NEURAL NETWORK BASED DETECTION OF PARTIAL DISCHARGE IN HV MOTORS

BY

Yahya Asiri

A Thesis Presented to the
DEANSHIP OF GRADUATE STUDIES

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS
DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

In

Electrical Engineering

June 2010

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS
DHAHRAN 31261, SAUDI ARABIA

DEANSHIP OF GRADUATE STUDIES

This thesis, written by **YAHYA AHMED ASIRI** under the direction of his thesis adviser and approved by his thesis committee, has been presented to and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements of degree of **MASTER OF SCIENCE IN ELECTRICAL ENGINEERING**.

Thesis Committee

Dr. Zakariya M. Al-Hamouz (Advisor)

Dr. Hussain N. Al-Duwaish (Co-Advisor)

Dr. Ibrahim M. El-Amin (Member)

Dr. Mohamed Mohandes (Member)

Alfred O. Vouk (Member)

Dr. Samir H Abdul-Jauwad

Department Chairman

Dr. Salam A. Zummo

Dean of Graduate Studies:

28/6/10

Date

To

Sharifa, Raneem, Ahmad and Yazeed

with

All

Love

ACKNOWLEDGMENTS

In the name of Allah, Most Gracious, Most Merciful, the source of all knowledge, wisdom, and strength. I acknowledge His unlimited mercy, guidance, and grace in making this work a success. The successful completion of this work was impossible without His help, assistance, and pleasing. And may His peace and blessings be upon his prophet Mohammed, a guidance and inspiration to our lives.

The acknowledgments are due to many contributors to this accomplishment, I would start with my advisors at King Fahd University of Petroleum and Minerals (KFUPM), the directions and advice of Prof. Zakariya Al-Hamouz and Dr. Hussain Al- Duwaish make the progress in this new field possible and achievable. Also, I am grateful to Prof. Ibrahim El-Amin and Dr. Mohamed Mohandes for their understanding, encouragement and cooperation during the period of thesis defense.

I owe the original suggestion to select the Partial Discharge (PD) topic to my colleague, Engineering Specialist of Saudi Aramco, Alfred Vouk when he recommended this field to be studied to satisfy mutual needs of Saudi Aramco and KFUPM. The phase of PD data collection exposed me to many main other contributors; without their cooperation and assistance; the training, validation and testing of the selected Artificial Neural Network was unattainable.

The role of our close partner, Siemens, was so essential when they shared with us their effort in PD detection field. Acknowledgments are due to Peter Feichtinger (IA&DT Siemens Global Account Manager), Olaf Schmitz (LD Business Development Director) and Dr. Martin Kaufhold (Quality & Technology VP) for their understanding and

cooperation to support my research. Also, many thanks to my mentor at Siemens LDA USA, Dimitre Rylow, for his understanding and cooperation; his understanding and consideration made me able to complete the final manuscript during my intern assignment with Siemens LDA.

ABB Saudi Arabia, ABB Switzerland and ABB India all participated effectively in collecting important PD trends using ABB color PD level coding. That job was organized by Venkat Rengamannar (ABB Local Business Unit Manager – Drives), Tom Bertheau (Sales Manager ABB Switzerland Ltd.) and conducted professionally by Cajetan T Pinto (Vice President, Global R&D Manager, Machines Service ABB India Ltd).

I would also like to extend my deep appreciation to the management of High Voltage Partial Discharge (HVPD) UK for their unprecedented efforts. They supplied us with the PD datasets that were the basis for PD NN training, validation and testing. The effort of Dr. Lee Renforth (Managing Director), Dr. Ross Mackinlay (Technical Director) and Alexander Lang (Senior Field Test & Development Engineer) was instrumental to accomplish my job.

I would like also here express my sincere appreciation and thanks to Abdulaziz Al Nuaim (Manager, Lines Maintenance East Division, Saudi Electricity Company) for his initiative to and enthusiasm to link me with PD data providers; his suggestions during the NN validation and testing helped a lot to reach to the desire results. In addition, I am appreciative to my friends Ahmed Asseri (Gap-Tech GM) and Attiyah Al Attiyah (PhD. Student at King Saudi University, Riyadh Saudi Arabia) for their help with MS Excel and MATLAB.

I am thankful and obliged to Jack Copper (CEO of NeuralWare) for his help with the NeuralSight NN Package discounted price and extended license; also Jack's effort is recognized in the review and editing of the thesis manuscript write-up. Acknowledgment is also due to Bob Everly (NeuralWare Customer Support Manager) for the extended training and assistance related to the installation, use and tuning of the Predict and NeuralSight NN software packages.

Special thanks to Prof. Magdy Salama (EE professor of Waterloo University Canada) and Dr. Ray Bartnikas of Hydro-Quebec/IREQ for their recommendations and advice relating to the use of NN PD classification.

At the end, my sincere, deep thanks and real appreciation to my family, my wife Sharifa, my daughter Raneem, my sons Ahmad and Yazeed who have been forbearing during the years of my MS study at KFUPM; without their encouragement, patience and understanding such achievement was impossible nor achievable.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

THESIS ABSTRACT

NAME: **Yahya Ahmed Asiri**

TITLE OF STUDY: **Neural Network Based Detection of Partial Discharge in HV Motors**

MAJOR FIELD: **Electrical Engineering**

DATE OF DEGREE: **June 2010**

The thesis discussed in general using one of the artificial inelegance techniques, Neural Networks (NN), to classify six (6) different types of Partial Discharge (PD). After discussing the importance rule of Electric Motors and their use in the wide range of applications, the use of different failures detection techniques is discussed.

The stator failures contribute about 30-40% of the total motor failures according to IEEE and EPRI. If the search is focused on High Voltage (HV) machines, IEEE statistics indicate that electrical insulation deterioration causes up to 90% of electrical failures of certain high voltage equipment

Such importance of the HV insulation system justifies studying one main cause of HV insulation which is PD. Large datasets were collected for PD defected HV motors as well PD-free machines. These sets of PD data were preprocessed and prepared for use with NN. The preprocessing phase of NN application to classify the PD types includes using some statistical techniques such as maximum and minimum values, Per Unit, and the envelop detection means; on the other hand, two techniques from the Signal Processing are in use such as Principal Component Analysis (PCA) and the Isometric Maps (ISOMAP).

Two NN packages are used to perform the PD classification. The famous scientific tool, MATLAB, is used to perform the PCA and the ISOMAP also to perform the NN PD classification. Another specialized NN tool is used to perform the multiple models NN building using NeuralSight of NeuralWare USA.

MATLAB was a perfect tool to calculate the PCA and ISOMAP reduced matrices but unfortunately it was not up to expectation in the NN PD classification. The NeuralSight was very accurate when it was trained and tested for the PD NN classification. Furthermore, it was achievable to use the advantage of multiple models to classify the multiple PD defects with recognition rate reached 98-99%, whereas the previous worldwide research works addressed in the literatures did not exceed the classification accuracy of 79%.

خلاصة الرسالة

الاسم: **يحيى أحمد عسيري**

عنوان الرسالة: **اكتشاف عيوب التفريغ الجزئي في محركات الجهد العالي باستخدام الشبكات العصبية**

التخصص: **هندسة كهربائية**

تاريخ المناقشة: **يونيو ٢٠١٠**

ناقشت هذه الأطروحة بشكل عام استخدام واحدة من تقنيات الذكاء الاصطناعي (الشبكات العصبية) لتصنيف ستة (٦) أنواع مختلفة من التفريغ الجزئي في عوازل محركات الجهد العالي. بعد مناقشة أهمية المحركات الكهربائية واستخدامها في مجموعة واسعة من التطبيقات، تم مناقشة استخدام تقنيات مختلفة في الكشف عن عيوب المحركات الكهربائية.

تسهم عيوب ملفات الجزء الثابت بنحو ٣٠-٤٠ ٪ من مجموع عيوب المحركات الكهربائية وفقا لإحصائيات IEEE و EPRI. بالتركيز على معدات الجهد العالي، نجد أن السبب الأول وفق إحصائيات IEEE يبين أن نسبة ما يصل الى ٩٠ ٪ من تعطل معدات الجهد العالي يمكن أن يعزى إلى تدهور نظام العزل الكهربائي. الأهمية المتعاظمة لنظام العزل الكهربائي في محركات الجهد العالي تبرر دراسة و بحث واحد من أهم أسباب فشل العزل و نعني هنا التفريغ الجزئي.

تم جمع بيانات وقياسات متعددة ومتنوعة عن التفريغ الجزئي في محركات الجهد العالي وتم أيضا جمع بيانات من محركات سليمة لا تعاني مشاكل التفريغ الجزئي. عولجت هذه القياسات و القراءات التي أعدت للاستخدام مع الشبكات العصبية خلال مرحلة التهيئة المبدئية باستخدام بعض الأساليب الإحصائية مثل القيم القصوى والدنيا، قيم الوحدة، ووسائل الكشف عن الغلاف. كذلك تم استخدام بعضا من تقنيات معالجة الإشارات مثل PCA و ISOMAP. عند إجراء تدريب و اختبار الشبكات العصبية تم استخدام اثنتين من البرمجيات هما البرنامج الشهير للتطبيقات العلمية ،MATLAB، الذي استخدم للحصول على ISOMAP ,PCA, و النماذج الأحادية للشبكات العصبية لأنواع التفريغ الجزئي المختلفة. كما استخدم برنامج NeuralSight كأداة أخرى متخصصة في تطبيقات الشبكات العصبية.

MATLAB كان أداة مثالية لحساب PCA و ISOMAP بينما لم يرتق للأسف للتوقعات في تصنيف عيوب التفريغ الجزئي. على العكس من ذلك كان أداء NeuralSight دقيقا للغاية عندما تم تدريب الشبكات العصبية واختبارها عليه. علاوة على ذلك، تمكنا من استخدام ميزة بناء نماذج متعددة لتصنيف العيوب المتداخلة من التفريغ الجزئي بدقة و صلت ٩٨-٩٩ % في حين أن البحوث السابقة التي أجريت عالميا لم تتجاوز نسبة دقة التصنيف فيها ٧٩ %.

ماجستير الهندسة
جامعة الملك فهد للبترول والمعادن
الظهران – المملكة العربية السعودية
يونيو - ٢٠١٠

CHAPTER 1

INTRODUCTION AND LITERATURE SURVEY

Electric motors play a pivotal role in various industrial plant processes for electrical to mechanical energy conversion. As a result, their reliability and availability is of utmost importance to industries [1]. Electric motors are considered industry workhorses, and their role is crucial and necessary for reliable and safe operation. They are generally robust and dependable but the aged ones eventually wear out. In few cases, even new motors may fail due to design deficiencies, incorrect operating conditions or improper installation.

Faults and failures of electric motors can lead to excessive downtime and result in large losses in terms of maintenance and revenues. Some failures may cause catastrophic safety impact on the whole facility. This valuable equipment is widely spread out in all fields ranging from fractional horsepower motors, such as laptop cooling fan motor, to ten thousands horsepower motors as in oil and gas applications. They are the main motive force in the commercial buildings, industrial facilities, transportation and appliances. Energy wise, motor systems are responsible for 63% of all electricity consumed by U.S. industry [2] [3].

In order to prevent productivity losses and achieve minimum machinery downtime, it is extremely important that such critical machines be constantly monitored and diagnosed for potential faults. Sources of failures may extend from mechanical faults such as broken rotor bars, damaged motor bearings and air-gap eccentricities to electrical faults such as stator winding shorts and supply voltage imbalance. A majority of these faults is

often based on the physical degradation of parts, and hence require much attention. While preventive and periodic maintenance are techniques often employed in industry, unnecessary replacement of healthy motor parts is a major problem. It is in this context that the usefulness of a system with capabilities to detect and diagnose mechanical faults can be realized. Fig. 1.1 shows the world's smallest electric motor while Fig 1.2 shows the largest one.

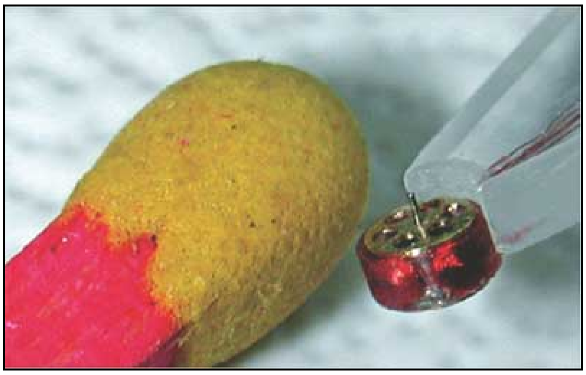


Figure 1.1: The world's smallest electric motor [5]

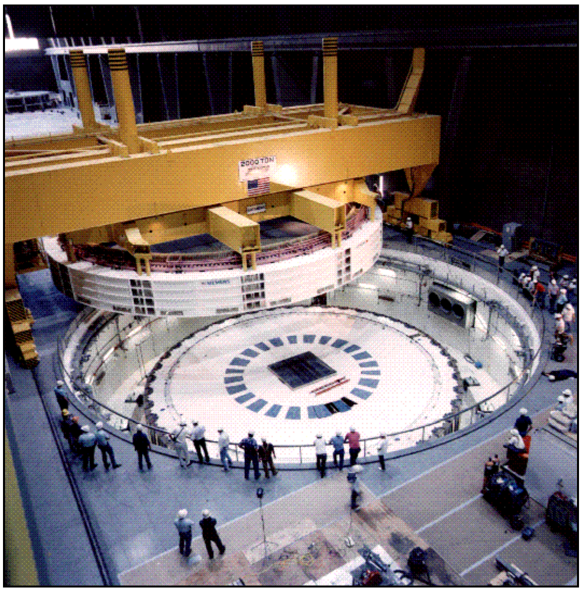


Figure 1.2: The 805MW motor [6]

Condition monitoring and diagnosis are important tasks in modern industrial systems having a high degree of automation. Existing industrial systems with high motor dependency already have a variety of sensor and control signals that can be used for monitoring. Of particular importance would be automatic detection and recognition of faults, such as the insulation failures, where an early warning of failure can prevent escalation of the problem and larger damages

1.1. IMPORTANCE OF ELECTRIC MOTORS

From ships to toys, from steel mills to phonographs, electric motors provide the driving power for a large and still increasing part of our modern industrial economy. The range of sizes and types of motors is large and the number and diversity of applications continues to expand. The computer, on which this manuscript is typed for example, has several electric motors inside, in the cooling fan and in the disk drives. There is even a little motor that is used to eject the removable disk from its drive. All around us there are electrical motors that move things around. Just about everything in one's life that whines, whirrs or clicks does so because an electric motor caused the motion. At a small end of the power scale, motors drive the hands in wristwatches, a job that was formerly done by a mechanical spring mechanism. At a large end of the power scale, motors rated in the hundreds of megawatts (MW) pump water uphill for energy storage tanks. Somewhat smaller motors, rated in the range of 12 to 15 MW, have taken over the job of propulsion for cruise ships, a job formerly done by steam engines or very large, low speed diesel engines [7].

The flexibility of electric motors and the possibility of transmitting electric power from one place to another makes the use of electric motors in many drive mechanisms attractive. Even in situations in which the prime mover is aboard a vehicle, as in diesel-electric locomotives or passenger ships, electric transmissions have displaced most mechanical or hydraulic transmissions. As well, because electric power can be delivered over sliding contacts, stationary power plants can provide motive power for rail vehicles. The final drive is, of course, an electric motor. The expansion of the use of electric motors' industrial, commercial and consumer applications is not at an end.

New forms of energy storage systems, hybrid electric passenger vehicles, and other applications not yet envisioned will require electric motors, in some cases motors that have not yet been invented [8].

Because of the nearly unlimited number of applications for electric motors, it is not hard to estimate that there are over 700 million motors of various sizes in operation across the world [9].

The high importance of such vital equipment justifies exerting the time and effort to develop early detection of motor abnormalities to avoid expensive failures. The electric motor is the single most common electromechanical energy conversion device available. It is used to drive numerous important propulsion and medium transfer units. The electric motors are considered inherently reliable due to their robust and relatively simple design. That said, electric motors fail most usually as a result of aging or poor construction and, if failure is of a catastrophic nature, hazards to production, safety, and the environment can often result. The optimum way of negating these dangers is by condition monitoring. This allows early identification of the degradation of the machine health and hence facilitates a

proactive response which minimizes downtime and maximizes productivity. Condition monitoring of electric machinery can significantly reduce the cost of maintenance and the risk of unexpected failures by allowing the early detection of potentially catastrophic faults. In condition-based maintenance, one does not schedule maintenance or machine replacement based on previous records or statistical estimates of machine failure. Rather, one relies on the information provided by condition monitoring systems assessing the machine's condition. Thus the key for the success of condition-based maintenance is having an accurate means of condition assessment and fault diagnosis [10]. As an example, Fig. 1.3 shows the motor applications in a typical steel mill. In this application, the all material handling functions are don through the electric motors.

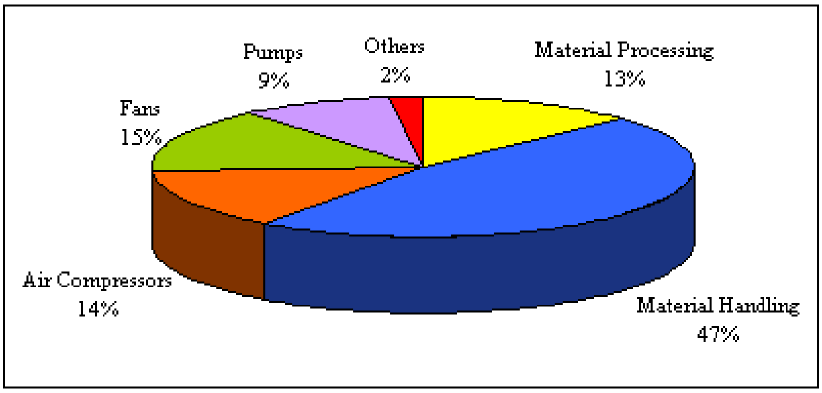


Figure 1.3: Motor applications distribution in a typical steel mill [1]

1.2. ELECTRIC MOTOR FAILURES REVIEW

The importance and the magnitude of such valuable machines justifies exerting the effort and dedication to study the distribution of electric motor failures. Tremendous research work was spent by individuals as well as institutes to collect and analyze motor

failures data. The major faults of electrical motors can broadly be classified as the following:

- bearing faults
- stator or armature faults
- broken rotor bar and end-ring faults
- eccentricity-related faults.

The motor's major component is the stator winding; its deterioration contributed to about 37% of motors failures, according to a study done by EPRI (Electrical Power Research Institute) as described in Fig. 1.4.

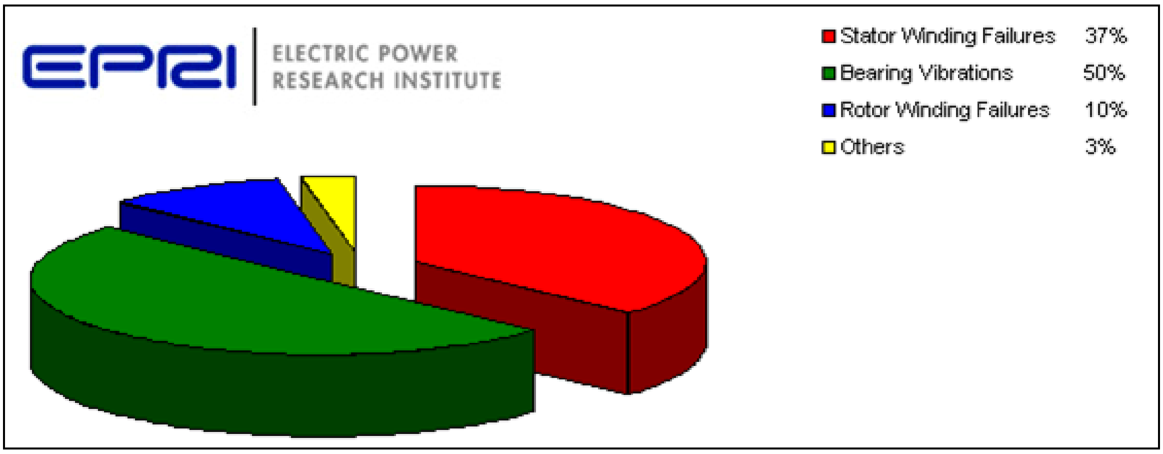


Figure 1.4: EPRI motor failures distribution [11]

According to an IEEE survey, the table 1.1 gives a detailed distribution for motor failures and Fig. 1.5 describes that graphically:

Table 1.1: IEEE failures percentage by component [12]

Bearing Related:	
• Sleeve bearings	16
• Antifriction bearings	8
• Seals	6
• Thrust bearings	5
• Oil leakage	3
• Other	3
Total	**41**
Stator Related:	
• Ground insulation	23
• Turn insulation	4
• Bracing	3
• Wedges	1
• Frame	1
• Core	1
• Other	4
Total	**37**
Stator Related:	
• Cage	5
• Shaft	2
• Core	1
• Other	2
Total	**10**

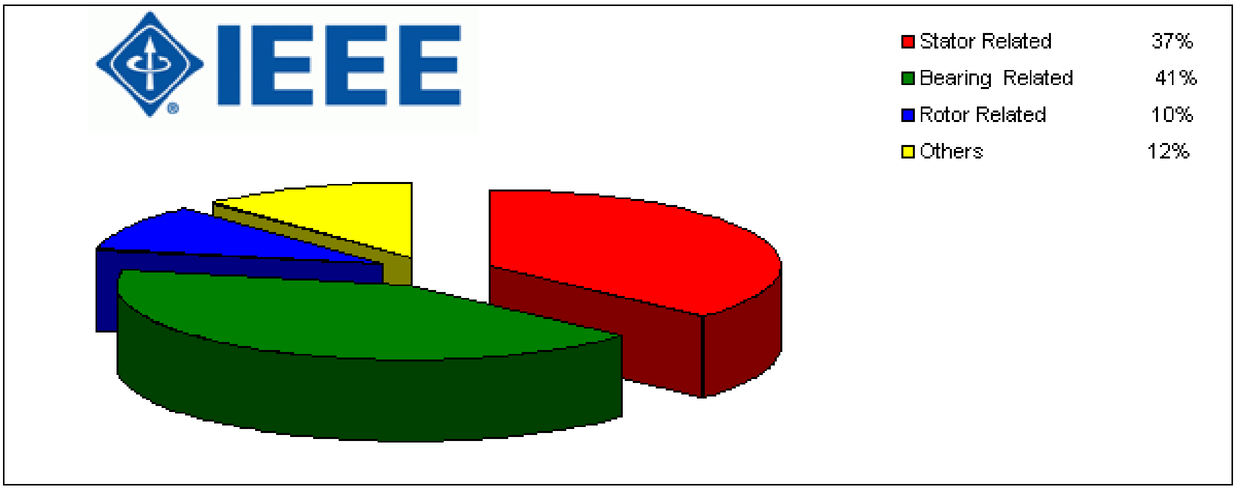


Figure 1.5: IEEE motor failures distribution [12]

Most stator winding failures occur as a result of deterioration of the insulation from various factors, mainly: thermal stresses (overheating); chemical attack from the environment; and abrasion due to excessive coil movement in the slot or end-windings. Due to heat stresses and normal aging, the insulation material loses its bonding properties, and air pockets are created in the windings where partial discharge occurs. Detailed description of insulation system and the related failures will be introduced in chapter 2 and chapter 3. The mentioned failures in EPRI and IEEE surveys can be described as follows:

1.2.1. Bearing Faults

The majority of electrical machines use ball or rolling element bearings and these are one of the most common causes of failure. These bearings consist of an inner and outer ring with a set of balls or rolling elements placed in raceways rotating inside these rings [13]. Even under normal operating conditions with balanced load and good alignment, fatigue failures may take place. These faults may lead to increased vibration and noise levels. Flaking or spalling of bearings might occur when fatigue causes small pieces to break loose from the bearing. Other than the normal internal operating stresses caused by vibration, inherent eccentricity, and bearing currents [14] due to solid state drives, bearings can be damaged by many other external causes such as the following [15]:

- contamination and corrosion caused by pitting and sanding action of hard and abrasive minute particles or corrosive action of water, acid, etc.

- improper lubrication; which includes both over and under lubrication causing heating and abrasion;
- improper installation of bearing; by improperly forcing the bearing onto the shaft or in the housing (due to misalignment), indentations are formed in the raceways.

Almost 40%–50% of all motor failures are bearing related. Sometimes bearing faults might manifest themselves as rotor asymmetry faults [16], which are usually covered under the category of eccentricity-related faults. Otherwise, the ball bearing related defects can be categorized as [17] outer bearing race defect, inner bearing race defect, ball defect, and train defect. The bearing overheating is common type among bearing failures; it is symptom of lake of lubrication or deteriorated balls. In Fig 1.6, the thermal imaging is used to scan the motor enclosure and detect the areas of “hot Spot”. Fig. 1.6 shows an overheated inboard bearing.

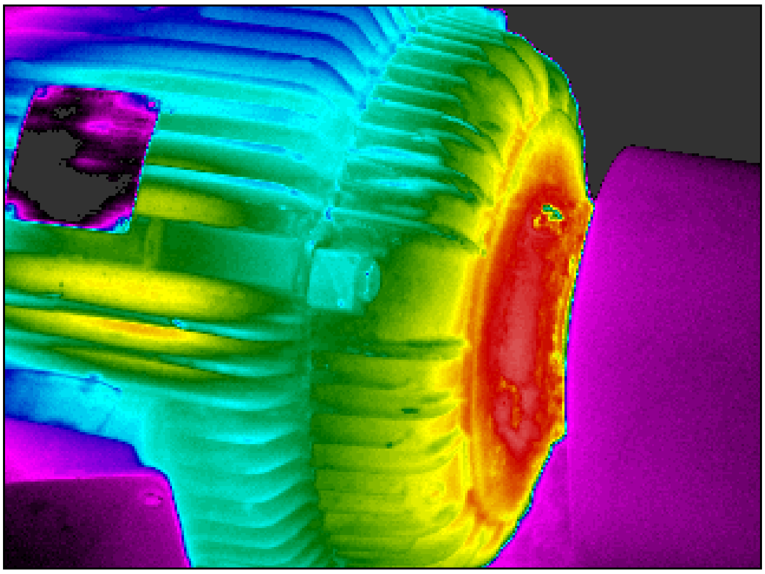


Figure 1.6: Overheated inboard bearing detected by infrared imaging

1.2.2. Stator Faults

Stator faults are usually related to insulation failure. In common parlance, they are generally known as phase-to-ground or phase-to-phase faults. It is believed that these faults start as undetected turn-to-turn faults that finally grow and culminate into major ones [18]. Almost 30%–40% of all reported induction motor failures fall into this category [18]. Armature or stator insulation can fail due to several reasons, primary among these are [19]:

- high stator core or winding temperatures;
- slack core lamination, slot wedges, and joints;
- loose bracing for end winding;
- contamination due to oil, moisture, and dirt;
- short circuit or starting stresses;
- electrical discharges;
- leakage in cooling systems.

The shortened winding is a major contributor to the stator failures. It is a result of damaged insulation. In Fig. 1.7, the stator winding was grounded due to failed turn insulation; that causes the winding live coil to touch the motor enclosure grounded frame.

Figure 1.7: Winding grounded at edge of slot

1.2.3. Rotor Faults

Unlike stator design, cage rotor design and manufacturing has undergone little change over the years. As a result, rotor failures now account for around 5%–10% of total induction motor failures. Cage rotors are of two types: cast and fabricated. Previously, cast rotors were only used in small machines. However, with the advancement in material science, casting technology can be used even for the rotors of machines in the range of 3000 kW [10]. Fabricated rotors can almost never be repaired once faults such as cracked or broken rotor bars develop in them. The reasons for rotor bar and end-ring breakage are several; they can be caused by the following [10]:

- thermal stresses due to thermal overload and unbalance, hot spots, or excessive losses, sparking (mainly fabricated rotors);
- magnetic stresses caused by electromagnetic forces, unbalanced magnetic pull, electromagnetic noise, and vibration;

- residual stresses due to manufacturing problems;
- dynamic stresses arising from shaft torques, centrifugal forces, and cyclic stresses;
- environmental stresses caused, for example, by contamination and abrasion of rotor material due to chemicals or moisture;
- mechanical stresses due to lose laminations, fatigued parts, bearing failure, etc.

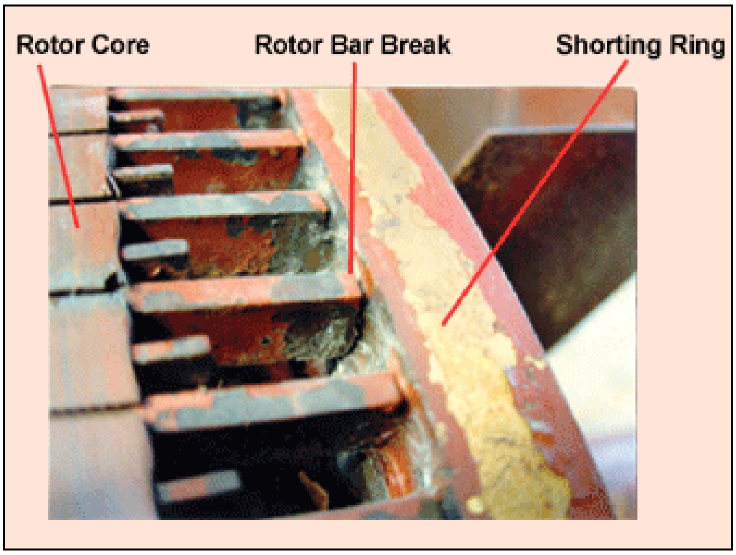


Figure 1.8: Broken rotor bar of 1700 hp motor

Fig. 1.8 shows a broken rotor bar as a result of mechanical stress or incorrect material selection

1.3. Electrical Problems Detection Techniques

Nowadays electric motors are used in a wide variety of industrial applications. They are the most used kind of electrical machines, for their reliability and simplicity of construction. But they are subject to failures, due to operating conditions or inherent to

the machine itself by construction [20]. This importance requires having monitoring schemes to keep an eye on the motor condition. Many condition assessment approaches were introduced in the industry to keep this equipment working at optimum conditions.

Condition monitoring of electric motors can considerably reduce the cost of maintenance and the risk of unexpected failures through the early detection of potential expected faults. In condition based assessment, one does not schedule maintenance or machine replacement based on previous records or statistical estimates of equipment failure. Rather, one relies on the information provided by condition monitoring systems assessing the machine's condition. Thus the key for the success of condition based maintenance is having an accurate means of condition assessment and fault diagnosis [10].

On-line condition monitoring uses measurements taken while the machine is operating, to determine if a fault exists. The monitoring process could be described as in Table 1.2.

Table 1.2: The on-line condition monitoring process [13]

Motor Component under Monitoring	Signals	Signal Processing	Fault Detection
▪ bearings ▪ stator winding ▪ rotor bar ▪ eccentricity	▪ vibration ▪ current ▪ magnetic flux ▪ voltage	▪ RMS ▪ Fourier transform ▪ time-frequency ▪ wavelet ▪ higher order stats ▪ Park's vector ▪ negative seq.	▪ model-based ▪ trending ▪ threshold ▪ multi-dimension ▪ neural networks ▪ fuzzy logic ▪ expert systems

As described before, the major faults of electric motors can broadly be classified as the following [21]:

- stator faults resulting in the opening or shorting of one or more of a stator phase winding;
- abnormal connection of the stator windings;

- broken rotor bar or cracked rotor end-rings;
- static and/or dynamic air-gap irregularities;
- bent shaft (akin to dynamic eccentricity) which can result in a rub between the rotor and stator, causing serious damage to stator core and windings;
- shorted rotor field winding;
- bearing and gearbox failures.

All listed above faults have one or more of the following symptoms as [22]:

- unbalanced air-gap voltages and line currents;
- increased torque pulsations;
- decreased average torque;
- increased losses and reduction in efficiency;
- excessive heating.

For the purpose of detecting such fault-related signals, many diagnostic methods have been developed so far. These methods to identify the above faults may involve several different types of fields of science and technology. They can be described as follows [21] [23]:

- electromagnetic field monitoring, search coils, coils wound around motor shafts (axial flux-related detection);
- temperature measurements;
- infrared recognition;
- radio-frequency (RF) emissions monitoring;

- noise and vibration monitoring;
- chemical analysis;
- acoustic noise measurements;
- motor current signature analysis (MCSA);
- model, artificial intelligence, and neural-network-based techniques.

1.3.1. Motor Failures Detection Signals

Since the construction of electric motors is highly symmetrical, the presence of any kind of fault affects its symmetry [13]. That symmetry leads to a resulting change in the interaction of flux between the stator and rotor, and leads to a change to the stator currents, voltages, magnetic field and machine vibration. That variation in the motor electrical signals could be utilized to detect motor failures online. Table 3.1 gives the matrix between the electric signals and possible motor failures:

Table 1.3: Motor failure- signal matrix [10]

	Bearing	Stator	Rotor	Eccentricity
Vibration	♦	♦	♦	♦
Current	♦	♦	♦	♦
Flux	♦	♦	♦	♦
Voltage & Current		♦	♦	♦

1.3.1.1. Vibration

Vibration could be defined as: “the oscillation of any object about some reference point”. It is caused by an alternating force which is present in a structure either because of

an external influence or excitation within the structure itself [22]. Vibration in the rotating machines, troublesome itself, may serve as an indicator of more serious trouble. Low frequency vibrations or those which cause parts to contact each other, often emit audible sounds. The vibrations most associated with machinery problems are seldom in the audible range. Vibrations cause damage due to the alternating force producing both impact and stress reversal. Vibration could be caused by one or more among the following causes [23]:

- unbalance
- misalignment
- eccentricity
- bent shaft
- shaft cracks
- mechanical looseness
- journal bearing faults
- rotor rub
- cavitation
- electrical motor problems
- gear faults
- rolling element bearing faults

Vibration monitoring is one of the oldest condition monitoring techniques, it is widely used to detect mechanical faults such as bearing failures or mechanical imbalance [20]. A piezo-electric transducer providing a voltage signal proportional to acceleration is often

used. This acceleration signal can be integrated to give the velocity or position. Fig. 1.9 shows the vertical and horizontal vibration probes that detects vertical and horizontal vibration.

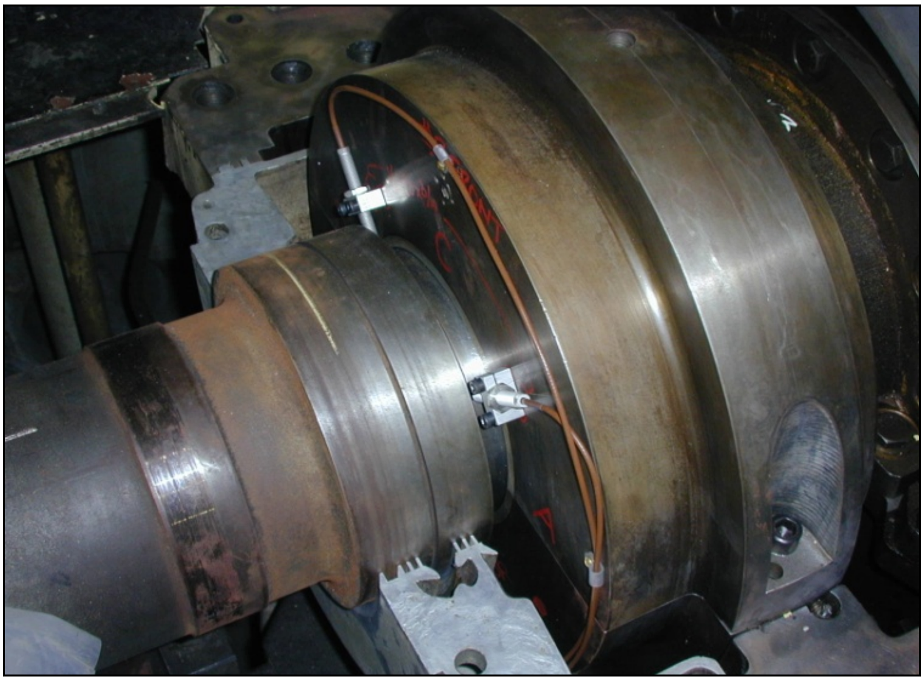


Figure 1.9: X & Y radial vibration proximity probes

1.3.1.2. Stator Current

The stator current is usually measured using clip-on Hall-Effect current probes. Stator current contains frequency components which can be related to a variety of faults such as mechanical and magnetic asymmetries, broken rotor bars and shorted turns in the stator windings. Most of the published research work in recent years has examined the use of the stator current for condition monitoring, particularly using frequency analysis [20]. The Motor Current Signature Analysis (MCSA) is considered as the most popular fault

detection method nowadays because it can easily detect the common machine fault such as turn-to-turn short circuit, cracked /broken rotor bars, bearing deterioration etc [21]. Motor Current Signature Analysis (MCSA) is a system used for analyzing or trending dynamic, energized systems. Proper analysis of MCSA results will assist the technician in identifying [21]:

- newly constructed winding health
- stator winding health
- rotor health
- air gap static and dynamic eccentricity
- coupling health, including direct, belted and geared systems
- load issues
- system load and efficiency
- bearing health

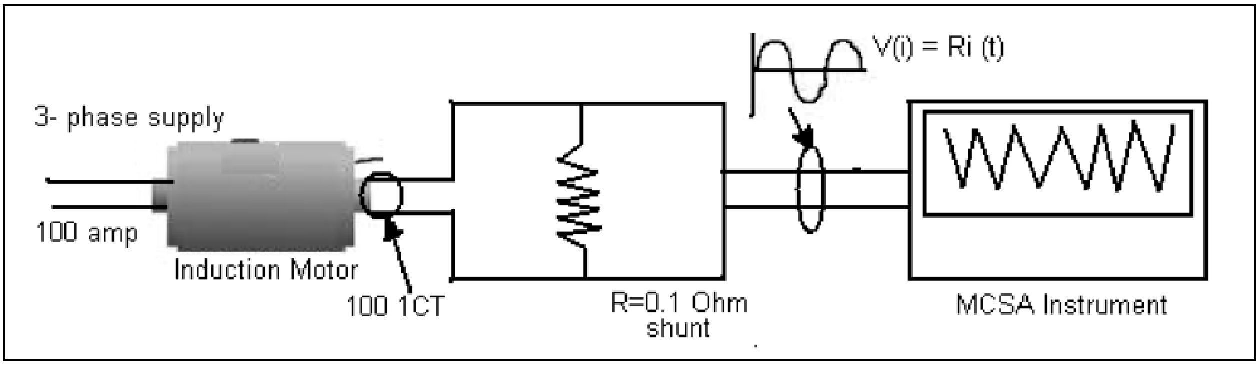


Figure 1.10: Motor current signature analysis concept

Fig. 1.10 gives the block diagram for the MSA monitoring setup.

1.3.1.3. Axial Magnetic Flux

The axial magnetic leakage flux of an induction machine is readily measured using a circular search coil which is placed on the non-drive (rear) end of the machine, concentric with the shaft. The search coil produces an output voltage which is proportional to the rate of change of the axial leakage flux. This signal contains many of the same frequency components which are present in the stator current. It is particularly useful for estimating the speed as it contains a strong component at the slip frequency [21].

Figure 1.11: Axial flux measurement set up

The leakage flux in the end winding space, a simplified presentation of which is shown in Fig. 1.12, is the result of the stator and rotor currents. Because of the inherent machine asymmetry, the leakage flux can always be detected even with symmetrical voltage of the power supply. The leakage flux spectrum corresponds to the result of the effects of both the stator and rotor current frequency components. In addition to the fundamental

frequency, the spectrum includes harmonics caused by stator currents, frequency components caused by the asymmetry of supply voltages and various types of other abnormal situations or failures such as eccentricity, stator phase to ground failures, turn to turn short failures of stator winding and rotor winding failures. In Fig. 1.11, the search coil measuring tool is used to detect the axial leakage flux.

1.3.1.4. Other Signals

Temperature measurement, partial discharge activities and stator voltage readings could be used also to monitor the electric motor commotion. Temperature sensors monitoring the bearings and stator windings have been traditionally used for condition monitoring [10]. Trending the temperature changes of stator windings or motor bearings gives a useful indication of machine overheating. Partial discharge measurement provides a practical insulation evaluation method to the user of large machines. It allows operators to monitor the insulation condition, so that insulation defects can be detected earlier [24]. Stator voltage measurement could be used as well to detect certain motor problems related to stator, rotor and eccentricity [13].

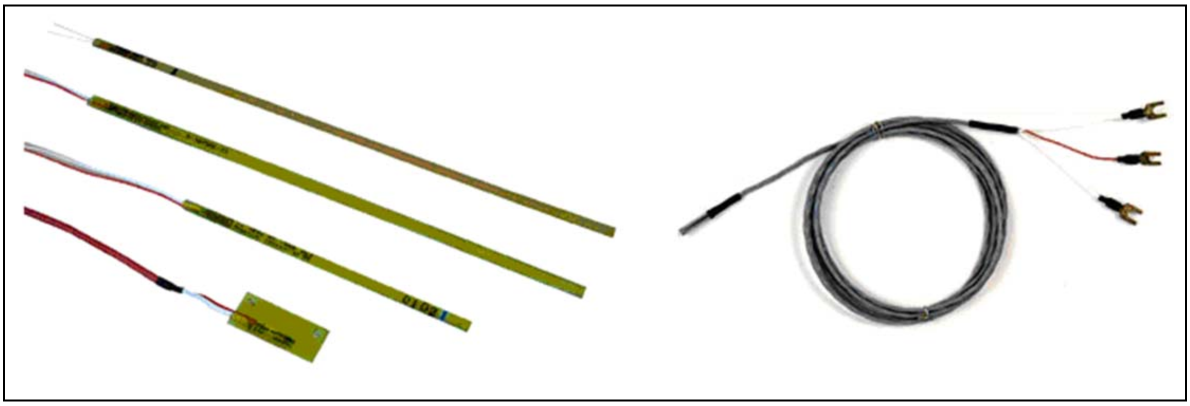


Figure 1.12: Motor temperature detectors (RTD :Resistance Temperature Detectors, L: Stator, R: Bearing)

Different types of RT's are show in Fig. 1.12 for different temperature measurement technique.

1.3.2. Motor Failures Signal Analysis Techniques

The collected motor signals that were discussed in the previous sections provide a wealth of information about the motor condition. Each motor failure has certain characteristics that could be reflected on the collected motor signal. Extracting failure type according to the collected signal is not an achievable task for human classification. Such a task needs applying certain signal processing techniques in order to generate features or parameters (e.g. amplitudes of frequency components associated with faults) which are sensitive to the presence or absence of specific faults [13]. In this section the following techniques will be discussed:

- RMS
- frequency analysis
- higher order statistics
- stator current park's vector
- negative sequence currents

1.3.2.1. RMS

Calculation of simple statistical parameters such as the overall root mean squared (RMS) value of a signal can give useful information. For instance, the RMS value of the vibration velocity is a convenient measure of the overall vibration severity [25]. In the

same way, the RMS value of the stator current provides a rough indication of the motor loading [13].

1.3.2.2. Frequency Analysis

Frequency analysis using the Fourier Transform is the most common signal processing method used for online condition monitoring. This is because many mechanical and electrical faults produce signals whose frequencies can be determined from knowledge of motor parameters such as the number of poles [13]. These fault signals appear in a variety of sensor signals including vibration, current and flux [23] [24]. Frequency analysis can thus provide information about a number of faults, though some faults produce similar fault frequencies and so require other information to differentiate them. It also allows the detection of low-level fault signals in the presence of large "noise" signals at other frequencies [13]. One famous application of frequency analysis in motor failures detection is the use of motor current spectrum to inspect the integrity of rotor bars. Fourier Transform usually used to scan the frequency spectrum of the line current to search for certain motor defects as in Fig. 1.13.

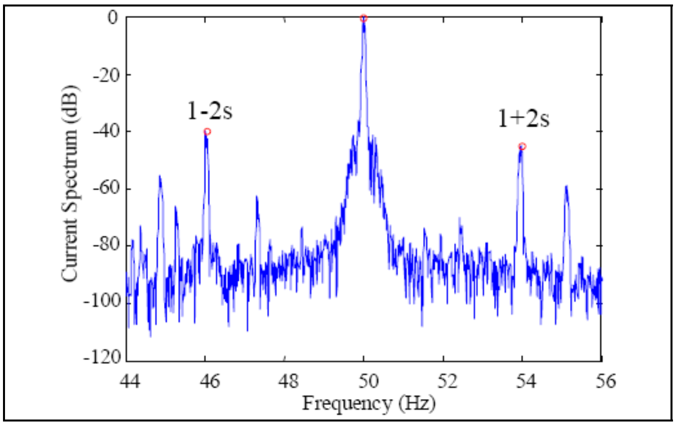


Figure 1.13: Current frequency spectrum showing broken bar sidebands for a motor with one broken bar [13]

1.3.2.3. Higher Order Statistics

Common statistical measures such as the mean or variance can be used to describe the probability density function of a time-varying signal. There are also higher order statistical measures such as kurtosis, which gives an indication of the proportion of samples which deviate from the mean by a small value compared with those which deviate by a large value. Some of these higher order statistical measures have the useful property that they are insensitive to Gaussian distributed measurement noise. These have been used to investigate the detection of machine faults [29][30]. It is possible to perform frequency analysis (Fourier Transform) of the higher order statistical measures to obtain what is called higher order spectra. These spectra allow the identification of components in a signal which have a fixed phase relationship and hence may originate from the same source [29].

1.3.2.4. Stator Current Park's Vector

The Park's vector is based on the locus of the instantaneous spatial vector sum of the three phase stator currents. This locus is affected by stator winding faults and air-gap eccentricity. The Park's vector can be analyzed graphically as shown, or by examining its frequency spectra [13].

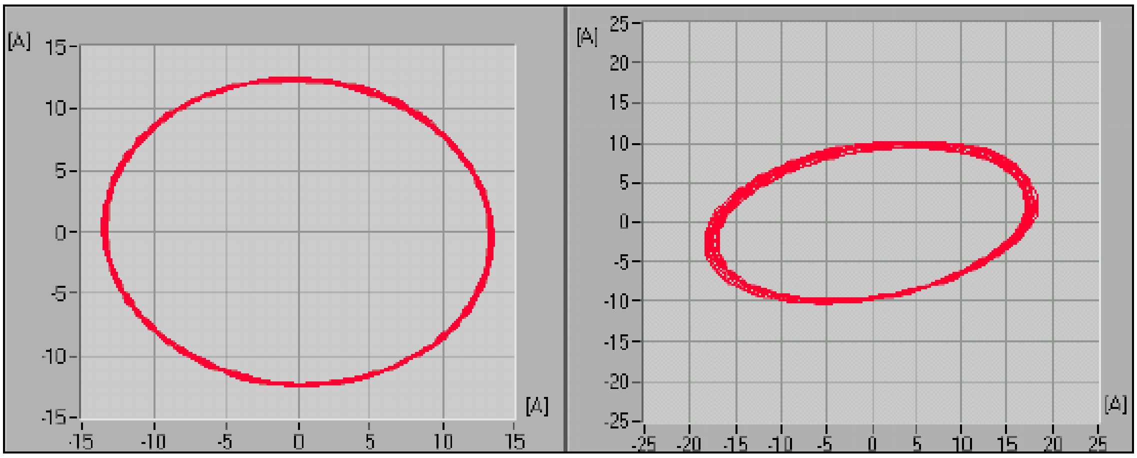


Figure 1.14: Geometric locus of the Park vector: for normal working conditions and coils in short circuit respectively [31]

The two ellipsoids in Fig1.14 are in use to compare different motor conditions. The result will be benchmarked with standard motor pattern to detect certain problems such as vibrations or rotor broken bars.

