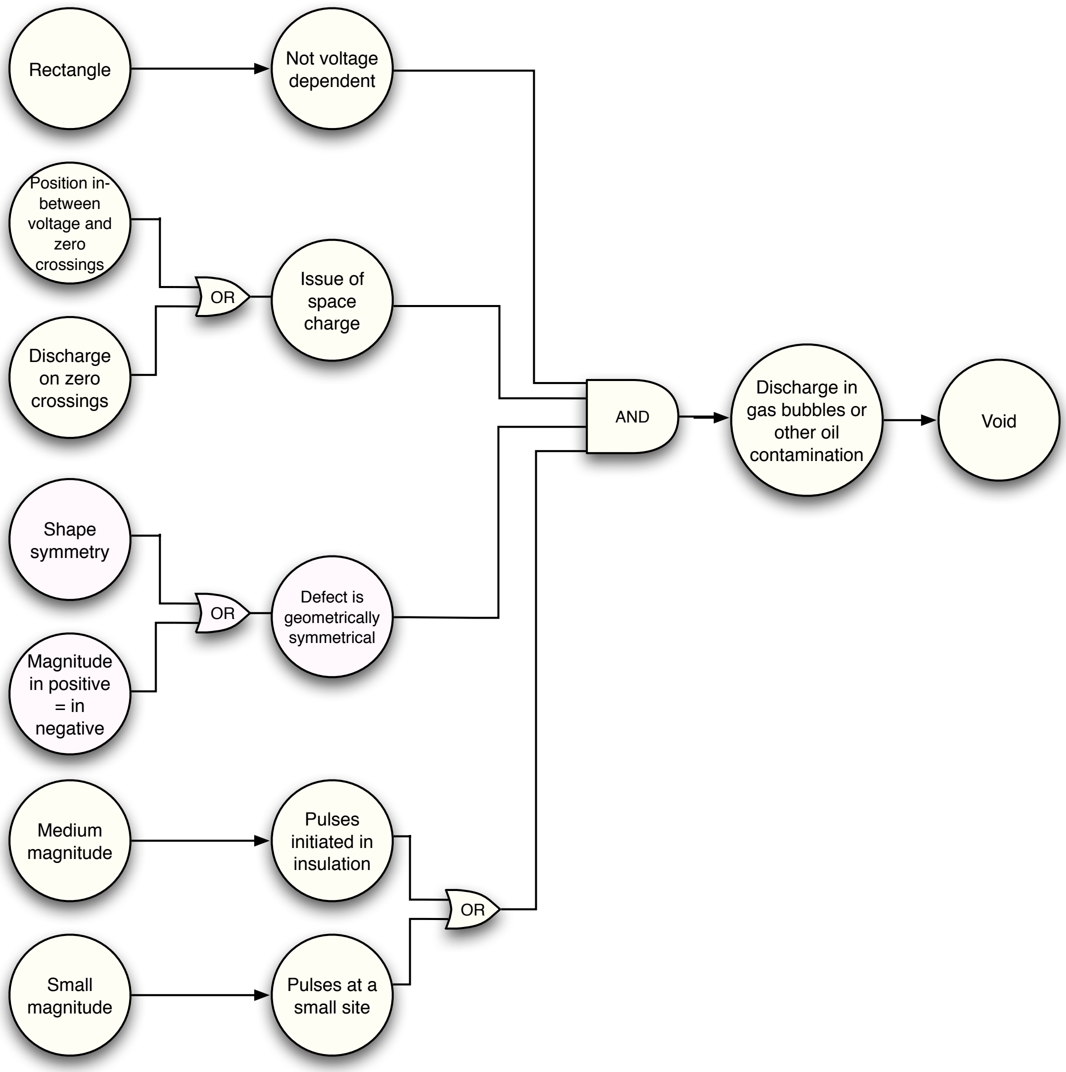
Surface Discharge

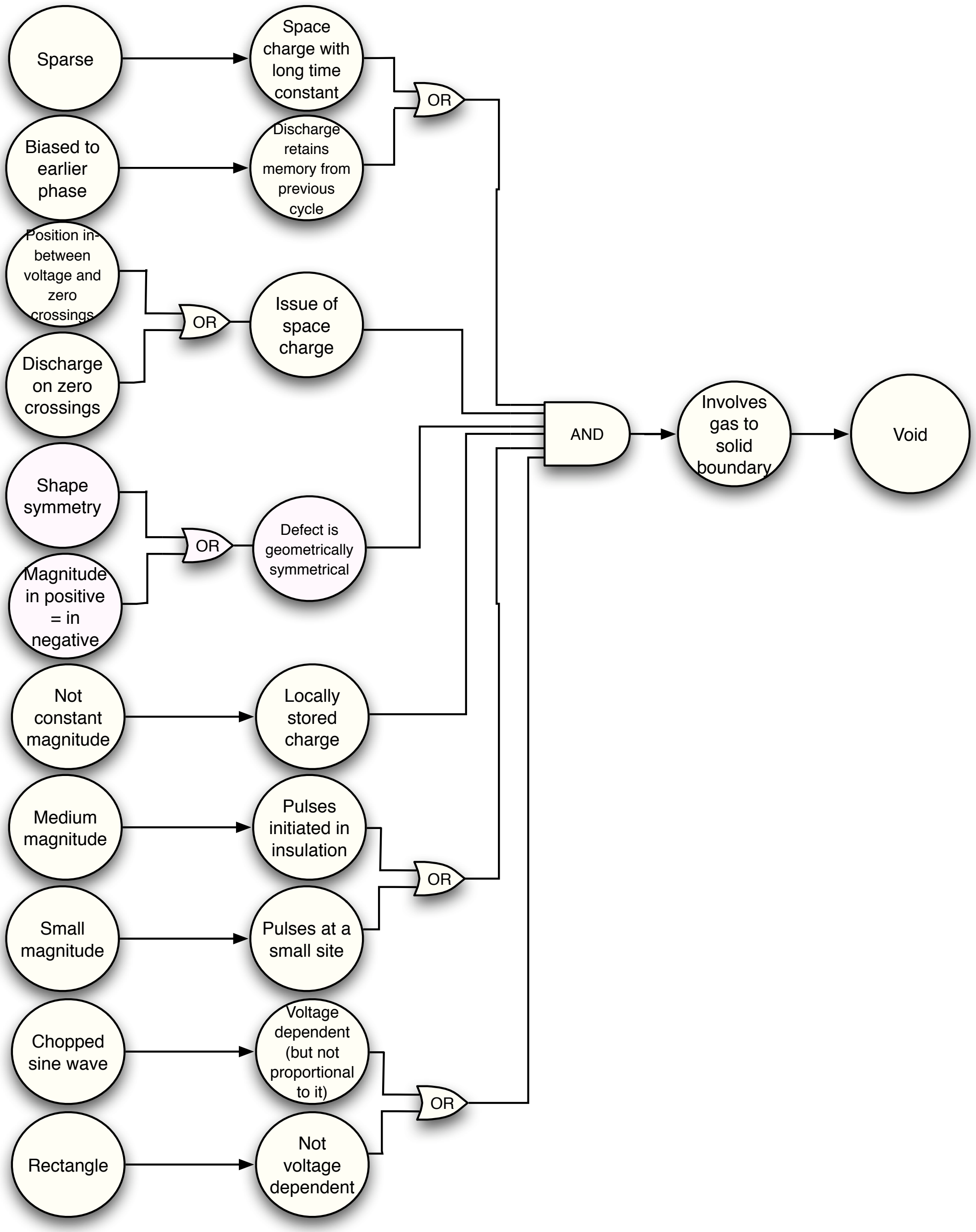


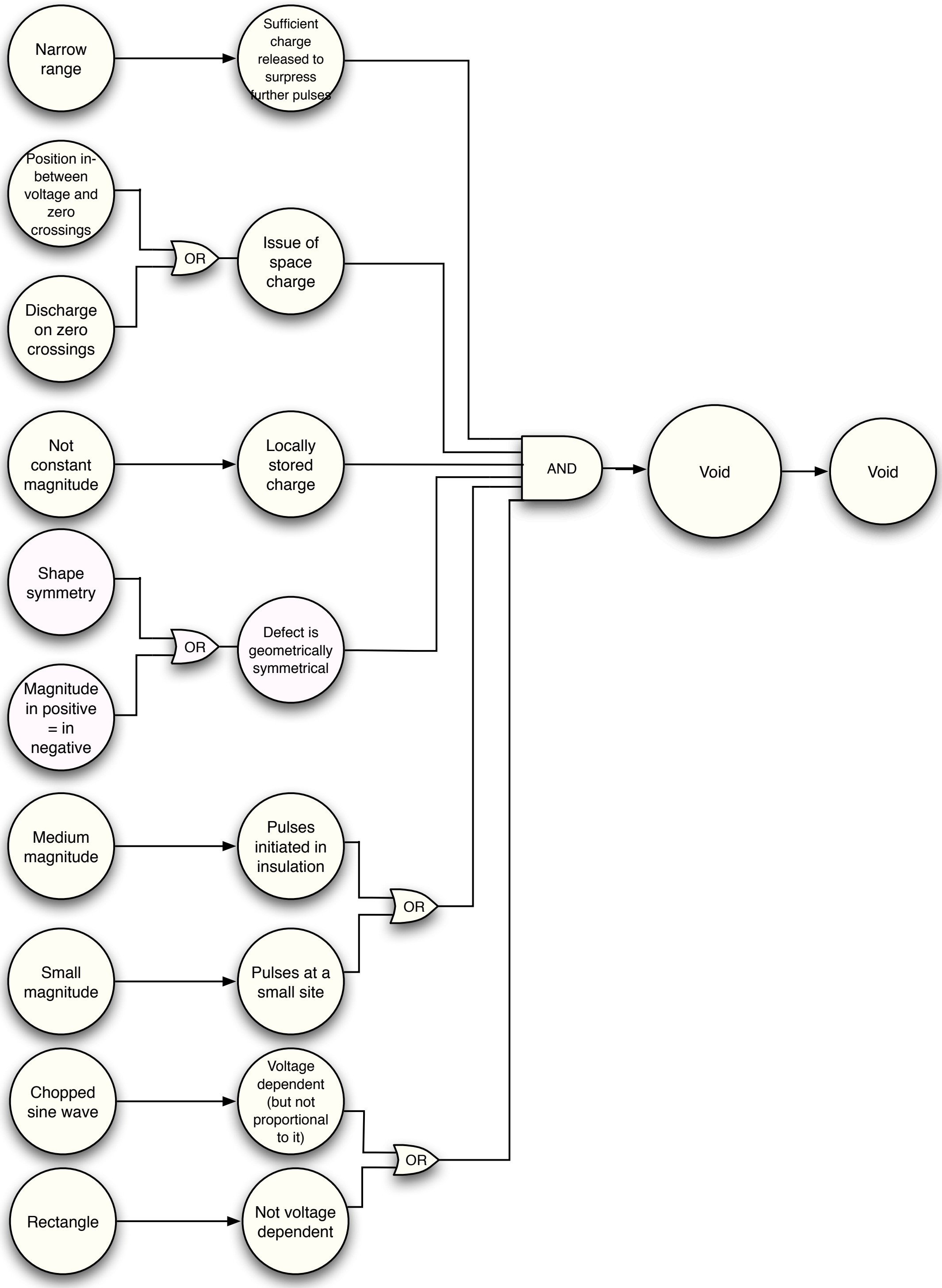

Sparse
Space charge with long time constant
OR
Biased to earlier phase
Discharge retains memory from previous cycle
Position in-between voltage and zero crossings
OR
Issue of space charge
Discharge on zero crossings
Shape symmetry
OR
Defect is geometrically symmetrical
Magnitude in positive = in negative
AND
Involves gas to solid boundary
Not constant magnitude
Locally stored charge
Medium magnitude
Pulses initiated in insulation
OR
Small magnitude
Pulses at a small site
AND
Surface Discharge
Chopped sine wave
Voltage dependent (but not proportional to it)
OR
Rectangle
Not voltage dependent
Narrow range
Sufficient charge released to surpress further pulses
AND
Discharge is on an unbound surface
Discharge in-between voltage and zero crossings
OR
Issue of space charge
Discharge on zero crossings


Rectangle
Not voltage dependent
Sparse
Space charge with long time constant
Not constant magnitude
PD site is not confined to one region
Shape symmetry
Magnitude in positive = in negative
OR
Defect is geometrically symmetrical
Discharge in-between voltage and zero crossings
Discharge on zero crossings
OR
Issue of space charge
Medium magnitude
Pulses initiated in insulation
Small magnitude
Pulses at a small site
OR
AND
Dielectric relaxation or surface flashover
Spurious low level surface discharge

Void

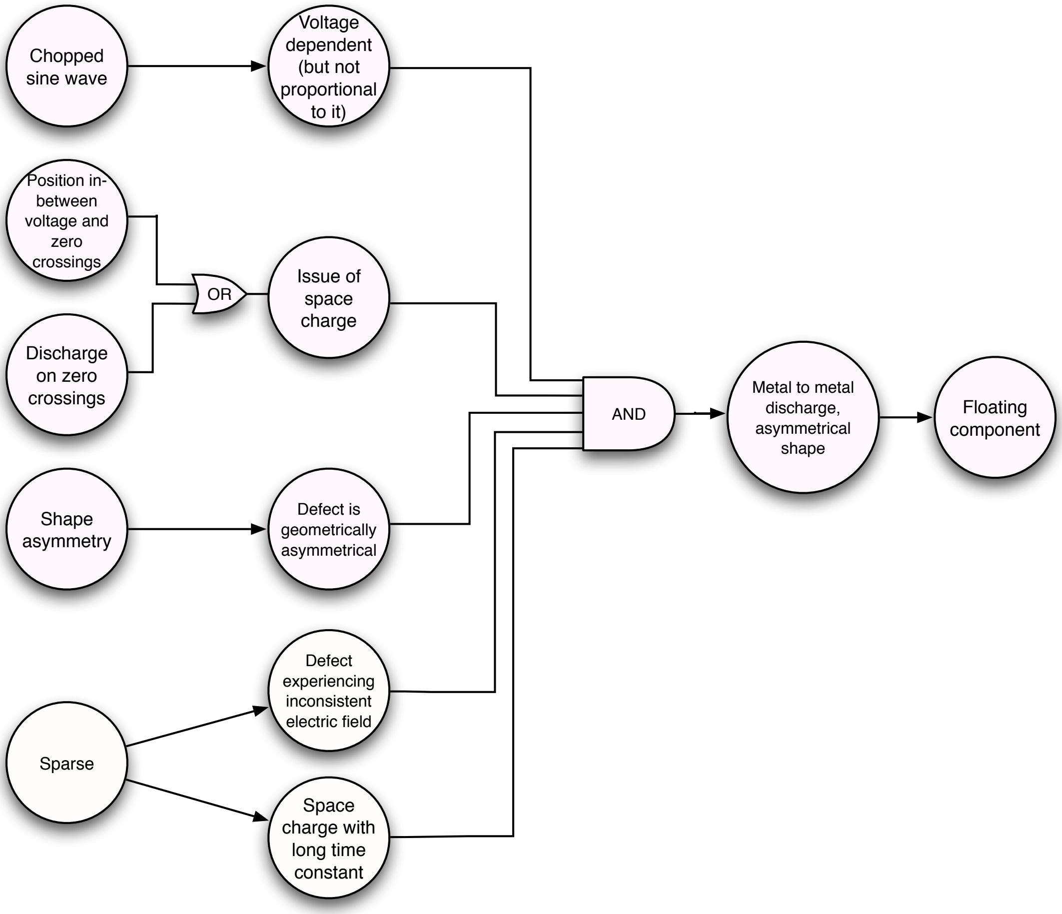

Rectangle
Not voltage dependent
Position in-between voltage and zero crossings
OR
Issue of space charge
Discharge on zero crossings
AND
Discharge in gas bubbles or other oil contamination
Void
Shape symmetry
OR
Defect is geometrically symmetrical
Magnitude in positive = in negative
Medium magnitude
Pulses initiated in insulation
OR
Small magnitude
Pulses at a small site