1.3.2.5. Negative Sequence Currents

When ideal three-phase voltages are applied to a perfectly symmetrical three-phase machine, the machine currents are equal in magnitude. A fault such as a shorted turn or eccentricity introduces an imbalance between the phases causing unbalanced phase currents. This imbalance increases with fault severity and can be described mathematically using a negative sequence current component [13]. These faults result in asymmetry in the machine impedance causing the machine to draw unbalanced phase currents. This is the result of negative-sequence currents flowing in the line [10]. However, negative-sequence currents can also be caused by voltage unbalance, machine

saturation, etc... It is reported that with these modifications, it is possible even to detect a one turn "bolted" fault out of a total 648 turns [10].

1.4. THESIS OBJECTIVES

The thesis objectives could be listed as in the following list:

- Studying the available sources and literatures to cover the electric motor applications and functions different applications.
- Studying the Neural Network basics and their applications in PD detection.
- Reviewing the previous done work in the field of NN PD classifications
- Working with the manufacturers of PD detection systems to create a mutual effort between the academic organization (KFUPM), industry and the end-users (Saudi Aramco) to investigate the possibility of NN pd classification
- Collecting enough field PD measurements to train, validate and test the developed NN models.
- Developing NN models that can be trained and used to classify the six (6) different types found in the literature.
- Testing and evaluating the performance of different NN types and the effect of specific tuning features of NN such as the number of layers, training function and transfer functions.

- Conducting real-time PD measurements and used it as Blind Dataset to test the developed NN models. The results will be benchmarked with human being classification done by PD Subject Matter Expert (SME)

.

1.5. THESIS ORGANIZATION

This thesis is organized in the following manner: Chapter 1 gives an introduction about the importance of electric motors and their role as a prime mover in industrial and residential applications. Motor failures are also reviewed and described; electrical faults such as shorted windings and insulation degradation are addressed. In addition, a thorough survey covers the mechanical related problems such as vibration and broken rotor bars. Fault detection methods and condition monitoring benefits are explained with emphasis on failure detection signals and the available analysis techniques.

Chapter 2 is dedicated to the thesis subject, Partial Discharge (PD). It starts with the fundamentals of high voltage insulation, the medium of PD activities. Then an introductory study is presented on the PD phenomenon itself. Also, the physics of PD is addressed to provide better understanding of PD. In addition, the chapter covers the different techniques that are used to detect the PD signal and the different industrial practice that are applied for different HV equipments; and it also compares the online PD measurement vs. offline measurement. The last part is devoted to list the available international standards that deal with the topic of PD such as IEEE 1434-2000 and IEC 60270.

Chapter 3 discusses the application of Neural Networks (NN) in the classification of PD types. The previous research work is presented through studying the available literature; the different NN types are listed with focus on the effect of the layers number, training time and transfer and training functions. The chapter also reviews the possible PD parameters that could be fed to the NN such as the PD Pulse-height in mV (picocoulombs pC's), phase angle and pulse repetition (pulse/sec). The effect of multiple PD defects, voltage level and the PD mechanism are discussed to discover their consequences on PD pattern recognition.

Chapter 4 describes the effort exerted to team up with the OEM's (Original Equipment Manufacturer) of the PD detection systems to collect the PD datasets. PD datasets include 250 readings for different PD types and 50 PD readings for healthy machines. The PD dataset processing also is explained using statistical as well as signal processing techniques to perform the dimensionality reduction task.

Chapter 5 introduces the main part of the thesis which is the NN training, testing and validation. MATLAB® and NeuralSight® NN packages were utilized heavily to perform the PD classification. The necessary adjustment and modification that should be applied on the input, target and blind PD data are described and discussed in this chapter. The results of the NN validation and testing using real field-test data are discussed and the effect of internal fine tuning on the SSE (Squared Summation Error) and the recognition rate.

Chapter 6 is a summery and conclusion followed by a list of references and an index of the MATLAB code.

CHAPTER 2

PARTIAL DISCHARGE BACKGROUND

In general, Partial Discharge (PD), as its name would suggest, is an electrical discharge that occurs across a portion of the insulation between two conducting electrodes, without completely bridging the gap. PD can occur in voids in solid insulation (paper, polymer etc), gas bubbles in liquid insulation or around an electrode in a gas (corona) [32]. PD activities might take a place during the normal operation of high voltage equipment where the insulation condition has deteriorated with age and/or has been aged prematurely by thermal over-stressing.

PD measurement could be used also as a quality measure to determine the improper installation, poor design or workmanship. After initiation, the PD can propagate and develop into electrical trees until the insulation is so weakened that it fails completely with breakdown to earth or between the phases of a 3-phase system [32]. Fig 2.1 shows PD treeing in a solid insulator.

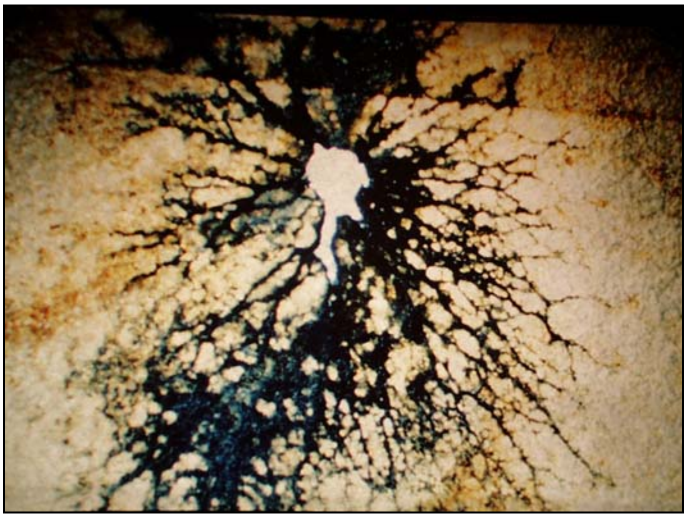


Figure 2.1: Treeing and paper degradation [32]

It is known that whilst some discharges can be extremely dangerous to the health of the insulation system (e.g. discharges within polymeric cables and accessories) other types of discharge can be relatively benign (e.g. corona into air from outdoor cable sealing ends).

Failure of High Voltage insulation is the No. 1 cause of HV system failures with IEEE statistics indicating that electrical insulation deterioration causes up to 90% of electrical failures of certain high voltage equipment [31].

On-line PD testing of MV and HV plant gives advance warning of pending insulation failure thus allowing the plant owner to take remedial action during planned outages. Unlike off-line testing, on-line PD testing and monitoring gives an accurate picture of the HV equipment health and performance under service conditions. One configuration of PD measurement is shown in Fig 2.2 during PD test at one of Saudi Aramco oil production facility.

Figure 2.2: Online PD measurement done at one of Saudi Aramco plants

Partial Discharge is a symptom of several stator winding problems caused by electrical, thermal, mechanical and chemical stresses. Partial discharges typically occur in

gas-filled voids that are found in all winding insulation systems. It is damaging to the organic resins used in insulation materials, but degradation of the winding is usually slow due to the use of discharge-resistant material called mica. It is because of this relatively slow aging process that periodic monitoring of PD activity makes sense. Partial discharge (PD) measurements have been made on the windings of rotating machinery for over 40 years [33].

2.1. FUNDAMENTALS OF HIGH VOLTAGE INSULATION

The selection of electrical insulation systems for rotating machines has always been dependent on the materials available, their cost, the technical needs of the motor or generator application, and the relative costs of the several manufacturing processes available at the time. In the early years of the industry, there was a near total reliance on naturally occurring materials and much trial and error experimentation to find systems that met minimum design criteria. Thus, operating temperatures, as well as mechanical and electrical stresses, were kept low to accommodate the limitations of these materials [34].

The basic function of insulation is to separate electrical circuits from each other and from metallic components at earth potential. From a practical engineering standpoint, insulators can be defined as materials which are poor electrical conductors, i.e. they have high electric resistance. Insulators, unlike metallic materials, have a decrease in resistance with increase in temperature. Between the groups of materials which can be defined as good conductors or poor insulators there is a further group which can be defined as poor conductors or poor insulators depending on the point of view [35].

In practice when considering materials for use in rotating electrical plant it is often useful to divide materials into the following categories [35]:

- conductor insulation
- tapes and flexible sheets
- rigid sheets and laminates
- sleevings and cables
- semi-conducting corona shield and stress grading materials
- bracing tapes, cords, ropes
- impregnating varnishes and resins

The stator winding and rotor winding consist of several components, each with their own function. Furthermore, different types of machines have different components. Stator and rotor windings are discussed separately below.

2.1.1. Stator Winding

The three main components in a stator are the copper conductors (although aluminum is sometimes used), the stator core, and the insulation. The copper is a conduit for the stator winding current. The copper conductors must have a cross section large enough to carry all the current required without overheating. Figure 2.3 shows the circuit diagram of a typical three-phase motor or generator stator winding.

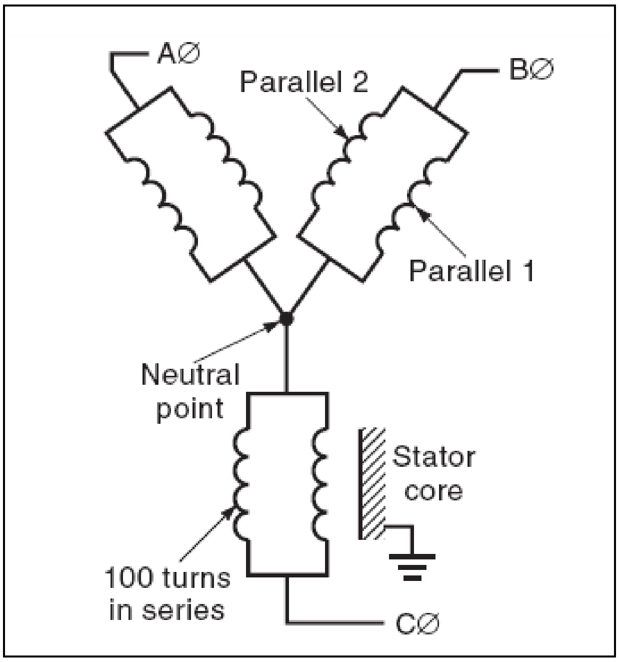


Figure 2.3: Schematic diagram for a three-phase, Y-connected stator or winding, with two parallel circuits per phase.

The diagram shows that each phase has one or more parallel paths for current flow. Multiple parallels are often necessary since a copper cross section large enough to carry the entire phase current may result in an uneconomic stator slot size. Each parallel consists of a number of coils connected in series. For most motors and small generators, each coil consists of a number of turns of copper conductors formed into a loop [34].

The stator core consists of thin sheets of magnetic steel (referred to as laminations). The magnetic steel acts as a low-reluctance (low magnetic impedance) path for the magnetic fields from the rotor to the stator, or vice versa for a motor. The steel core also prevents most of the stator winding magnetic field from escaping the ends of the stator core, which would cause currents to flow in adjacent conductive material. The final major component of a stator winding is the electrical insulation. Unlike copper conductors and magnetic steel, which are active components in making a motor or generator function, the insulation

is passive. That is, it does not help to produce a magnetic field or guide its path. Generator and motor designers would like nothing better than to eliminate the electrical insulation, since the insulation increases machine size and cost, and reduces efficiency, without helping to create any torque or current [36].

Insulation is "overhead," with a primary purpose of preventing short circuits between the conductors or to ground. However, without the insulation, copper conductors would come in contact with one another or with the grounded stator core, causing the current to flow in undesired paths and preventing the proper operation of the machine. In addition, indirectly cooled machines require the insulation to be a thermal conductor, so that the copper conductors do not overheat. The insulation system must also hold the copper conductors tightly in place to prevent movement. The stator winding insulation system contains organic materials as a primary constituent. In general, organic materials soften at a much lower temperature and have a much lower mechanical strength than copper or steel. Thus, the life of a stator winding is limited most often by the electrical insulation rather than by the conductors or the steel core. Furthermore, stator winding maintenance and testing almost always refers to testing and maintenance of the electrical insulation.

2.1.2. Insulated Rotor Windings

In many ways, the rotor winding has the same components as the stator, but with important changes. In all cases, copper, copper alloy, or aluminum conductors are present to act as a conduit for current flow. However, the steady-state current flowing through the rotor winding is usually DC (in synchronous machines), or very low frequency AC (a few

Hz) in induction machines. This lower frequency makes the need for a laminated stator core less critical. The conductors in rotor windings are often embedded in the laminated steel core or surround laminated magnetic steel. However, round rotors in large turbogenerator and high speed salient pole machines are usually made from forged magnetic steel, since laminate magnetic steel rotors cannot tolerate the high centrifugal forces. Synchronous machine rotor windings, as well as wound rotor induction motors, contain electrical insulation to prevent short circuits between adjacent conductors or to the rotor body. The insulating materials used in rotor windings are largely composites of organic and inorganic materials, and thus have poor thermal and mechanical properties compared to copper, aluminum, or steel. The insulation then often determines the expected life of a rotor winding.

2.1.3. Stator Winding Insulation System

The stator winding insulation system contains several different components and features, which together ensure that electrical shorts do not occur, that the heat from the conductor I^2R losses are transmitted to a heat sink, and that the conductors do not vibrate in spite of magnetic forces. The basic stator insulation system components are the:

- strand (or subconductor) insulation
- turn insulation
- groundwall (or ground or earth) insulation
- corona protection

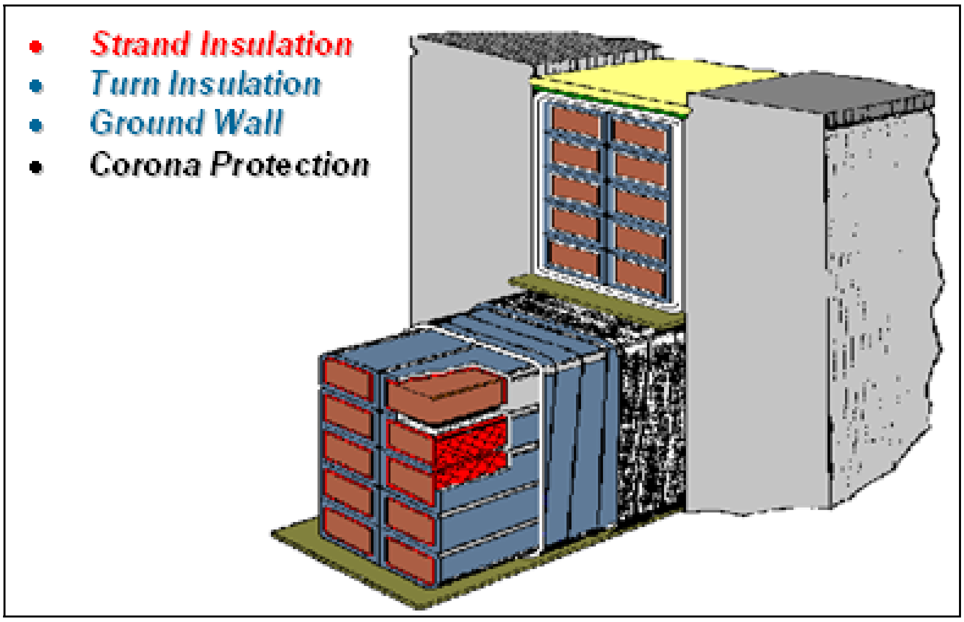


Figure 2.4: Stator insulation material classification [37]

Figures 2.3, 2.4 and 2.5 show cross sections of random-wound and form-wound coils in a stator slot, and identify the above components. Note that the form-wound stator has two coils per slot; this is typical. Figure 2.6 and 2.7 are photographs of the cross section of a multiturn coil. In addition to the main insulation components, the insulation system sometimes has high-voltage stress-relief coatings and end-winding support components.

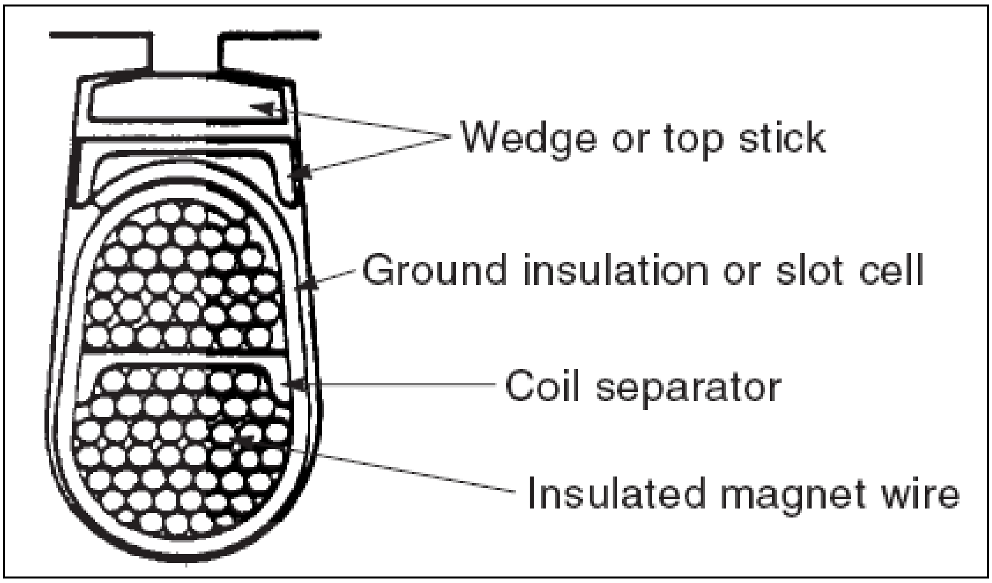


Figure 2.5: Cross section of a random stator winding slot.

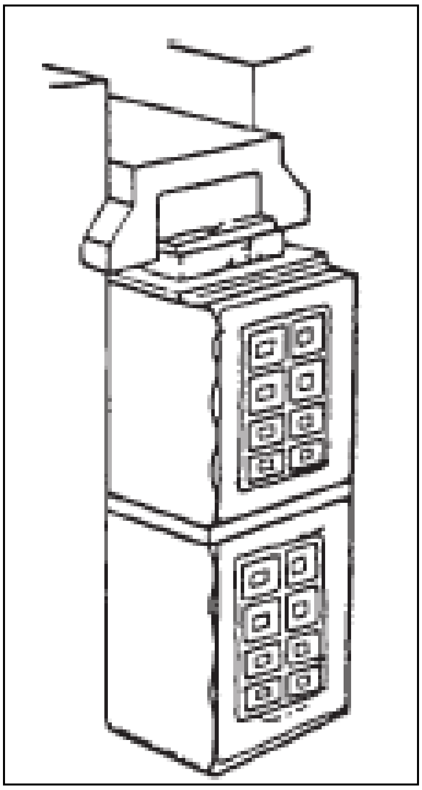


Figure 2.6: Cross sections of slots containing directly cooled Rebel bars.

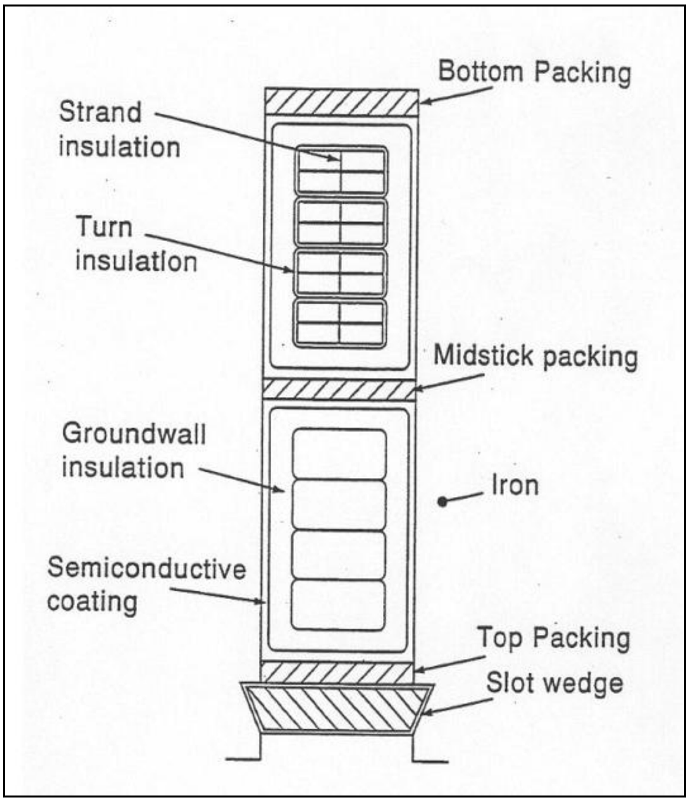


Figure 2.7: Cross sections of slots containing form-wound multiturn coils

2.1.3.1 Strand Insulation

In random-wound stators, the strand insulation can function as the turn insulation, although extra sleeving is sometimes applied to boost the turn insulation strength in key areas. Many form-wound machines employ separate strand and turn insulation. The following mainly addresses the strand insulation in form-wound coils and bars. Strand insulation in randomwound machines will be discussed as turn insulation. There are both electrical and mechanical reasons for stranding a conductor in a formwound coil or bar. From a mechanical point of view, a conductor that is big enough to carry the current needed in the coil or bar for a large machine will have a relatively large cross-sectional area. That is, a large conductor cross section is needed to achieve the desired ampacity.

Such a large conductor is difficult to bend and form into the required coil/bar shape. A conductor formed from smaller strands (also called subconductor) is easier to bend into the required shape than one large conductor. From an electrical point of view, there are reasons to make strands and insulate them from one another. It is well known from electromagnetic theory that if a copper conductor has a large enough cross-sectional area, the current will tend to flow on the periphery of the conductor. This is known as the skin effect. The skin effect gives rise to a skin depth through which most of the current flows. The skin depth of copper is 8.5 mm at 60 Hz. The strand insulation is shown by cross section for a winding coil.

Figure 2.8: Turn cross section showing the strand insulation

2.1.3.2 Turn Insulation

The purpose of the turn insulation in both random- and form wound stators is to prevent shorts between the turns in a coil. If a turn short occurs, the shorted turn will appear as the secondary winding of an autotransformer as shown in Fig. 2.9.

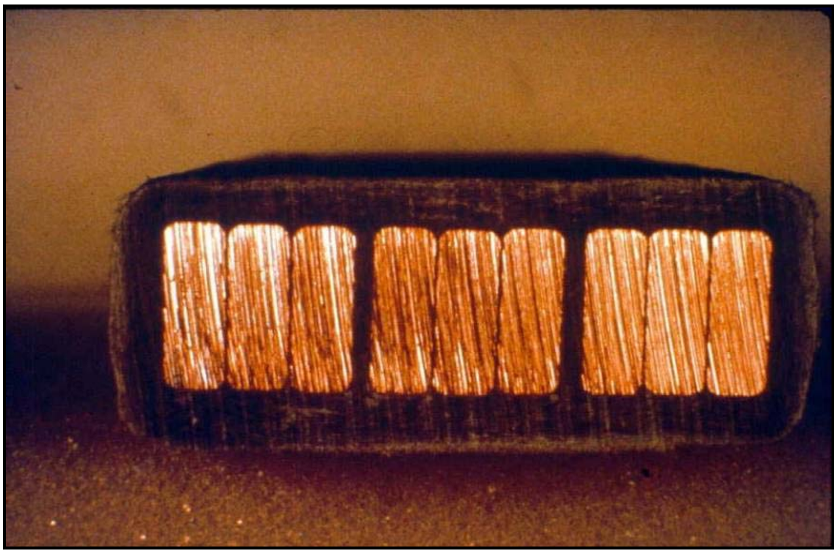


Figure 2.9: Turn cross section showing the strand insulation

If, for example, the winding has 100 turns between the phase terminal and neutral (the "primary winding"), and if a dead short appears across one turn (the "secondary"), then 100 times normal current will flow in the shorted turn. Consequently, a huge circulating current will flow in the faulted turn, rapidly overheating it. Usually, this high current will be followed quickly by a ground fault due to melted copper burning through any groundwall insulation. Clearly, effective turn insulation is needed for long stator winding life. The power frequency voltage across the turn insulation in a random-wound machine can range up to the rated phase-to-phase voltage of the stator because, by definition, the turns are randomly placed in the slot and thus may be adjacent to a phase-end turn in another phase, although many motor manufacturers may insert extra insulating barriers between coils in the same slot but in different phases and between coils in different phases in the end-windings [34].

2.1.3.3 Groundwall Insulation

Groundwall insulation is the component that separates the copper conductors from the grounded stator core. Groundwall insulation failure usually triggers a ground fault relay, taking the motor or generator off-line. Thus the stator groundwall insulation is critical to the proper operation of a motor or generator. For a long service life, the groundwall must meet the rigors of the electrical, thermal, and mechanical stresses that it is subject to as shown in fig. 2.10.

Figure 2.10: Coil cross section showing the groundwall insulation

2.2. WHAT IS PARTIAL DISCHARGE (PD)

Partial discharge could be defined as an electrical pulse or discharge in a gasfilled void or on a dielectric surface of a solid or liquid insulation system. This pulse or discharge only partially bridges the gap between phase insulation to ground, or phase-to-phase insulation. A full discharge would be a complete fault between line potential and

ground. These discharges might occur in any void between the conductor and the ground. The voids may be located between the conductor and insulation wall, or internal to the insulation itself, or between the outer insulation wall and the ground frame. The pulses occur at high frequencies; therefore, they attenuate quickly as they pass through a short distance. The discharges are effectively small sparks occurring within the insulation system, therefore deteriorating the insulation, and can eventually result in complete insulation failure [39].

IEEE Std. 1434-2000, IEEE Trial-Use Guide to the Measurement of Partial Discharges in Rotating Machinery, defines PD as:

"An electrical discharge that only partially bridges the insulation between conductors. A transient gaseous ionization occurs in an insulation system when the electric stress exceeds a critical value, and this ionization produces partial discharges" [36].

While IEC 60270, High-voltage test technique-Partial discharge measurements, defines PD as:

"Localized electrical discharge that only partially bridges the insulation between conductors and which can or cannot occur adjacent to a conductor" [40].

This pulse or discharge only partially bridges the gap between phase insulation to ground, or phase-to-phase insulation. A full discharge would be a complete fault between line potential and ground. These discharges might occur in any void between the conductor and the ground.

The following characteristics might be addressed to describe PD from a different prospective [40]:

- PD can develop at locations where the dielectric properties of insulating material are inhomogeneous [40].
- PD occurs when the local field strength of each inhomogeneity exceeds its breakdown field [37]. Air: 27 kV/cm and Polymers: 4000kV/cm (1bar) [42].
- Q transferred depends on void dimensions, breakdown voltage and the dielectric properties (surface properties, kind of gas, gas pressure, etc.) [40].
- inorganic mica components of HV machines insulation system resist the PD activities [40].
- PD is a symptom of insulation deficiencies, like manufacturing problems or in-service deterioration [40].
- time of failure may not correlate with PD levels, but depends significantly on other factors such as operating temperature, wedging conditions, degree of contamination, etc. [40]
- PD as pulses having duration of much less than 1 ps and amplitude ranges from several thousand picocoulombs to ten thousands picocoulombs [40].
- "Corona" is a form of partial discharge that occurs in gaseous media around conductors which are remote from solid or liquid insulation [40].

- PD is often accompanied by emission of sound, light, heat, and chemical reactions [40].
- PD creates voltage pulses at (~50 to 250 MHz) [43].

PD is a symptom of several stator winding problems caused by electrical, thermal, mechanical and chemical stresses. Partial discharges typically occur in gas-filled voids that are found in all winding insulation systems.

PD measurements have been made on the windings of rotating machinery for over 40 years. The electrical insulation of these windings may be prone to PD activity as a result of internal delaminations and of surface or slot discharge. These kinds of PD activity, when the machine is in normal operation, can result in significant deterioration over a period of time. Experience has indicated that PD measurements can be useful for assessing the condition of complete windings as well as of individual formwound coils and bars.

Because the PD involves a flow of electrons and ions across a small distance in a finite period of time, a small current flows every time the PD occurs. The current flow creates a voltage pulse across the impedance of the insulation system.

The measurement and the analysis of the specific PD behavior can be efficiently used for quality control of new windings and winding components and for early detection of insulation deficiencies caused by thermal, electrical, ambient and mechanical ageing factors in service, which might result in an insulation fault [37]

A considerable number of different electrical pulse sensing systems are in use. The machine design and PD activity may define the type of sensors and the installation required.

When a PD event occurs at some location in a winding, the injected charge first flows into the capacitance to ground at the injection site, thereby modifying the local voltage. This voltage change immediately becomes the crest of a wave that propagates in both directions away from the injection site. The nature of the wave at any location away from the injection site depends entirely on the impedance along the path it had to traverse.

Because PD pulse rise times may be in the nanosecond range at the injection site, the initial voltage wave has frequencies from the kilohertz to the gigahertz range.

Three types of PD according to the location within the insulation system [41]:

- internal PD - occurs when there are voids within the coil. The interior surfaces of the voids are deteriorated by a steady bombardment of electrons and disassociated ions from the gaseous medium. Internal PD usually takes many years to result in failure.
- slot PD - occurs due to the capacitive current flowing through the coil insulation to the core of the motor. If the coil side loses contact with the core, a very high voltage develops between the two, causing PD. Slot discharges involve higher voltage levels than internal PD and can destroy the groundwall insulation if they continue over an extended period of time.

- endwinding PD - occurs at the endwinding of the stator. Endwinding contamination from oil films or moisture cause electrical tracking and associated PD on the insulation surface.

Fig. 2.11 shows the potential locations of PD activity within the HV stator winding.

According to the National Fire Protection Association (NFPA 70B), the leading cause of electrical failures is insulation breakdown [44]. The National Electrical Code (NEC) states that these partial discharges are the first indication of insulation deterioration.

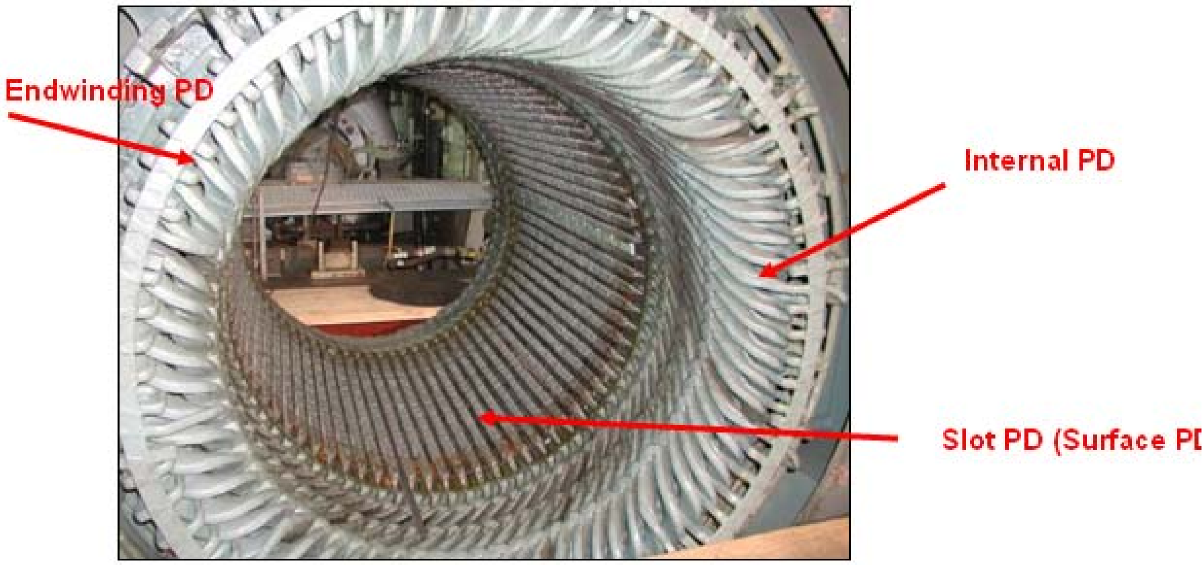


Figure 2.11: PD types according to location

For more than 50 years, companies have performed partial discharge testing on electrical assets as part of ongoing predictive maintenance programs. Data obtained through partial discharge testing and monitoring can provide critical information on the

quality of insulation and its impact on overall equipment health. Because partial discharge activity is often present well in advance of insulation failure, asset managers can monitor it over time and make informed strategic decisions regarding the repair or replacement of the equipment. These predictive diagnostics help companies to prioritize capital and MRO (Maintenance Repair and Operation) investments before an unexpected outage occurs.

Partial discharge testing results can help predict future performance and reliability of critical assets, including:

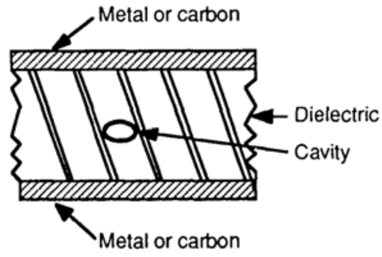
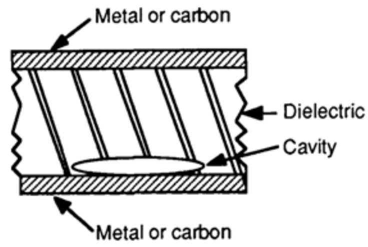
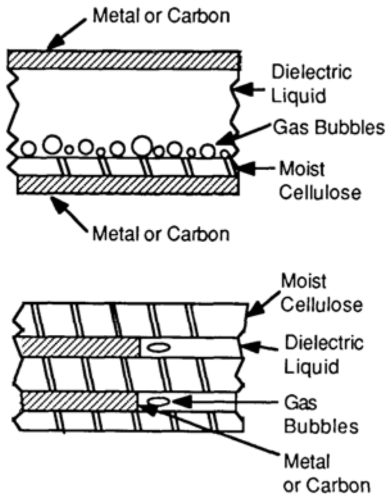
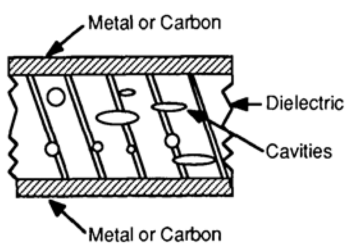
- motors and generators
- cables, splices, and terminations
- power transformers and bushings
- switchgear

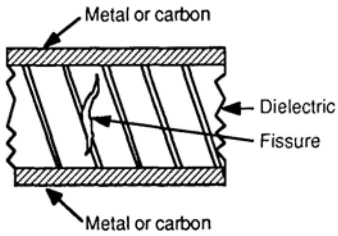
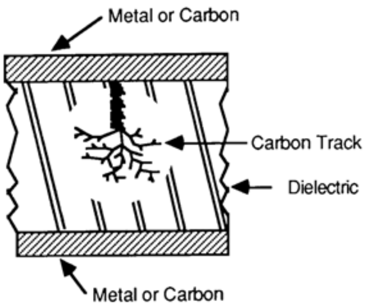
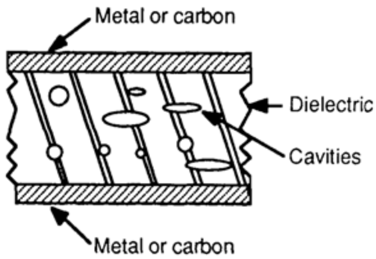
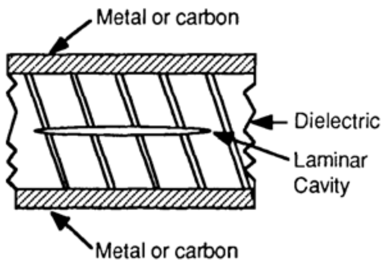
Failures are not limited to service aged equipment. Acceptance testing on newly-installed equipment builds in reliability right from startup. Acceptance Testing can:

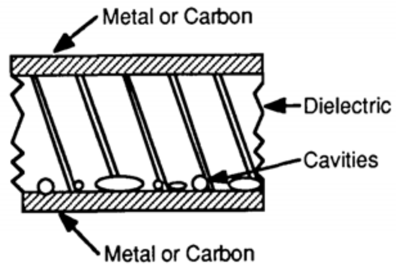
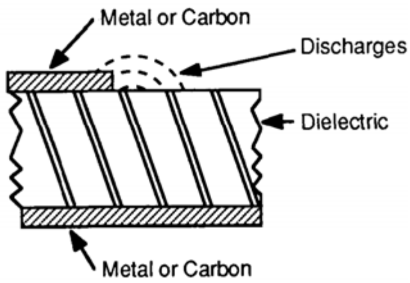
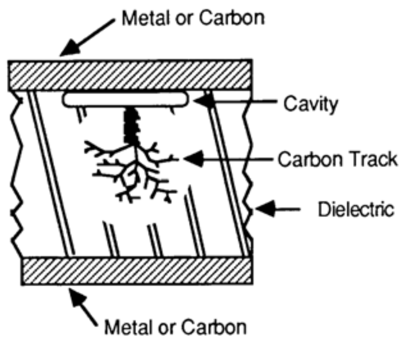
- verify original manufacturers test data and identify damaged insulation that occurred from improper installation, poor design, and/or poor workmanship during or after installation.
- identify premature failures and capture baseline data to trend asset health over the asset's life cycle to ensure maximum return on investment.

According to the location of the gasfilled void, one of the references [45] [46] was successful to differentiate between 10 different types as described in Table 2.1.

Table 2.1: PD gasfilled location [48] [49].

Class	**Description of PD**	**Illustration**
1	PD in solid dielectric bounded cavity	
2	Cavity between metal on one side and dielectric on the other	
3	Gas bubbles in insulating liquid in contact with moist cellulose (e.g. oil impregnated paper)	
4	PD in number of cavities of various shapes, or on external dielectric surface, or high tangential stress	

5	PD at fissures in elastomeric insulation in the direction of the field	
6	Active growth of a carbon track in organic material	
7	Conducting particles formed in voids in cast resin insulation	
8	Laminar cavities in machine insulation	

9	Surface discharges between external metal and dielectric surfaces	
10	Tracking of contaminated organic insulation	

Recently, PD measurement has become the most important on-site diagnostic method for electric power apparatus, thanks to development of methods for eliminating on-site noises through the hardware and software techniques, including measurements in the high frequency range. In addition, various PD pattern recognition techniques for measured data have been proposed to separate PD from noise and to classify different PD sources.

However, PD generated from on-site electric power facilities are complex and different from those measured at the laboratory through artificially generated defects. Also, the result of on-site PD measurement can be changed according to the type and location of the

sensor. Therefore, PD pattern recognition programs based on PD data from the laboratory models can show lower performance for on-site PD measurement.

Due to this problem, algorithms based only on laboratory data, and which may show good performance in the laboratory, are not as suitable as pattern recognition algorithms based on collecting on-site data and learning PD characteristics from the real-world data.

2.3. PARTIAL DISCHARGE THEORY

Partial discharge theory involves an analysis of materials, electric fields, arcing characteristics, pulse wave propagation and attenuation, sensor spatial sensitivity, frequency response and calibration, noise and data interpretation [47]. This section provides simplified models and relates the characteristics of these models to the interpretation of PD test results. First, a few technical concepts will be presented relating to PD. As mentioned above, PD can be described as an electrical pulse or discharge in a gas-filled void or on a dielectric surface of a solid or liquid insulation system [47]. This pulse or discharge only partially bridges the gap between phase insulation to ground, or phase-to-phase insulation. These PD events might occur in gasfilled void between the winding cooper conductor and the grounded motor closure. The voids may be located between the copper conductor and insulation wall, or internal to the insulation itself, between the outer insulation wall and the grounded frame, or along the surface of the insulation. The pulses occur at high frequencies; therefore they attenuate quickly as they pass to ground. The discharges are effectively small arcs occurring within the insulation system, therefore deteriorating the insulation, and can result in eventual complete

insulation failure [47]. These different locations of PD could be illustrated as in Fig. 2.12 for internal gasfilled voids and as in Fig. 2.13 for the surface PD.

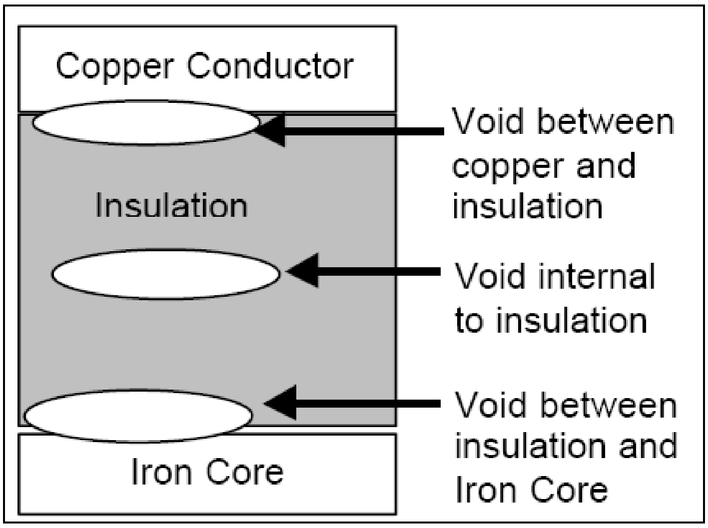


Figure 2.12: PD within insulation system [44]

The insulator surface could also be an area for PD activities. This type of the PD is known as treeing or tracking. These discharges can bridge the potential gradient between the applied voltage and ground by cracks or contaminated paths on the insulation as in Figure 2.13.

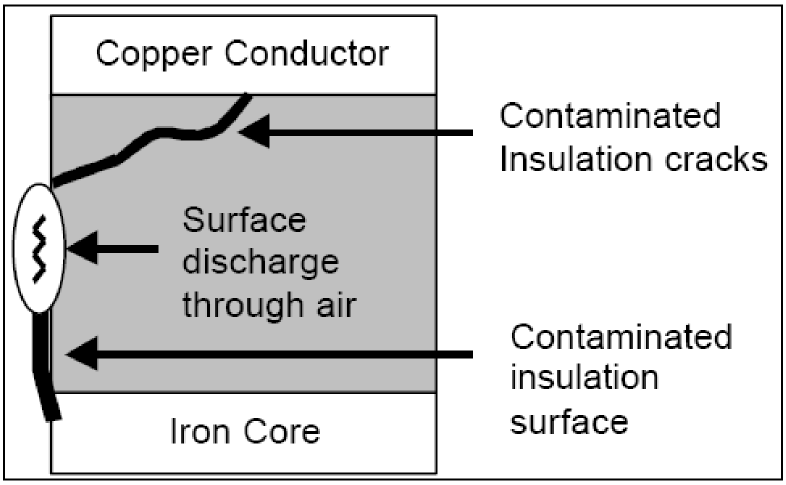


Figure 2.13: Surface PD [44]

A simplified model of an insulation system can be represented by a capacitance and resistance in parallel [48] as shown in Fig. 2.14. This model is the model used in the power factor testing of insulation systems. Leakage current is split between the resistive and capacitive paths.

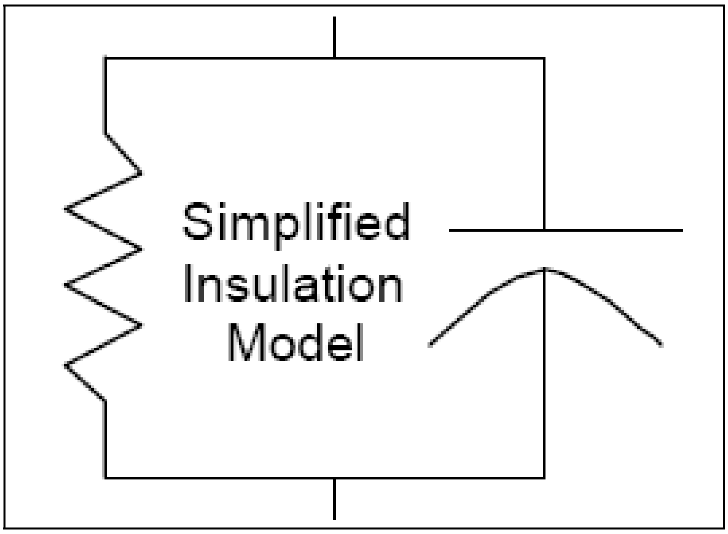


Figure 2.14: Simplified Insulation Model [45]

This model underlies the problem with partial discharge detection. The insulation medium, which is being exposed to the partial discharges, acts to attenuate the signal, therefore weakening the damaging signal which we are trying to identify at sensor locations. In addition, the attenuated partial discharge signal can be masked by sources of electrical noise. The electrical design handbook [46] states: “Discharges once started usually increase in magnitude with stressed time, but discharges can become short circuited by semiconducting films inside the void and discharging is terminated.” The referenced semiconducting films can also consist of carbonization of the organic insulation material within the void due to the arcing damage. Therefore the model of the partial discharge void is similar to that of the insulation medium itself. Actual failure

modes have indicated a drop in partial discharge intensity shortly prior to complete failure. This would occur when the internal arcing had carbonized to the point where the resistive component of the model was low enough to prevent a build-up of voltage across the void. This new low resistive component would also allow higher current flows, and additional heating and resultant insulation damage [47]. The above model, including the resistive component correlates to the actual failure mode of a partial discharge void, with the resistive component passing more leakage current as the partial discharges increase with time. One form of this resistive component is visible tracking on the surface of insulation. An explanation of tracking, and how surface partial discharges are related to the development of tracking follow [50]: "Tracking damage has been traced entirely to the locally intense heat caused by leakage currents. These currents flow thru any contaminated moisture film on the bridging insulating surface. As long as this film is fairly broad and continuous, the heat associated with the leakage current is spread over a wide area and is dissipated. However, heating promotes film evaporation. This causes the film to break up into small pools or islands. Each break in the film tends to interrupt a segment of the leakage current, causing a tiny arc. Even though the arc is small, severe local heating results. The intense heat of the leakage current arc is sufficient to cause a molecular and chemical breakdown of the underlying insulation. On organic materials, a frequent by-product of arcing is carbon." The above "tiny arc" along the insulation surface can be represented by partial discharge activity. Fig. 2.15 illustrates the failure mode of deteriorated insulation related to the intensity of partial discharge measurements.