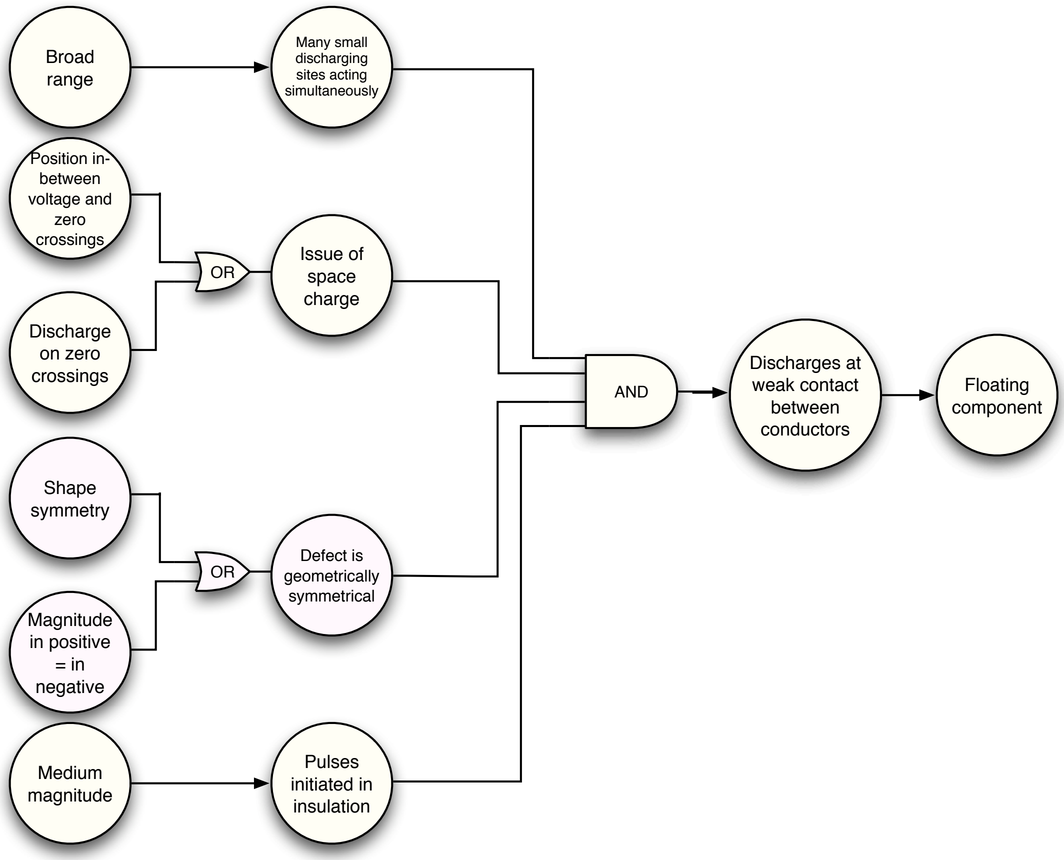

Sparse
Space charge with long time constant
OR
Biased to earlier phase
Discharge retains memory from previous cycle
Position in-between voltage and zero crossings
OR
Issue of space charge
Discharge on zero crossings
AND
Involves gas to solid boundary
Void
Shape symmetry
OR
Defect is geometrically symmetrical
Magnitude in positive = in negative
Not constant magnitude
Locally stored charge
Medium magnitude
Pulses initiated in insulation
OR
Small magnitude
Pulses at a small site
Chopped sine wave
Voltage dependent (but not proportional to it)
OR
Rectangle
Not voltage dependent

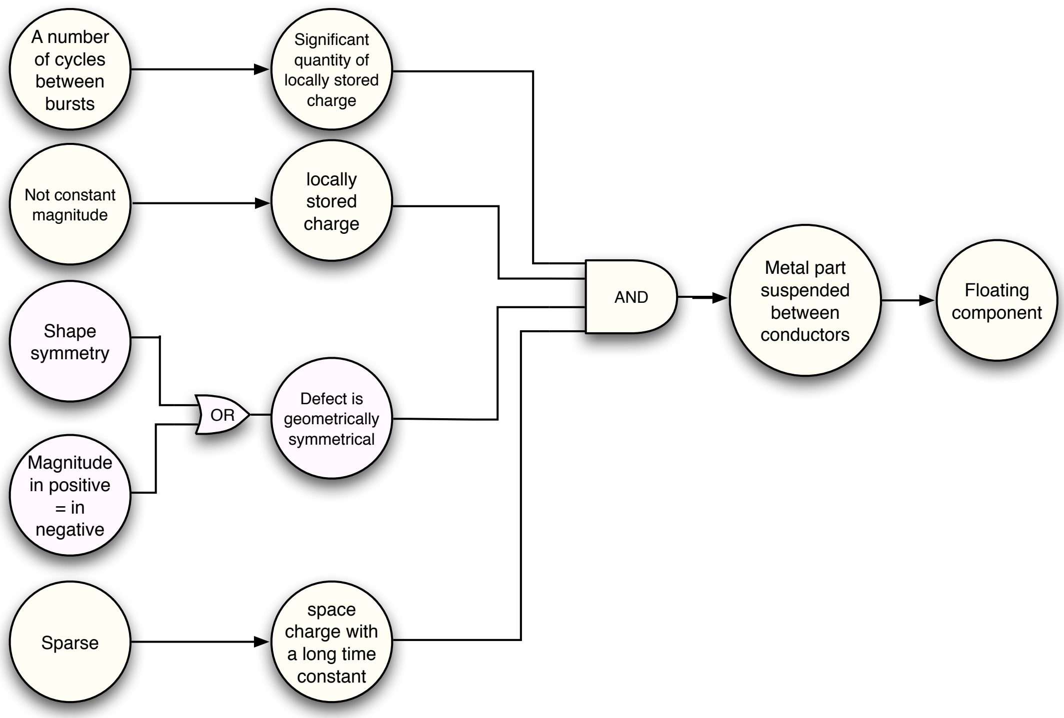


Narrow range
Sufficient charge released to surpress further pulses
Position in-between voltage and zero crossings
Discharge on zero crossings
OR
Issue of space charge
Not constant magnitude
Locally stored charge
AND
Void
Void
Shape symmetry
Magnitude in positive = in negative
OR
Defect is geometrically symmetrical
Medium magnitude
Pulses initiated in insulation
OR
Small magnitude
Pulses at a small site
Chopped sine wave
Voltage dependent (but not proportional to it)
OR
Rectangle
Not voltage dependent