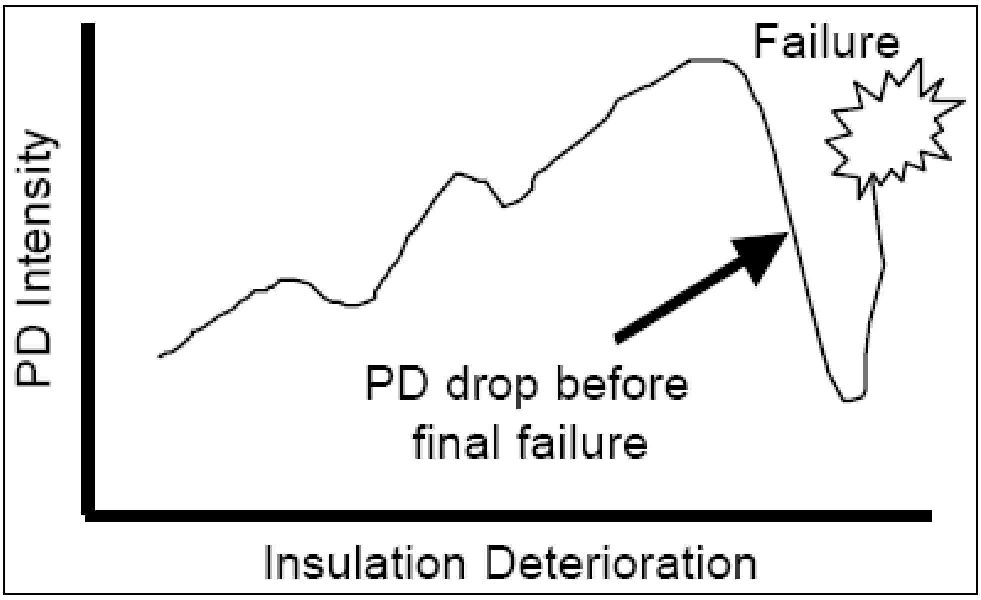


Figure 2.15: PD versus insulation failure mode [47]

Figure 2.16 illustrates a busbar which has as a progressive tracking highlighted for presentation purposes. At the point near eventual failure, the tracking and resistive component of the insulation have increased to the point where partial discharges have been reduced, since the "tiny arcs" have caused the carbonization and tracking, therefore providing a direct path for current flow. At this point, evidence of insulation deterioration is usually detected by traditional methods of insulation resistance, or megger testing. For the above reason, partial discharge on-line testing and traditional insulation resistance testing are complimentary. On-line partial discharge testing can detect insulation in the progressive phases of deterioration, with trending identifying problems long before eventual failure. Traditional insulation resistance testing provides a "current-state" of the insulation system.

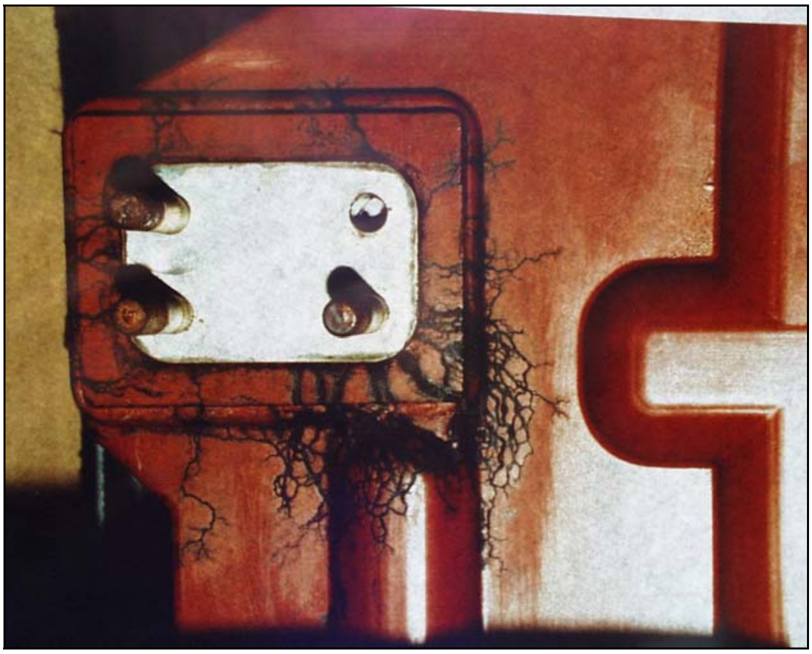


Figure 2.16: Busbar with progressive tracking

A model of the two voids insulation is shown below in Fig. 2.17. This model could be used in understanding the PD mechanism Three concepts should be reviewed to understand the PD mechanism;   the first concept to review is the characteristic trait that partial discharges occur only during the first and third quarter of each cycle. This is the initial rising positive signal, and the initial rising negative signal.

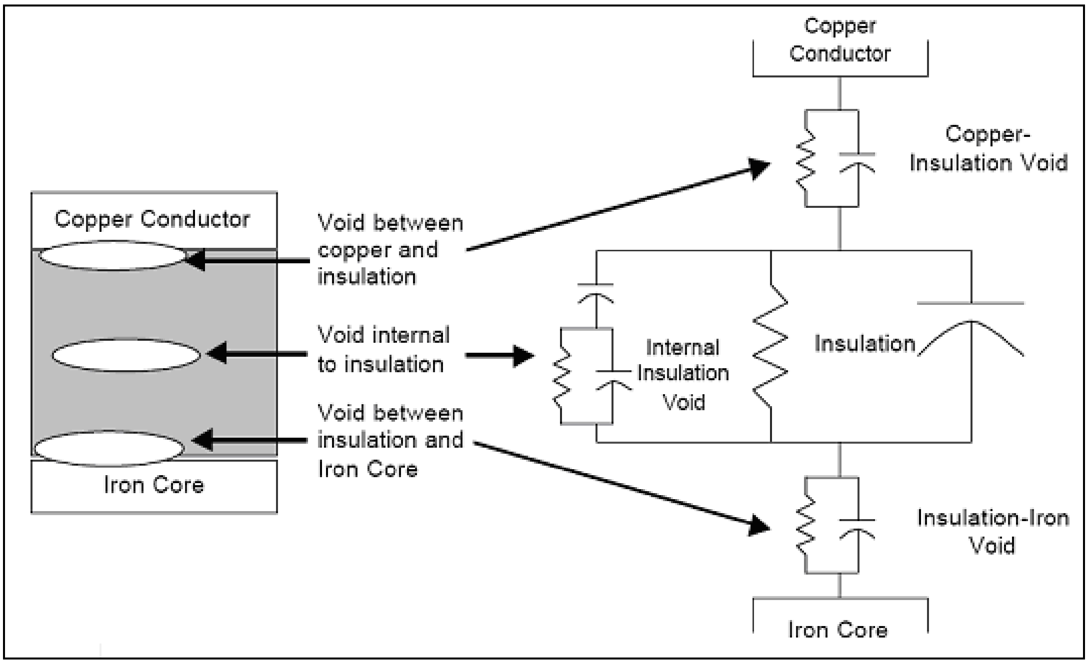


Figure 2.17: Insulation system partial discharge model [47]

This model could be used in understanding the PD mechanism. Three concepts should be reviewed to understand the PD mechanism; the first concept to review is the characteristic that partial discharges occur only during the first and third quarter of each cycle. This is the initial rising positive signal, and the initial rising negative signal as shown in Fig. 2.18 at 45 ° and 125°; also Fig. 2.20 shows that physical concept.

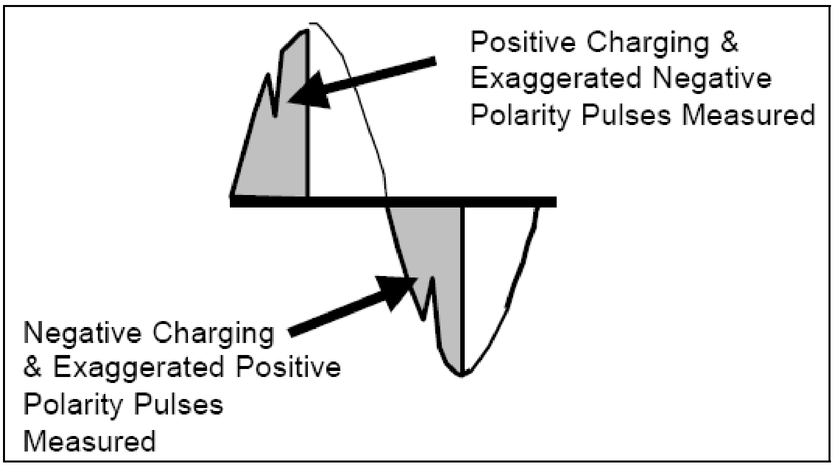


Figure 2.18: Exaggerated positive & negative polarity pulses [47]

The actual field readings show that the positive charging occurs at 45 ° and the negative one occurs at 125°. Effectively, during the initial rising positive signal, all of the capacitive components are being charged until the partial discharge inception voltage is reached across each specific void, and partial discharges commence. When the positive wave cycle begins to decrease the positive voltage across each void is reduced, since some capacitive charge remains. Some level of charge must exist since the voltage across a capacitor cannot be changed instantaneously. During the first quarter cycle a positive charge is created and the resultant partial discharges. During the third quarter cycle, this positive charge is effectively reversed, resulting in a positive charge in the reverse direction, and the resultant partial discharges [47].

The second concept to review is that partial discharges are measured as voltage pulses; therefore, during the positive waveform cycle, a discharge, or a partial short circuit, results in a negative, downward oriented pulse. This is referred to as a partial discharge with a negative polarity, and occurs during the first quarter-cycle of increasing positive voltage applied to the void. During the third quarter-cycle, a partial short-circuit results in a positive, upward oriented pulse. This is referred to as a partial discharge with a positive polarity and occurs during the third quarter-cycle of the increasing negative voltage applied. These partial discharges, which are measured as a high frequency change in the power signal in millivolts to a few volts, cannot be observed with a standard scope; therefore they are exaggerated in Figure 2.18 for illustration purposes [47]. As stated, since the pulse of voltage change is being measured, the negative polarity pulses occur during the first quarter cycle, or during the rising positive cycle of the wave; and conversely, the positive polarity pulses occur

during the third quarter cycle, or during the rising negative cycle of the wave [47]. The partial discharge magnitude is related to the extent of damaging discharges occurring, therefore related to the amount of damage being inflected into the insulation. The pulse repetition rate indicates the quantity of discharges occurring, at the various maximum magnitude levels. Both play a role in determining the condition of the insulation under test. Whereas seldom possible with on-line motors, the maximum magnitude level should be calibrated to reflect the actual charge, measured in picocoulombs. The benefits of such calibration are offset by the relative comparison of similar motors, and more importantly by trending of the partial discharge activity over time. On-line partial discharge testing allows for such trending and analysis of the electrical equipment. The illustration of the partial discharge activity relative to the 360 ° of an AC cycle allows for identifying the prominent root cause of partial discharges, therefore appropriate corrective actions can be implemented [47].

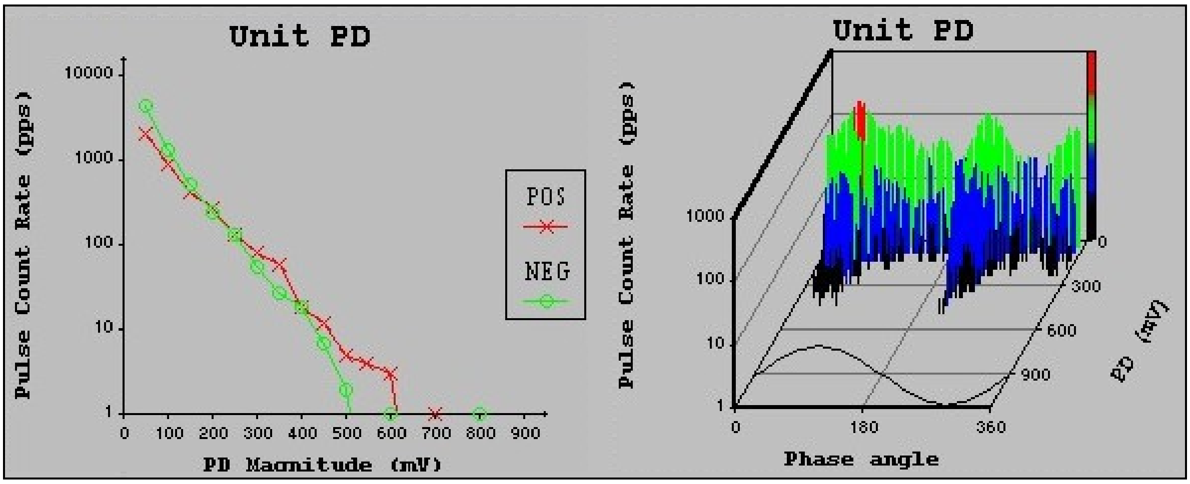


Figure 2.19: PD 2D and 3D measurements [48]

The third concept to review is the effect of high negative polarity pulses, occurring during the first quarter cycle of the positively rising wave, in relation to the high positive

polarity pulses, occurring during the third quarter cycle; and vice versa. It has been found that if the positive polarity discharges exceed the negative polarity discharges then the probable root causes are either voids between the insulation and iron core (slot discharges), or at the winding end-turns, or surface partial discharges. It has also been found that if the negative polarity discharges exceed the positive polarity charges then the probable root cause is voids in between the copper conductor and insulation. This interesting phenomenon is related to the applied voltage level to the void, the void's geometric shape and the specific materials that are acting as the anode and cathode. The critical material is the cathode, since the cathode supplies free electrons to allow the partial discharges to continue.

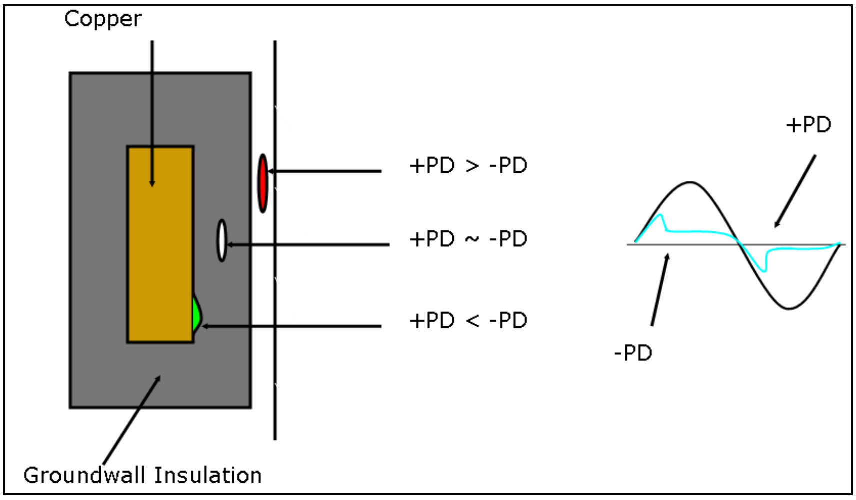


Figure 2.20: Predominance in PD pulse polarity [51]

As illustrated in Figure 2.20 the various anodes and cathode materials are shown for the rising positive and negative parts of the AC cycle, which are the two areas where discharges are measured.

2.4. AVAILABLE TECHNIQUES TO DETECT PD

Partial discharges are small electrical pulses from the electrical breakdown in a void or in a highly stressed electric field of the insulation, e.g. a dielectric surface in a solid or liquid insulation system. PDs cause a degradation process of the insulating material by the change of electric field energy into kinetic energy of electric charges. PDs have only a small short time influence on the electrical firmness of electrical resources [49]. On the other side, the long time influence shows a destructive effect. If the void is in an organic solid or liquid, the PD will degrade the organic material and the insulation of the equipment might fail [50].

IEC 60270 stats that the PDs are often accompanied by emission of sound, light, heat, and chemical reactions. This activity includes macroscopic, physical effects like pressure wave (sound), light, chemical reactions, and high frequency waves.

Accordingly, different measuring methods depending on the electrical equipment are used for PD behavior analysis. These techniques include [49]:

- Conventional electrical measurement integration at frequency domain Narrow - band, Wide - band Integration at time domain
- Electrical measurement with high frequencies HF / VHF method (20 MHz to 300 MHz) and UHF method (300 MHz to 3 GHz)
- Acoustic measurement (10 Hz to 300 kHz)
- Optical measurement
- Chemical measurement

According to elementary communication theory, the measured signal energy increases linearly with the bandwidth. For the PD measurement, it was recognized that the signal is constant over the measured frequency spectrum. For on-site measurements in the

electromagnetic disturbed environment of different high voltage equipment, modern methods in combination with digital technology (digital filters as well as suitable algorithms) of interference suppression shall be developed [49]. The high frequency PD impulses are superposed with the supply voltage and must be coupled out of the test circuits. The test set up consists of a high voltage source, a coupling capacitance and measurement impedance (quadrupoles). The PD impulse from the HV equipment appears on the measuring impedance via the coupling capacitor. Each PD causes a short high frequency signal, which can be detected with the impedance. Different systems, which employ different bandwidths, can be used to measure and analyzed the detected signals. They can be built as a narrow- or a wide-band system. Narrow band PD measuring systems have a small bandwidth (9 kHz) and a centre frequency, which can be varied over a wide frequency range. The response of this system to a PD impulse is a transient oscillation with positive and negative peak values. Wide band PD measuring systems have a bandwidth of a few 100 kHz, so the response of a PD impulse of such a wide band system is well-damped oscillation. So the apparent charge and the polarity of the PD signal can be determined [48] as illustrated in Fig. 2.19. The measurement systems detect the apparent charge, the phase position to the test voltage and the number of discharges over a given gate time interval. Further parameters can be calculated by usage of stored data.

2.4.1. UHF Measurement of Partial Discharges

In recent years the ultra high frequency (UHF) method was established as the usual PD measuring procedure in GIS systems (increasingly also applications by transformers). The ultra high frequency PD detection is based on the detection of the high frequency signals

generated in the event of discharges. PD impulses of very short duration (< ns), produce electromagnetic waves, whose spectrum reaches up to the GHz range. Capacitive sensors, as like antennas, have been developed, which can detect transient waves [49].

Two types of PD measurement can be recognized. These are the narrow band technique with a measurement bandwidth of only a few MHz, and the broadband method, whereby the PD signal is detected in the time domain, over a frequency range typically up to 2 GHz (Figure. 2.22). The measuring sensitivity is comparable or rather higher than a conventional PD measurement. It has to be considered that no direct correlation between the PD intensity detected in the UHF-band and the apparent charge exists. A detection of partial discharges with the UHF-method is possible, but there is no measurement of the apparent charge according to IEC 60270 [44]. Fig.2.21 shows the UHF coupling capacitor and the two possible method for the signal processing (NB or WB).

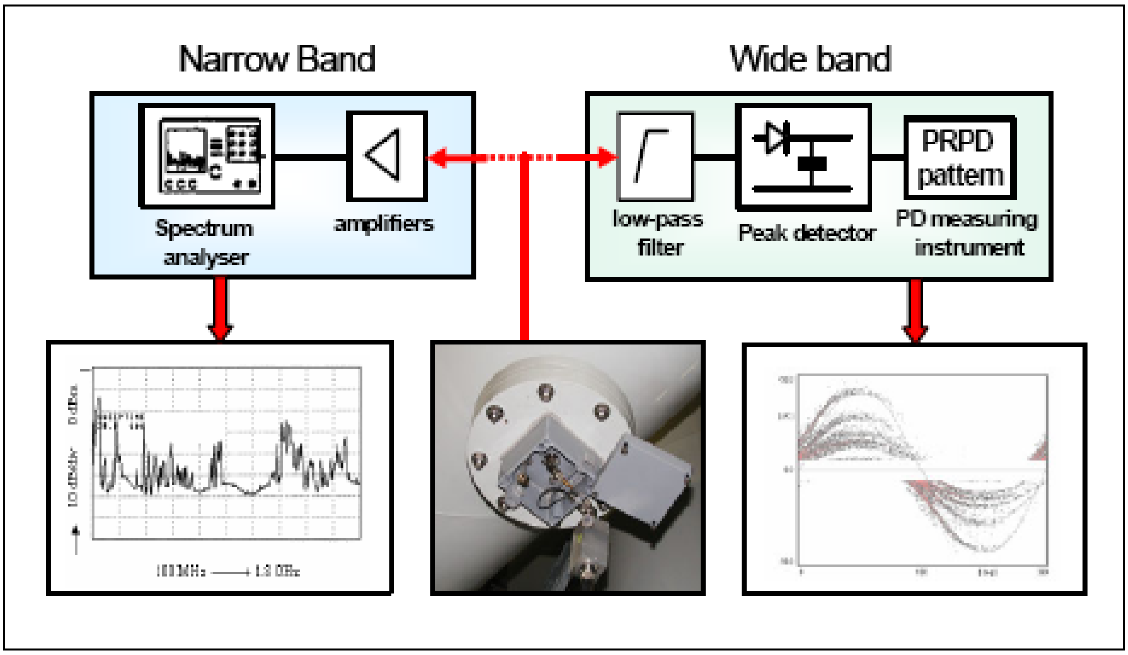


Figure 2.21: UHF PD measurement [49]

2.4.2. HF Measurement of Partial Discharges

This method is based on the frequency characteristics of a discharge pulse. PDs, for example in polymeric insulations, show duration of several nanoseconds at the point of origin. A transformation of the time signals in frequency domain shows a PD frequency spectrum up to the range of 100 MHz. For the measurement of PD, inductive and capacitive sensors are used. As an example of an inductive PD measurement, a time variable magnetic field is inductive collected with a Rogowski coil surrounding a conductor (Fig. 2.22). Beneficial for this method is the galvanic isolated survey of the PD current, as well as the exact failure location by moving the coil [49].

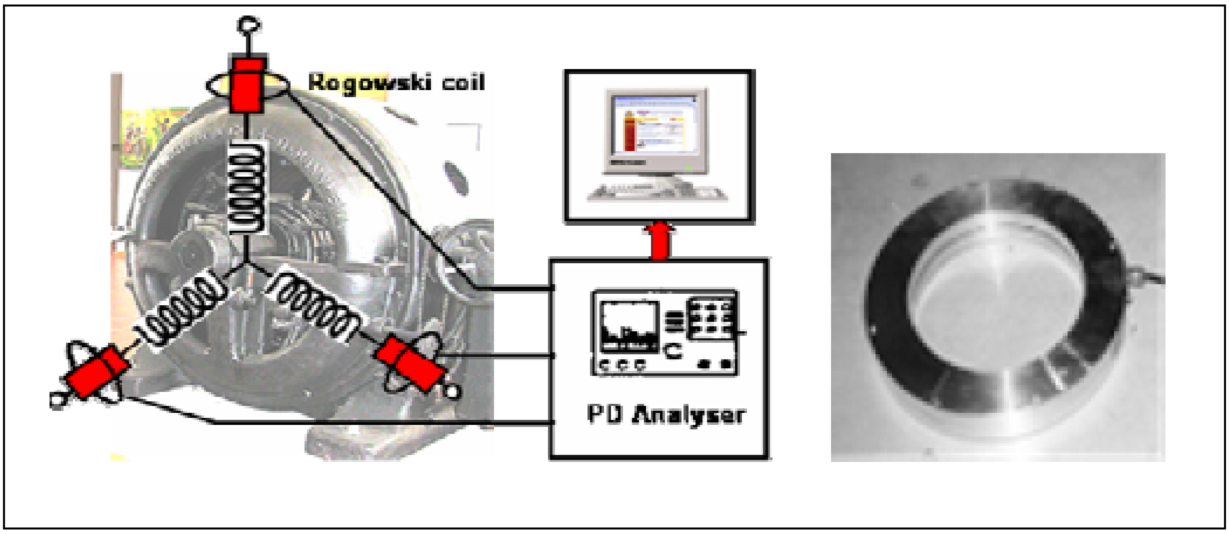


Figure 2.22: Measuring for HF PD detection on machines VHF PD coupler, split ring Rogowski coil [51]

2.4.3. Acoustic Measurement of Partial Discharges

The main field of application of the acoustic detection of partial discharge is the location of discharge sources which represent alternative defective areas of equipment. The principle of the acoustic PD detection is the detection of the pressure waves generated

by the discharge within the insulation. The discharge appears as a small "explosion", which excites a mechanical wave, and propagates through the insulation. The propagation speed of the acoustic wave depends on the surrounding medium. Likewise, reflection and refraction, geometrical spreading of the wave and absorption in the materials lead to changes of sound propagation, which must be considered during detection and interpretation. Because of the short duration of the PD impulses, the resulting compression wave has frequencies in the ultrasonic region. The frequency range is between 10 Hz and 300 kHz. In air and gases, microphones are usually employed as sensors. Microphones produce a voltage proportional to the pressure of the sonic wave. Piezo-ceramic transducers as acoustic emission sensors or accelerometers offer the best sensitivity for detection of ultrasonic waves in the enclosure [53]. Fig. 2.23shows the location for the acoustic sensor and the steps that should carried out to read the PD values.

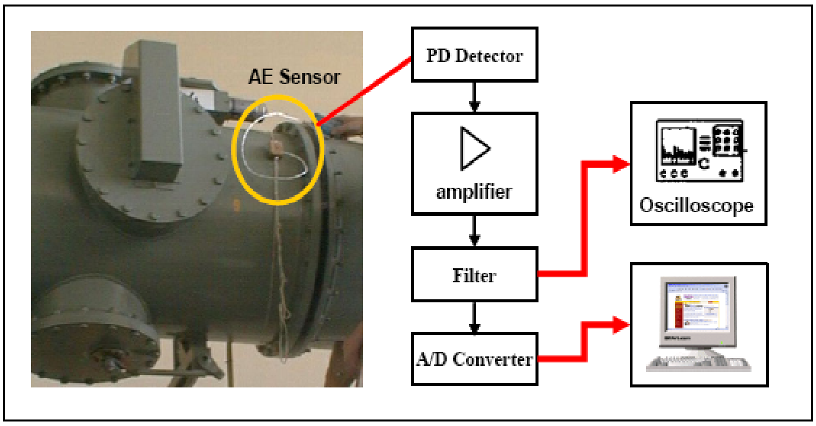


Figure 2.23: Acoustic PD detection system [59]

2.4.4. Chemical Verification of Partial Discharges

Partial discharge activity results in changes to the chemical composition of the insulation oil phases. These changes have been exploited in the detection of PD activity.

In insulating liquids, usually gaseous compound are developed, which can be identified with the help of a Gas-in-Oil analysis. Thereby the developed fission gases depend on the power density as well as the insulation materials. If PDs occur in air, the chemical reactions between the components of air generate and ozone. The determination of ozone concentration makes conclusions concerning the PD activity possible, for example in air-cooled machines. However, a disadvantage of the chemical procedures is the integrative character, which does not allow statements about the current operating condition. It is not possible to indicate nature, intensity, extent or location of a single PD. Fig. 2.24 illustrated the Gas-in-Oil analysis instrument.

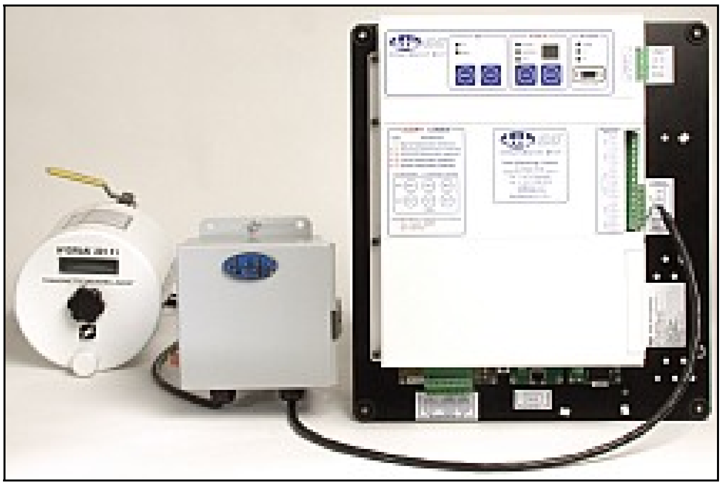


Figure 2.24: Results of Gas-in-Oil analysis could be used to detect the PD in transformer oil

2.4.5. Opto-Acoustic Partial Discharge Measurement

During a partial discharge in gas or oil an acoustic wave in sonic and ultrasonic ranges are generated. If a PD in the surrounding medium arises, the pressure wave result in a deformation of an optical fiber and its optical transmission characteristic is changed.

This fact is used by the opto-acoustical sensor principle. It comes to a mechanical stress and a stretch of the fiber, as well as an influence of the polarized light used by the fiber.

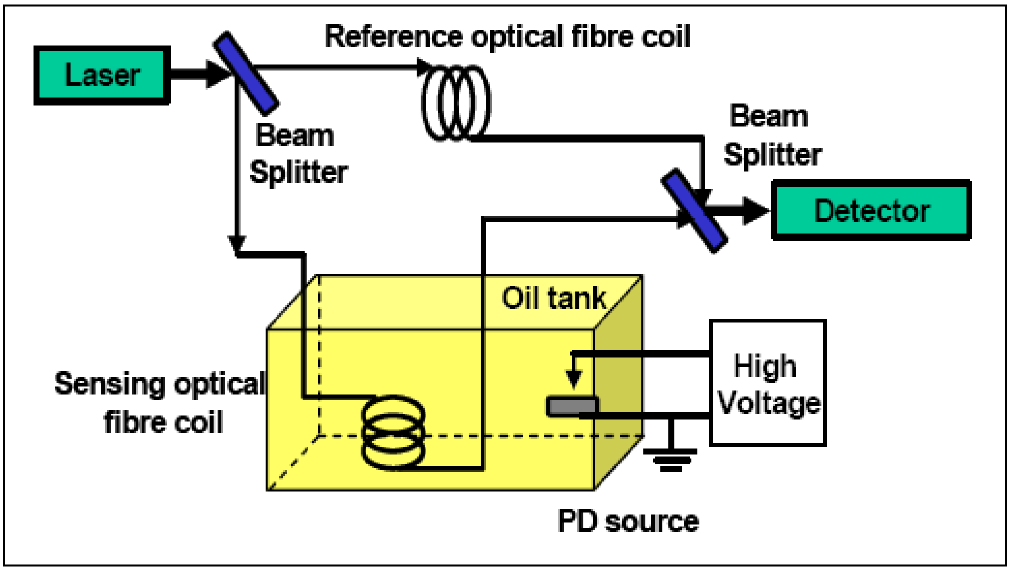


Figure 2.25: Experimental setup of the optical interferometric detection of PD [54]

The result is a change of the optical distance as well as the polarization condition. The advantage of such system is the immunity to electromagnetic fields, high flexibility, high sensitivity and large bandwidth [54]. Fig. 2.25 gives block diagram represntation for the system components for the Opto-Acoustic Partial Discharge Measurement

2.4.6. Optical Partial Discharge Detection

Each partial discharge produces a light emission as a result of various ionization, excitation and recombination processes during the discharge. This emission transports information about the energy level of the discharge. Depending on the surrounding isolating medium (its chemical components - air, SF6, oil) and different factors (temperature, pressure …) the optical spectrum is between the UV range and the infrared

range. If the HV equipment is enclosed and light-tight (environment light is totally excluded), as a transformer or GIS, an optical detection is possible. The advantage of this method is the immunity to EMC, the insensitivity to electromagnetic and acoustic interference sources. The optical measurement is a very sensitive method in comparison to the conventional electrical or acoustic techniques especially by on-site measurements [55] as shown in Fig. 2.26 for the optical sensors and the photomultiplier.

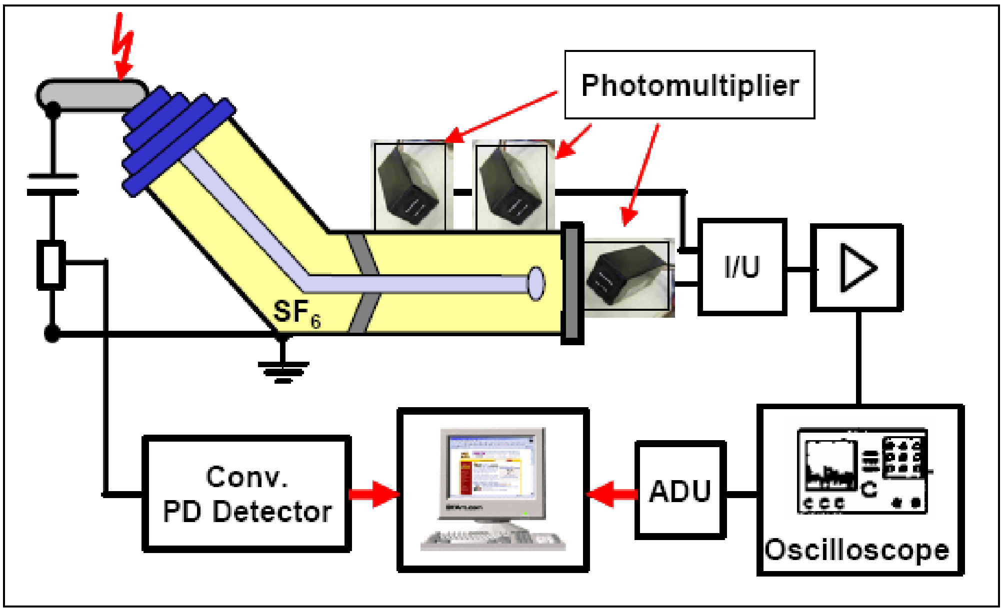


Figure 2.26: Test arrangement for optical PD measurement

PD pattern recognition is the ability to recognize and distinguish between different types of PD within the electrical insulating systems. The phase resolved Partial discharge (PRPD) analysis or PD pattern is a significant method to present and interpret the PD measuring results. Different PD sources (external or internal PD) and different locations can be recognized by this pattern. Fig. 2.27 explains the available techniques to perform the PD pattern recognition.

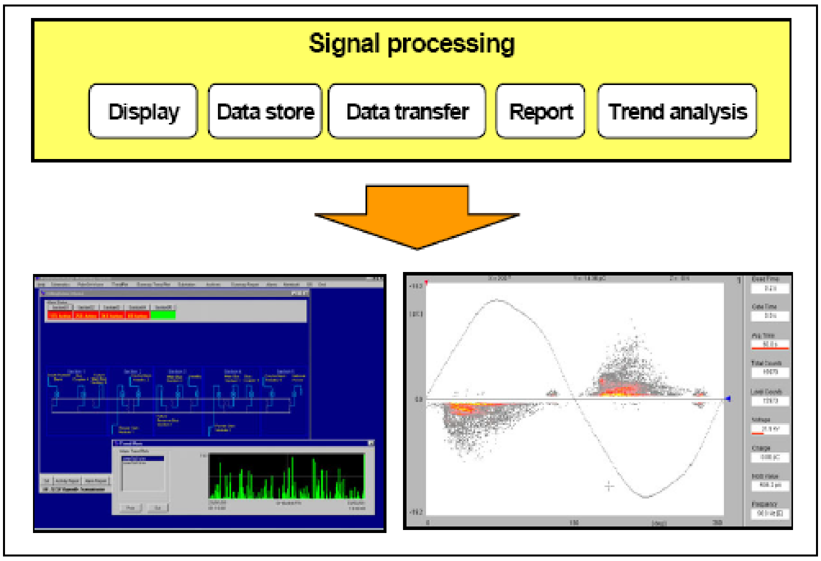


Figure 2.27: Example for signal processing

Computerized techniques with statistical parameters take into consideration the stochastic nature of the PD process, and techniques, which require no statistical precondition of the data, for example neural networks, may be employed [56]. Developments are accomplished in the following areas:

- Statistical Analysis
- Neural Networks
- Fuzzy Logic
- Wavelet Transformation
- Fractal Analysis
- Time vs. Frequency clustering.

Using any technique to detect the PD on any type of HV equipment will provide many advantages to help reliable and economical operation for any plant. Many benefits have been realized by manufacturers and end-users through monitoring PD activities. PD mentoring provides users a huge benefit in the form of one or more of the following:

- Avoid unnecessary rewinds on older machines by maximizing the operating hours from a stator winding.
- Avoid unexpected in-service failures of the stator winding; and extend up-time between outages
- Find a problem and correct it before it has a chance to damage the winding.
- Find problems on new machines which may still be under warranty.
- Assess the quality of maintenance repairs and/or rewinds with before and after reading.
- Compare results from similar machines to focus maintenance on those with higher levels of PD.
- Some insurance companies recognize the PD test and may give rebates.
- Improve the overall reliability of motors and generators.
- Accomplish all this while the machine remains in operation (On-Line).
- Prevents catastrophic failure of stator insulation system and reduces forced outage time by giving an early warning of stator insulation system deterioration.
- Extends the lifetime of stator insulation by identifying the early stages of repairable insulation damage and making timely repair.
- Enables efficient maintenance planning by eliminating premature rewinding of stator winding and reducing maintenance costs.
- Enables efficient use of limited manpower by establishing priorities for maintenance or repair of multiple units.

- Partial Discharge measurements are simple and safe to perform by operations personnel and do not require a large external AC power supply or high voltage power source.
- Gives specific information for assessing repairs or rewinds by identifying the type of the insulation deterioration (e.g. slot discharge), its probable cause (e.g. loose winding) and its severity (degenerating, stabilizing, or improving).
- Confirms effectiveness of repairs, by comparing the partial discharge readings taken before and after repair of the machines.

This method will avoid taking an operating machine out of service or extend an outage to do perform other tests when on-line Partial Discharge testing indicates a healthy stator winding.

2.5. ONLINE PD MEASUREMENT VS. OFFLINE MEASUREMENT

The strength and weakness of each technique could be summarized by the following chart:

Table 2.2: Comparison between Online and offline PD measurement [57]

Technique	Strength	Weakness
Online PD Detection	▪ realistic operating conditions (electric field / current, mechanical forces / vibration / temperature) ▪ no interruption / cost effective ▪ easy trending of PD activity ▪ early detection of incipient insulation faults ▪ no external power source needed ▪ testing at various load conditions	▪ considerable interference / noise ▪ noise may mask actual problems ▪ superposition of several PD sources ▪ experience required for data analysis ▪ localization of PD sources difficult

Offline PD Detection	▪ lower interference/noise level ▪ voltage variability: “PD” = f(U) ▪ measurement of PDIV, PDEV ▪ easy localization of PD sources ▪ additional dielectric measurements ▪ visual inspection; maintenance work	▪ external power source needed ▪ machine must be out of service ▪ time consuming / expensive ▪ entire winding incl. neutral end is at high voltage ▪ no realistic stress conditions ▪ additional PD sources that are not active during operation

2.6. PD International Standards

For many years, the measurement of partial discharges has been employed as a sensitive means of assessing the quality of new insulation as well as a means of detecting localized sources of PD in electrical winding insulation arising from operational stresses in service. Compared with other dielectric tests (i.e. the measurement of dissipation factor or insulation resistance) the differentiating character of partial discharge measurements allows localized weak points of the insulation system to be identified [40].

Table 2.3: PD International Standards

Standard	Scope
IEC 60270	<u>**High-voltage test techniques – Partial discharge measurements:**</u> This International Standard is applicable to the measurement of partial discharges which occur in electrical apparatus, components or systems when tested with alternating voltages up to 400 Hz or with direct voltage.
IEC TS 60034-27	<u>**Off-line partial discharge measurements on the stator winding insulation of rotating electrical machines:**</u> This part of IEC 60034 which is a technical specification provides a common basis for – measuring techniques and instruments, – the arrangement of test circuits, – normalization and testing procedures, – noise reduction, – the documentation of test results, – the interpretation of test results with respect to partial discharge off-line measurements on the stator winding insulation of rotating electrical machines when tested with alternating voltages up to 400 Hz. This technical specification applies to rotating machines having bars or form wound coils with conductive slot coating. This is usually valid for machines with voltage rating of 6 kV and higher. The measurement methods described in this specification may also be applied to machines without conductive

IEC 60505	**<u>Evaluation and qualification of electrical insulation systems:</u>** This International Standard establishes the basis for estimating the ageing of electrical insulation systems (EIS) under conditions of either electrical, thermal, mechanical, environmental stresses or combinations of these (multifactor stresses). It specifies the principles and procedures that should be followed, during the development of EIS functional test and evaluation procedures, to establish the estimated service life for a specific EIS. This standard is for use by all IEC technical committees responsible for equipment having an EIS.
IEEE 1434-2000,	**<u>IEEE Trial-Use Guide to the Measurement of Partial Discharges in Rotating Machinery:</u>** This guide discusses both on-line and off-line partial discharge (PD) measurements on complete windings of any type, as well as measurements on individual form-wound coils and bars. Measurements selected from those that are outlined may be appropriate for application during the manufacture, installation, operation, and maintenance of windings of ac rotating machinery.
ASTM D 1868	**<u>Standard Test Method for Detection and Measurement of Partial Discharge (Corona) Pulses in Evaluation of Insulation Systems:</u>** This test method covers the detection and measurement of partial discharge (corona) pulses at the terminals of an insulation system under an applied test voltage, including the determination of partial discharge (corona) inception and extinction voltages as the test voltage is raised and lowered. The test method is also useful in determining quantities such as apparent charge and pulse repetition rate together with such integrated quantities as average current, quadratic rate and power. The test method is useful for test voltages ranging in frequency from zero (direct voltage) to approximately 2000 Hz.

CHAPTER 3

USE OF NEURAL NETWORKS IN PARTIAL DISCHARGE DETECTION

3.1. NEURAL NETWORK INTRODUCTION

The artificial neural network (ANN) imitates information processing in nature and more specifically in biological nerve cells. It consists of a large number of simple processing units called neurons connected to each other by weights called synapses. The neurons are grouped in layers and are connected to all neurons of the preceding and the following layers. The structure of an ANN consists of an input layer, an output layer and one or more hidden layers. The study of neural networks was initially motivated by insights into how biological brains – and in particular, mammalian brains (natural neural networks) – function. Put simply, mammalian brains learn as connections between neurons are strengthened – the result of electrochemical processes triggered by external or internal stimuli ("experiences"). Figure 3.1 depicts a biological neuron (the cell body, or Soma) and its connections. Together they comprise the basic building blocks for biological brains. A fundamental characteristic of biological brains is that they consist of a huge number of neurons connected in parallel. Similarly, artificial neural networks consist of a relatively smaller number of processing elements (software structures) connected in parallel.

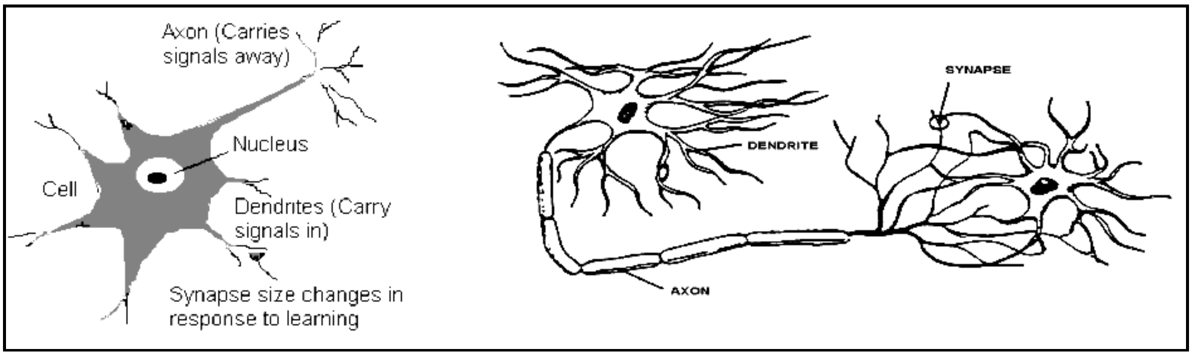


Figure 3.1: A Biological Neuron [64]

Table 3.1 [65] compares basic attributes of natural and artificial neural networks.

Table 3.1: Neural Network Attributes [65]

	Human Brain	ANN
Neurons	$10^{10} – 10^{11}$	10^{1} - 10^{3}
Synapses (Connections)	$10^{13} – 10^{14}$	10^{1} - 10^{6}
Response Time	10^{-3} Sec	$10^{-8} – 10^{-6}$
Processing	Highly Parallel	Mostly Sequential

A neuron computes a weighted sum of the incoming signals and then uses a non-linear activation function to determine its activation state [58] [59]. The weights represent the strengths of the connections and they can be positive (excitory) or negative (inhibitory). The activation function is usually a threshold, sigmoid or logistic [60]. An ANN evolves a non-linear mapping between the input and output patterns during the learning phase. This information is stored in the connection weights and neuron biases in order to use during the classification phase. As soon as the NN topology is decided, the connection

weights and biases must be adjusted to produce the desired mapping. It should be noted that the number of neurons in the output layer is the same as the number of categories or classes into which the input information is divided. The number of neurons in the input layer is equivalent to the number of features extracted from the input patterns [58]. Recently the application of NNs to the determination of the PD source has become a new trend in the diagnosis of HV insulation [61]. Just as mankind was learning and developing by means of thousands of trials, errors and improvements from the errors, NNs also provide brain-like capabilities for solving problems - they learn by examples. NNs basically belong to 'nonparametric' methods. This means that usually it is not necessary to make any assumptions about data structure. In statistics various preliminary conditions, e.g. data from normal populations, must be fulfilled in order to carry out the analysis. The problem to be dealt with here is to assign 'unknown' PD patterns to known ones. Today, the most used NN for such classification purposes are the back-propagation network, as used in [6-8], the Kohonen self-organizing map, as used in [88], and the learning vector quantization network, as 'perhaps the most cited classification network' [63]. Generally the structure of a NN is based on a three-layer system: input layer, hidden layer(s) and output layer. Basically, the IL may have several input neurons or processing elements, and is driven by the data obtained by the PD measuring system. Then, the HL characterizes the typical structure of the NN and differs for diverse NN. Finally, the OL is defined according to user expectancies and can be represented by one or more PE.

3.2. APPLICATION OF NN IN PD DETECTION

Multilayer artificial neural networks (ANNs) have been successfully applied in various pattern classification problems [66] [67]. The basic advantage of an ANN over other classifiers is its ability to learn from examples. Knowledge in the training set is extracted and stored in the connection weights and neuron biases during the learning phase. There are several different types of ANN structures used in PD recognition. They are: back-propagation neural net, Kohonen self-organizing feature map, learning vector quantization network, counter propagation neural net, modular and cascaded neural nets. During the learning phase, these ANNs are presented with PD feature vectors with known defects/sources. Artificial neural networks (NN) have a great potential in areas such as pattern recognition; this in turn has encouraged their use in the diagnosis of PD patterns [68] [69] [70]. However, it should be emphasized that the success of the strategy of PD pattern recognition using the NN is highly contingent upon the information provided to the network. Such information consists of a number of features that are extracted from the PD pattern so as to optimize the likelihood of the correct interpretation of the available PD data. The parameters that have been generally provided to the NN to recognize the PD patterns are ϕ, ΔQ and N . However, it is found that there may arise certain disparities in the measurement of these parameters especially when the statistical time lag becomes unduly long. Under such circumstances, a discharge will tend to occur at a voltage considerably in excess of the normal inception voltage. As a result, the PD pattern will be altered, in a statistical sense, due to the variations in the value of the breakdown voltage at which the discrete discharges will take place; consequently, there are some valid arguments regarding the suitability in the use of these parameters as the only guiding basis

in the PD recognition task. In addition, when discharges between dielectric surfaces are involved, the occurrence of multiple discharge sites and their statistical distribution over the dielectric surface due to fluctuations in the deposited surface charge density will lead to further randomness in the discharge sequence [71].

3.3. BACK PROPAGATION ALGORITHM

The back propagation (BP) algorithm is a kind of supervised learning algorithm. The learning process involves repetitive presentation of input patterns along with the desired output; the weights and biases are updated until the error becomes acceptably low. In this process, the class to which each input belongs is known a priori [72]. This process is carried out in two steps, a forward and a backward step. The weights and biases are randomly initialized to small values. In the forward step, an input pattern is provided and the outputs of all neurons in each layer are computed. The error of the output layer is found by comparing the obtained output and the desired one. Then the backward step consists of the back propagation of errors, and the weights and biases are updated so as to minimize the overall error. It has to be noted that single-layer NN may only solve linearly separable problems. In the case of PD, there is non-linearity interrelating the various quantities, so the use of multiple hidden layers is mandatory. The number of hidden layers is an important question in this respect. Too simple an ANN may not grasp the essence of the problem and may make similar errors for training and test data, whereas a too complex ANN may master the training data perfectly but it may not succeed in generalizing correctly [60], resulting in an over-fit model.

An improved back propagation algorithm was used to accelerate the training speed in the case of transformer insulation diagnosis based on dissolved gas analysis (DGA) techniques. The adaptive learning rate method was designed to shorten the learning procedure [73]. An adaptive wavelet classification network was also proposed. It is a kind of enhanced BP algorithm in which the wavelet theory was adapted for optimizing the parameters of the network. It has the advantage of avoiding falling into the local minimum point during the learning procedure. In practice, the classification results show that the generalization capability is satisfactory and the recognition rate is high [74] as shown in Fig. 3.2.

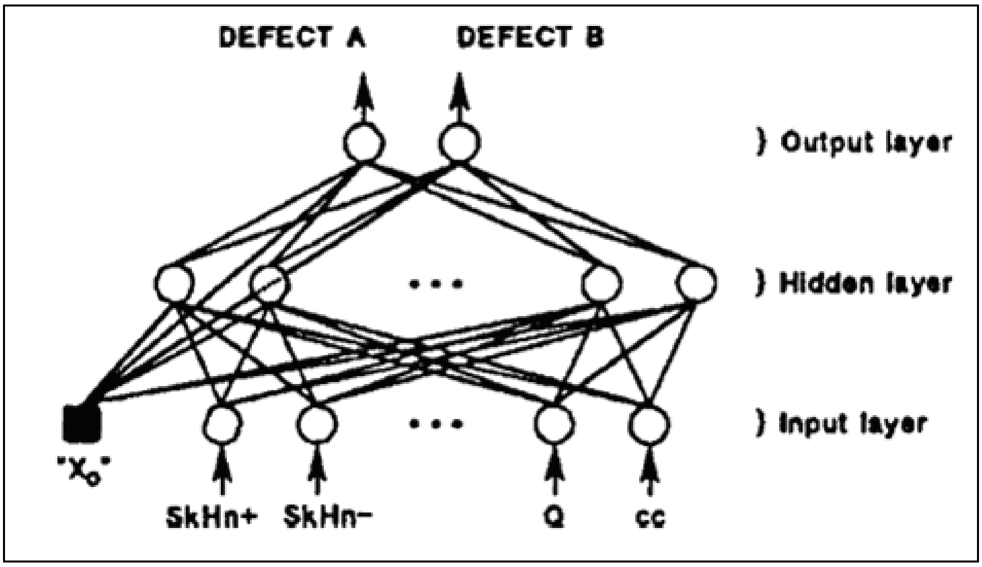


Figure 3.2: Structure of BP network with three layers. Defects refer to insulation defects which result in PD [19]

3.4. KOHONEN SELF-ORGANIZING NETWORK

The Kohonen self-organizing map basically transforms a multidimensional input space to the two-dimensional NN in a non-linear way [75]. Each processing element of

the input and output layers is fully connected to all elements of the Kohonen layer [77]. During the learning process the Kohonen processing element with the smallest Euclidean distance adjusts its weights closer to the input data. The neighboring elements in the Kohonen layer also adjust their weights closer to the same input data. The output layer begins to operate when the learning coefficients in the Kohonen self-organizing network become small or zero [75][80]. Fig.3.3 gives the standard layer configuration for the SOM

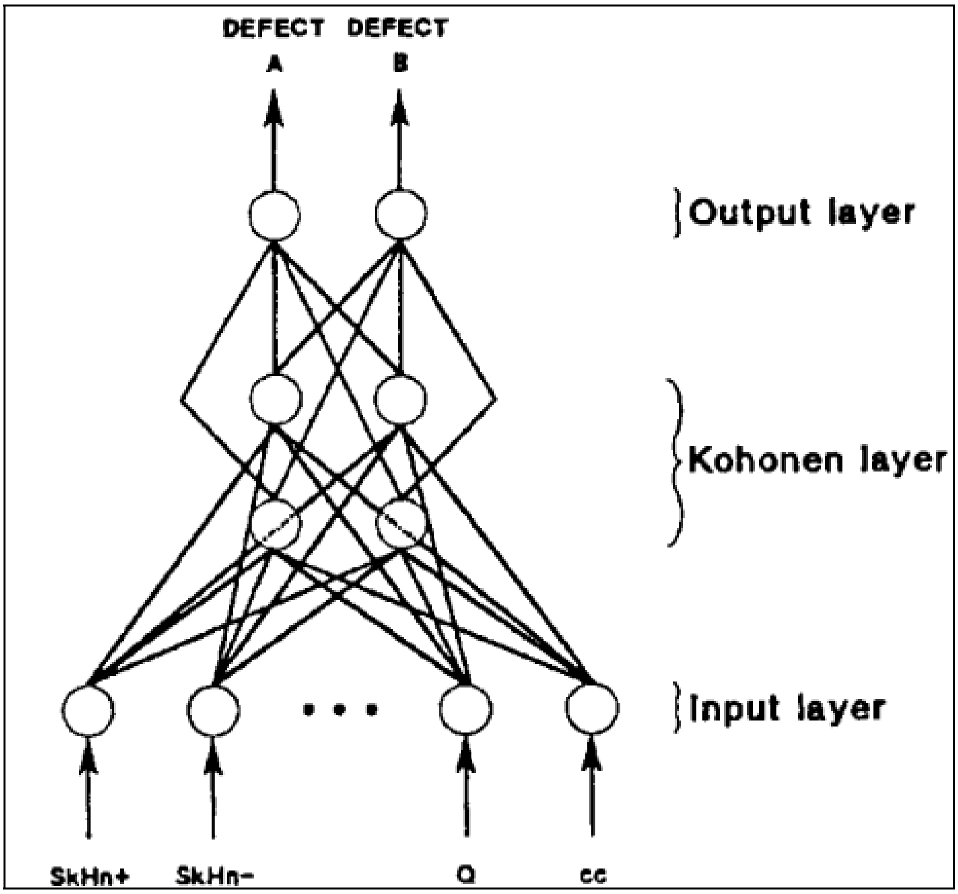


Figure 3.3: Kohonen self-organizing network with classification. Defects refer to insulation defects which result in PD [76]

3.5. LEARNING VECTOR QUANTIZATION NETWORK

The typical structure of this NN was originally suggested by Kohonen and consists of the input layer, the Kohonen layer with the same number of the processing elements for each class and the output layer [75][76]. The learning fingerprint is called the learning vector. In learning process, the Euclidean distance between learning vector and weights of each processing elements is calculated. The winner will be the processing element which has nearest distance. After the learning process, corresponding weights will be changed to ensure that the probability of winning for this learning vector will be increased next time. The authors of [77] studied power transformer DGA data and proposed that the fuzzy logic be incorporated into the learning vector quantization (LVQ). The novelty was to incorporate the fuzzy logic into the NN. The LVQ network is responsible for the classification of the possible fault conditions, whereas the fuzzy logic determines which conclusion may be drawn from the LVQ and be the final answer to the transformer condition.

3.6. PD PARAMETERS USED AS INPUT FOR A NN

The section above described to some extent the structure of various NN structures. However, one of the most important aspects of an NN is the sort of PD parameters used as inputs. Since there are a variety of PD detection techniques, both classical [77] and modern pulse-height and phase analysis [78] or PD wideband waveform, a NN may use a variety of PD parameters as inputs. Pulse-height and phase analysis PD data seem to be the most popular with researchers tackling the question of PD recognition. Two- or three-

dimensional PD patterns may also be chosen as inputs. In [41], the PD pulses occurring in each cycle were sorted out on their amplitude and phase angle. Well-defined defects were studied, and the recognition rate was reported to be 79%, a main achievement at that time, if comparable with recognition rates reported in [80] 81]. The NN reported in [35], however, was also subjected to a trial and error approach, already commented upon in [86]. The NN which was used in [41] was rather large (having 512 input neurons) and thus resulted in lengthy training times [73]. PD parameters recorded in [77] were the PD counts, average and maximum PD magnitudes with respect to the phase angle. Recognition rates of more than 90% were reported for defects enclosed in a bushing, corona discharges and surface discharges. Their work was carried out in a laboratory free of interference (except that due to local radio broadcasting). The authors were aware of this weakness in their work, pointing out that ‘‘because of low noise . . . we only need to take the lowest statistical moments to extract the features of the discharge pattern; undue influence of the noise in an industrial environment [may occur]. “Although averaging would reduce noise, it may still be necessary to use higher statistical moments to form the feature vector, especially when the number of PD sources to be recognized is large.’’

Pulse height and phase analysis were also used (together with noise suppression) for PD pattern recognition elsewhere [70] [71]. Orthogonal transforms extracted from this data (Fourier, Walsh–Hadamard and Haar) were used for the redundant diagnostic concept. Although this method was very successful with PD diagnosis in commissioning tests and for triangular-shaped voltage waveforms (94% and 100% respectively), it registered rather low recognition rates for monitoring tests (63%).

3.7. INFLUENCE OF THE PD MECHANISM ON PATTERN RECOGNITION

Due to the stochastic behavior of PD, it is true that in most cases the PD pulse and phase patterns and their related parameters have been taken into account as inputs for the NN. It is also true that such patterns may give significant information as to the state of insulation, and they are often used for monitoring [85] [29]. Such techniques are thought to give more information than conventional PD detection apparatus. The latter are single-purpose and cannot be modified according to the specific conditions of a PD measurement or tested equipment, their analog components may change their quality parameters in time, and they are mechanically sensitive and rather expensive [84].

3.8. THE PROBLEM OF MULTIPLE PD DEFECTS

A variety of defects have been investigated and recognized during the research efforts by the insulation community. In [41], a 79% recognition rate was reported for defects such as a flat cylindrical cavity and a needle touching the cavity, well defined in specimens. Elsewhere, the NN was trained to recognize internal PD pulses, external burst disturbances and other external PD pulses [82]. Well defined defects, such as spherical cavities, surface discharges in air with a rod–plane electrode arrangement and metallic–dielectric parallel air gap discharges under a very divergent field, in samples have also been the subject of intense investigation, and recognition rates as high as 98.9% have been reported [87]. Enclosed cavities of different sizes have been successfully recognized [88], whereas a greater variety of defects (electrode bounded cavity, point-to-dielectric gap in

air, corona discharge in air, surface discharge in air, electrical treeing in polyethylene and stochastic discharge sequence) have been recognized in [89].

3.9 INFLUENCE OF THE VOLTAGE LEVEL

It has already been reported that the applied voltage may be 10%–20% higher than that of the inception level and that lowering the voltage nearing inception makes pattern recognition more difficult [89]. Tests at inception level merit special attention, particularly in the light of some experimental evidence presented in [90] [91]. Certain defects may be excited at a certain voltage but others may be excited at even higher voltages. Therefore, at various voltage levels, it is likely to get different (or at least additional, if the voltage is raised) defects discharging and consequently slightly different PD patterns. This must also be taken into account in the design of future experiments.

CHAPTER 4

DATA COLLECTION AND DATA PREPROCESSING

Once the decision has been made to solve any problem using neural network approaches, there is a need to gather data for training purposes. The training data set includes a number of cases, each containing values for a range of input and output variables. The first decisions to be taken: which variables to use, and how many (and which) cases to gather. The choice of variables (at least initially) is guided by intuition. A problem expert with domain knowledge will give an idea of which input variables are likely to be influential. As a first pass, the variables that are thought influential could be tried. Neural networks process numeric data in a fairly limited range. This presents a problem if data is in an unusual range, if there is missing data, or if data is non-numeric. Fortunately, there are methods to deal with each of these problems. Numeric data is scaled into an appropriate range for the network, and missing values can be substituted with the mean value (or other statistic) of that variable across the other available training cases [89]. The number of cases required for neural network training frequently presents difficulties. There are some heuristic guidelines, which relate the number of cases needed to the size of the network (the simplest of these says that there should be ten times as many cases as connections in the network) [89]. Actually, the number needed is also related to the (unknown) complexity of the underlying function which the network is trying to model, and to the variance of the additive noise. As the number of variables increases, the number of cases required increases nonlinearly, so that

with even a fairly small number of variables (perhaps fifty or less) a huge number of cases are required.

For most practical problem domains, the number of cases required will be hundreds or thousands. For very complex problems more may be required, but it would be a rare (even trivial) problem which required less than a hundred cases. If the data is sparser than this, no enough information to train a network, and the best which can be done is probably to fit a linear model. If a larger, but still restricted, data set is available, it is possible to compensate to some extent by forming an ensemble of networks, each trained using a different re-sampling of the available data and then average across the predictions of the networks in the ensemble. Many practical problems suffer from data that is unreliable: some variables may be corrupted by noise, or values may be missing altogether. Neural networks are noise tolerant. However, there is a limit to this tolerance. If there are occasional outliers far outside the range of normal values for a variable, they may bias the training. The best approach to such outliers is to identify and remove them (either discarding the case, or converting the outlier into a missing value). If outliers are difficult to detect, a city block error function may be used, but this outlier-tolerant training is generally less effective than the standard approach [89].

4.1 DATA COLLECTION

This part was the most critical and difficult part of this thesis. Many PD OEMs were contacted to seek their participation in such research. The companies and PD monitoring system OEM’s shown in Table 4.1 were approached to get field measurements and readings for different PD types.

Table 4.1: Main PD measurements providers (partners)

Saudi Aramco	Iris Canada
Siemens AGE	ABB Switzerland ABB India
pdTech	HVPD

4.2 Description of Partners PD Datasets

4.2.1. Saudi Aramco & Iris Power Engineering

The reason behind selecting this topic was the availability of PD system installed on trial basis at one of Saudi Aramco Plants. At Shedgum Gas Plant (ShGP), 16 large high-voltage motors were in operation since 1970s. The Consulting Service Department [90] conducted a technology item to pilot PDTrac [91] online PD monitoring. At the beginning, there was an impression that enough datasets are available to train, validate and test the proposed NN. While the online PD monitoring system performance was satisfactory for the operation and maintenance purposes, the collected PD datasets were inadequate to train a NN to classify the different PD types. Another shortcoming was limited winding failures that could be related to PD activity. As shown in Fig. 4.1.

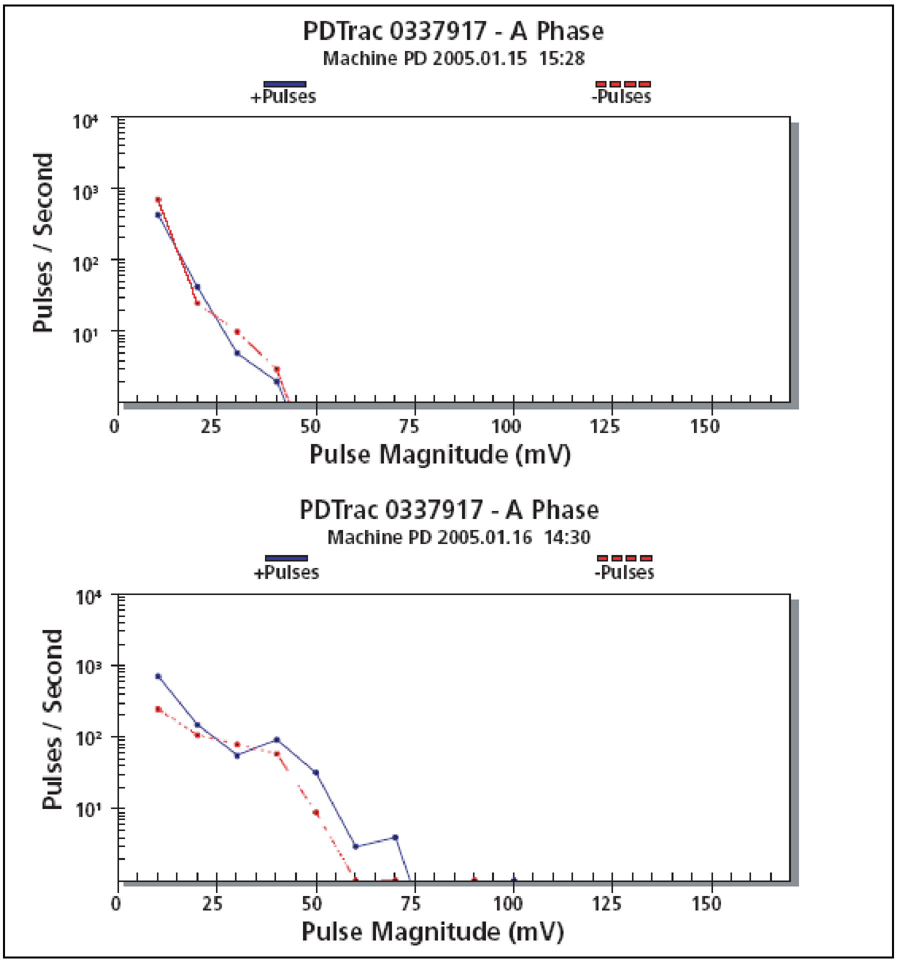


Figure 4.1: 2D PD measurement by PDTrac [90]

At that point, Iris was contacted to get an access to their PD measurement database where they archive thousands of real PD readings for customers since 1980s. An agreement was reached to get about 1000 cases for different real measurements covering the different PD types such as internal PD, surface PD and end winding PD. Also these measurements should include readings for healthy machines. Unfortunately, Iris was unable to provide the agreed PD readings; instead eight (8) measurements were shared without any proper PD classification. Furthermore, and as a new dilemma, no output text file was available. That file is essential to generate the PRPD (Phase Resolved Partial

Discharge) which is the only tool that is used to generate the PD pattern over the 360 °. At the point, the decision was made to search for other PD monitoring OEM to get more detailed PD measurements.

4.2.2. Siemens

Siemens R&D in Germany was the first firm that was contacted to overcome the lack of PD data. Siemens efforts in the PD business were documented in a technical paper prepared by three scientists at IPH High Voltage Lab Berlin [92]. Siemens R&D was very cooperative and supplied several Excel spread sheets for different PD types. All trends were supplied as image taken from the PD meter without any tabulated details. A trial was done to digitize these PRPD trends to convert the image to pC/Deg without success. This difficulty prevented any use of Siemens PD trends.

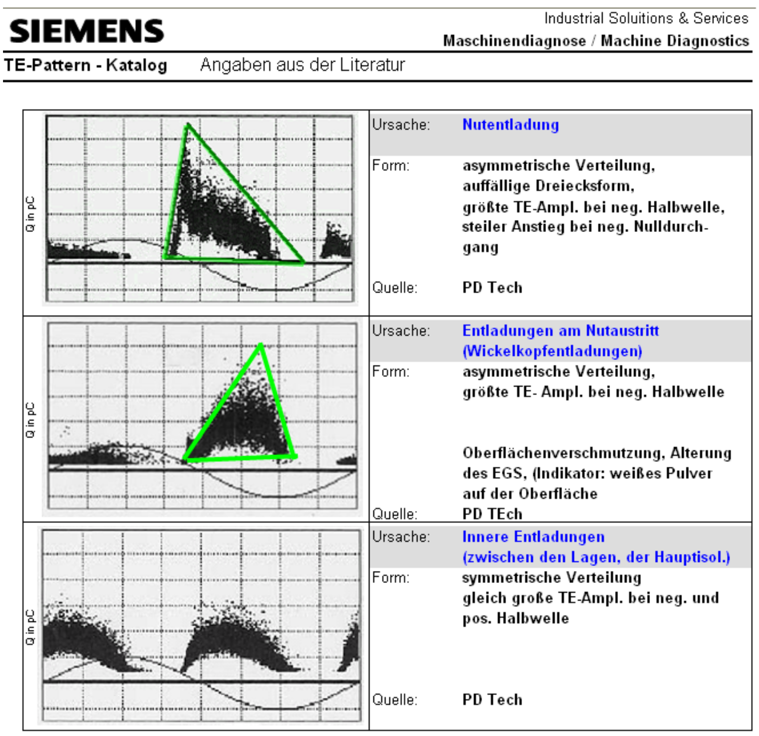


Figure 4.2: PD trends as supplied by Siemens

4.2.3. ABB

Such course of action was carried out with ABB Switzerland and India to get enough PD data for NN training and evaluation. ABB provided excellent set of PRPD color coded as in Fig. 4.3 and the corresponding data text tabulated files.

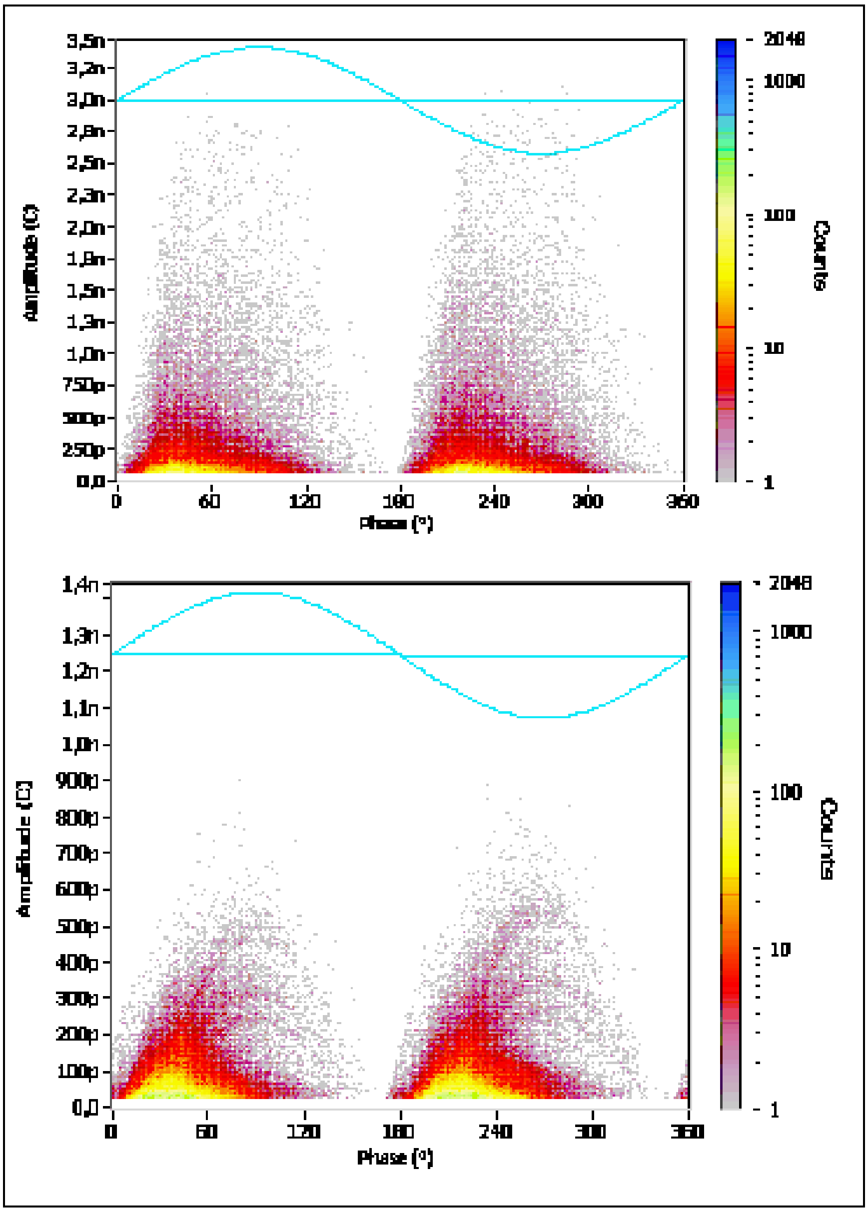


Figure 4.3: PD trends as supplied by ABB

Although ABB had supplied high quality PD trends, it was not feasible to generate satisfactory data sets to cover all PD types. ABB trends were very limited and inconsistent. Consequently the search continued to collect sufficient PD data.

4.2.4. pdTECH

pdTECH is a Swiss based specialized company in the PD business. Many other PD monitoring OEMs are using pdTECH logarithmic color coded concept to generate PRPD.

pdTECH also have a wide range of PD measurement tools that cover rotating equipment, transformers and switchgears. pdTECH supplied two (2) cases and only; many attempts were exerted to attract their interest to continue the cooperation without success. pdTECH PD datasets were very promising; it was found that many references in PD recognition are using the color coded PRPD.

4.2.5. HVPD

HVPD (formerly known as IPEC HV) is an English company located in Manchester UK. They specialize in PD detection. HVPD products range includes motors, generators, transformers, cables and switchgears. HVPD was introduced to us by some contacts at Saudi Electric Company (SEC). HVPD already installed a number of PD detection systems at some sites of SEC network. HVPD was the best partner; they showed a real interest to supply the needed PD datasets. They were able to collect, classify and communicate three hundreds (300) PD pdg files (gold files); furthermore they worked with us closely to verify

the results at the field through conducting real-time measurements at Qatif Producing Facility of Saudi Aramco.

HVPD developed state-of-art PD measurement setup with friendly user interface. The distribution of the Rogowski coils as PD detection sensors is shown in Fig. 4.4.

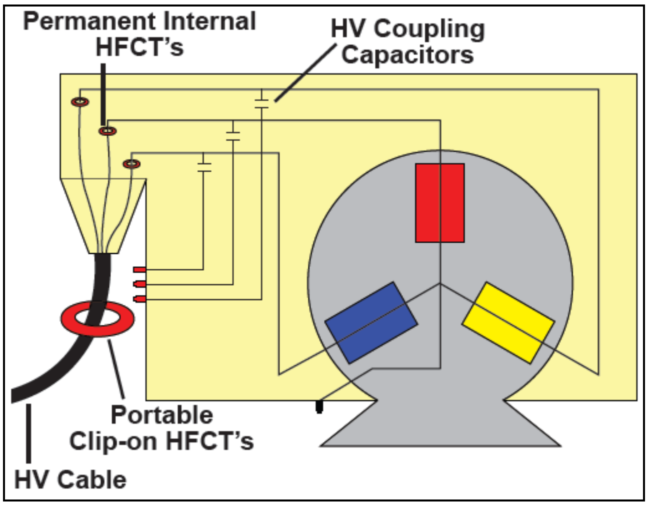


Figure 4.4: HVPD sensor options for rotating HV machines

HVPD PD measurement data is available for online and offline testing. The PD test could be conducted measurement through HFCT (High Frequency Coupling Capacitors) or through Rogowski coils. The measurement period could be set according to the required test procedure (mins-hours).

After conducting the PD test, all trends will be stored on the tester internal memory as a Gold file (xxx.pdg). Gold files are prepared to be processed by PDreader software. PDreader is very powerful tool helps the end user to read PD activity as:

- peak vs. time (mV/sec) as in Fig. 4.5.
- PRPD (mV/Deg) as in Fig. 4.6.
- output ASCI (txt file)

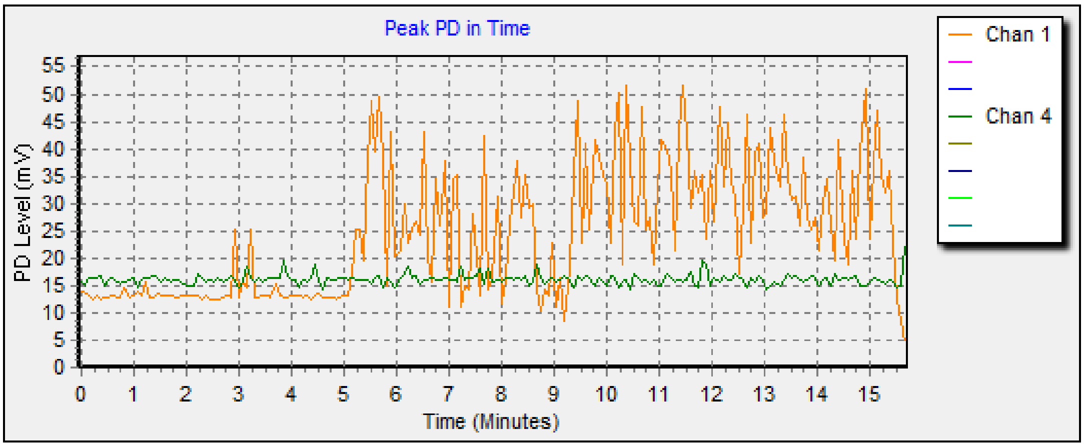


Figure 4.5: PDGold© software showing 3x phases of PD data

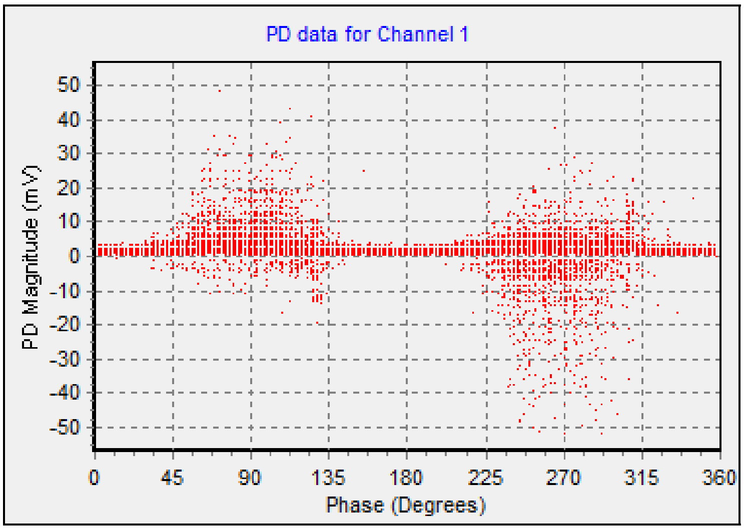


Figure 4.6: PDGold© software showing 1x PRPD

As mentioned above, HVPD provided 300 different readings for 6 different PD type:

1. internal PD	50 measurements
2. corona PD	50 measurements
3. slot PD	50 measurements

4. endwinding PD 50 measurements
5. surface PD 50 measurements
6. healthy 50 measurements

These 300 data records will be the base of NN training and validation to classify the different PD types.

4.3. PD DATASETS PREPROCESSING

As known in NN computational process, the preprocessing phase is the most important phase during the training period. NN input requirement limits the dimension of input matrix, the input matrix should comply with the accepted NN input to be [2 X A] matrix. The HVPD datasets don't comply with this requirement where it could be found some sets with 100 X 200, 200 X 200, 500 X 200….etc (in some cases we can find 1500 X 200 data file). PRPD (Phase Resolved Partial Discharge) was the tool used by many references to perform the NN classification using pattern recognition technique [93] [94] [95] [96] [97].... etc.

As mentioned above, 600 data records are avilable of real PD measurements. The following types are the available data category:

- peak vs. time (mV/sec)
- PRPD (mV/Deg)
- output ASCI (txt file)

It is needed to generate the PRPD for each dataset to prepare the standard pattern for the NN classification. Peak values could not be used since they will differ from machine to other based on the voltage level and the severity of the PD. As seen in Figure 4.10 (PDGold© software showing 1x PRPD), PDreader is able to generate the PRPD, but the data for that pattern is imbedded in the PDreader. When HVPD was approached to reveal that feature they denied. The excuse was that PDreader was design in that way and they are not ready to modify their standard tool to suit our purpose.

The 600 output ASCI files structure was reviewed intensively, the following attribute was noticed as in Fig. 4.7:

- all matrices have the same number of columns
- different number of rows are existing where the number of rows corresponds to the time of the test

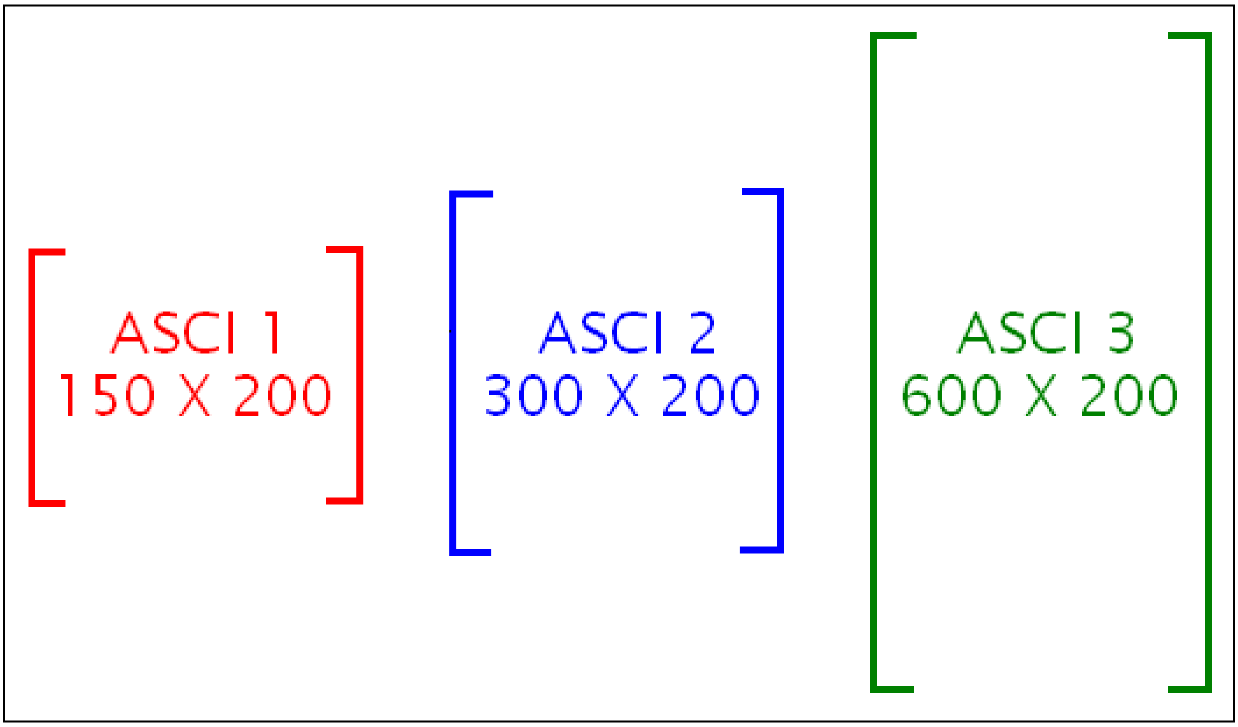


Figure 4.7: Different matrix dimension for ASCI output files

Since the PDreader is using only these different ASCI files to generate the PRPD for each measurement, and the fixed column index is fixed (200) that draws attention to each matrix and the way to scale the 360 ° to 200 points on the phase axis of the PRPD. All that could be used to reshape the different 600 ASCI files to (mV/Deg).

1. use the ASCI files to reconstruct peak time curve: Using PDreader for the pdg file (D102 - 2 Internal.PDG), the software generates the trend in Fig. 4.8:

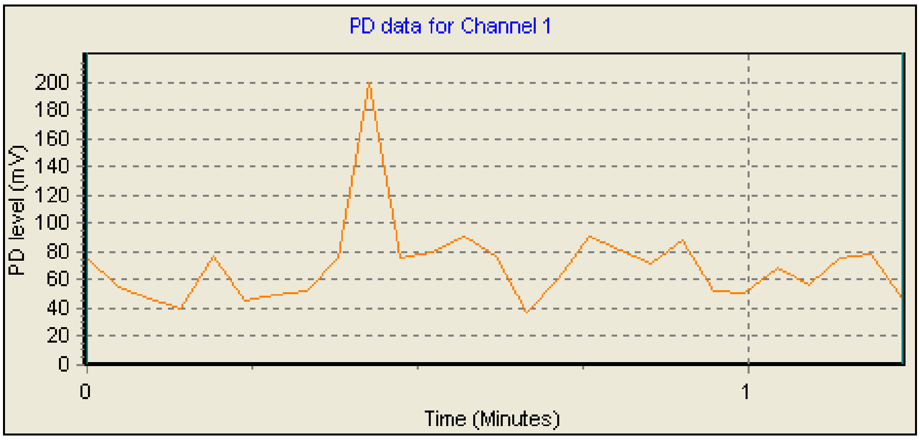


Figure 4.8: PDreader trending for Ch. 1 peak vs. time

Using the ASCI output file, the trend in Fig. 4.9 is generated

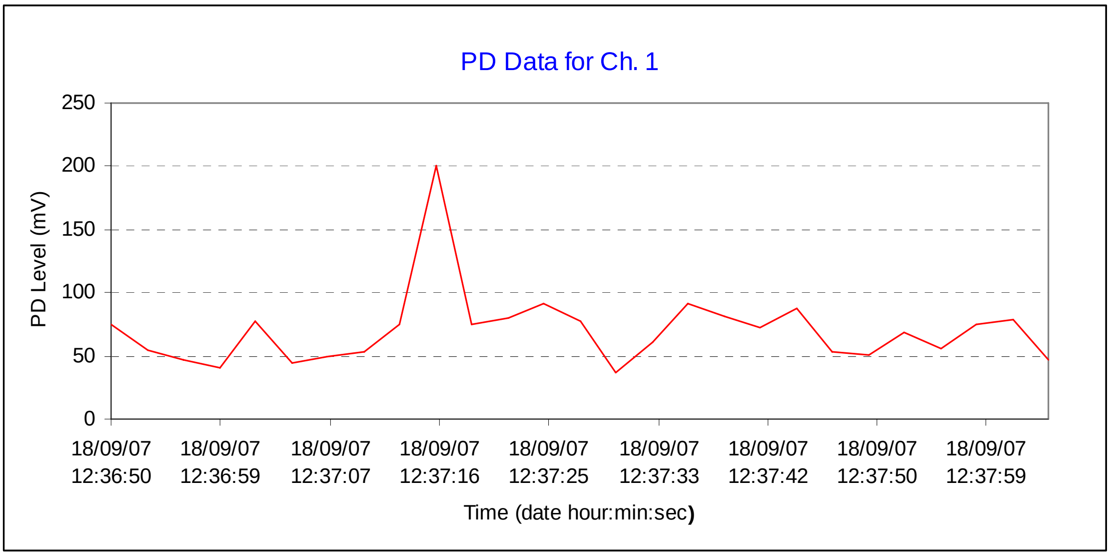


Figure 4.9: Ch. 1 peak vs. time extracted from the output ASCI

Comparing the peak vs. time trending in Fig's. (4.13 &4.14) reveals that identical curves were generated; which implies that the extraction method was correct and accurate.

2. using PDreader, generate the PDRPD for D102 - 2 Internal. PDG generates:

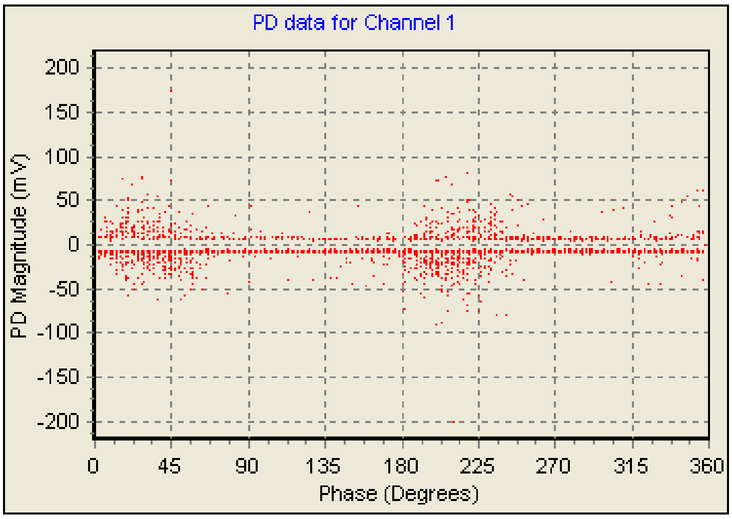


Figure 4.10: PRPD as generated by PDreader

If the reconstruction is successful, it is possible to decide that the goal to extract the the PRPD from the ASCI output file is achived. Returning to the Figure 4.11, the 200 fixed column index may give a hint to link the 200 index with the 360°. It is possible to assume that PDreader scales the 360° to 200 steps.

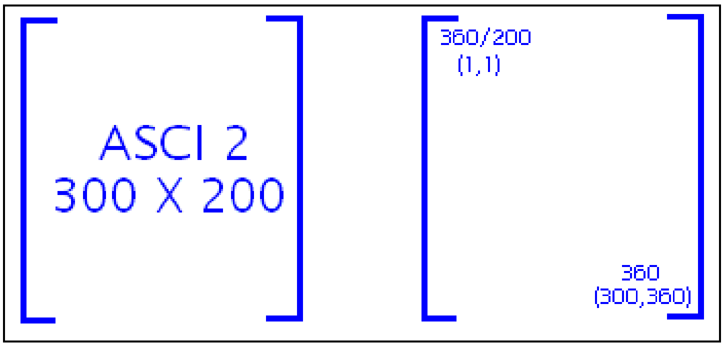


Figure 4.11: ASCI converted to angle vs. mV

Plotting the peak vs. time PD data in a modified arrangement generates the following curves:

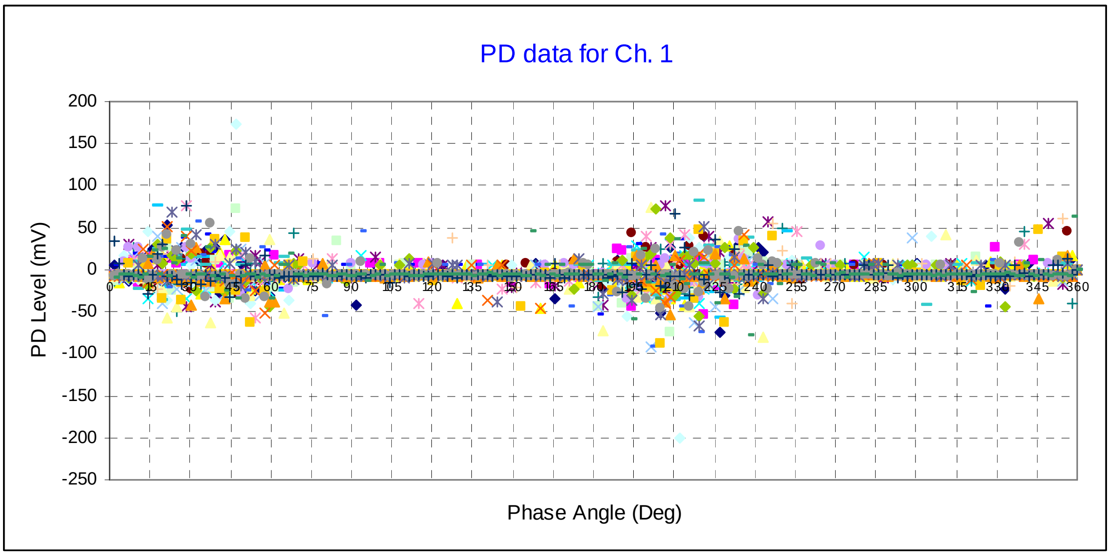


Figure 4.12: PDPR for each individual series

Figure 4.17 shows the plotting the "TRANSPOSED" matrix to have the PD mV readings at each angle of the new proposed scale (360/200).

The nature of the PRPD is cumulative; in other words, PRPD is usually generated by taking the reading of PD activity (mV, μV, peco C) at sequenced intervals. These timed measurements are related to certain phase angles of the main supply AC sine wave. Taking that into consideration, all 300 could be accumulated series as shown in shown in Figure 4.17 to a single series.

That was possible when the 300X200 matrix converted to 60000X2 matrix. Plotting the converted single matrix provides the cumulative curve shown in Fig. 4.13.

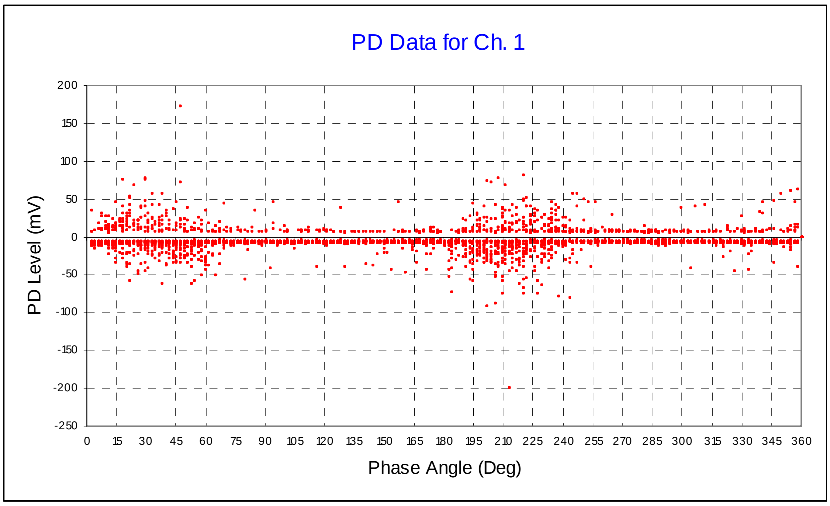
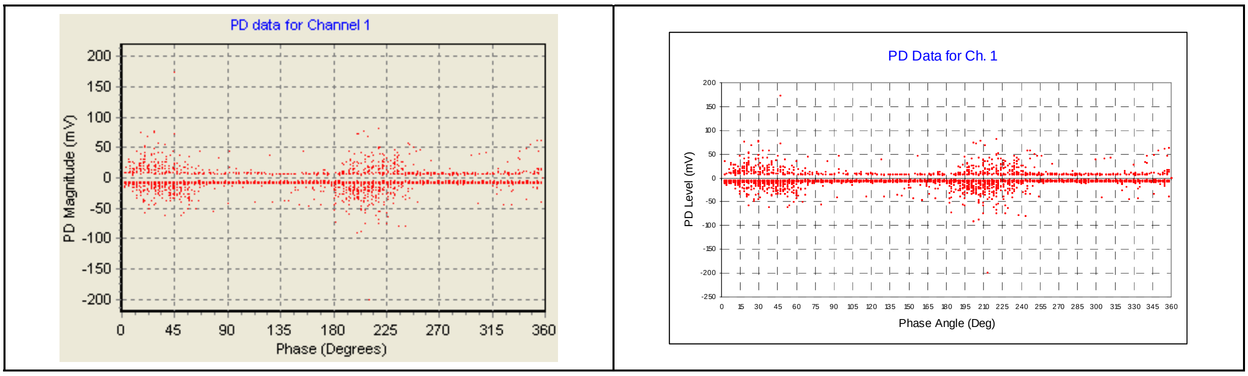


Figure 4.13: PDPR for cumulative series

Let us now compare PDreader PRPD with the reconstructed PRPD:



As shown in above comparison, it is possible to conclude that the reconstructed PRPD and the actual one 100% identical patterns; which confirms that the reconstruction technique was 100% accurate.