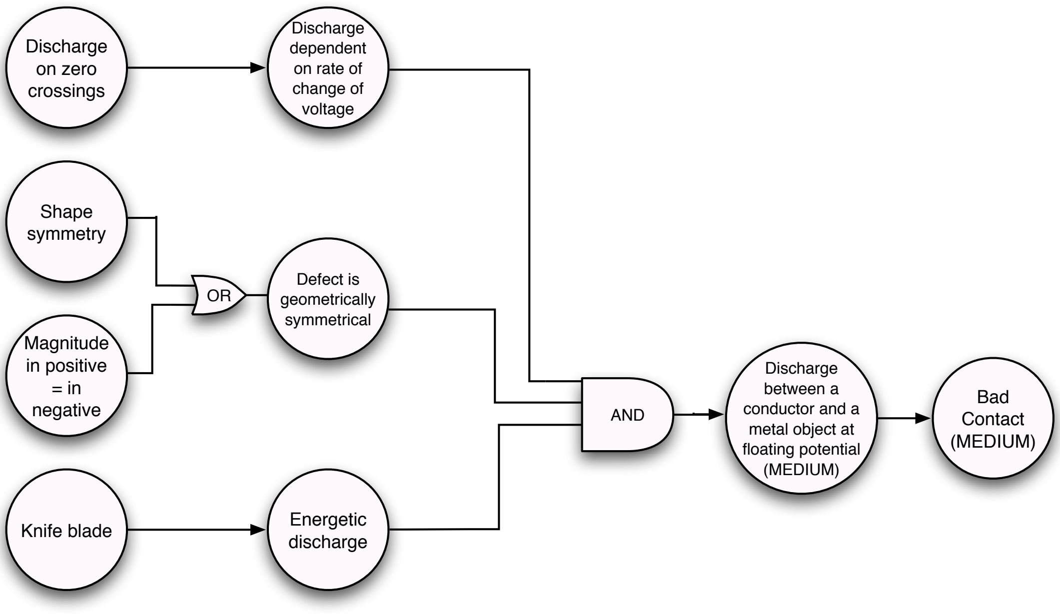
Floating Component

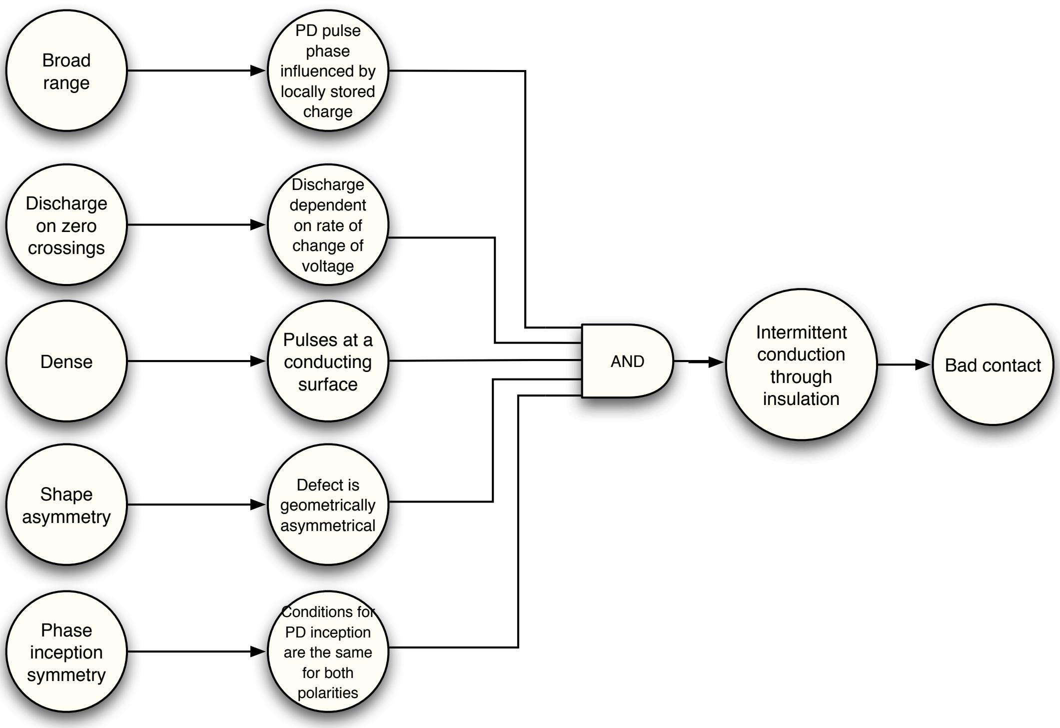



Broad range
Many small discharging sites acting simultaneously
Position in-between voltage and zero crossings
OR
Issue of space charge
Discharge on zero crossings
Shape symmetry
OR
Defect is geometrically symmetrical
Magnitude in positive = in negative
Medium magnitude
Pulses initiated in insulation
AND
Discharges at weak contact between conductors
Floating component

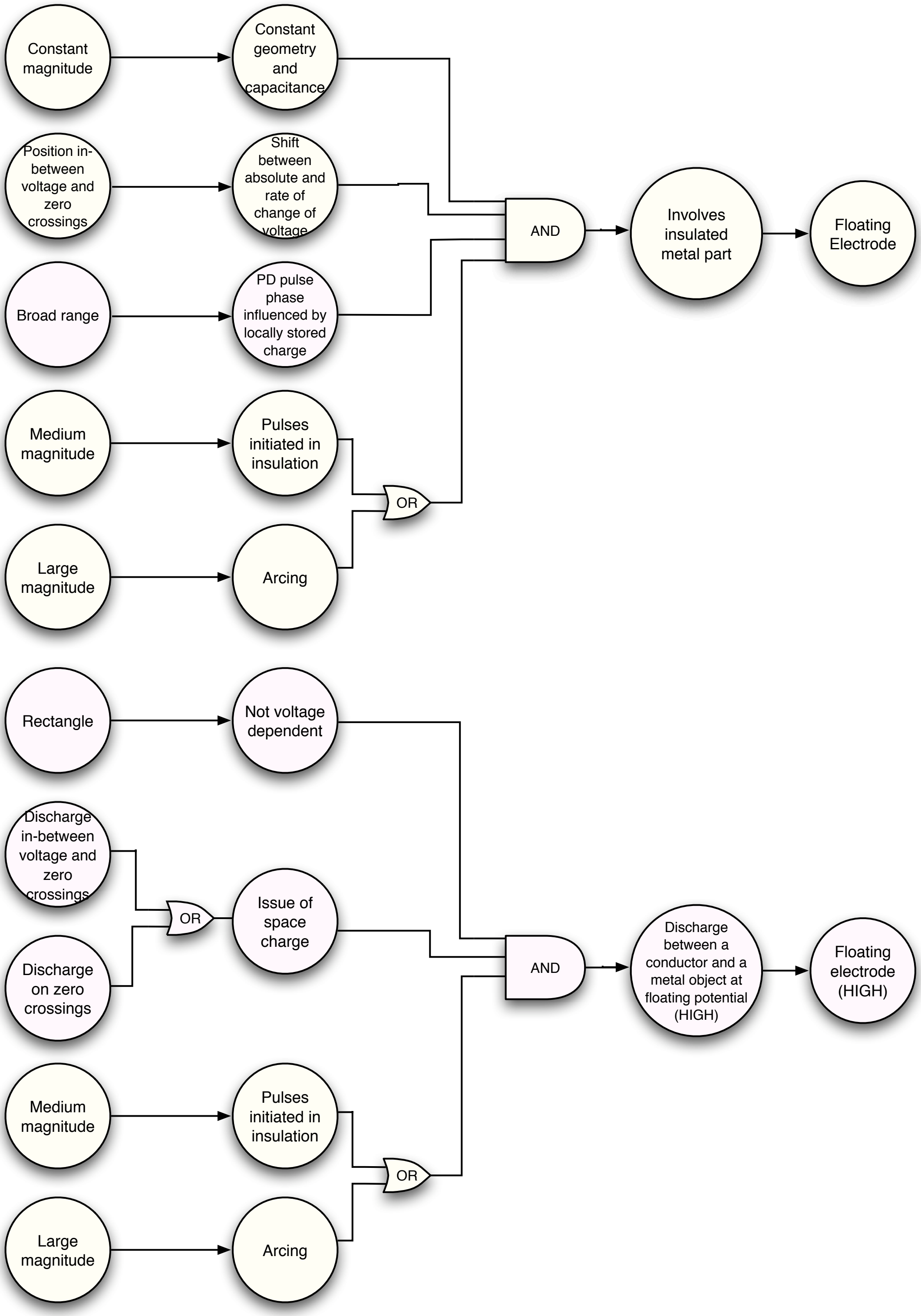

A number of cycles between bursts
Significant quantity of locally stored charge
Not constant magnitude
locally stored charge
Shape symmetry
OR
Defect is geometrically symmetrical
Magnitude in positive = in negative
Sparse
space charge with a long time constant
AND
Metal part suspended between conductors
Floating component