4.4. STATISTICAL AND SIGNAL PROCESSING TECHNIQUES FOR DIMENSIONALITY REDUCTION

Based on the verified extraction of PRPD in the previous section, the following statistical features could be extracted:

1. Max-Min (envelope)
2. Max-Min (pu)
3. Max + |Min| (pu)

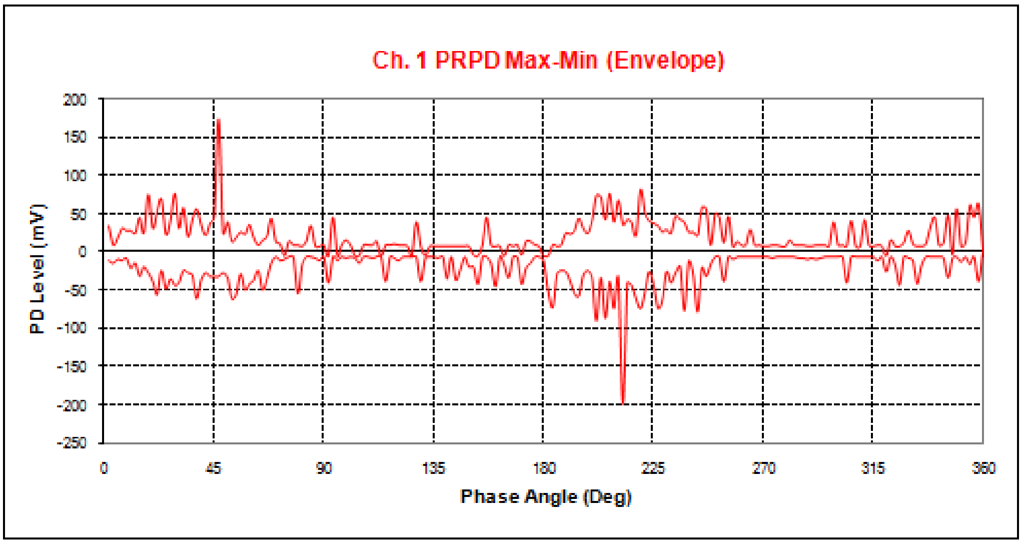


Figure 4.14: Reduced PRPD using Max-Min values

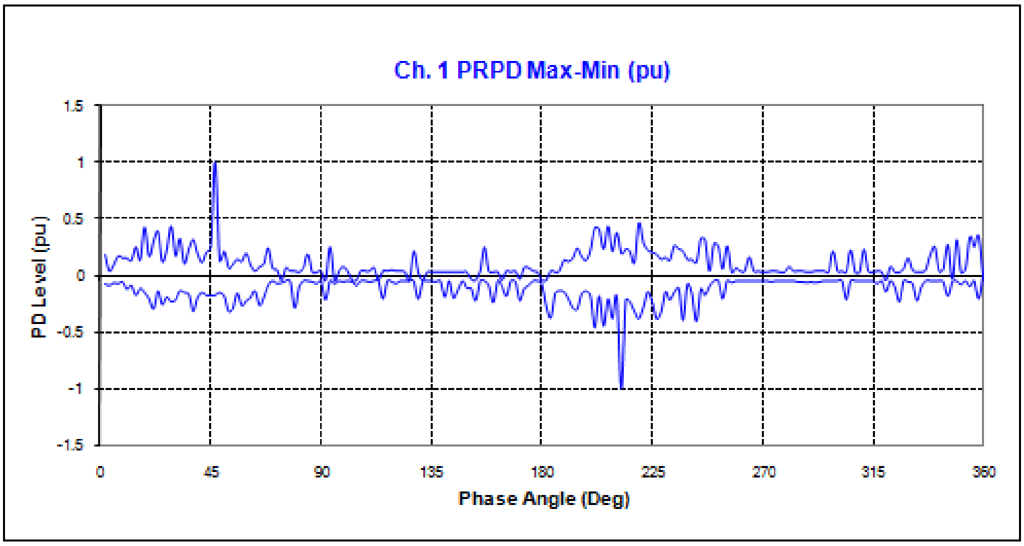


Figure 4.15: Reduced PRPD using Max-Min (pu) values

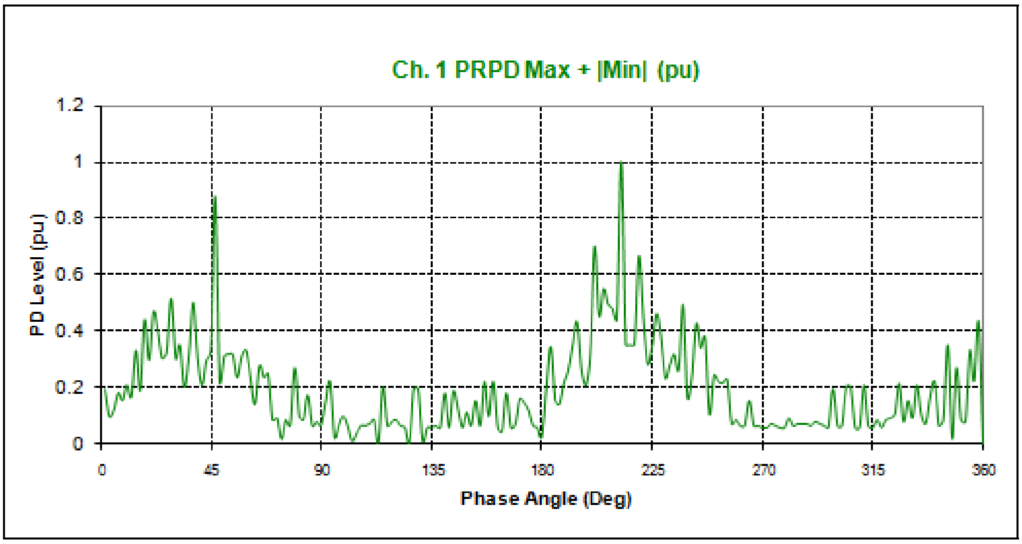


Figure 4.16: Reduced PRPD using Max + |Min| (pu) values

The previous approaches were the simple statistical techniques usually tried at the beginning to train the selected PD NN. In this research, other advanced techniques from the Signal Processing will be examined such as:

1. Principal Component Analysis (PCA)

2. Isometric Feature Mapping (ISOMAP)

Using Dimensionality Reduction Graphic User Interface (GUI), the above reduction techniques will be performed using MATLAB® to perform the feature extraction for the PD datasets.

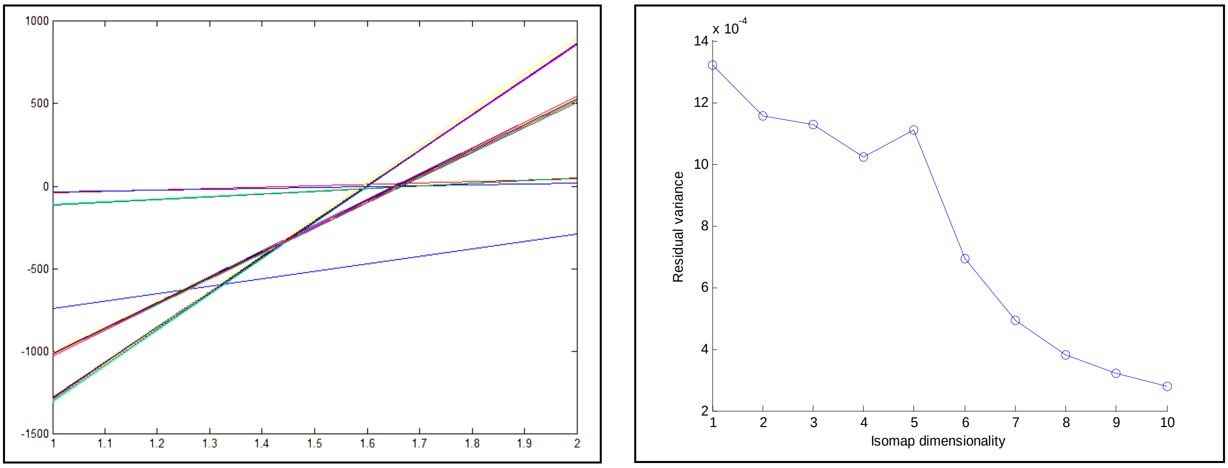


Figure 4.17: Reduced PRPD using PCA and ISMAP

CHAPTER 5

RESULTS AND ANALYSIS OF PD CLASSIFICATION NEURAL NETWORK

In this chapter, the power of neural networks will be utilized to perform the Phase Resolved Partial Discharge (PRPD) Pattern Recognition. PD pattern recognition has been reported in many applications of artificial intelligence; researchers have reported various neural network models capable for pattern recognition, models that have the function of self-organization and can learn to recognize patterns [101] [102]. Many are hierarchical networks consisting of layers of neuron-like cells. The ability to process information increases in proportion to the number of layers in the network. Pattern recognition is the primary use of this mechanism. Pattern recognition is a popular application in that it enables the full set of human perceptions to be acquired by a machine [103].

5.1. NN USE FOR PD PATTERN RECOGNITION

PD pattern recognition is widely considered as an effective method to evaluate insulation condition of high voltage apparatuses. PD pattern recognition is an important tool in HV insulation diagnosis. A PD pattern recognition approach based on neural networks is proposed in this paper. The recognition rate and reliability are extremely high as compared to the results presented in the literature. It is also suitable for identifying discharges with multiple sources. The capability of the approach was demonstrated by classification of the patterns measured in laboratory experiments [104].

Classically, NN PD pattern recognition is divided into a number of different stages. In the context of vision, the different stages are: acquisition, concern with digitizing the data coming from a sensor such as narrow-band, wide-band frequency PD detector, localizing, which involves extracting the object from its background, and representation which is finding a set of significant features on the object.

The object is then represented by a real number, a word within a grammar, a graph or any element from a set of representations. The final stage, the decision stage, consists of dividing the set of object representations into number of classes. The last two phases, representation and decision, are the associative phases [103].

The patterns obtained with PD detectors contain characteristic features of the source/class of the respective partial discharge process involved. The recognition of the source from the data represents the classification stage. Usually, this stage consists of a two-step procedure, i.e., extraction of feature vector from the data followed by classification/recognition of the corresponding source. The various techniques available for achieving the foregoing task are examined and analyzed; while some success has been achieved in the identification of simple PD sources, recognition and classification of complex PD patterns associated with practical insulating systems continue to pose appreciable difficulty [105]. Recently, many methods have been employed for the pattern recognition of PD, including back-propagation multilayer neural networks expert systems, and fuzzy classification. However, the training process of multilayer neural networks is often very slow, and the training data must be sufficient and compatible. The expert system method and the fuzzy classification method acquire the knowledge of human expertise to build a knowledge base and a fuzzy rule base [107].

5.2. PD CLASSIFICATION USING MATALB NN TOOLBOX

MATLAB® (Matrix Laboratory) is a high-level technical computing language and interactive environment for algorithm development, data visualization, data analysis, and numerical computation. Using MATLAB, technical computing problems could be solved faster than with traditional programming languages, such as C, C++, and FORTRAN [108].

5.2.1. MATLAB NEURAL NETWORK TOOLBOX

Neural Network Toolbox™ extends MATLAB with tools for designing, implementing, visualizing, and simulating neural networks. Neural networks are invaluable for applications where formal analysis would be difficult or impossible, such as pattern recognition and nonlinear system identification and control. Neural Network Toolbox software provides comprehensive support for many proven network paradigms, as well as graphical user interfaces (GUIs) that enable you to design and manage your networks. The modular, open, and extensible design of the toolbox simplifies the creation of customized functions and networks [109].

5.2.2. PD CALCIFICATION USING MATLAB NN TOOLBOX

As mentioned in section 4.2.5, HVPD supplied us with the following PD datasets described in Table 5.1:

Table 5.1: 6 different PD types datasets were supplied by HVPD (total 300)

Internal PD: 50 Measurements	Corona PD: 50 Measurements	Slot PD: 50 Measurements
Endwinding PD: 50 Measurements	Surface PD: 50 Measurements	Healthy: 50 Measurements

To perform the required prepossessing to prepare the above PD matrices to be fed to the NN input, the following Dimensionality Reduction techniques have been applied from Table 5.2:

Table 5.2: The proposed 5 techniques for Dimensionality Reduction

Max-Min (envelope)	Max-Min (pu)	Max + |Min| (pu)
Principal Component Analysis (PCA)	Isometric Feature Mapping (ISOMAP	

Another MATLAB Toolbox is designed to facilitate the use of MATALB neural Network. After loading the ASCI text files of the PD reduced matrix, the "nntool" command will initiate the GUI of MATLAB NN Toolbox:

Neural Network MATALB Toolbox offers many types of NN algorithms that could be used to train and validate the NN. These types include:

- Cascade-forward backprop
- Competitive
- Elman backprop
- Feed-forward backprop
- Feed-forward distributed time delay
- Feed-forward distributed-delay
- Generalized regression
- Hopfield
- Layer Recurrent

- Linear layer (design)
- Linear layer (rain)
- LVQ
- NARX
- NARX Series-Parallel
- Perceptron
- Probabilistic
- Radial basis (exact fit)
- Radial basis (fewer neurons)
- Self-organized map

It is a time consuming task to test the performance of all listed types of NN, instead the following networks will be tried:

- Feed-Forward BackProp (FFBP)
- Generalized Regression (GR)
- Radial Basis (exact fit) (RB)

The above three (3) networks were selected through the discussion with the thesis NN advisor.

Using MATLAB NN Toolbox needs certain modifications and adjustment to be done on the PD input matrix, target column and Blind Data. This task is required to comply with standard forms of input and target matrix of MATLAB NN Toolbox:

1. MATLAB NN Toolbox does not accept the nonnumeric output column which contains the PD type; instead the PD type will be replaced in Table 5.3:

Table 5.3: Target column adjustment for Matlab NN Toolbox

PD Type	NN Output Representation
Corona	000
Endwinding	001
Internal	010
Slot	011
Surface	100
Healthy	101

2. transposing the PD matrix since the “nntool” performs the training, validation and testing vertically. Each column will represent PD readings at different PRPD angles. The PD classification will end each column.
3. the PRPD angles column must be deleted; otherwise the output PD target matrix will not be accepted by the “nntool” due to inconsistent matrix.

Such adjustment and modifications are not needed for the other NN tool (NeuralSight®).

To test the NN recognition accuracy and also to provide an independent Blind Data (not part of training PD datasets), actual PD field measurements have been conducted at one of Saudi Aramco operational plants (Qatif Production Facilities). Two (2) 13.2kV 7MW, 9 MW Alstom compressors motors at were examined looking for any PD activities. In Fig. 5.1, HVPD test engineer and Saudi Aramco field engineer are both conducting a PD real-time field PD measurements used in later stage to test and validate the developed NN.

Figure 5.1: Actual field PD test done by HVPD and Saudi Aramco using HVPD Longshot™ and 80 pF IRIS capacitive couplers

The measurement PD values and readings were analyzed at HVPD HQ in UK by their subject matter experts to determine the PD severity as well as the PD typ. The thorough study of the PD patterns yields the following results [110] as reported by the HVPD HQ in Manchester UK in Tables 5.4 and 5.5:

Table 5.4: PD field test results by HVPT Ltd UK [110]:

Test Number	Rotating Machine Reference	Condition Color Code	Insulation Condition	Maximum PD Measurement	PD Type
Saudi Aramco	**Tested on: 10th June 2009**		**Alstom Compressor Motors**	**No's 300 & 310**	
1	**QM-05-KM 300 Atmospheric Compressor – 7MW**		Probable Inspection	22802 pC *	Internal PD Combined with Surface Discharge
2	**QM-05-KM 310 LP Compressor – 9MW**		Probable Inspection	28792 pC*	Internal PD Combined with Surface Discharge

Table 5.5: PD field level color coding [108]:

Insulation Condition Assessment	Color Code	PD in Slot Section	PD in End Windings
New/Excellent		< 2000 pC	< 2000 pC
Good		2000 – 4000 pC	2000 – 4000 pC
Average		4000 – 10000 pC	4000 – 10000 pC
Still Acceptable		10000 – 15000 pC	10000 – 15000 pC
Probable Inspection		15000 – 20000 pC	15000 – 30000 pC
Problem/Unreliability		>20000 pC	>30000 pC

After performing the necessary matrices tuning, and having the independent Blind Data, the next step is due to start the training, testing and validation of PD NN’s. The possible combination of 3 NN and 5 Preprocessed (reduced) PD matrix, about 15 different training session (3_NN X 5_Reduced_Matrix = 15_Training Sessions). It is planned also for each NN type to test the effect of various parameters on the NN performance including:

- Training time (epochs)
- Number of layers
- Training function
- Adaption function
- Performance function
- Transfer function

Considering all possible combination will be resulting in about 90 training sessions. With the available computation recourses, such a massive task is extremely difficult to be accomplished. To deal with such situation, the first NN type, Feed-forward backprop (FFBP), will be trained with all different possible combination. The best-fit results of FFBP will be generalized with other 2 NN’s to compare the optimal possible performance for each NN type.

5.2.2.1. Feed-Forward BackProp (FFBP)

The basic architecture of a Feed-Forward Backpropagation net is shown in Figure 5.3. While there can be many hidden layers, this network will be illustrated with only one hidden layer. Also the number of neurons in the input layer and that in the output layer are determined by the dimensions of the input and output patterns, respectively. It is not easy

to determine how many neurons are needed in hidden layer. Here it is shown the layout with twenty neurons in the input layer, four neurons in hidden layer and twenty neurons in the output layer, with a few representative connections [109].

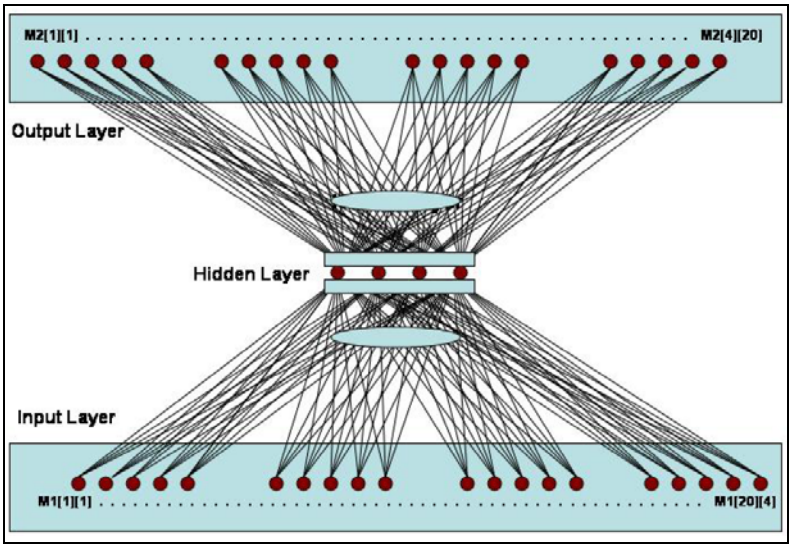


Figure 5.2: Feed-Forward Backpropagation NN [107]

The network has three fields of neurons: one for input neurons, one for hidden processing elements, and one for the output neurons. Connections are for feed forward activity. There are connections from every neuron in field A to everyone in field B, and in turn, from every neuron in field B to every neuron in field C. Thus there are two sets of weights [107]. FFBP will be applied on the statistical reduced PD matrices. Also, PD reduced matrices using the SP techniques will be used to train FFBP NN. Using MATLAB NN Toolbox requires segregating the input training data from the target PD classification column as described in Table 5.6.

Table 5.6: FFBP on Max-Min PD

5.2.2.1.1:	**FFBP**	
Input Matrix	Max_Min_IP	398 X 300
Target Matrix	Max_Min_TGT	1 X 300

The starting point in the NN training using MATALB NN Toolbox will be performing the 60sec. training for FFBP using the other default settings for Transfer Fn., Training Fn. Adaption Learning Fn., and Layers Number. Figures from 5.3 to 5.9 explain the use of MATLAB NN Toolbox.

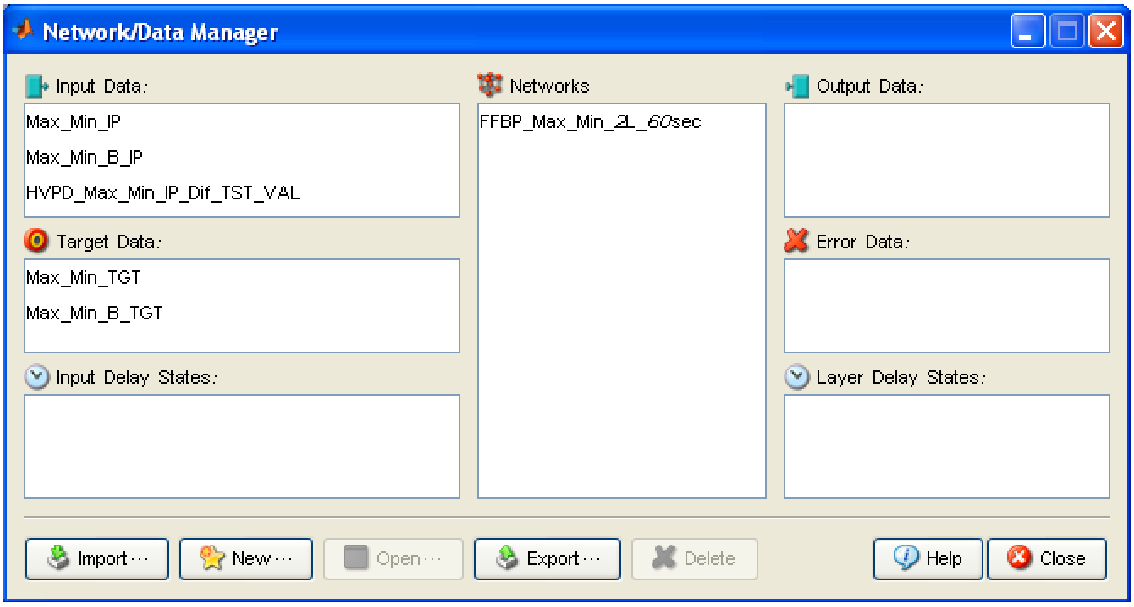


Figure 5.3: GUI window to load the input, target, blind input and blind target matrices

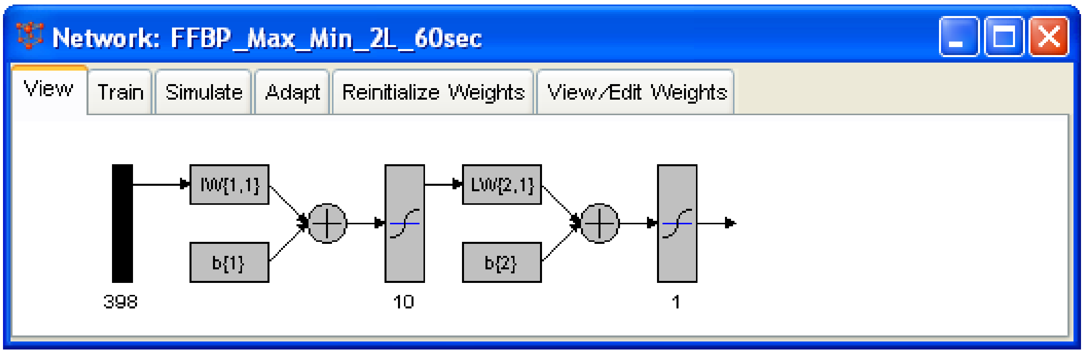


Figure 5.4: FFBP block diagram as created by MATLAB

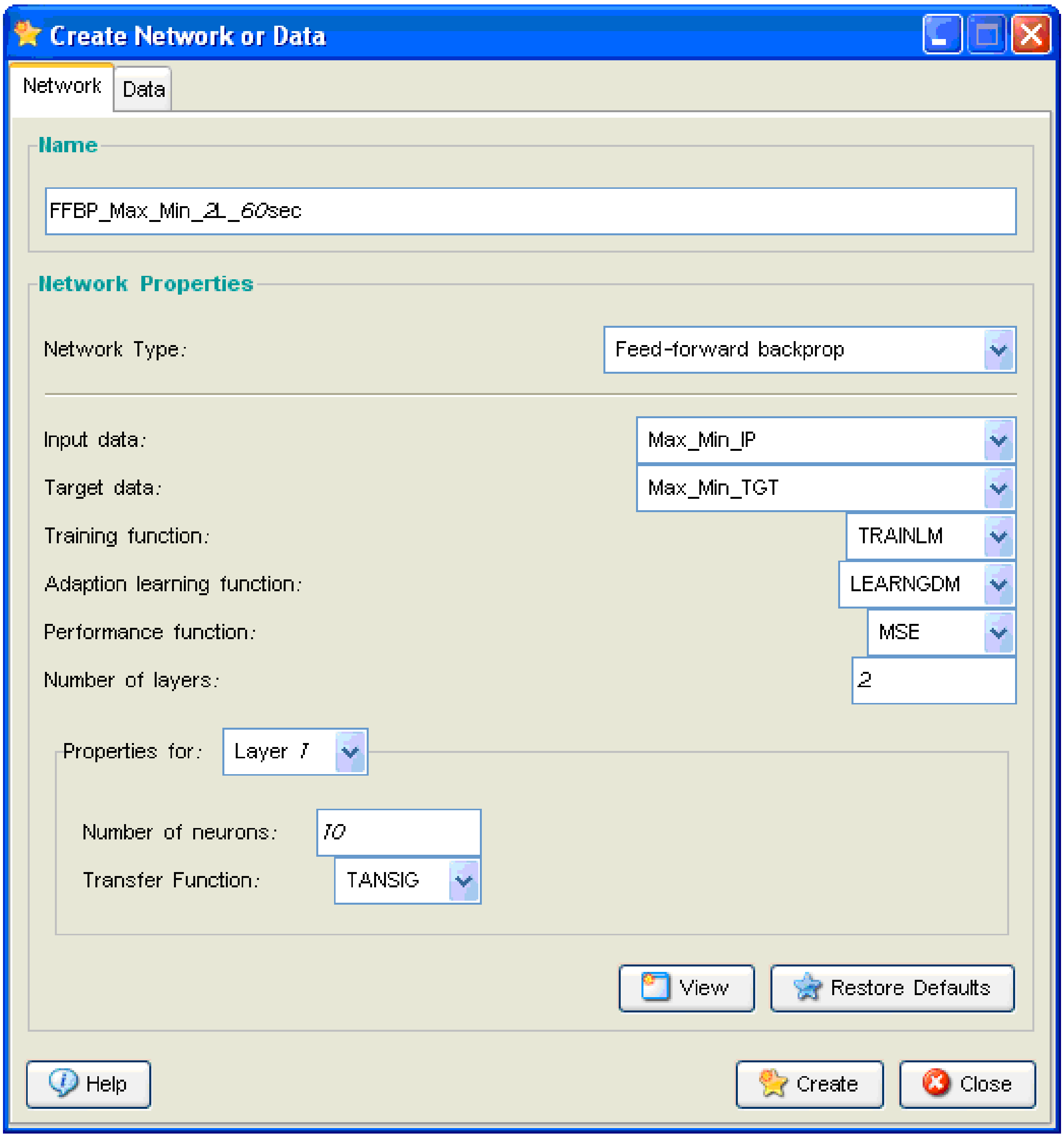


Figure 5.5: Creating FFBP [TRAINLM, LEARNGDM, MSE and TANSIG]

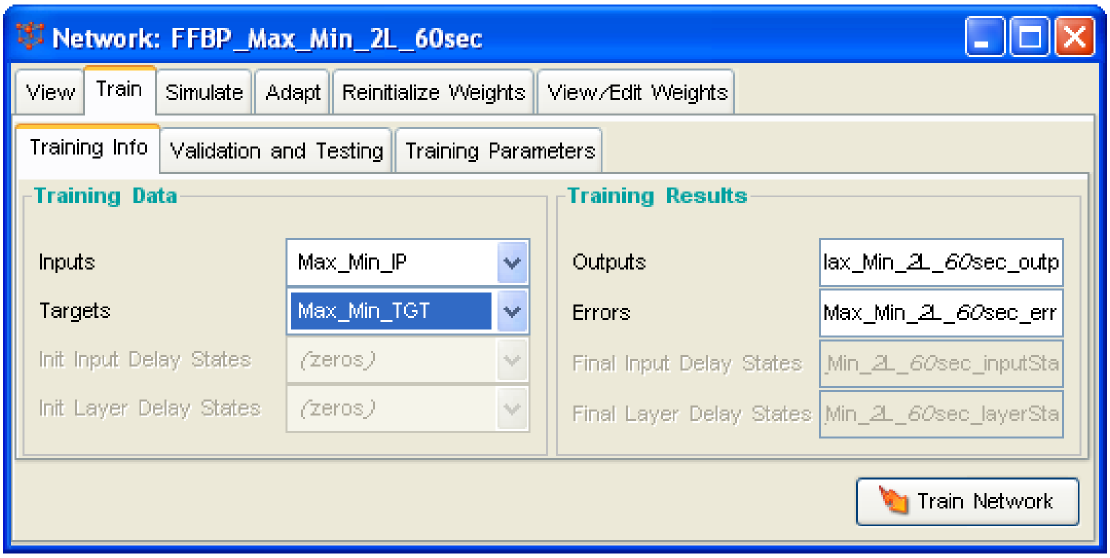


Figure 5.6: Selecting the Input and Target datasets

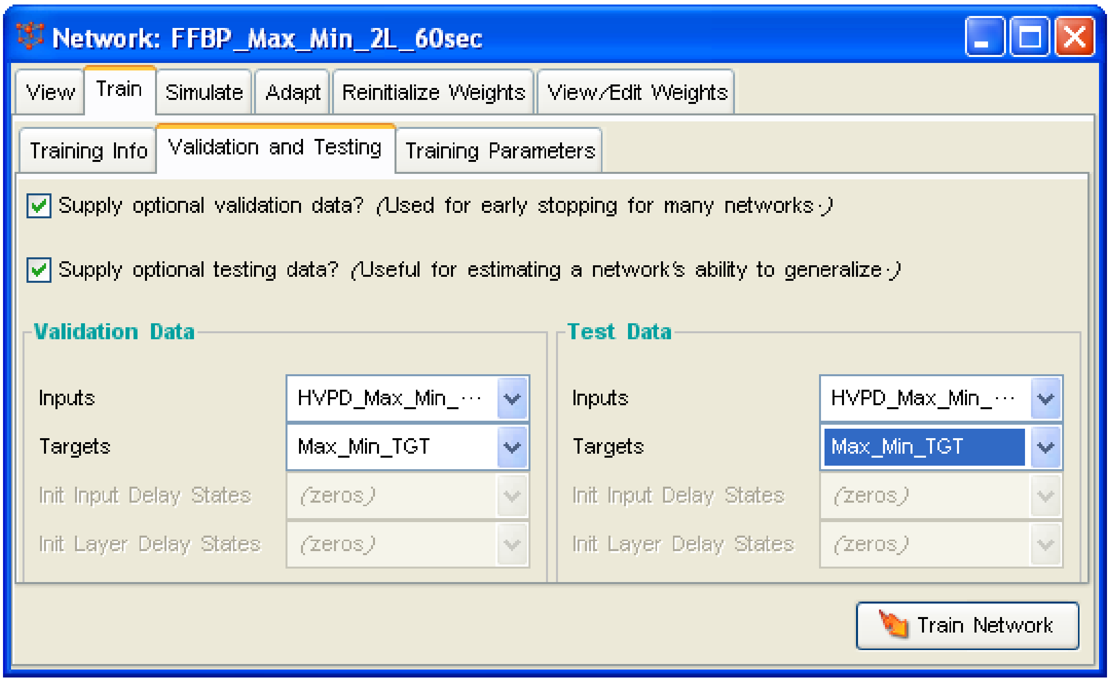


Figure 5.7: Selecting the validation and testing data

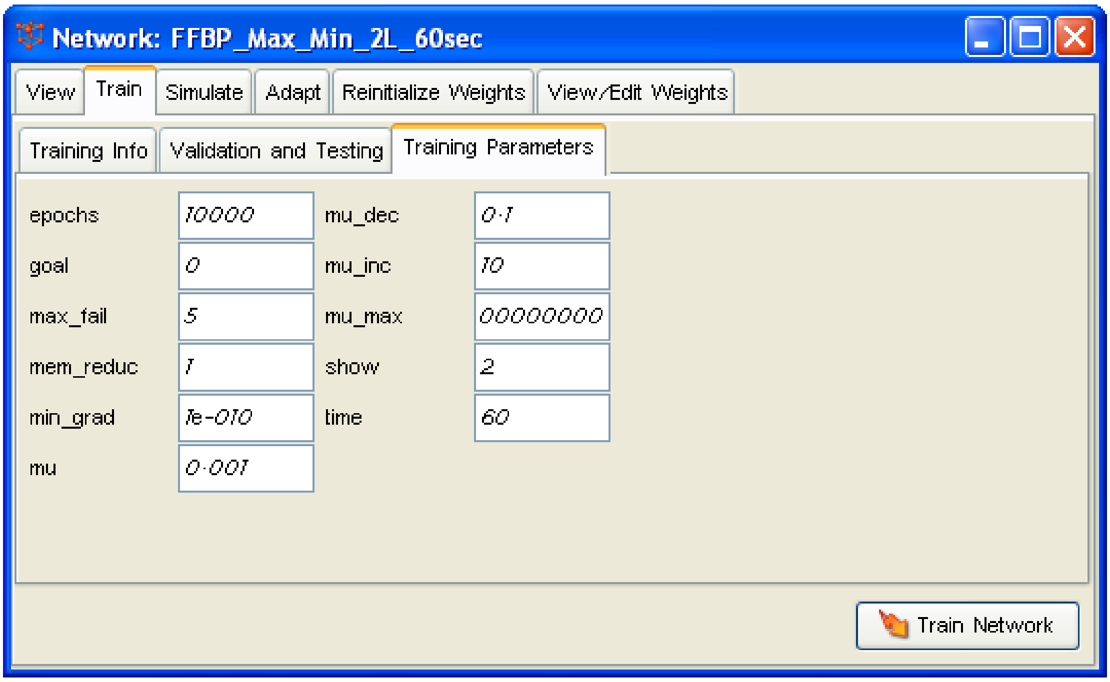


Figure 5.8: Selecting the training parameters

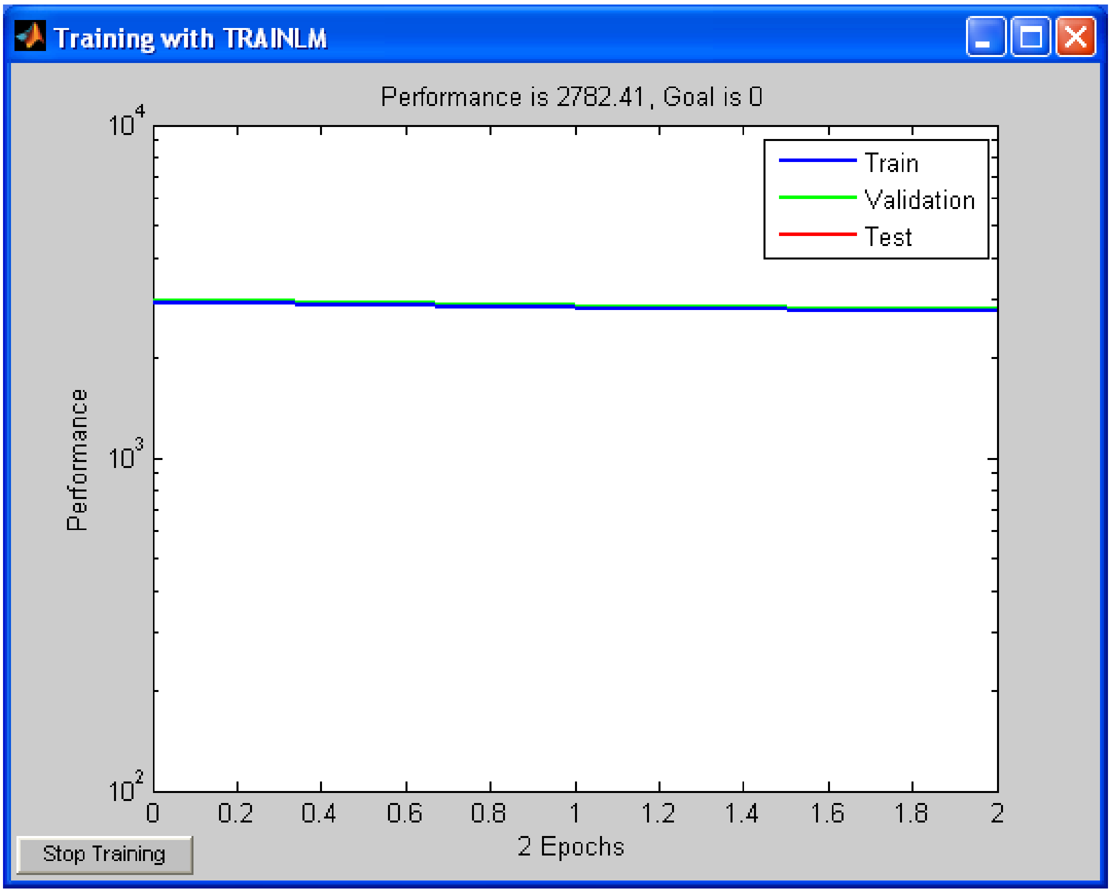


Figure 5.9: Training and validation results [FFBB Max_Min 2L 60sec]

The above performance gives the following results for NN output and errors when the the same input PD matrix is used for the validation and testing in Fig. 5.10 and 5.11 for the input and target simulated NN results.

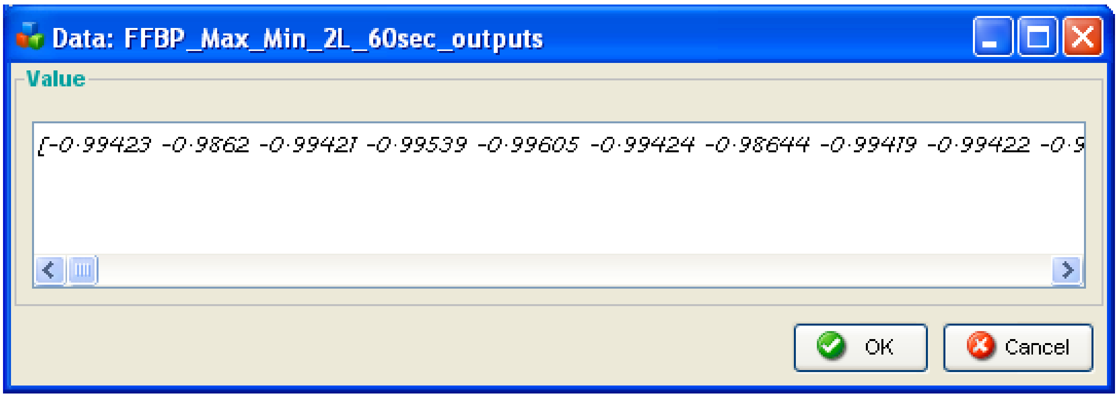


Figure 5.10: FFBP output values [FFBB Max_Min 2L 60sec]

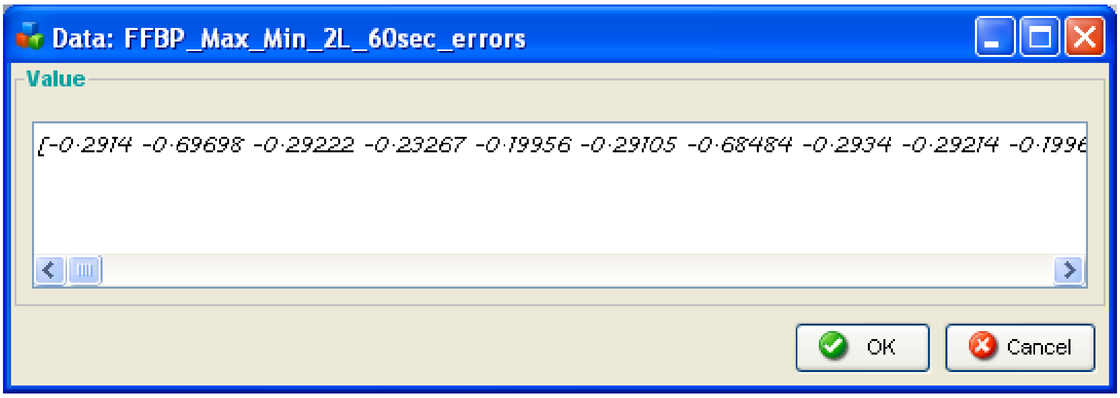


Figure 5.11: FFBP error values [FFBB Max_Min 2L 60sec]

When the trained FFBP used to test the Blind Dataset using the results from the field-test mentioned above, the following

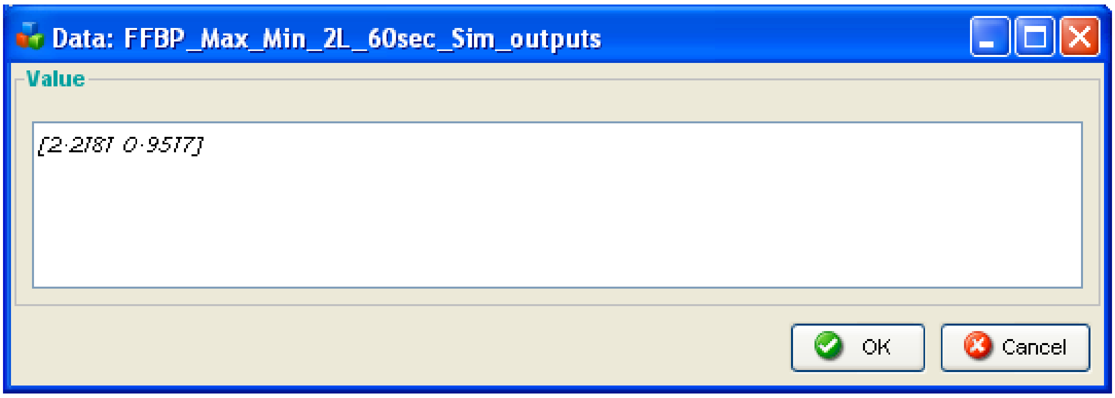


Figure 5.12: Simulation outputs for Blind Data [FFBB Max_Min 2L 60sec BD=011]

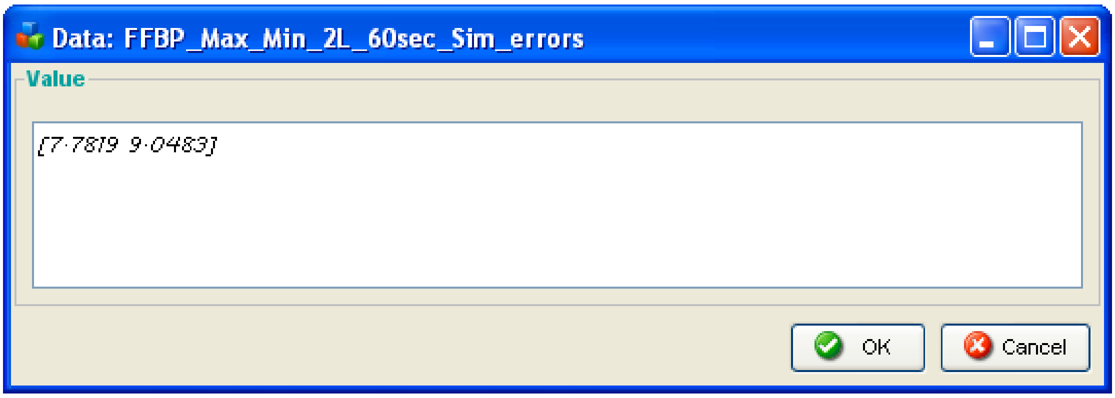


Figure 5.13: Simulation errors for Blind Data [FFBB Max_Min 2L 60sec BD=011]

Now, the training time will be increased to 6000sec with keeping the number of layers as before (2L).

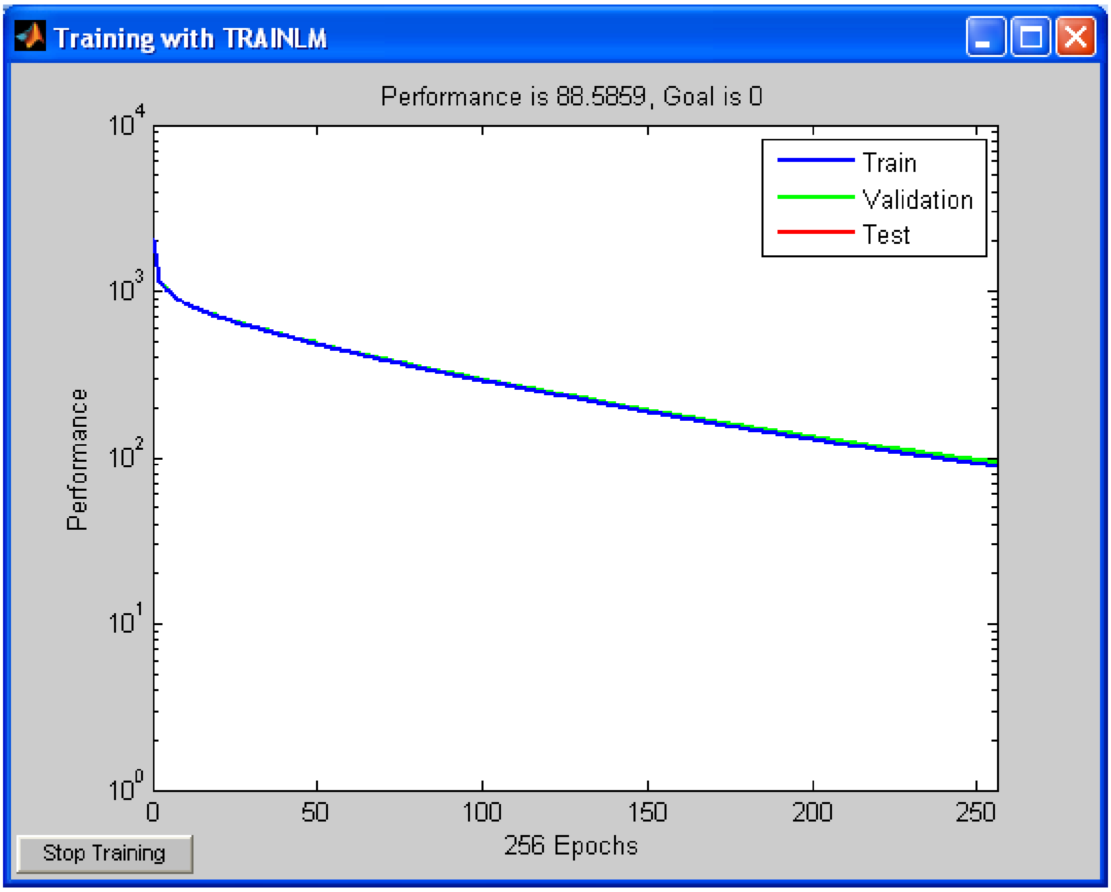


Figure 5.14: Training and validation results [FFBB Max_Min 2L 6000sec]

Although the overall performance was improved, still the SES is high (88.58).