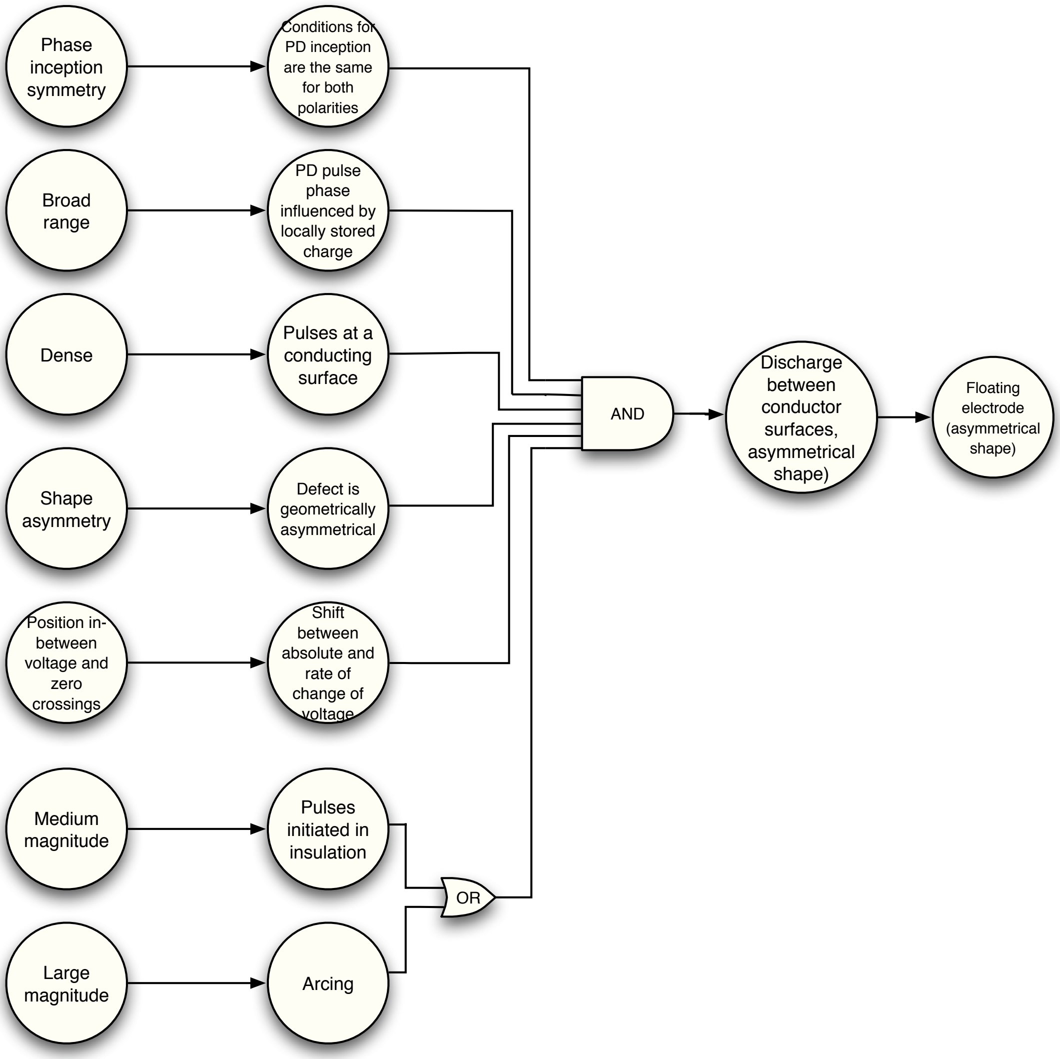
Bad Contact

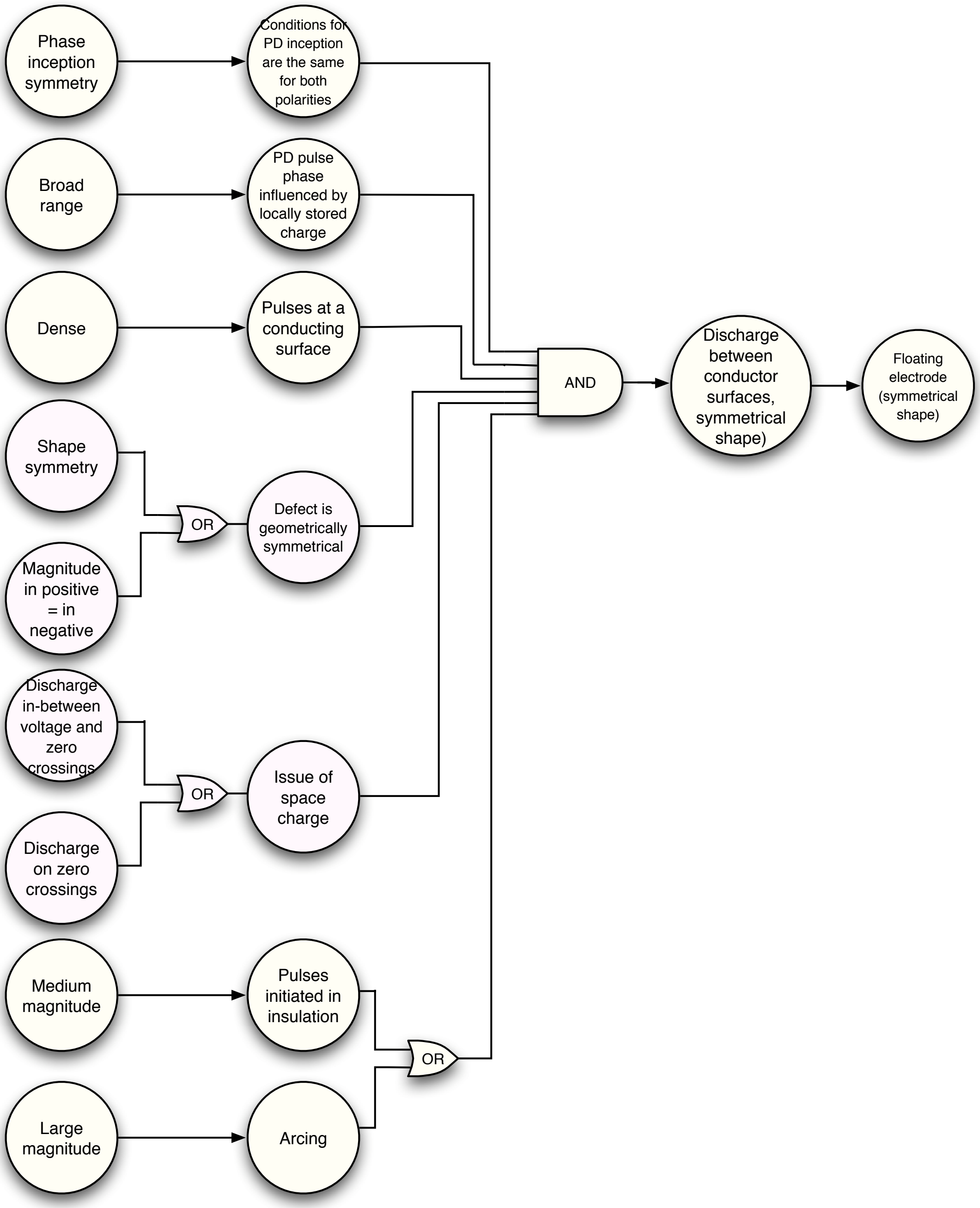

Discharge on zero crossings
Discharge dependent on rate of change of voltage
Shape symmetry
OR
Magnitude in positive = in negative
Defect is geometrically symmetrical
Knife blade
Energetic discharge
AND
Discharge between a conductor and a metal object at floating potential (MEDIUM)
Bad Contact (MEDIUM)