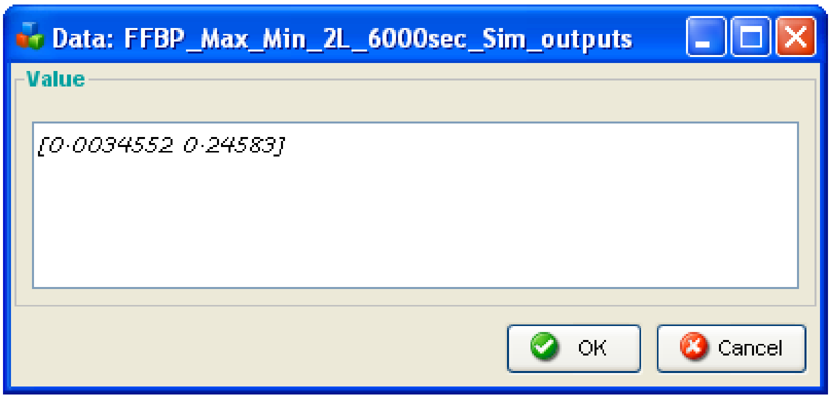


Figure 5.15: Simulation outputs for Blind Test [FFBB Max_Min 2L 6000sec BD=011]

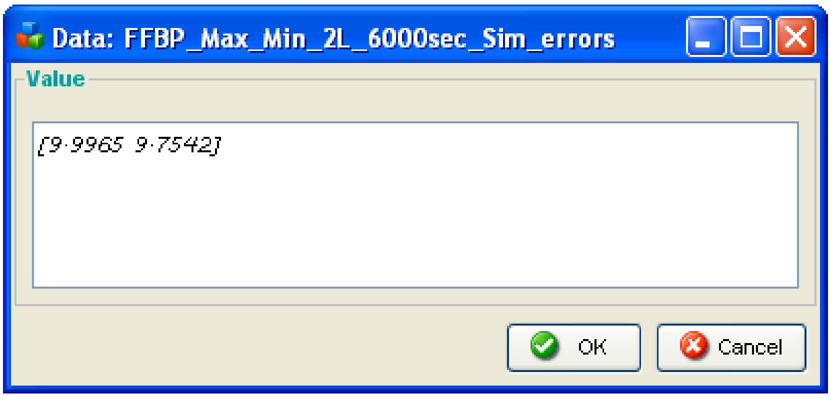


Figure 5.16: Simulation errors for Blind Data [FFBB Max_Min 2L 6000sec BD=011]

Through a quick comparison, it was noticed that changing the output format from decimal to binary jeopardized the accuracy severely. Now, the table 5.4 will be converted from binary to the decimal as in Table 5.7:

Table 5.7: Target column adjustment form Binary to Decimal

PD Type	NN Output Representation Binary	NN Output Representation Decimal
Corona	000	0
Endwinding	001	1
Internal	010	2
Slot	011	3
Surface	100	4
Healthy	101	5

The last training session will be repeated once more with the following conditions:

1. NN: FFBP NN
2. Layers: 2L
3. Epochs: 10000
4. Time: 6000sec
5. Target Format: Decimal

Reviewing Fig. 5.17 shows the massive improvement in the training performance and the reduction of SSE from 88.5859 to 0.000956343 (Goal = 0)

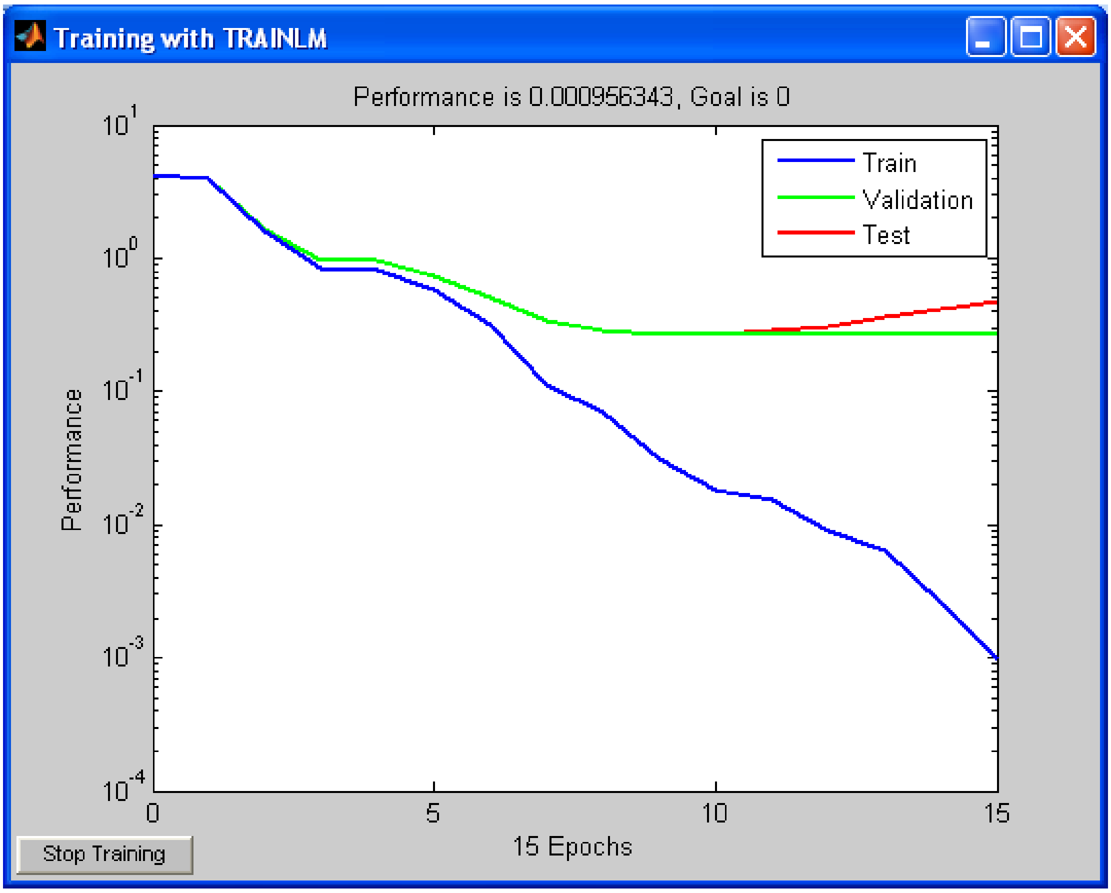


Figure 5.17: Training and validation results [FFBB Max_Min 2L 6000sec Dec]

Now, the improvement in SSE will be reflected on the testing data accuracy as well as the classification of Blind Data.

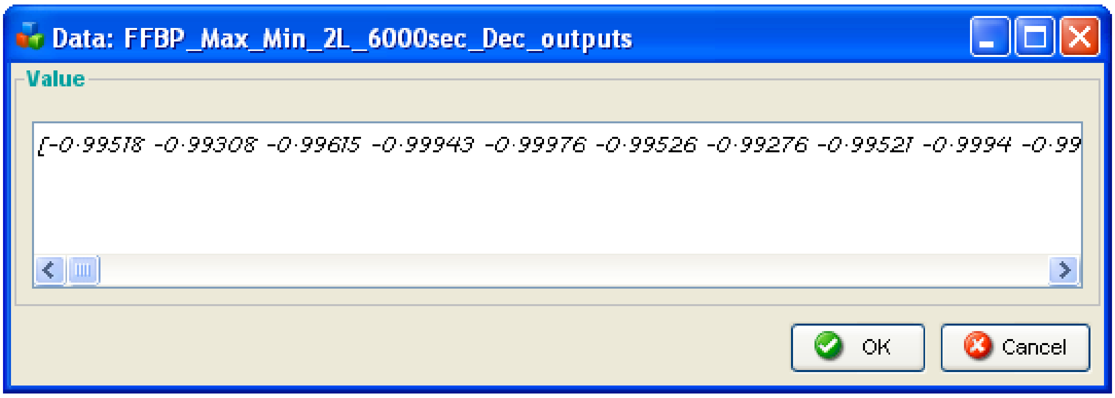


Figure 5.18: FFBP output values [FFBB Max_Min 2L 6000sec Dec]

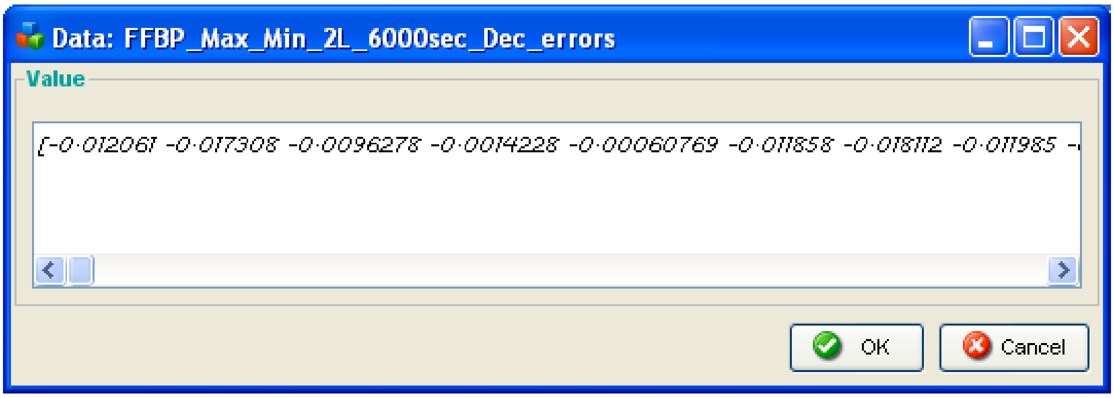


Figure 5.19: FFBP error values [FFBB Max_Min 2L 6000sec Dec]

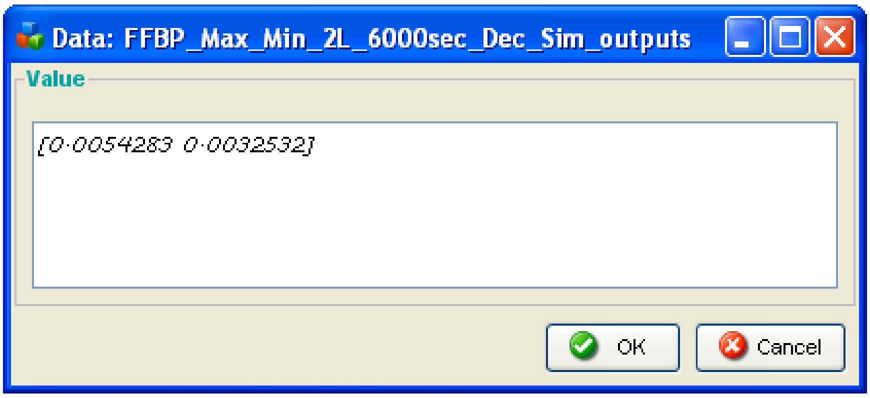


Figure 5.20: Training outputs for Blind Data [FFBB Max_Min 2L 6000sec BD=3]

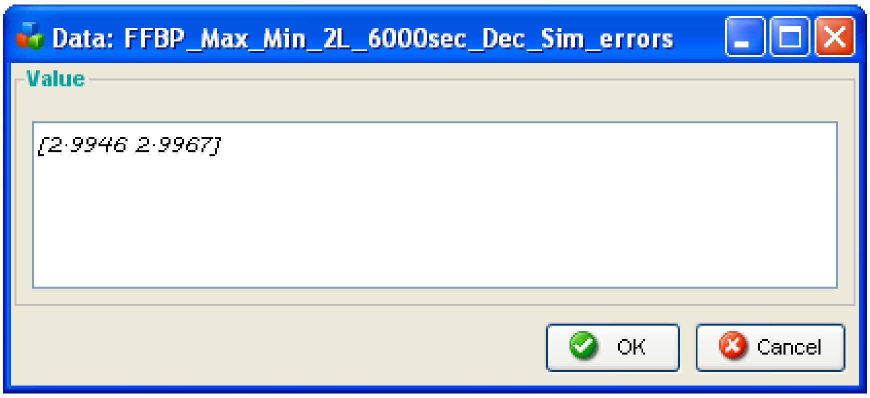


Figure 5.21: Training errors for Blind Data [FFBB Max_Min 2L 6000sec BD=3]

Using these results, the FFBP NN can be improved as follows:

1. NN: FFBP NN
2. Layers: 10L
3. Epochs: 10000
4. Time: 6000sec
5. Target Format: Decimal

Figures from 5.22 to 5.26 illustrate the steps that were performed by MATLAB Toolbox to train the FFBP NN under the listed conditions from 1 to 5 above.

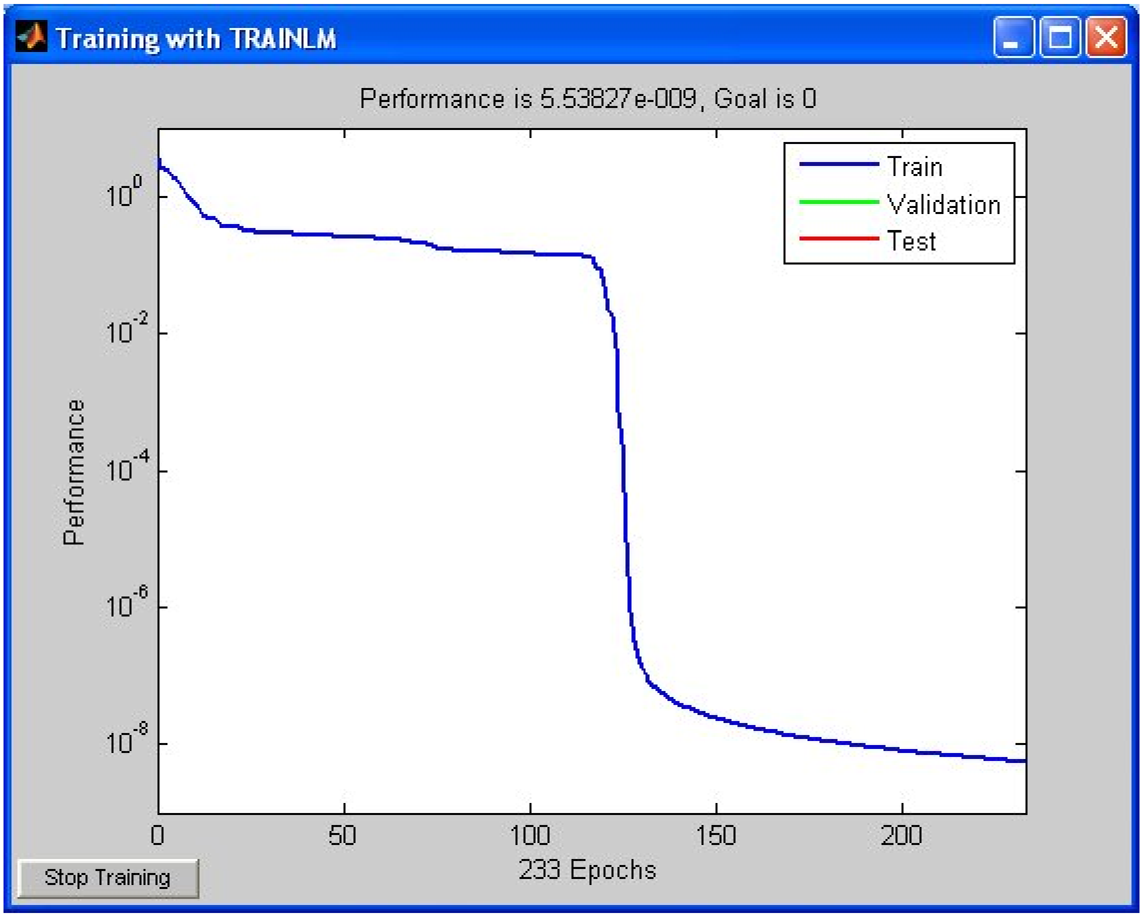


Figure 5.1: Training and validation results [FFBB Max_Min 10L 6000sec Dec]

The new SSE is 5.53827E-9. It is expected that the results of the training session to be more accurate; also that is valid for blind datasets simulation. That because the very low SSE (E-9) decreases the mismatching between the input and the validated and tested datasets. The SSE will be calculated to monitor the improvement in the classification accuracy.

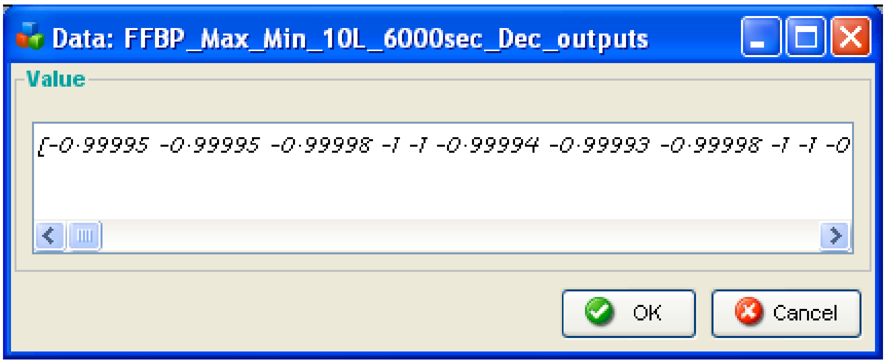


Figure 5.23: FFBP output values [FFBB Max_Min 10L 6000sec Dec]

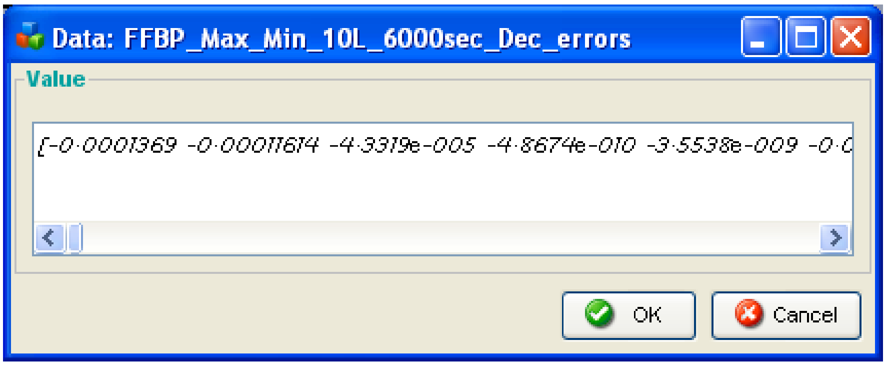


Figure 5.24: FFBP error values [FFBB Max_Min 10L 6000sec Dec]

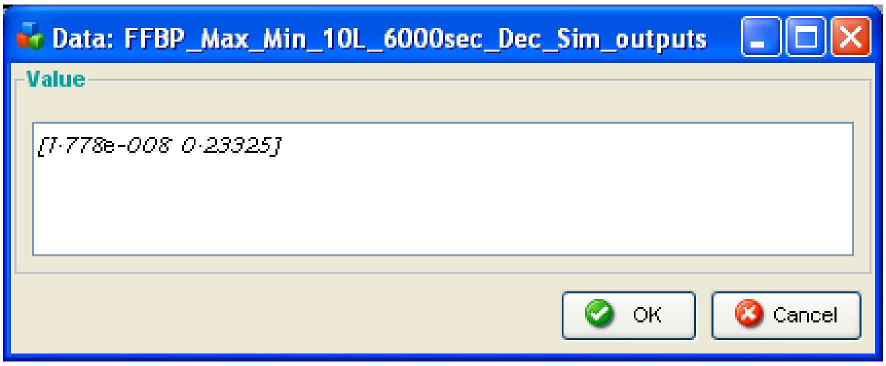


Figure 5.25: Simulation outputs for Blind Data [FFBB Max_Min 10L 6000sec BD=3]

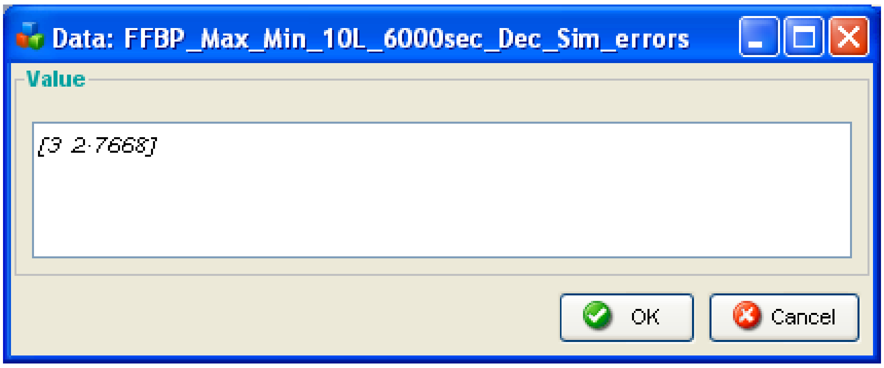


Figure 5.26: Simulation errors for Blind Data [FFBB Max_Min 2L 6000sec BD=3]

The performance of each training session could defined be calculating the SSE (Sum of Squared Error) divided by number of outputs. Performance usually calculated to evaluate the accuracy of the NN by taking the difference between actual outputs and simulated outputs.

Table 5.8: Performance comparison

NN	Target B or D	Training	NN Performance MATLAB	Simulation Performance Calculated
FFBP	B	2L 60 sec.	2782.41	$\frac{e_1^2+e_2^2}{2}=\frac{7.7819^2+9.0483^2}{2}=71.21485$
FFBP	B	2L 6000 sec.	88.5859	$\frac{e_1^2+e_2^2}{2}=\frac{9.9965^2+9.7542^2}{2}=97.53721$
FFBP	D	2L 6000 sec.	0.000956343	$\frac{e_1^2+e_2^2}{2}=\frac{2.9946^2+8.97392^2}{2}=8.97392$
FFBP	D	10L 6000 sec.	5.53827E-9	$\frac{e_1^2+e_2^2}{2}=\frac{3^2+2.7668^2}{2}=8.327591$

Table 5.8 shows a comparison between the four training cases of FFBP NN with different target representation (Binary or Decimal), training time and different number of hidden layers.

Four (4) subgroups selected among the input data were simulated using the last EBP network (with the best overall performance = 1.24153E-7). The new performance values will be calculated and compared with the results and errors of the Blind Data simulation as described in Table 5.9 and Fig.5.27.

Table 5.9: Performance comparison

	Input	Output	ABS(Error)	Performance
Sim. 1 Input Subrgp. 1	5	4.9983490	1.651E-03	1.64E-07
	0	0.0007420	7.416E-04	
Sim. 2 Input Subrgp. 2	0	0.0004440	4.442E-04	1.72E-07
	0	0.0003840	3.837E-04	
Sim. 3 Input Subrgp. 3	5	4.9997370	2.630E-04	5.24E-08
	5	4.9998110	1.890E-04	
Sim. 4 Input Subrgp. 4	3	3.0000090	8.598E-06	4.59E-11
	1	0.9999960	4.235E-06	
Sim. 5 Blind Data	2	0.0906	1.909E+00	6.32E+00
	2	5	3.000E+00	

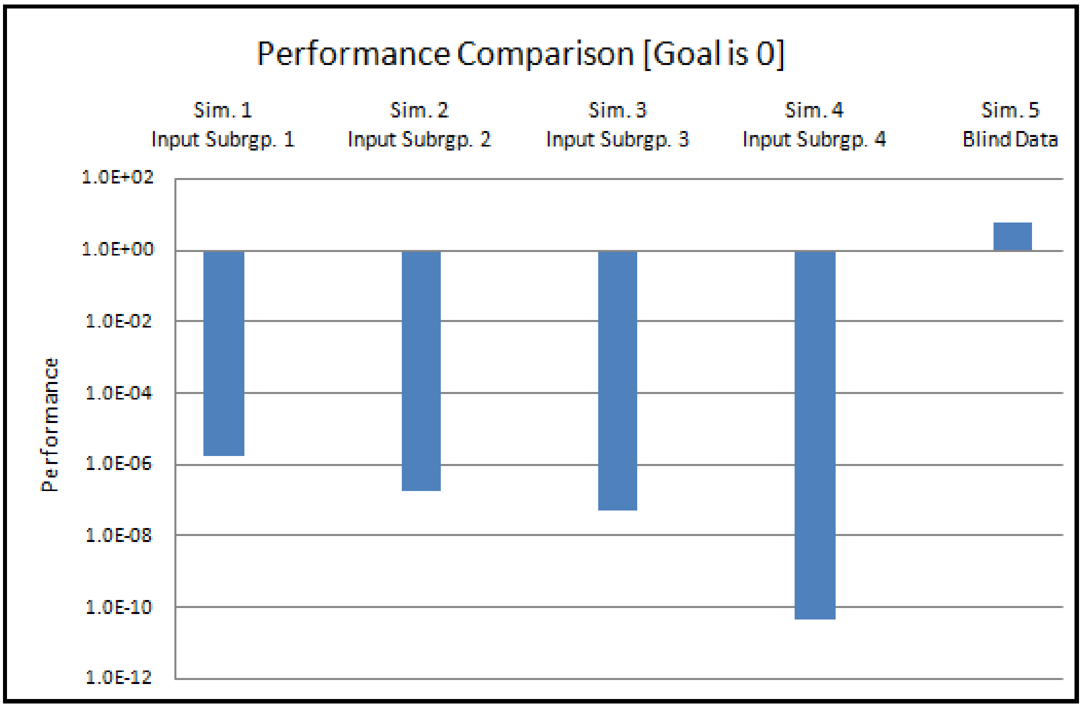


Figure 5.27: Performance comparison [FFBP 10L 4_ Input 1_Blind t=6000 sec.]

The previous comparisons show that the improvement in the overall network performance degrades the simulation performance of the Blind Data. One proposal to explain that behavior is the following: the NN when the training time or number of layers were increased would improve the knowledge of the NN on the training dataset which increase the neurons and links. The tendency to improve the internal NN knowledge which could be understood as the NN is trying to memorize the behavior more than doing the NN calculation. That also is known as “Overfitting”.

The previous step-by-step approach leads us to the way that could accelerate the study of the FFBP NN with the other reduced matrices (Max_Min pu, Max+|Min| pu, PCA and ISOMAP).

The proposal of the follow-chart in the next page could be used to accelerate the training and reduce it from 90 training sessions to 22 sessions.

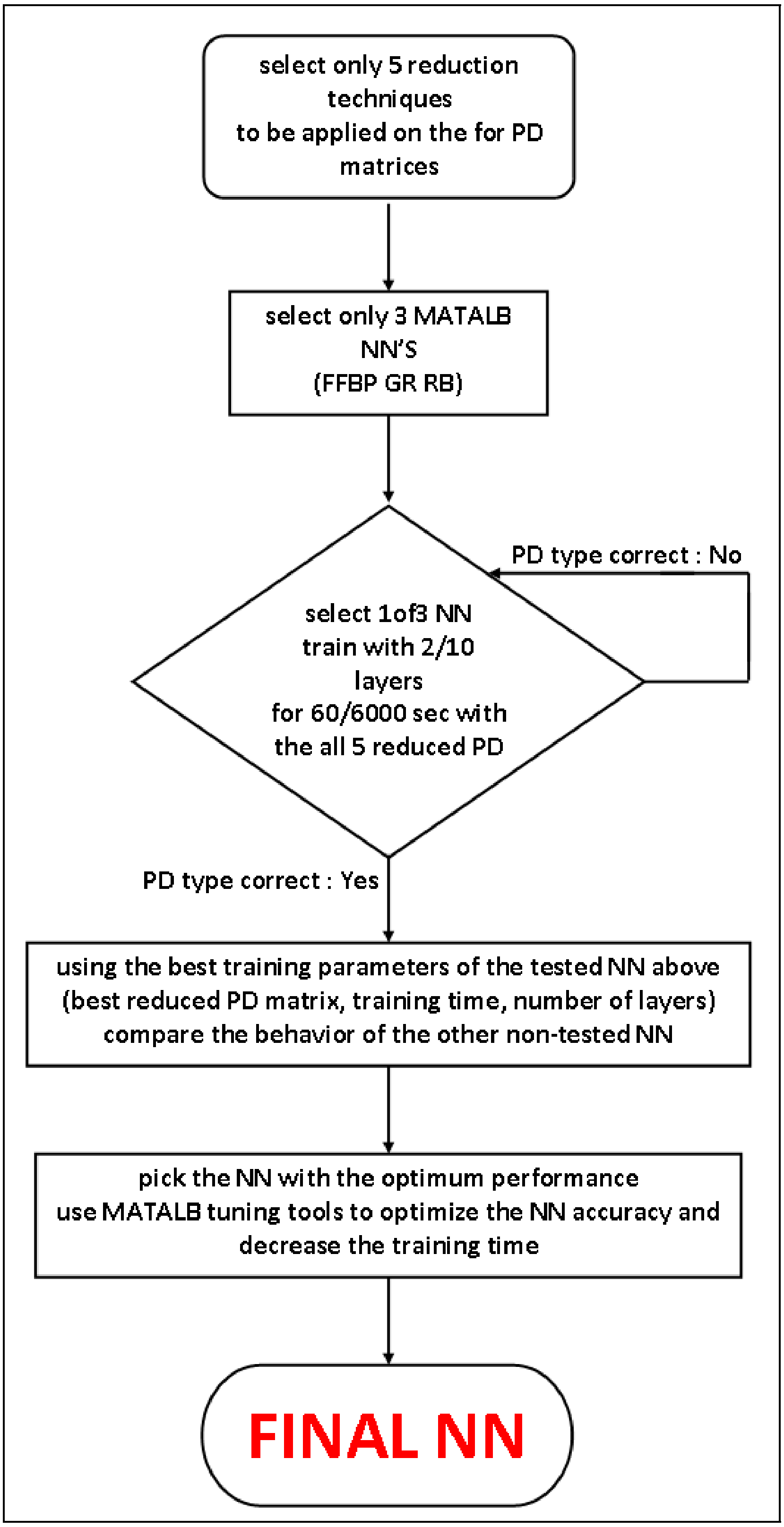


Figure 5.28: NN Training flow chart

Table 5.10: FFBP on Max-Min PD

5.2.2.1.2:	**FFBP**	
Input Matrix	Max_Min_pu_IP	398 X 300
Target Matrix	Max_Min_pu_TGT	1 X 300

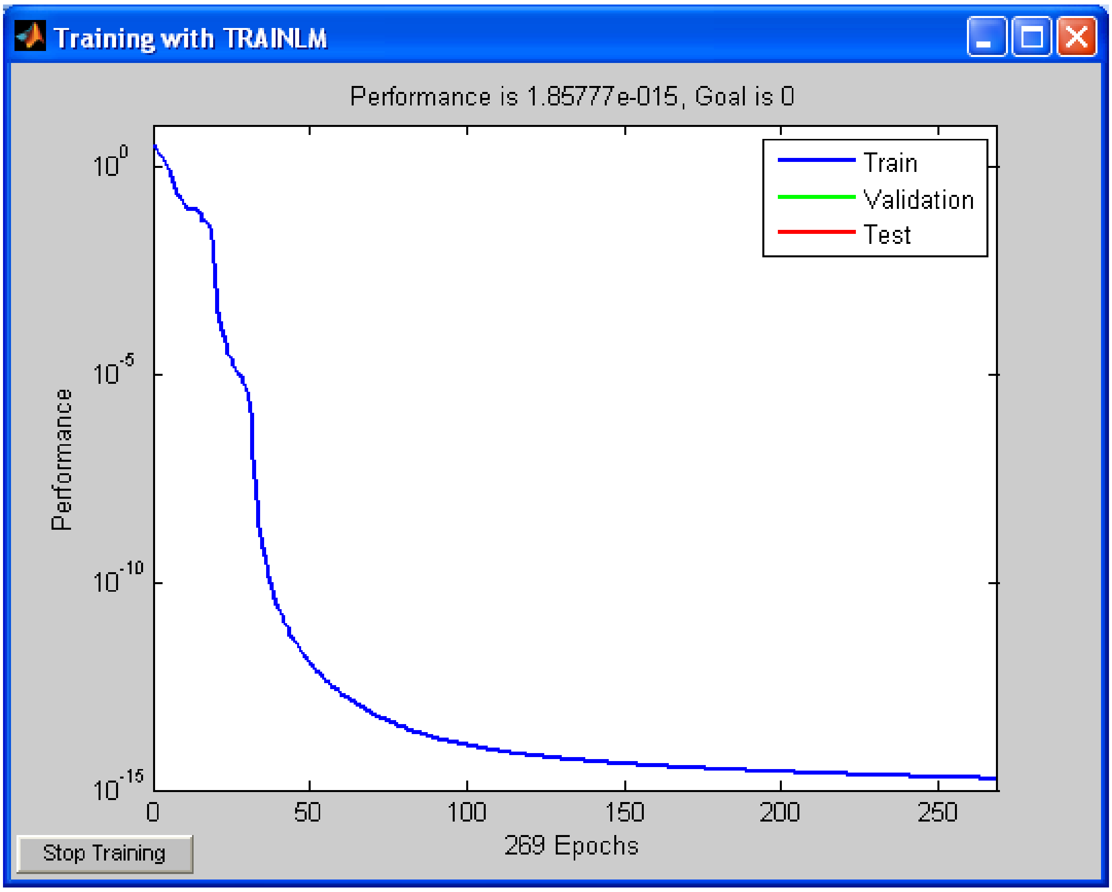


Figure 5.29: Training and validation results [FFBB Max_Min_pu 10L 6000sec Dec]

Using the MATLAB NN GUI is not friendly; each slight modification requires running the GUI from the beginning and start loading all matrices from zero bases. Even changing the training time from 60sec to 61sec requires going in the loading phase using Network/Data Manager.

To overcome this problem, a generic MATLAB code was developed to include all possible combinations agreed to be carried out. An *.m file was developed to perform the training, validation and simulation of the three (3) networks using the five (reduction) techniques.

The code is available in the index. Running the code gives the following results:

Table 5.11: FFBP training and simulation results

Network Reduction Tech_#L_Time	Training Error	Simulation Error
FFBP Max_Min_10L_6000sec	5.53827E-9	8.32759112
FFBP Max_Min_pu_10L_6000sec	1.85777E-15	4.508258
FFBP Max_AbsMin_10L_6000sec	4.25862E-6	12.456876
FFBP Max_Min_PCA_10L_6000sec	5.327867E-5	17.27654
FFBP Max_Min_ISOMAP_6000sec	2.2356754E-4	18.87698

5.2.2.2. Generalized Regression (GR)

The generalized regression neural network (GRNN) was introduced by Nadaraya and Watson and rediscovered by Speech to perform general (linear or nonlinear) regressions. The GRNN was applied to solve a variety of problems like prediction, control, plant process modeling or general mapping problems. Other stochastically based neural networks, the so-called probabilistic neural networks, are used for classification. The

concept of the GRNN is based on nonparametric estimation commonly used in statistics. The essence of nonparametric estimation is nonlimiting to an assumed-usually in an arbitrary way-parametric class of models. Such approach was applied by several authors who created nonparametric algorithms based on the Parzen method and orthogonal series [109].

The Generalized Regression Neural Network is a neural network architecture that can solve any function approximation, problem. The learning process is equivalent to finding a surface in a multidimensional space that provides a best fit to the training data, with the criterion for the "best fit" being measured in some statistical sense. The generalization is equivalent to the use of this multidimensional surface to interpolate the test data [112].

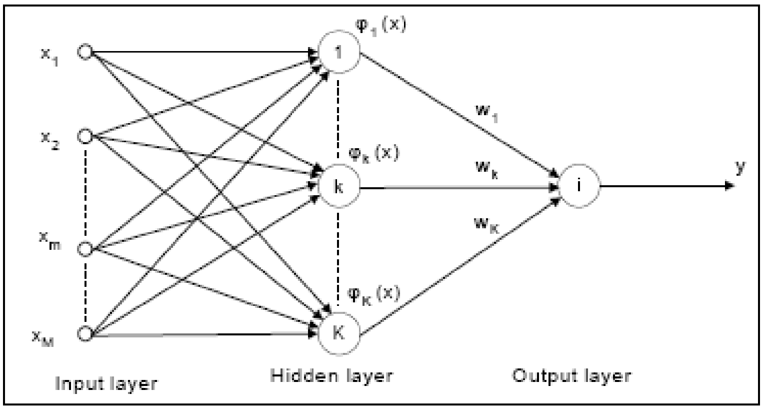


Figure 5.30: General Regression Neural Network architecture

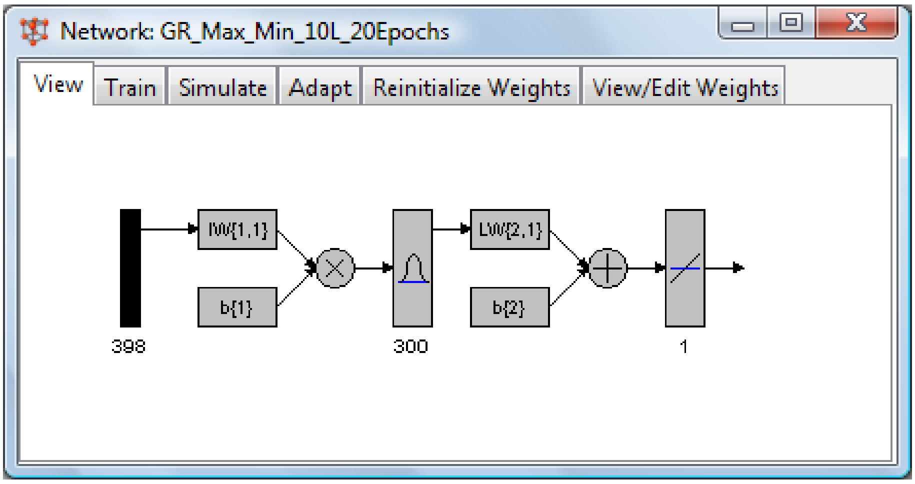


Figure 5.31: GR block diagram as created by MATALAB

Running the MATALB code used for FFBP generates the following results:

Table 5.12: Training and simulation results

Network Reduction Tech_#L_Time	Simulation Error
GR Max_Min	0
GR Max_Min_pu	8.5269E-139
GR Max_AbsMin	0
GR Max_Min_PCA	0
GR Max_Min_ISOMAP	4

5.2.2.3. Radial Basis (RB)

Among the different types of neural networks Radial Basis Neural Network (RBNN) have received much attention in the recent past because it provides better accuracy and generalization for a wide range of pattern recognition applications while providing a faster

training algorithm. It is a type of feedforward, supervised neural network where Gaussian function is being used most frequently as the activation function of hidden nodes. Major difference of RBNN over the other type of neural networks is its two stage training procedure. An RBNN is typically trained in two stages:

- Basis function is being determined by unsupervised techniques using input data alone.
- Layer weights are adjusted by a supervised learning technique.

When training an RBNN or any other neural network a common challenge faced by the designers is choosing an appropriate structure for the neural network. Determining parameters such as number of hidden nodes in the hidden layer has been normally considered as a difficult task when determining the structure. Traditionally, the number of nodes is generally determined using a trial and error method by a human supervisor. The network is trained with several choices for the number of hidden nodes and its performance is measured [113]

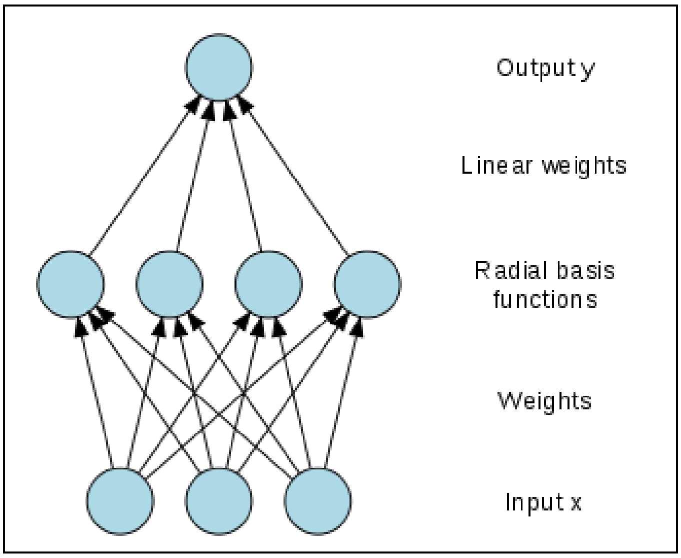


Figure 5.32: Architecture of a radial basis function network.

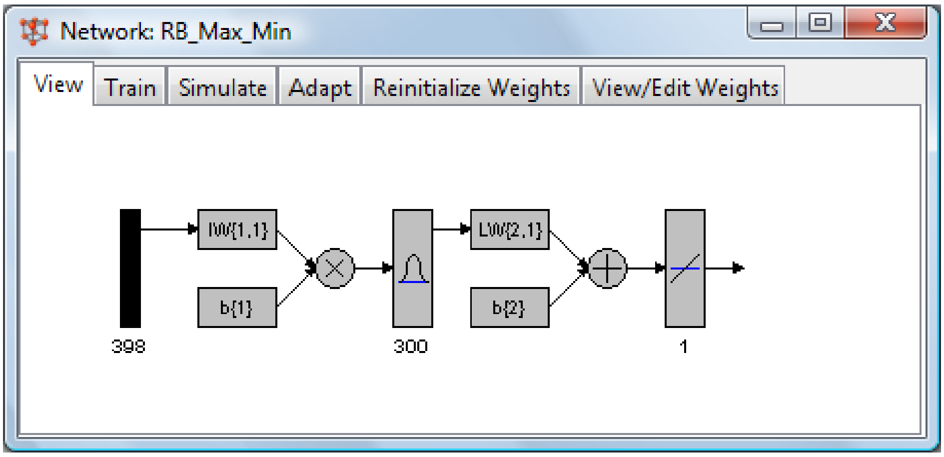


Figure 5.33: RB block diagram as created by MATLAB

Running the MATALB code used for FFBP generates the following results:

Table 5.13: RB training and simulation results

Network Reduction Tech_#L_Time	Simulation Error
RB Max_Min	9
RB Max_Min_pu	1
RB Max_AbsMin	9
RB Max_Min_PCA	4
RB Max_Min_ISOMAP	4

5.2.2.4. Best-fit MATLAB NN

Based on the above results, the General Regression Neural Network could be considered as the best-fit NN.

(GRNN) is the best NN generated using the NN Toolbox of MATLAB. Since the fine tuning features such as training function and transfer function are not available to adjust in this type of MATALAB NN's, the generated GRNN could be considered as the best-fit MATALAB NN.

5.3. PD CLASSIFICATION USING NEURALSIGHT NN PACKAGE

The unsatisfactory performance of the MATLAB NN Toolbox raises up the need to try another NN tool since many references reported better recognition rates and more accurate PD Classification. The use of NeuralWare software was reported in a referenced MS thesis at University of South Florida USA. The author reported accuracy ranges from 70.45% to 99.40% in localizing the PD source within a generator system. In that work, the author only used NeuralWare software to perform the NN.

5.3.1. NeuralSight Neural Network Background

The NeuralSight Model Generator (NeuralSight) is a Java®-based Graphical User Interface (GUI) for the NeuralWare® NeuralWorks Predict® neural network modeling engine. NeuralSight is the most recent and most advanced version of NeuralWare software. NeuralSight supports automated, unattended creation and evaluation of neural

network models that can subsequently be incorporated into domain-specific applications. The NeuralSight Model Generator provides an efficient and highly automated mechanism for building and evaluating neural network models. If the task is to build prediction or classification models, after you specify a small set of general parameters to guide the model building process, and (optionally) error levels that models must not exceed, NeuralSight builds and evaluates models based on the specifications and retains only models that meet the specifications [115].

If the task is to build Self-Organizing Map models, NeuralSight builds many models with different map dimensions, based on minimum and maximum dimensions that you specify. You also specify the number of models that you want. The model building process ends either because enough models that meet the performance criteria have been built, or the time you specified for model building has elapsed. You can then review the performance information generated by NeuralSight and decide which models are the best ones to use in your specific application [115].

5.3.2. How to Use NeuralSight

The NeuralSight has a friendly user interface enables the user to navigate through the different steps in very symmetric.

After the installation, the Predict NN engine is available for use through the command line or through the NeuralSight GUI. The GUI starts with the following dialog box:

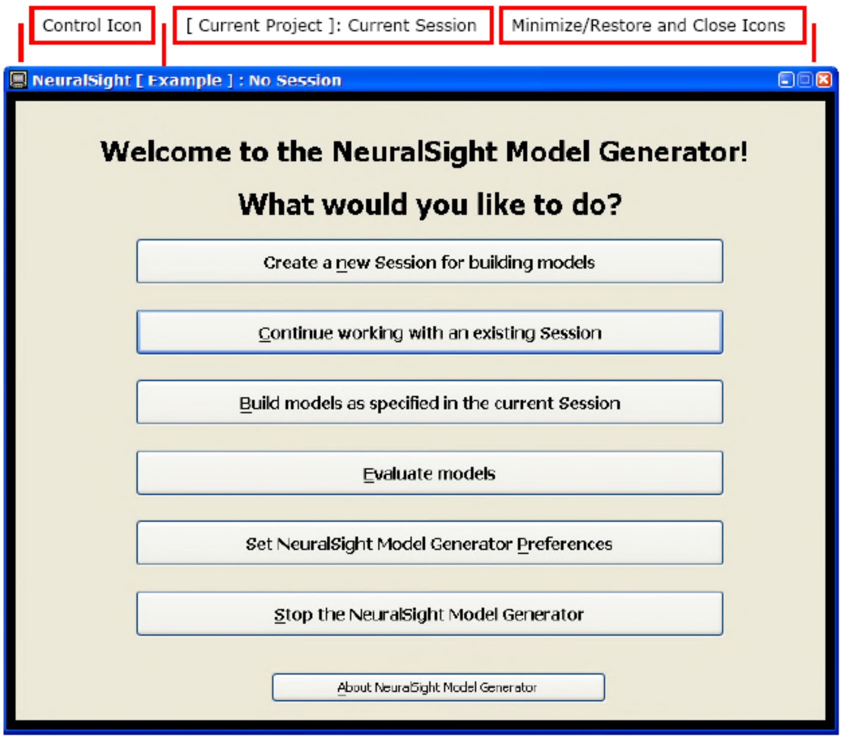


Figure 5.34: NeuralSight GUI

First step is to "Create a new session for building models".

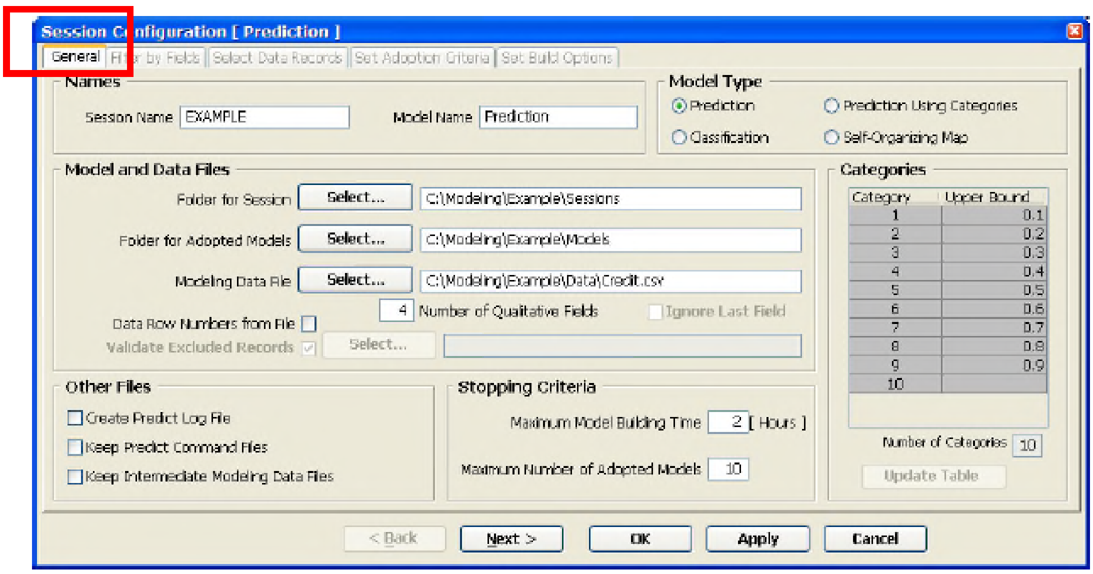


Figure 5.35: NeuralSight Configuration Tap

After setting the preferences, preferences could be adjusted as in the following dialog box:

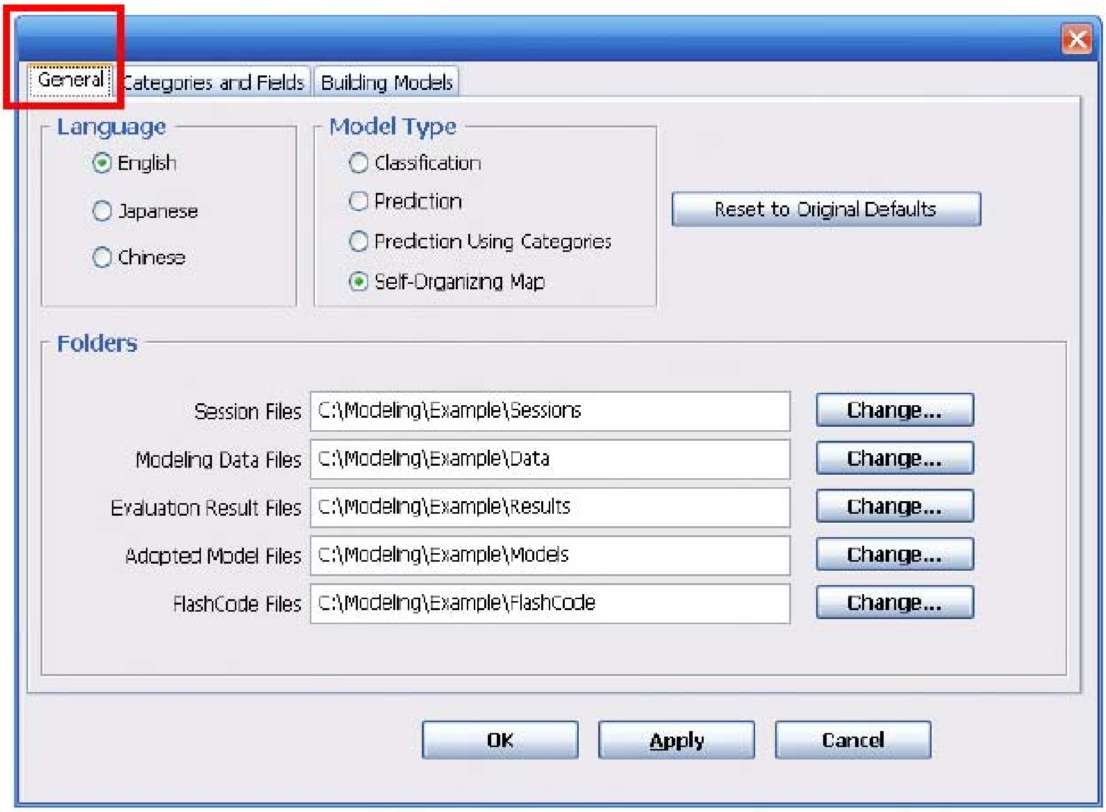


Figure 5.36: Generator preferences setting Tap

At that stage, building the models could be through the following menu:

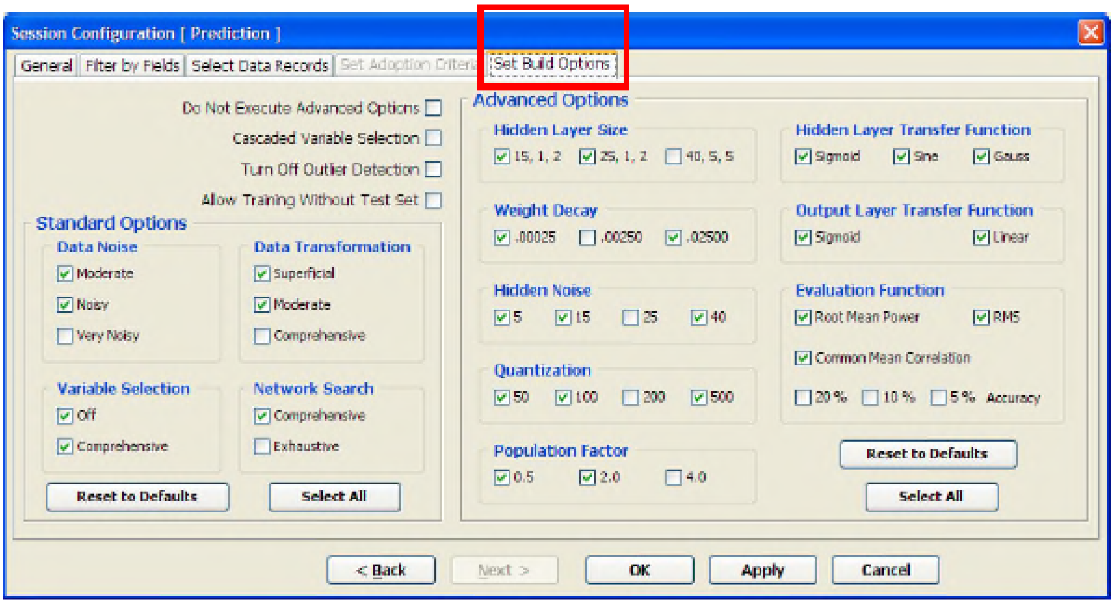


Figure 5.37: Building options tap

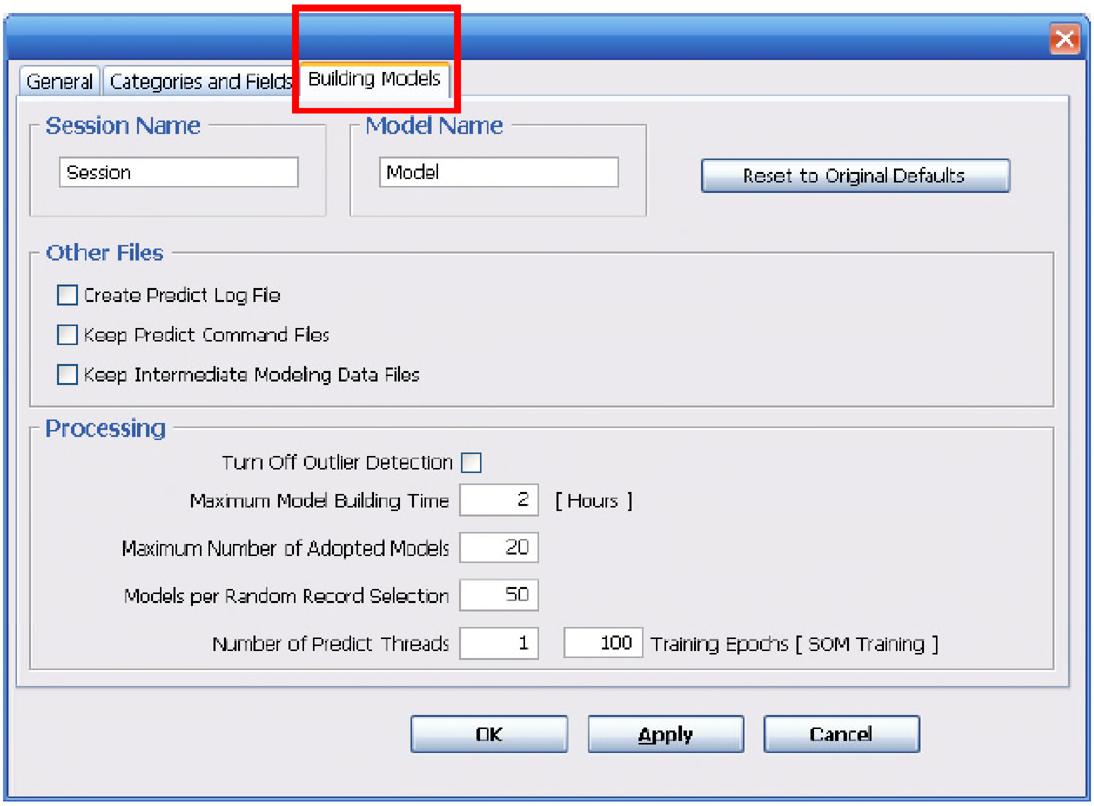


Figure 5.38: Building models tab

When training session done, evaluating the generated models could be started.

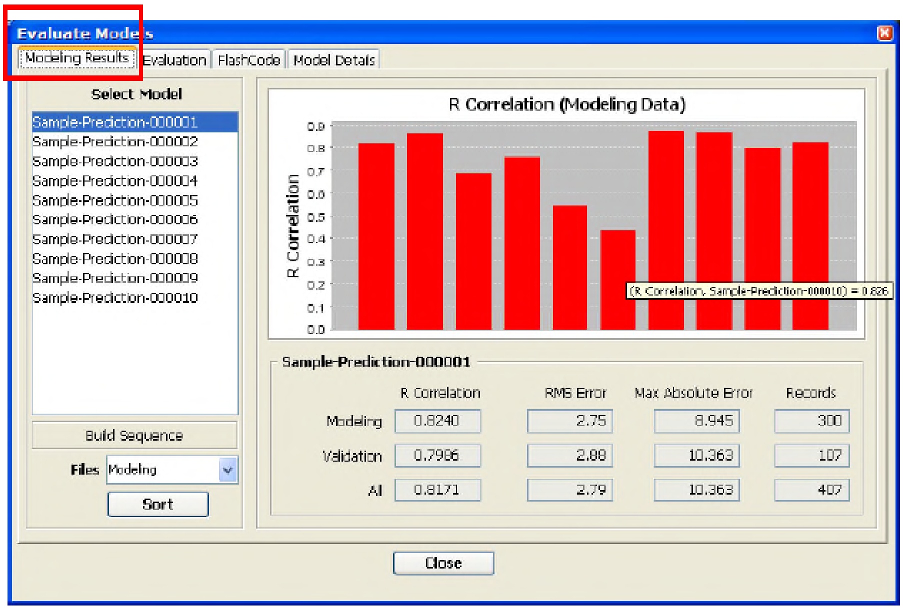


Figure 5.39: Modeling Results Tab

Up to 2000 models could be evaluated using a blind test data and write the results in txt file.

5.3.3. PD Calcification using NeuralSight

5.3.3.1. Reduced Matrix: Max_Min

The first NN to be built by NeuralSight is the Max_Min reduced PD matrix. Through this reduction technique, the “Envelope” pattern of the PRPD will be utilized to train and test the NN.

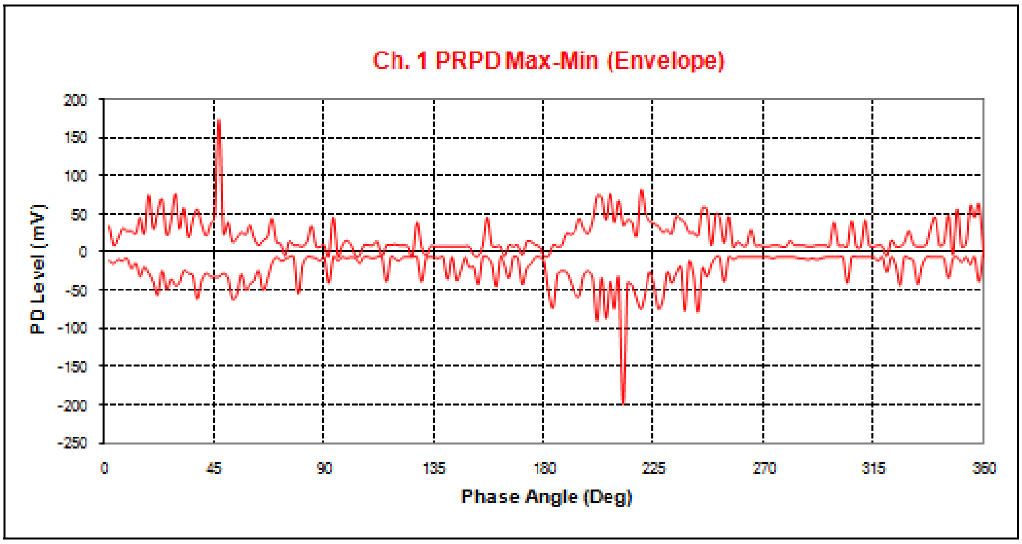


Figure 5.40: Reduced PRPD using Max_Min values

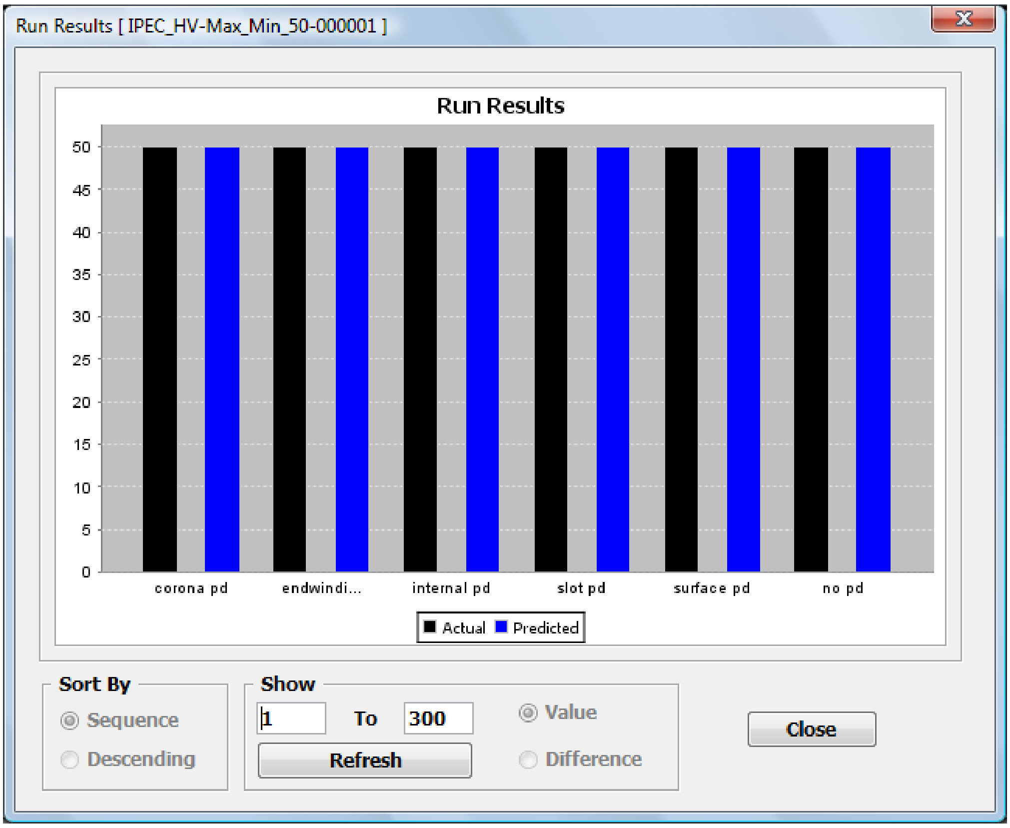


Figure 5.41: Most accurate NeuralSight model for Max_Min PD reduced matrix

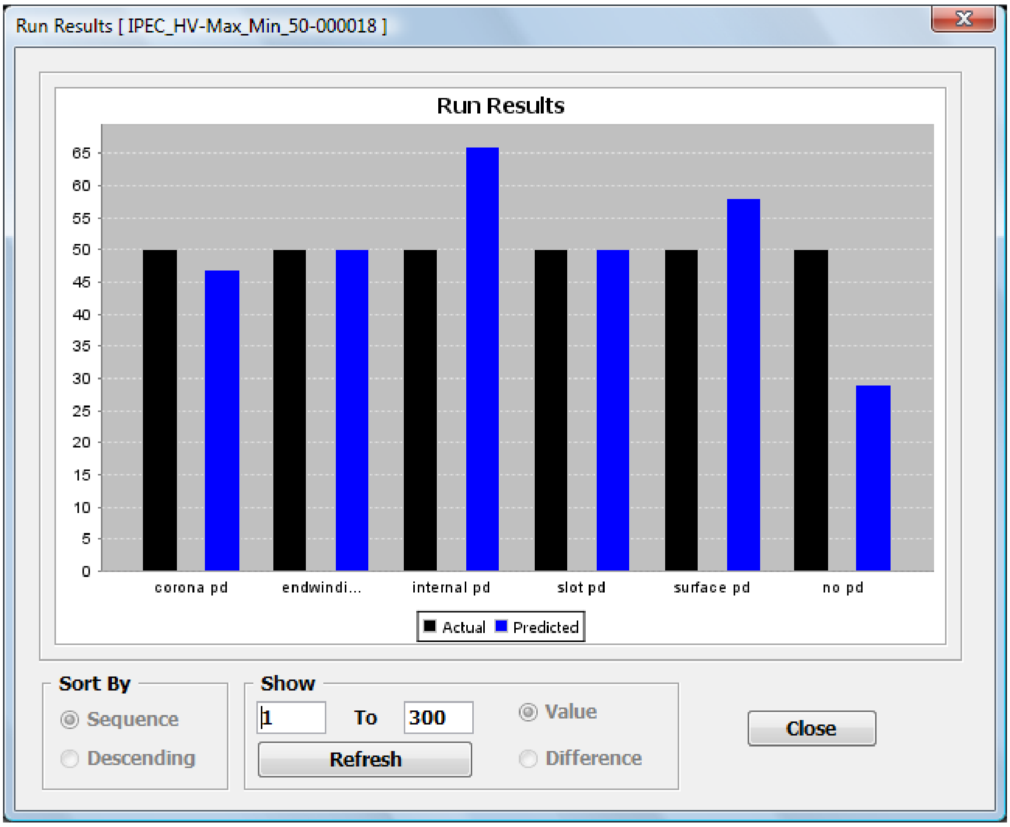


Figure 5.42: Less accurate NeuralSight model for Max_Min PD reduced matrix

The preferences of the NeuralSight were adjusted to generate 999 models. The average accuracy ranges from 100% to 75.8%.

Testing the blind PD data collected from Saudi Aramco plant generates the following result:

Table 5.14: PD classification using NeuralSight Max_Min reduced models

PD Type	**%**
Corona PD	0.336043428
Endwinding PD	4.016448175
Internal PD	45.09978424
No PD	0.975702307
Slot PD	49.32724203
Surface PD	0.24478006

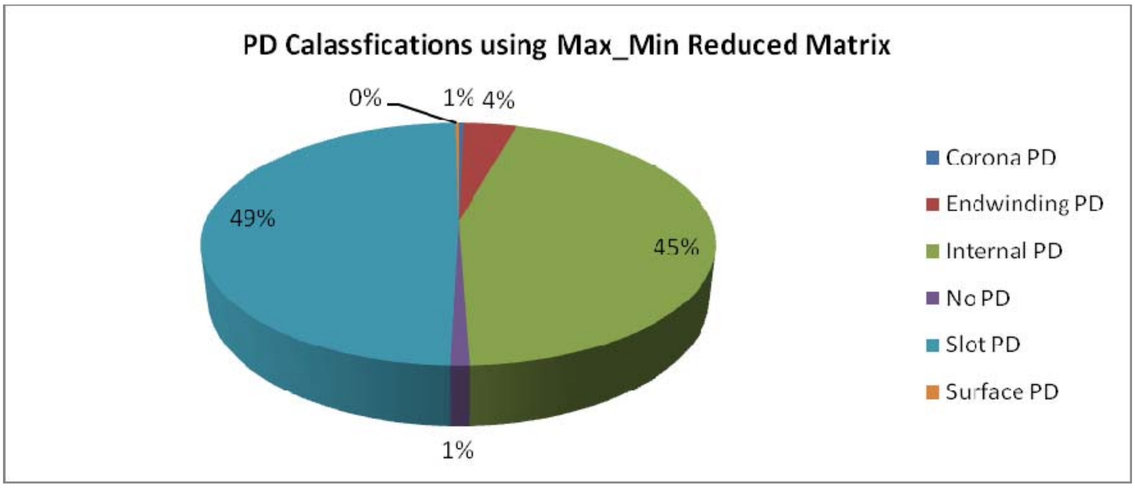


Figure 5.43: PD classification using NeuralSight Max_Min reduced models

5.3.3.2. Reduced Matrix: Max_Min_pu

The third NN to be built by NeuralSight is the [Max_Min]pu reduced PD matrix.

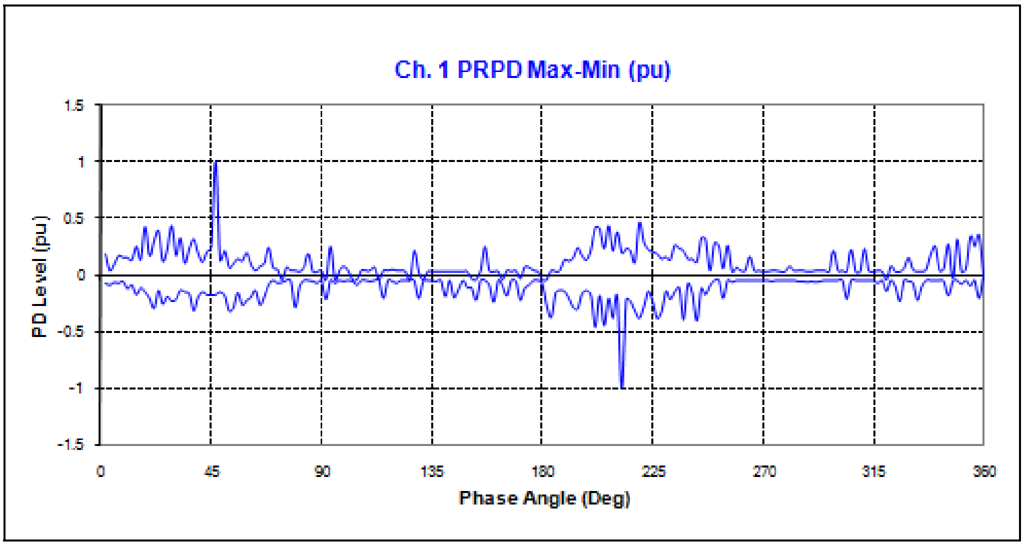


Figure 5.44: Reduced PRPD using [Max_AbsMin]pu values

The preferences of the NeuralSight were adjusted to generate 999 models. The average accuracy ranges from 100% to 64%.

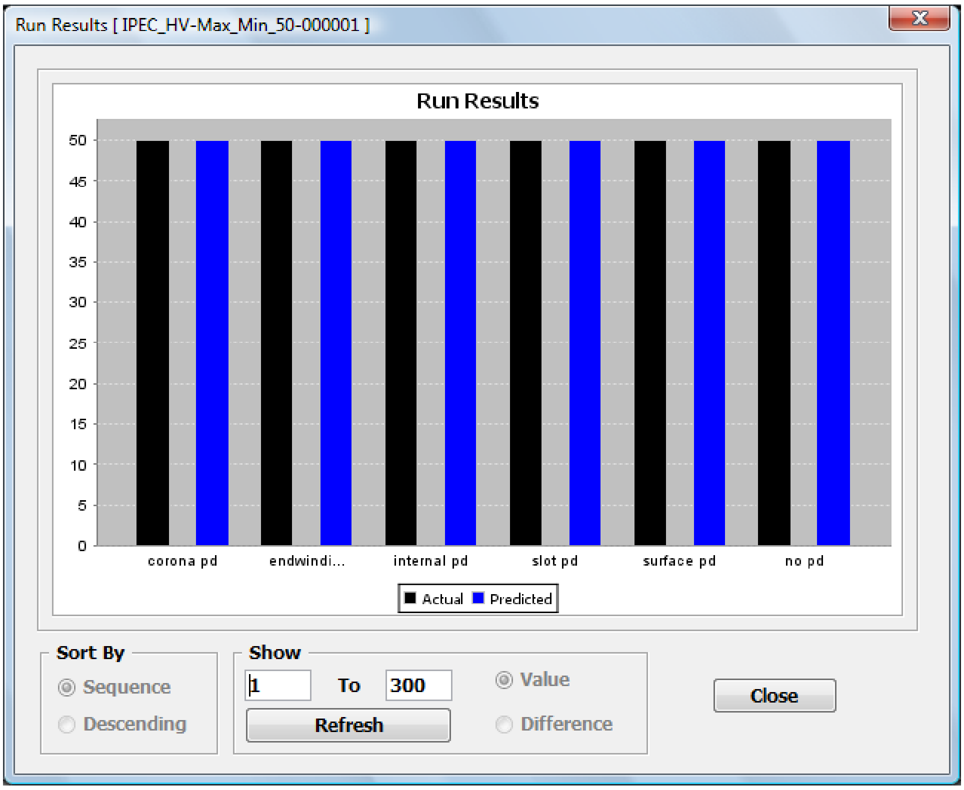


Figure 5.45: Most accurate NeuralSight model for Max_Min PD reduced matrix

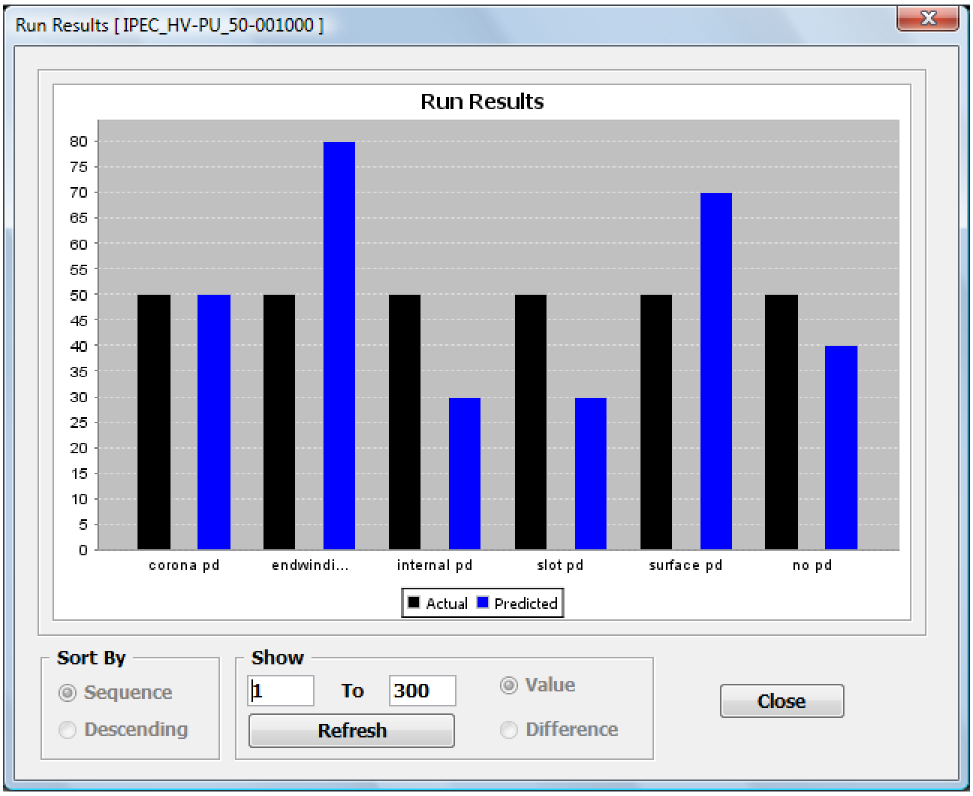


Figure 5.46: Less accurate NeuralSight model for Max_Min_pu PD reduced matrix

Testing the blind PD data collected from Saudi Aramco plant generates the following result:

Table 5.15: PD classification using NeuralSight Max_Min_pu reduced models

PD Type	%
Corona PD	0.336043428
Endwinding PD	4.016448175
Internal PD	45.09978424
No PD	0.975702307
Slot PD	49.32724203
Surface PD	0.24478006

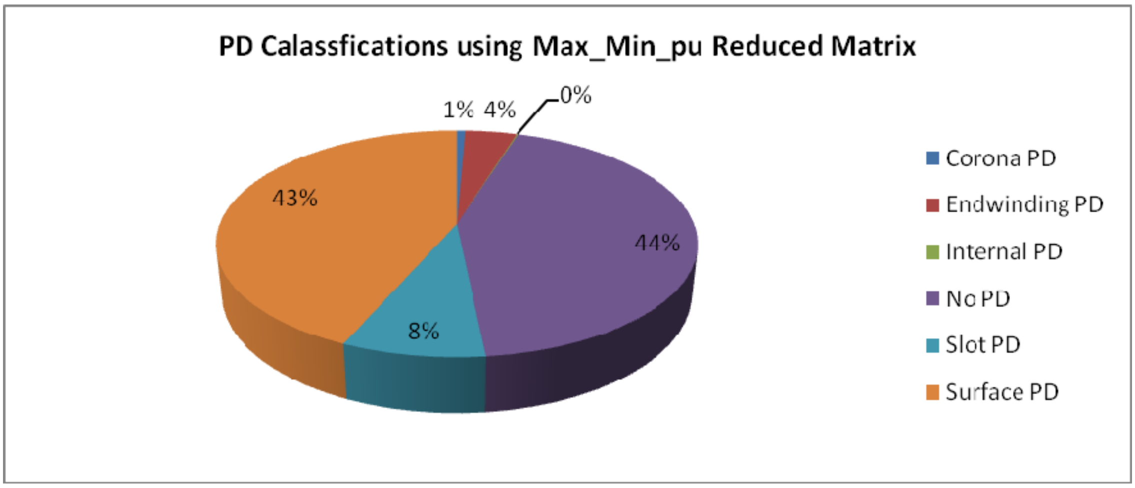


Figure 5.47: PD classification using NeuralSight Max_AbsMin_pu reduced models

5.3.3.3 Reduced Matrix: Max_AbsMin_pu

Same approach could be used now to build the NN models using the Max_Min_pu reduced PD matrix.

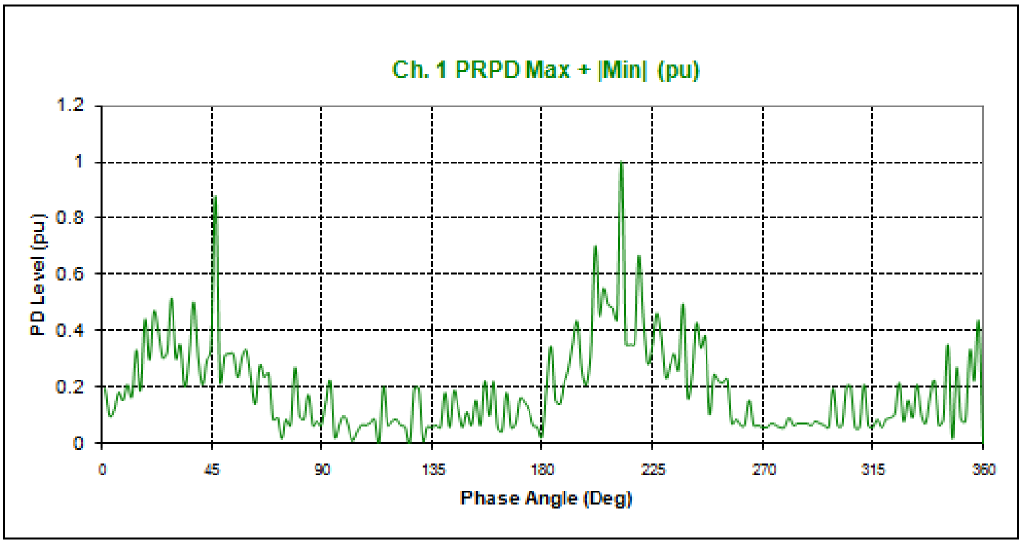


Figure 5.48: Reduced PRPD using Max_Min_pu values

The preferences of the NeuralSight were adjusted to generate 999 models. The average accuracy ranges from 100% to 61%.

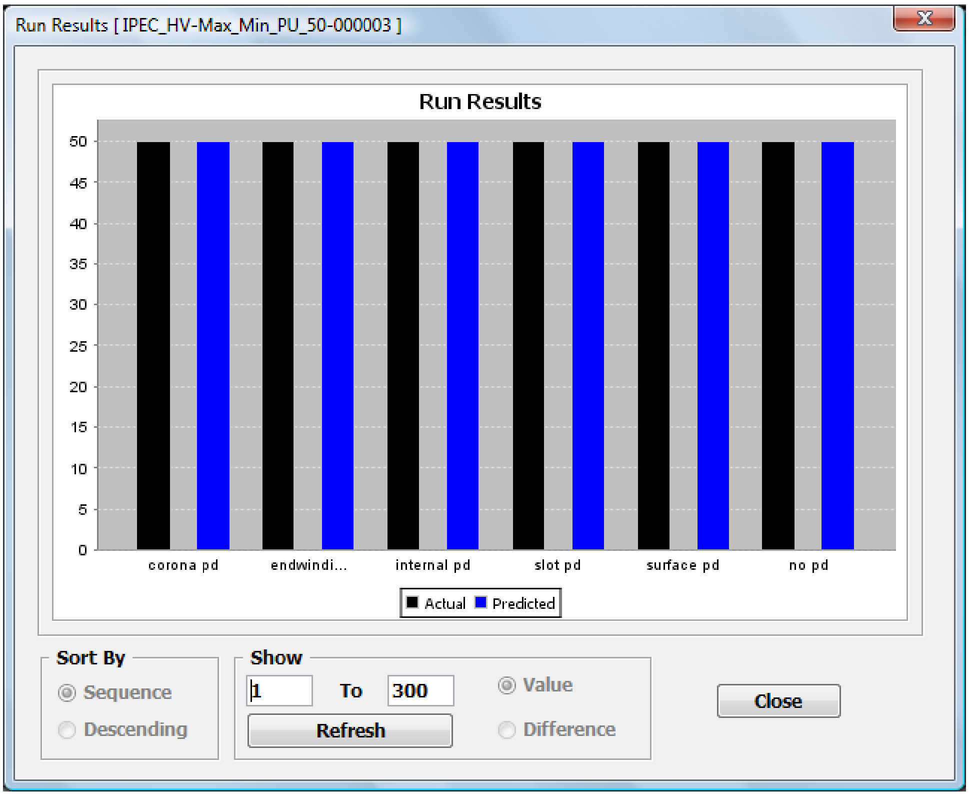


Figure 5.49: Most accurate NeuralSight model for Max_Min PD reduced matrix

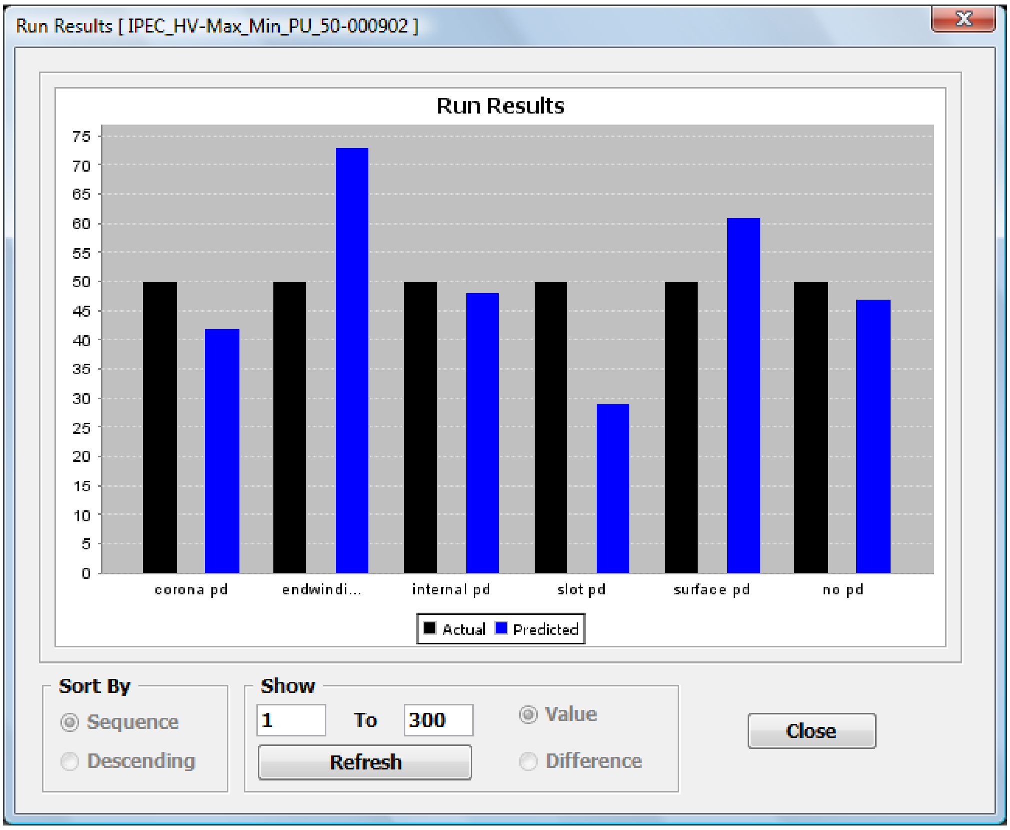


Figure 5.50: Less accurate NeuralSight model for Max_Min PD reduced matrix

Testing the blind PD data collected from Saudi Aramco plant generates the following result:

Table 5.16: PD classification using NeuralSight Max_AbsMin pureduced models

PD Type	**%**
Corona PD	93.07213314
Endwinding PD	1.178909486
Internal PD	2.359916462
No PD	0.870696734
Slot PD	0.878372911
Surface PD	1.639971194

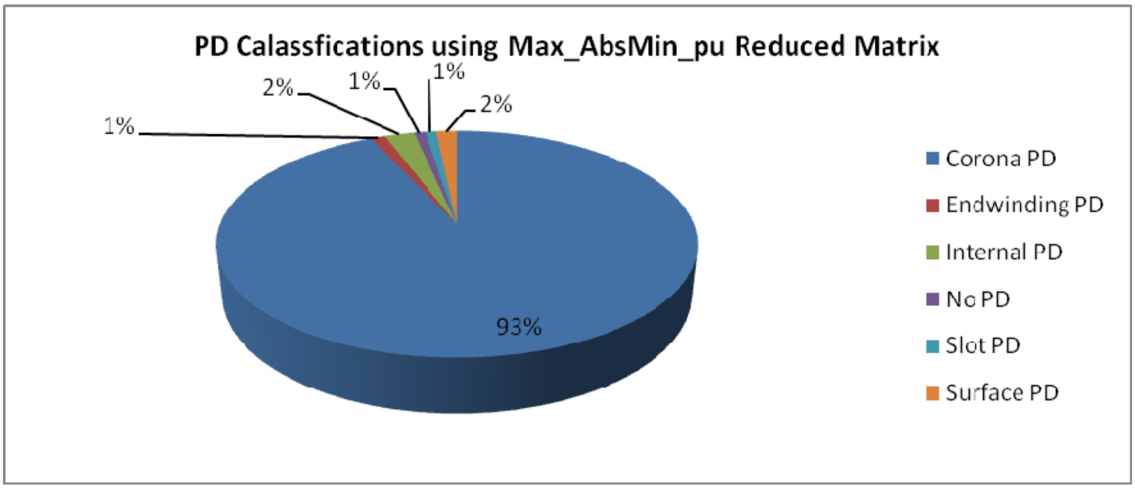


Figure 5.51: PD classification using NeuralSight Max_AbsMin_pu reduced models

5.3.3.4 Reduced Matrix: PCA

Previous section (5.3.2.3) was the last part of the statistical reduced matrices. This section will start using the reduced PD matrices that were generated by the signal processing techniques. The PCA reduced matrix is used to train and test the NeuralSight NN models.

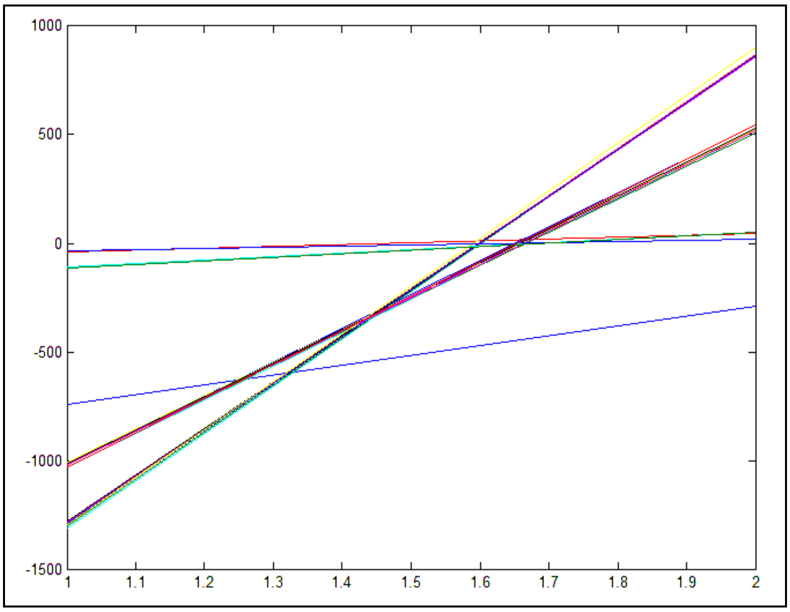


Figure 5.52: Reduced PRPD using PCA values

The preferences of the NeuralSight were adjusted to generate 999 models. The average accuracy ranges from 100% to 75.8%.

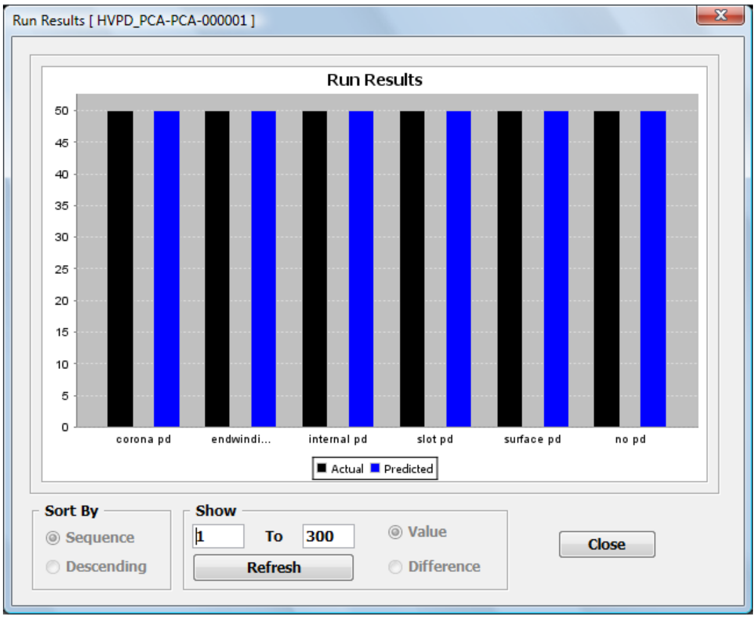


Figure 5.53: Most accurate NeuralSight model for Max_Min PD reduced matrix

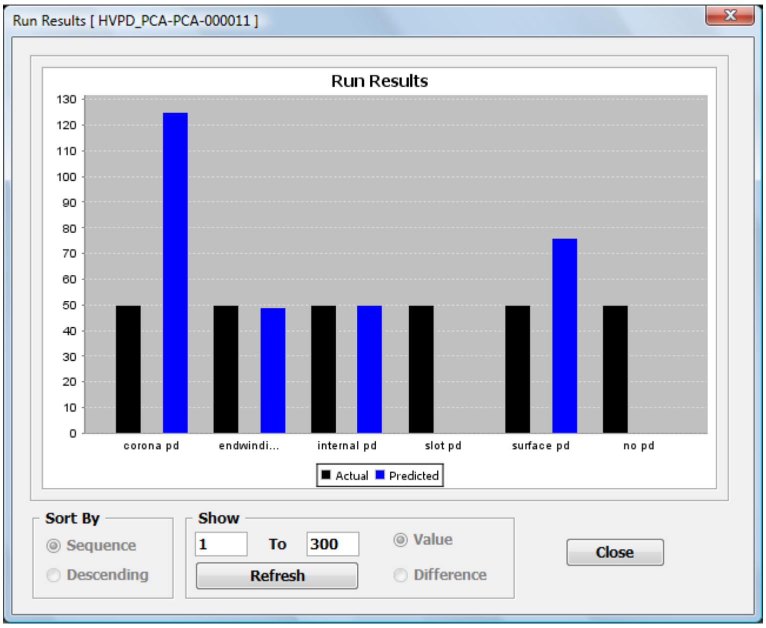


Figure 5.54: Less accurate NeuralSight model for PCA PD reduced matrix

Testing the blind PD data collected from Saudi Aramco plant generates the following result:

Table 5.17: PD classification using NeuralSight PCA reduced models

PD Type	%
Corona PD	87.54917652
Endwinding PD	4.383608765
Internal PD	0.118749088
No PD	0.070586569
Slot PD	0.008525392
Surface PD	7.869353725

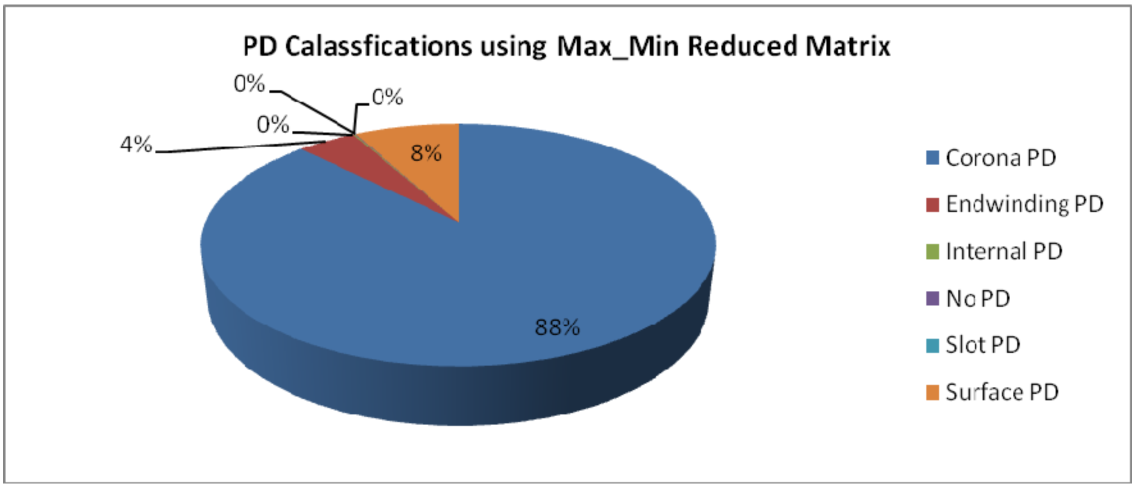


Figure 5.55: PD classification using NeuralSight Max_Min reduced models

5.3.3.5 Reduced Matrix: ISOMAP

The last section in the training of NeuralSight NN is the use of ISOMAP PD reduced matrices.