Broad range
PD pulse phase influenced by locally stored charge
Discharge on zero crossings
Discharge dependent on rate of change of voltage
Dense
Pulses at a conducting surface
Shape asymmetry
Defect is geometrically asymmetrical
Phase inception symmetry
Conditions for PD inception are the same for both polarities
AND
Intermittent conduction through insulation
Bad contact

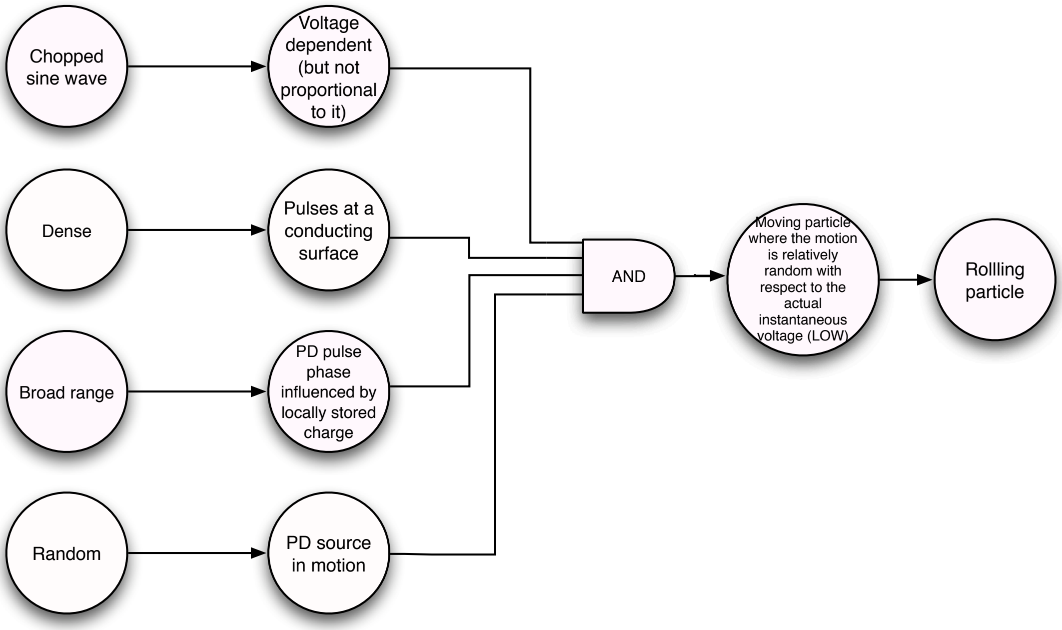
Floating Electrode



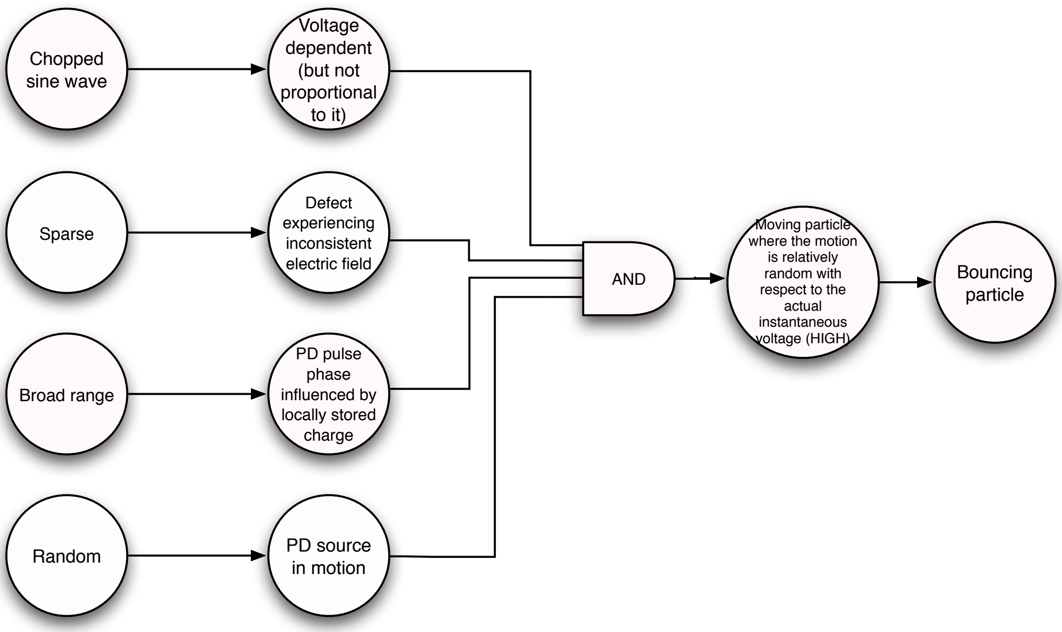

Phase inception symmetry
Conditions for PD inception are the same for both polarities
Broad range
PD pulse phase influenced by locally stored charge
Dense
Pulses at a conducting surface
Shape asymmetry
Defect is geometrically asymmetrical
Position in-between voltage and zero crossings
Shift between absolute and rate of change of voltage
Medium magnitude
Pulses initiated in insulation
Large magnitude
Arcing
OR
AND
Discharge between conductor surfaces, asymmetrical shape)
Floating electrode (asymmetrical shape)


Phase inception symmetry
Conditions for PD inception are the same for both polarities
Broad range
PD pulse phase influenced by locally stored charge
Dense
Pulses at a conducting surface
Shape symmetry
OR
Defect is geometrically symmetrical
Magnitude in positive = in negative
Discharge in-between voltage and zero crossings
OR
Issue of space charge
Discharge on zero crossings
Medium magnitude
Pulses initiated in insulation
OR
Large magnitude
Arcing
AND
Discharge between conductor surfaces, symmetrical shape)
Floating electrode (symmetrical shape)

Rolling Particle



Bouncing Particle



Do not Diagnose