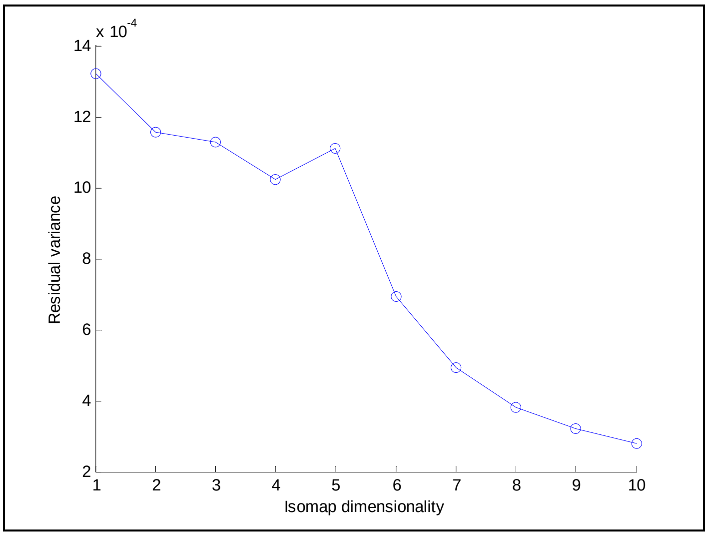


Figure 5.56: Reduced PRPD using ISOMAP values

The preferences of the NeuralSight were adjusted to generate 999 models. The average accuracy ranges from 95.7 % to 74 %.

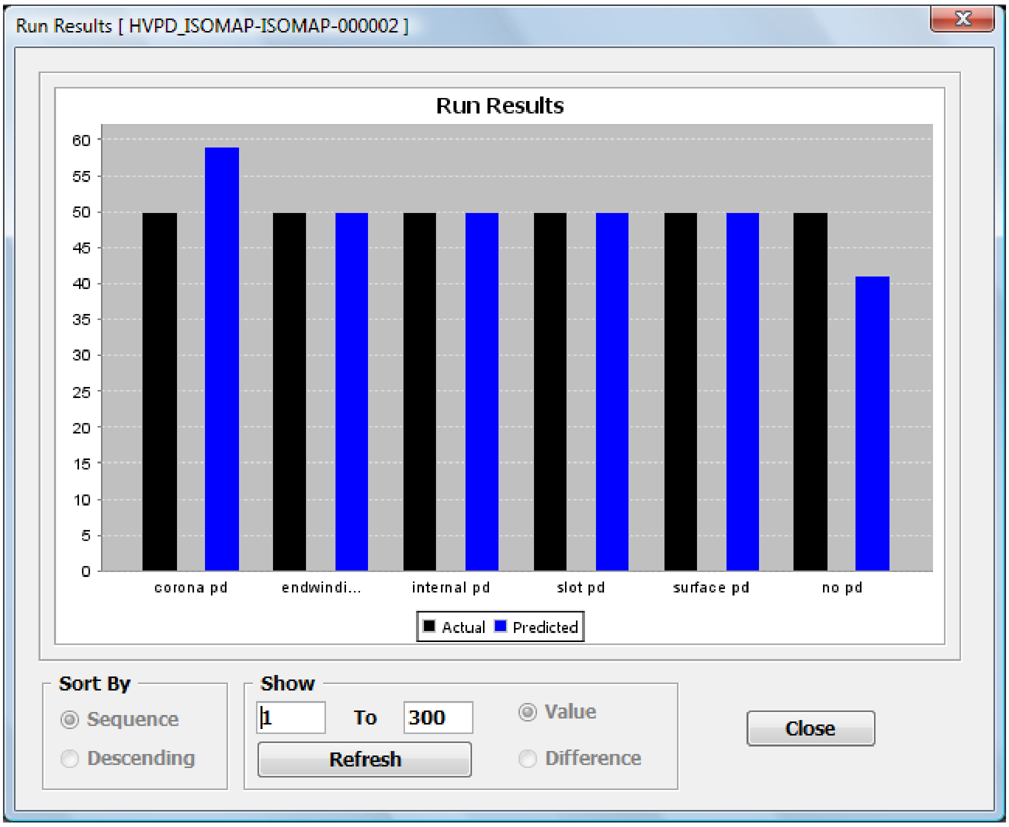


Figure 5.57: Most accurate NeuralSight model for ISOMAP PD reduced matrix

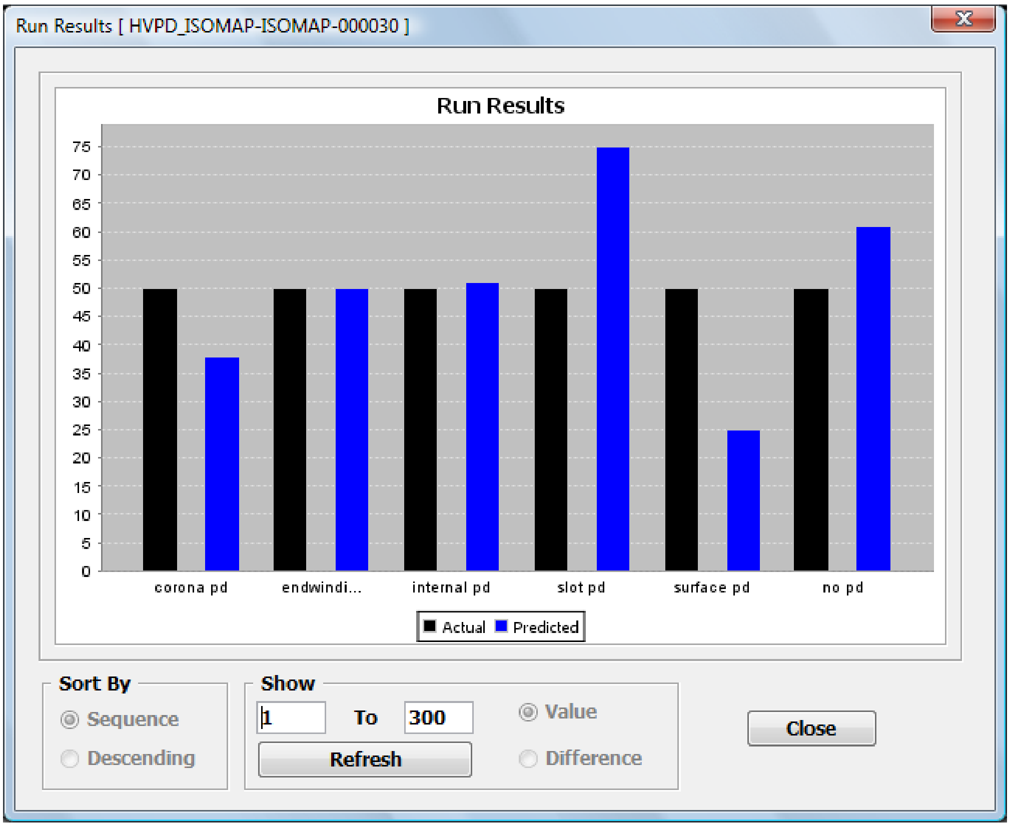


Figure 5.58: Less accurate NeuralSight model for ISOMAP PD reduced matrix

Testing the blind PD data collected from Saudi Aramco plant generates the following result:

Table 5.18: PD classification using NeuralSight ISOMAP reduced models

PD Type	**%**
Corona PD	0.128853457
Endwinding PD	37.38849011
Internal PD	0.426698397
No PD	1.07653281
Slot PD	0.029589259
Surface PD	60.94983571

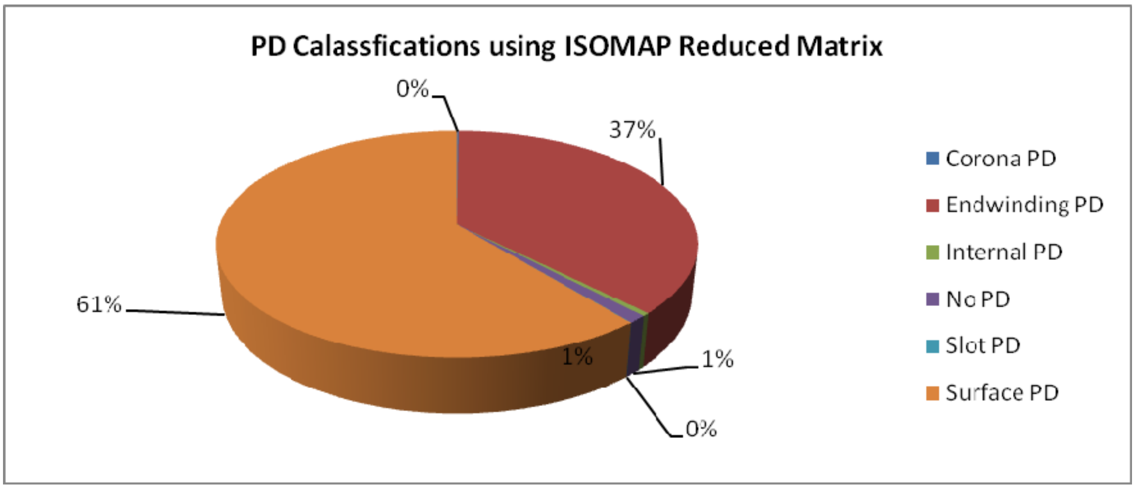


Figure 5.59: PD classification using NeuralSight ISOMAP reduced models

5.4. MATLAB or NeuralSight when You Perform PD NN Classification

Based on the results obtained in the previous sections relating to the MATLAB NN Toolbox and the NeuralSight, The NeuralSight will be the most accurate NN tool that could be used to perform the PD calcification. That judgment is based on:

Table 5.19: MATLAB or NeuralSight when You Perform PD NN Classification

MATLAB	NeuralSight
Needs 3 steps to adjust and modify the NN input matrix and the target matrix	No adjustments are needed
The NN Toolbox GUI is not friendly use	Simplified GUI
Need deep knowledge in the NN field	Could be used by the beginners
Single NN model	Up to 2000 NN models
Subjected to the overfitting in FFBP	Not subjected to the overfitting
Could not used for multiple PD defects	Good tool to classify multiple PD defects

5.5. How to Relate the PD Activities with the Motor Condition

The accumulated experience of the PD knowledge is utilized by the PD test engineers and motor service shops to link the different PD detected activates to visual symptoms or/and possible causes. The joint task of PD condition provider, service team and the end user helps to activate a certain course of actions to save running motors and to allow the Operation and Maintenance to arrange for the required corrective actions. The following table surmises fruitful and long discussions with the PD monitoring systems OEM's.

Table 5.20: Possible Cause, Visual Symptoms and Possible Course of Action

PD Type	Possible Cause	Visual Symptom	Course of Action
Slot	• voids in insulation • delamination caused by thermal aging • loose wedges caused by vibration	• White Powder deposits and ozone production • Oil, grease dust present	• assess magnitude of PD (cumulative and absolute) • if significantly high monitor and trend to gain more information If levels dangerously high recommend maintenance or rewind
Endwinding	• bar Vibration • deteriation of stress grading areas • contamination	• white powder deposits and ozone production • insulation discoloration	• assess magnitude of pd (cumulative and absolute) • if significantly high monitor and trend to gain more information if levels dangerously high recommend maintenance or rewind
Internal	• contamination • foreign objects in stator • brush sparking	• white powder deposits and ozone production • insulation discoloration	• assess magnitude of pd (cumulative and absolute) • remove foreign objects! trend and monitor situation
Corona	• humidity in stator area • contamination	• white powder deposits and ozone production • oil, grease dust present	• assess magnitude of pd (cumulative and absolute) • improve ambient conditions remove humidity and contaminants trend and monitor situation
Surface	• humidity in stator area • contamination	• White Powder deposits and ozone production • Oil, grease dust present	• assess magnitude of PD (cumulative and absolute) • if significantly high monitor and trend to gain more information If levels dangerously high recommend maintenance or rewind

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1. CONCLUSION

This thesis has demonstrated the ability of Neural Networks (NN) to classify six (6) different types of Partial Discharge (PD) in blind tests, as found in the insulation of High Voltage (HV) electric motors. The recognition rates exceed the reported 79% as stated in the literature survey, and all the results of the developed NN's PD classification were benchmarked against human being PD pattern recognition. Through the communication with the leading manufacturers of PD monitoring systems worldwide, 300 datasets were collected for healthy as well as PD defected HV motors. The datasets include real field readings for 250 measurements for Internal, Surface, Corona, Slot, Endwinding PD types and 50 measurements for healthy machines.

The PRPD (Phase Resolved Partial Discharge) was the base of the NN pattern recognition training, testing and validation. The PRPD patterns were created through self effort using unrefined raw PD data.

Statistical techniques such as Max_Min, Max_Min per unit, and envelop detection techniques were used to perform the preprocessing phase. Also some Signal Processing techniques were investigated such as the PCA and ISOMAP.

MATLAB and NeuralSight NN packages were used to perform the training, test and validation of developed NN. The performance of MATLAB was great to generate the PCA and ISOMAP of reduced matrices during the data preprocessing phase. On the other

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1. CONCLUSION

This thesis has demonstrated the ability of Neural Networks (NN) to classify six (6) different types of Partial Discharge (PD) in blind tests, as found in the insulation of High Voltage (HV) electric motors. The recognition rates exceed the reported 79% as stated in the literature survey, and all the results of the developed NN's PD classification were benchmarked against human being PD pattern recognition. Through the communication with the leading manufacturers of PD monitoring systems worldwide, 300 datasets were collected for healthy as well as PD defected HV motors. The datasets include real field readings for 250 measurements for Internal, Surface, Corona, Slot, Endwinding PD types and 50 measurements for healthy machines.

The PRPD (Phase Resolved Partial Discharge) was the base of the NN pattern recognition training, testing and validation. The PRPD patterns were created through self effort using unrefined raw PD data.

Statistical techniques such as Max_Min, Max_Min per unit, and envelop detection techniques were used to perform the preprocessing phase. Also some Signal Processing techniques were investigated such as the PCA and ISOMAP.

MATLAB and NeuralSight NN packages were used to perform the training, test and validation of developed NN. The performance of MATLAB was great to generate the PCA and ISOMAP of reduced matrices during the data preprocessing phase. On the other

hand, the training sessions of MATLAB NN Toolbox tended to go in mode of "OVERFITTING". It was expected that increasing the training time or/and the number of hidden layers would improve the training performance as well as the recognition rate; oppositely, we noticed that increasing the training time or number of hidden layers makes the performance of the NN testing using a new Blind Dataset worse. That can be explained by stating that MATALB will improve only the performance of the training through increasing the neurons and links; the NN in this case is essentially memorizing the behavior rather than doing the NN calculation (i.e., learning) to perform the classification using the NN algorithms. Furthermore, MATLAB NN Toolbox needs three (3) different adjustments and modifications to be done on the input and target PD data. Also, using MATLAB NN Toolbox generates only one NN model. Such output NN model is useless in the cases of multiple overlapped PD defects.

Oppositely, NeuralSight NN package shows an excellent performance to classify the six (6) different PD types and gives an accurate result when it was tested by the Blind Data. NeuralSight produces up to 2000 models that could be used as "VOTING" tool when multiple PD defects exist. The recognition rates exceed the reported 79% as stated in the literature survey. Certain reduction techniques showed very high performance and accurate PD classifications. Envelop approaches using the maximum and minimum was the most accurate NN input for the NeuralSight. The same conclusion is valid for the normalized envelope reduced PD matrix using the per-unit values of maximum and minimum PRPD. The absolute PD values of the PRPD, PAC and ISOMAP gave less accurate PD classification.

All results of the developed NN's PD classification were benchmarked against human being PD pattern recognition. Two (2) extracted inputs from 13.2kV motors installed at an oil production facility of Saudi Aramco were simulated using the trained NN's and compared with the classification of PD subject matter experts (SEM) of PD testing reputable manufacturer. The PD simulated classification results were found in agreement with the classification of SME's; the matched results of the two different PD classification methods (NN and Human) were also noticed in overlapped and mixed PD patterns such in case of multiple PD defects.

When NeuralSight compared with the MATLAB, it is found more friendly use and it does not require a deep knowledge in the NN. It also accepts the datasets that were generated by the PDgold HVPD software without any modifications.

6.2. RECOMMENDATION FOR FUTURE WORK

The NN based PD type classification have been investigated and analyzed in this work but still there is space for future expansion of the research.

Different reduction techniques such as Fourier Transform and Wavelet Transforms could be tested to check the performance accuracy and the effect of number of layers.

Another area could be explored is using different PD representation; Phase Resolved Partial Discharge (PRPD) was the base of the NN training and validation when the accumulative PD level (mV or μC) was monitored over the 360 ° phase angle of AC

source. Another method could be proposed is the Pulse Level Count/Time. In this method, the number of pulses at certain PD level is counted over the time. The trend is always decreasing from the high level pulse rate to low level (the number of sever pulses occurs less than the weak PD pulses).

Also, other tuning feature of MATLAB NN Toolbox could be tried such as training function, adaption function, performance or/and transfer function.

In this work, only two (2) NN tools were used (MATLAB and NeuralSight). Other NN packages could be tested to be compared with the performance of the above mentioned tools.

At the end, the developed NN algorithms could be tested on other HV equipments such as transformers, cables and GIS's.

REFERENCES

[1] Lourenco Mafika Thusi, “Determining the Optimal Technique for Early Detection of Broken Rotor Bars in Medium Voltage Squirrel Cage Induction Motors during Operation,” Thesis of Master of Science in Engineering at University of Witwatersrand, Johannesburg, South Africa, 2009.

[2] U.S. Department of Energy, “Cost Reduction Strategies: Improving the Energy Efficiency of Motor Systems,” Office of Industrial Technologies, Energy Efficiency and Renewable Energy, May 07.

[3] Douglas R. Malcolm, “An energy diet for electric motors: The growing cost of energy for manufacturing puts stress on maintaining a competitive edge in the marketplace. Learn five steps to turn waste into profit without spending a fortune,” PlantServices.com, 2006, http://www.plantservices.com/articles/2006/313.html

[4] Jarmo Ilonen,Joni-Kristian Kamarainen,Tuomo Lindh, Jero Ahola, Heikki Kälviäinen and Jarmo Partanen, “Diagnosis Tool for Motor Condition Monitoring,” IEEE Transactions on Industry Applications, Vol. 41, No. 4, July/August 2005.

[5] Elektro-Journal, November 2009 Issue, “The World's Smallest Electric Motor,” http://www.elektor.com/magazines/elektor-us-editions/2009/11-november.1174465.lynkx .

[6] SCL Engineering & Inspection, "Grand Coulee 94-98 Stator Replacement," http://www.sclqa.com/sclqa_main_site/site_pages/past%20projects.htm.

[7] Manuelle, P. ; Singam, B. ; Siala, S, "Induction Motors Fed by PWM MV7000 Converters Enhance Electric Propulsion Performance," Converteam SAS, Parc d'activites Techn'hom, Belfort, France, Power Electronics and Applications, 2009. EPE '09. 13th European Conference on Power Electronics and Applications, 2009. (Barcelona) 8-10 Sept. 2009 pp.1-7 ISBN:978-1-4244-4432-8

[8] H. Wayne Beaty and James L. Kiriley, "Electric Motor Handbook," First Edition. ISBN: 0-07-035971-7, © 2005 The McGraw-Hill Companies, Inc.

[9] Ali Emadi, "Energy-Efficient Electric Motors," Third Edition, ISBN: O-8247-573-l © 2005 Marcel Dkkei Printing House.

[10] Suri Sathya, Prashant Shyam, Sunder Satya and Krishna Sharma, "Computer Aided Online Fault Diagnosis of Induction Motors," 9th International Conference Electrical Power Quality and Utilization, Barcelona, 9-11 October 2007.

[11] EPRI, "Improved motors for utility applications and improved motors for utility applications industry assessment study," Vol. 1, EPRI EL-2678, 1763-1, final report, and Vol. 2, 1763-1 final report, October 1982.

[12] Motor Reliability Working Group, IEEE Transactions on Industry Applications “Report of Large Motor Reliability Survey of Industrial and Commercial Installations,” Part I and II, Vol. IA-21, No. 4, pp.863-872.

[13] M.L. Sin, W.L. Soong and N. Ertugrul, “Induction Machine On-Line Condition Monitoring and Fault Diagnosis – A Survey” AUPEC2008 : 28 September - 1 October 2008 : Australasian Universities Power Engineering Conference, Christchurch, New Zealand. / pp. 1-6

[14] S. Chen and T. A. Lipo, “Bearing currents and shaft voltages of an induction motor under hard- and soft-switching inverter excitation,” IEEE Trans. Ind. Appl., vol. 34, no. 5, pp. 1042–1048, Sep./Oct. 1998.

[15] S. Nandi and H.A. Toliyat, “Condition Monitoring and Fault Diagnosis of Electrical Machines – A Review,” IEEE Ind. Appl. Society Annual Meeting, 1999.

[16] P.J. Tavner, “Review of condition monitoring of rotating electrical machines,” School of Engineering, Durham University, South Road, Durham, DH1 3LE, UK. Published in IET Electric Power Applications Received on 23rd June 2007, Revised on 13th November 2007

[17] Wei Zhou ; Habetler, T.G. ; Harley, R.G. and Bin Lu, “Incipient Bearing Fault Detection via Stator Current Noise Cancellation using Wiener Filter,” Diagnostics for Electric Machines, Power Electronics and Drives, 2007. SDEMPED 2007. IEEE International Symposium

[18] G. B. Kliman, W. J. Premerlani, R. A. Koegl, and D. Hoeweler, “A new approach to on-line fault detection in ac motors,” in Proc. IEEE Industry

Applications Soc. Annual Meeting Conf., San Diego, CA, 1996, pp. 687–693.

[19] KeSheng Wang, “Vibration Monitoring on Electrical Machine using Vold-Kalman Filter Order Tracking,” Master of Science in the Department of Mechanical and Aeronautical Engineering, University of Pretoria, 2008

[20] S. Su, and R. Dua, “Signature Analysis of Mechanical Watch Movements,” Institute of Precision Engineering, The Chinese University of Hong Kong, Shatin, N. T., Hong Kong, Received 10 January 2007

[21] Suri Prashant, S. Sunder, K. Krishna S. Sharma, “Computer Aided Online Fault Diagnosis of Induction Motors”, 9th International Conference. Electrical Power Quality and Utilization (EPQU'07)

[22] Neelam Mehla, Ratna Dahiya “An Approach of Condition Monitoring of Induction Motor Using MCSA,” International Journal of Systems Applications, Engineering & Development Volume 1, Issue 1, 2007.

[23] Department of Electrical Engineering, , University of Oulu, University of Oulu, Finland “Condition Monitoring of Squirrel-Cage Motors by Axial Magnetic Flux Measurements,”, 2003

[24] Yafei Zhou, MIEEE, A I Gardiner, G A Mathieson, Y Qin “New Methods of Partial Discharge Measurement for the Assessment and Monitoring of Insulation in Large Machines,” Industrial Research Limited. Electrical Insulation Conference, 1997, and Electrical Manufacturing & Coil Winding Conference. Proceedings.

[25] Dhaval Shah, Subhasis Nandi, and Prabhakar Neti, “Stator-Interturn-Fault Detection of Doubly Fed Induction Generators Using Rotor-Current and Search-Coil-Voltage Signature Analysis,” IEEE Transactions On Industry Applications, Vol. 45, No. 5, September/October 2009

[26] Rosero, J. ; Cusido, J. ; Espinosa, A.G. ; Ortega, J.A. ; Romeral, L., “Fault Detection Analysis in Induction Motors by Injecting Additional Test Signal,” IEEE Trans. IEEE ISIE 2006, July 9-12, 2006, Montreal, Quebec, Canada.

[27] M.E.H. Benbouzid, “A Review of Induction Motors Signature Analysis as a Medium for Faults Detection,” IEEE Trans. on Ind. Electronics, vol. 47, no. 5, Oct. 2000, pp. 984-993.

[28] Intesar Ahmed and Manzar Ahmed, “Comparison of Stator Current, Axial Leakage Flux and Instantaneous Power to Detect Broken Rotor Bar Faults in Induction Machines,” 2008 Australasian Universities Power Engineering Conference (AUPEC'08)

[29] A.C. McCormick, “Cyclostationary and Higher Order Statistical Signal Processing Algorithms for Machine Condition Monitoring,” Ph.D. Thesis, Department of Electronic and Electrical Engineering, University of Strathclyde, 1998.

[30] Gaalvez-Carrillo, M. ; Kinnaert, M., “A Signal-Based Approach for Detection and Isolation of Current Sensor Faults in Induction Motors,” Power Electronics and Applications, 2009. EPE '09. 13th European Conference on

[31] C. J. Verucchi, G. G. Acosta and F. A. Benger “A Review on Fault Diagnosis of Induction Machines,” Latin American applied research, versión impresa ISSN 0327-0793, Bahía Blanca Apr-Jun 2008.

[32] High Voltage Partial Discharge (HVPD) Ltd, “What Is Partial Discharge and Why Should We Test for It,” http://www.hvpd.co.uk/technical Website technical article, 2010

[33] Vouk A., Asiri Y. and Al-Hamouz Z., "Online PD Monitoring Insures Reliable Operation of 24000 hp Motors in the Saudi Arabian Deserts", INSUCON 2009, Birmingham, May 26-28, 2009.

[34] Greg C. Stone, Edward A. Boulter, Ian Culbert, Hussein Dhirani, “Electrical Insulation for Rotating Machines Design, Evaluation, Aging, Testing, and Repair,” IEEE Press Series on Power Engineering. 2004

[35] VonRoll ISola Training Program, Electrical Insulating Materials, April 1998 VonRoll ISola catalogue.

[36] B. K. Gupta et al., “Turn Insulation Capability of Large AC Motors, Part 3—Insulation Coordination,” IEEE Trans EC, Dec. 1987, pp. 674–679.

[37] B. J. Moore, R. H. Rehder, and R. E. Draper, “Utilizing Reduced Build Concepts in the Development of Insulation Systems for Large Motors,” In Proceedings of IEEE Electrical Insulation Conference, Cincinnati, October 1999, pp. 347–352.

[38] IEC TS 60034-27, Off-line partial discharge measurements on the stator winding insulation of rotating electrical machines.

[39] IEEE Std 1434-2000, IEEE Trial-Use Guide to the Measurement of Partial Discharges in Rotating Machinery” Approved 26 April 2000 IEEE-SA Standards Board.

[40] IEC 60270, High-voltage test technique-Partial discharge measurements.

[41] MS thesis titled “Detection and Position Location of Partial Discharges in Transformers Using Fiber Optic Sensors,” by Lijun Song, December, 2004 Blacksburg, Virginia U.S.A.

[42] Partial discharge Basics of Monitoring, PD Tech Power Engineering AG.

[43] Derek Mitchell, Iris Power Engineering Inc., Toronto, Canada, “On-Line Partial Discharge Testing: A Predictive Maintenance Tool for Motors and Generators,”.

[44] Emerson Electric Co., “Partial Discharge Testing & Monitoring Solutions,” http://www2.emersonprocess.com/en-US/brands/electricalreliabilityservices/plcs/PredictiveDiagnostics/Pages/PartialDischargeTestingMonitoring.aspx.

[45] Nattrass, D.A, “Partial discharge measurement and interpretation,” IEEE Electrical Insulation Magazine May/June 1988-Vol. 4.

[46] Satish L, Gururaj B, “Partial discharge pattern classification using multilayer neural network,” Proc. IEE A July:323–330.

[47] Gabe Paoletti, P.E. and Alex Golubev, PhD, “Partial Discharge Theory and Technologies Related to Traditional Testing Methods of Large

Rotating Apparatus," R&D Predictive Diagnostics Cutler-Hammer Engineering Services.

[48] D. Fink, H. W. Beaty, "Standard Handbook for Electrical Engineers, Pages 4-117, 118," McGraw Hill Book Company, 1987.

[49] C.H. Flurscheim, "Power Circuit Breaker Theory and Design," Pages 556-557, Peter Peregrinus Ltd. on behalf of the Institution of Electrical Engineers, 1985.

[50] Westinghouse Electrical Maintenance Hints, Pages 19-14 and 15, and Page 7-23, Westinghouse Electric Corporation Printing Division, Trafford, PA, 1976.

[51] Derek Mitchell, "On-Line Partial Discharge Testing: A Predictive Maintenance Tool for Motors and Generators," Iris Power Engineering Inc., Toronto, Canada, 2007

[52] Mark G. Turner and Dr. Edward Gulski, "Pattern Recognition for Partial Discharge Measurement," Tettex Instruments Division, Haefely Test AG, Dietikon, Website Technical Reference 2010.

[53] Chen Min ; Urano, K. ; Li You-Cheng ; Jinno, A., "Application of Combined PD Sensor for GIS PD Detection and Condition Monitoring" 2008 International Conference on Condition Monitoring and Diagnosis, Beijing, China, April 21-24, 2008

[54] Markalous, S. ; Tenbohlen, S. ; Feser, K, "Detection and Location of Partial Discharges in Power Transformers using Acoustic and

Electromagnetic Signals," Dielectrics and Electrical Insulation, IEEE Transactions on December 2008.

[55] M. Muhr, R. Schwarz, "Optische Teilentladungstetektion für Betriebsmittel der elektrischen Energietechnik, Dissertation, Abteilung für Hochspannungstechnik," Institute of High Voltage Engineering and System Management, Graz University of Technology, 2006

[56] R. Bartnikas, "Partial Discharges, Their Mechanism, Detection and Measurement," IEEE Transactions on Dielectrics and Electrical Insulation Vol. 9 No. 5, October 2005.

[57] IPEC High Voltage Ltd Manchester, UK "PD?......or Not PD?, that is the question," PD Measurements of Rotating HV Machines 2008.

[58] MS thesis titled "Detection and Position Location of Partial Discharges in Transformers Using Fiber Optic Sensors" by Lijun Song, December, 2004 Blacksburg, Virginia U.S.A.

[59] Nattrass D.A., "Partial discharge measurement and interpretation," IEEE Elect. Insul. Mag., 1988.4, (3), pp. 10-23.

[60] Satish L, Gururaj BI (1993) "Partial discharge pattern classification using multilayer neural network," Proc. IEE A July:323–330

[61] Subhasis Nandi, Hamid A. Toliyat, and Xiaodong Li, Student Member, IEEE Condition Monitoring and Fault Diagnosis of Electrical Motors—A Review. IEEE Transactions on Energy Conversion, Vol. 20, No. 4, December 2005.

[62] Partial discharge Basics of Monitoring, PD Tech Power Engineering AG

[63] Greg C. Stone, Edward A. Boulter, Ian Culbert, Hussein Dhirani, Electrical Insulation for Rotating Machines Design, Evaluation, Aging, Testing, and Repair, IEEE Press Series on Power Engineering, 2006.

[64] Jack Copper, Dennis Price, "Creating And Evaluating Neural Network Predictive Models For Electricity Demand And Price Forecasting," Asia-Pacific Power and Energy Engineering Conference (APP EEC 2009), March 28-30, 2009, Wuhan, China

[65] Kurzweil, R. (1999) The Age of Spiritual Machines. London: The Orion Publishing Group Ltd.

[66] R. P. Lippman, "An Introduction to Computing with Neural Nets'," IEEE Acoustics, Speech and Signal Processing Magazine, pp. 4-22, 1987.

[67] D. E. Rumelhart and J. L. McClelland, "Parallel Distributed Processing," Explorations in the Microstructure of Cognition, Vol. 1, MIT Press, 1986.

[68] H. G. Kranz a.nd R. Krump, "The Abilities of Self Operating Expert Systems for Statistical Partial Discharge Analysis of GIS Test Signals," 6th International Symposium of High Voltage Engineering, New Orleans, 2009.

[69] H. Suzuki and T. Endoh, "Pattern Recognition of Partial Discharge in XLPE Cables Using a Neural Network," IEEE Trans. o Electr. Ins., Vol. 27, pp. 543-549, 1992.

[70] N. Hozumi, T. 0ka.moto and T. Imaju, "Discrimination of PD Patterns Using Neural Networks", IEEE Trans. on Electr. Ins., Vol. 27, pp. 550-556, 1992.

[71] Amira A. Mazroua, M. M. A. Salama and R. Bartnikas "PD Pattern Recognition with Neural Networks Using the Multilayer Perceptron Technique," Department of Electrical and Computer Engineering, University of Waterloo, Waterloo, Ontario and Institut de Recherche, d'Hydro-QuCbec, Varennes, Quebec, Canada, 2007.

[72] B. J. Moore, R. H. Rehder, and R. E. Draper, "Utilizing Reduced Build Concepts in the Development of Insulation Systems for Large Motors," In Proceedings of IEEE Electrical Insulation Conference, Cincinnati, October 1999, pp. 347–352.

[73] Satish L, Zaengl WS, "Artificial neural networks for recognition of 3-d partial discharge patterns," IEEE Trans Diel Electr Insul 1:265–274. 1994.

[74] Werle P, Akbari A, Borsi H, Gockenbach E (2001) "Partial discharge localization on power transformers using neural networks combined with sectional winding transfer functions as knowledge base,". Paper presented at the 3rd International Symposium on Electrical Insulation Material (ISEIM), Himeji, Japan, 19–22 November 2005.

[75] Gabe Paoletti, P.E. Division Application Engineer Alex Golubev, PhD Manager, R&D, Predictive Diagnostics, Cutler-Hammer Engineering Services, Partial Discharge Theory and Applications to Electrical Equipment. 2008.

[76] IEC TS 60034-27, Off-line partial discharge measurements on the stator winding insulation of rotating electrical machines.

[77] Derek Mitchell, Iris Power Engineering Inc., Toronto, Canada, On-Line Partial Discharge Testing: A Predictive Maintenance Tool for Motors and Generators, 2008.

[78] IPEC High Voltage Ltd, Manchester, UK PD Measurements of Rotating HV Machines 2008

[79] High Voltage Engineering and Testing Textbook, Chapter I7: Partial discharge measuring technique by E. Gockenbach

[80] M. Muhr, R. Schwarz, Institute of High Voltage Engineering and System Management, Graz University of Technology, Graz, Austria Partial discharge measurement as a Diagnostic Tool for HV-Equipments, 2006

[81] Cachin Ch, Wiesmann HJ (1995) PD recognition with knowledge based preprocessing and neural networks. IEEE Trans Electr Insul 2:578–589.

[82] N. Hozumi, T. Okamoto, T. Imajo, "Discrimination of Partial Discharge Patterns Using Neural Network", IEEE Trans. on Elect. Insul., Vol. 27, pp. 550-556, 1992.

[83] A. Schnettler, V. Tryba, "Artificial Self-organizing Neural Network for Partial Discharge Recognition", Archiv fur Elektrotechnik, Vol. 76, pp. 1-6, 1993.

[84] B. T. Phung, T. R. Blackburn, R. E. James, "The Use of Artificial Neural Networks in Discriminating Partial Discharge Patterns", Proc. 6th Int. Conf. on Dielectric Materials, Measurements and Applications, Manchester, 1992.

[85] Neural Computing, Reference manual, Neuralware, Pittsburgh, 1991.

[86] Satish L, Zaengl WS (1994) “Artificial neural networks for recognition of 3-d partial discharge patterns,” IEEE Trans Die Electr Insul 1:265–274

[87] Tu YM, Huang JM, Gao N, Yan Z (1997), “Transformer insulation diagnosis based on improved NN analysis,” In: Proceedings of the 5th International Conference on Prop. and Appl Diel Mat, Seoul, Korea. IEEE, New York, pp 263–266

[88] Gao W, Gao N, Yan Z (1998), “Application of adaptive wavelet classification network for fault diagnosis in oil-immersed power equipment,” Trans China Electrotechnol Soc 6:33–38 (in Chinese).

[89] Kohonen T (1990) “The self-organizing map,” Proc IEEE 78:1464–1480

[90] Gulski E, Krivda A (1993) Neural networks as a tool for recognition of partial discharges. IEEE Trans Electr Insul 28:984–1001

[91] Yang HT, Liao CC, Chou JH (2001) Fuzzy learning vector quantization networks for power transformer condition assessment. IEEE Trans Diel Electr Insul 8:143–149.

[92] Statistica for academia “Neural Networks,” StatSoft, Inc. USA, 2010.

[93] Alfred Vouk, “Installation of Remote Continuous PD Monitoring on Gas Compression Plant Motors,” Saudi Aramco Journal Of Technology Summer 2006.

[94] IRIS Power Engineering Mississauga, Ontario, Canada, Website article 2010.

[95] R. Heinrich, S. Schaper, W. Kalkner R. Plath A. Bethge, “Synchronous Three Phase Partial Discharge Detection on Rotating Machines,” Technical University Berlin, Germany, Institute for High Voltage Engineering, IPH High Voltage Lab Berlin, Germany, Siemens AG Berlin, Germany

[96] Y Tian, P L Lewin, A E Davies, S J Sutton and S G Swingier, “Application-of Acoustic Emission Techniques and Artificial Neural Networks to Partial Discharge Classification,” High Voltage Laboratory, University of Southampton, Southampton, UK, 2005.

[97] Kyu-Bock Cho, Joo-Young Oh, “An Overview of Application of Artificial Neural Network to Partial Discharge Pattern Classification,” Dept. of Electrical Engineering Hanseo University, Korea, 2001.

[98] A.Yamazaki, Y.Tsutsmi, T.Yonekura, “Partial Discharge Recognition using a Neural N e t w o r k,” Ibaraki University, Japan, 2005

[99] R. Candela, G. Mirelli, Fl. Schifani, “PD Recognition by Means of Statistical and Fractal Parameters and a Neural Network,” Dipattimento di Iiigcppria lilcttrico Universiti di l’nlcrmo, I’ihmnio, Ital, 1998.

[100] Hung-Cheng Chen, Po-Hung Chen*, Meng-Hui Wang “Partial Discharge Classification Using Neural Networks and Statistical Parameters,” Department of Electrical Engineering, National Chin-Yi University of Technology, Taipei, Taiwan, 2007.

[101] Y. Liu and H. Ma, "Pattern recognition using ω-orbit finite automata," K. H. Tzao, Editor, Proc. SPIE 1606, Boston, MA, Nov. 1991, pp.226-240.

[102] T. Pawlicki, D-S. Lee, J. Nu11, and S. Srihnri, "Neural networks and their application to handwritten digit recognition," Proc. TEEE International Conference on Neural Networks: VoI. II, San Diego, CA, 1988, pp.63-70.

[103] Hede Ma, "Technical report: Pattern Recognition Using Neural Networks," Department of Engineering Technology, Savannah State College, Savannah, GA 31404.

[104] Yuming Tu , Wang, Z.D. and Crossley, P.A. "Partial Discharge Pattern Recognition Based on 2-D Wavelet Transform and Neural Network Techniques," Power Engineering Society Summer Meeting, 2002 IEEE Volume: 1, Page(s): 411 - 416 vol.1.

[105] N. Sahoo, M. Salama and R. Bartnikas "Trends in Partial Discharge Pattern Classification: A Survey," Department of Electrical & Computer Engineering, University of Waterloo, Waterloo, Ontario, N2L 3G1 Canada, Institut de Recherche d'Hydro-Quebec, Varennes, QC J3X 1S1, Canada, IEEE Transactions on Dielectrics and Electrical Insulation Vol. 12, No. 2; April 2005.

[106] Jeong-Tae Kim ; Won Choi ; Sung-Kwun Oh ; Keon-Jun Park and Grzybowski, S. "Partial Discharge Pattern Recognition Using Fuzzy-Neural Networks (FNNs) Algorithm," Dept. of Electr. Eng., Daejin Univ., Pocheon. IEEE International Power Modulators and High Voltage Conference, Proceedings of the 2008.

[107] Wen-Yeau Chang "Application of Self Organizing Map Approach for Partial Discharge Pattern Recognition of Insulators," Dept. of Electr.

Eng., St. John's Univ., Taipei, Taiwan. Proceedings of the 9th International Conference on Properties and Applications of Dielectric Materials, July 19-23, 2009, Harbin, China.

[108] MATLAB© R2007b Release Notes. 2007 by The MathWorks, Inc.

[109] MATLAB product page for Neural Network Toolbox, MathWorks webpage http://www.mathworks.com/products/neuralnet/description1.html, 2008.

[110] Alexander Lang, "In-Service, On-Line Partial Discharge (PD) Testing of 2x 13.2kv Alstom Compressor Motors Demo Test Report," HVPD Ltd, UK, June 2009.

[111] Leszek Rutkowski, "Generalized Regression Neural Networks in Time-Varying Environment," IEEE TRANSACTIONS ON NEURAL NETWORKS, VOL. 15, NO. 3, MAY 2004.

[112] Ileana Popescu, Philip Constantinou, Miranda Nafornita, Ioan Nafornita, "Generalized Regression Neural Network Prediction Model for Indoor Environment" Computers and Communications, 2004. Proceedings. ISCC 2004. Ninth International Symposium on Issue Date: 28 June-1 July 2004.

[113] Yasantha N Hettiarachchi, H.L. Premaratne, "A New Parameter Determining Mechanism for Radial Basis Neural Networks," 8th Hybrid Intelligent Systems, Conference (HIS 2008), Barcelona, Spain 10-12 September 2008

[114] K. Smith, “Locating Partial Discharge Phenomena in a Power System Using Neural Networks,” Department of Computer Science and Engineering, University of South Florida, 2001

[115] NeuralSight® User guide, NeuralWare 2008.

APPENDIX

MATLAB CODES:

1 DIMENSIONALITY REDUCTION

```
function edagui
% EDAGUI  Exploratory Data Analysis Graphical User Interface
%   This is the main entry point for the EDA GUI Toolbox. This toolbox
is
%   meant to accompany the EDA Toolbox described in 'Exploratory Data
%   Analysis with MATLAB' by Martinez and Martinez, CRC Press.
%
%   One does not have to use this GUI to invoke the others. Each GUI
%   accessed via this one can be called separately. This GUI is for
%   convenience and to provide a suggested roadmap for exploratory data
%   analysis.
%
%   A list of GUIs available in this toolbox are:
%
%   loadgui:        Load the data set and other optional information.
%   transformgui:   Apply various transorms to the data.
%   gedagui:        Tools for visualizing the data.
%   univgui:        Methods for visualizing distributions of features.
%   bivgui:         Methods for visualizing distributions of 2 features.
%   tourgui:        Conduct grand tours and permutation tours.
%   ppedagui:       Projection pursuit for EDA.
%   mdsgui:         Classical and metric multidimensional scaling.
%   dimredgui:      Principal component analysis and nonlinear
%                   dimensionality reduction.
%   kmeansgui:      Implements k-means method for clustering.
%   agcgui:         Agglomerative clustering methods.
%   mbcgui:         Model-based clustering method for finding groups.

%   EDA GUI Toolbox, Wendy and Angel Martinez, November 2006,
%   martinezw@verizon.net.



ud = get(0,'userdata');

H.fig = figure('Tag','edagui',...
    'position',[150 150 726 524],...
    'resize','off',...
    'toolbar','none',...
    'menubar','none',...
    'numbertitle','off',...
    'name','Exploratory Data Analysis GUI');

%     'CloseRequestFcn','close(ud.guis)');
```

```
% put this in there to make sure the fonts look good with the later
% versions of matlab.
if strcmp(version('-release'),'14')
    set(0,'DefaultUicontrolFontname','Sans Serif');
end

%     'CloseRequestFcn','edagui(''close'')');

H.plots = [];
H.Z = [];

if ~isempty(ud)
    % Then something is there already. Add necessary handles to the
    % structure.
    ud.guis = [ud.guis(:); H.fig];
else
    % Set the usual stuff and save in root.
    ud = userdata;
    set(0,'userdata',ud)
end

% set up all of the frames first.
uicontrol(H.fig, 'style','frame',...
    'position',[15 375 700 95]);

uicontrol(H.fig, 'style','frame',...
    'position',[15 220 700 150]);

uicontrol(H.fig,'style','frame',...
    'position',[15 120 700 95]);

uicontrol(H.fig,'style','frame',...
    'position',[15 5 700 110]);

%%%%%%% TEXT BOXES %%%%%%%%%%%%%%
% set up all of the text boxes
uicontrol(H.fig,'style','text',...
    'position',[220 485 300 27],...
    'fontweight','bold',...
    'fontsize',14,...
    'backgroundcolor',[.8 .8 .8],...
    'string','Exploratory Data Analysis')

% title text
uicontrol(H.fig,'style','text',...
    'position',[20 445 600 20],...
    'fontweight','bold',...
    'horizontalalignment','left',...
    'string','Set Up Data: These options can be used with all sections
below.')

uicontrol(H.fig,'style','text',...
    'position',[20 345 600 20],...
    'fontweight','bold',...
```

```
    'horizontalalignment','left',...
    'string','Graphical EDA: Use these functions to visually explore
your data set - both variables and observations.')

uicontrol(H.fig,'style','text',...
    'position',[20 190 600 20],...
    'fontweight','bold',...
    'horizontalalignment','left',...
    'string','Dimensionality Reduction: Use these functions to reduce
the number of variables in your data set.')

uicontrol(H.fig,'style','text',...
    'position',[20 90 600 20],...
    'fontweight','bold',...
    'horizontalalignment','left',...
    'string','Search for Groups: Use these functions to search for
groups or clusters.')


%%%%%%% BUTTONS  1st Frame  %%%%%%%%%%%%%%%%%%%%
uicontrol(H.fig,'style','pushbutton',...
    'position',[20 415 170 23],...
    'string','LOAD DATA',...
    'tooltipstring','This will bring up the Load Data GUI',...
    'callback','loadgui')

uicontrol(H.fig,'style','text',...
    'position',[200 418 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Load the data and labels for class, cases, and
variables.')

uicontrol(H.fig,'style','pushbutton',...
    'position',[20 385 170 23],...
    'string','TRANSFORM',...
    'tooltipstring','This will bring up the Transform Data GUI.',...
    'callback','transformgui')

uicontrol(H.fig,'style','text',...
    'position',[200 388 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','With this GUI, you can sphere the data and apply other
common transforms.')


%%%%%%%%%  BUTTONS  2nd FRAME  %%%%%%%%%%%%%%%%%%%%%%

uicontrol(H.fig,'style','pushbutton',...
    'position',[20 327 170 23],...
    'string','GRAPHICS',...
    'tooltipstring','This will bring up the Graphical EDA GUI.',...
    'callback','gedagui')
```

```
uicontrol(H.fig,'style','text',...
    'position',[200 330 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Visualize using 2D/3D scatterplots, parallel coordinate
plots, Andrews'' curves, scatterplot matrix.')

uicontrol(H.fig,'style','pushbutton',...
    'position',[20 301 170 23],...
    'string','SHAPES - UNIVARIATE',...
    'tooltipstring','This will bring up a GUI to explore single
dimensions.',...
    'callback','univgui')

uicontrol(H.fig,'style','text',...
    'position',[200 304 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Construct boxplots, histograms, q-q plots to understand
the distribution of single variables.')


uicontrol(H.fig,'style','pushbutton',...
    'position',[20 275 170 23],...
    'string','SHAPES - BIVARIATE',...
    'tooltipstring','This will bring up a GUI to explore two dimensions
simultaneously.',...
    'callback','bivgui')

uicontrol(H.fig,'style','text',...
    'position',[200 278 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Explore two variables at a time with hexagonal binning,
bivariate histograms, and polar smooths.')


uicontrol(H.fig,'style','pushbutton',...
    'position',[20 249 170 23],...
    'string','DATA TOURS',...
    'tooltipstring','This will bring up the GUI to do grand tours and
the like.',...
    'callback','tourgui')

uicontrol(H.fig,'style','text',...
    'position',[200 252 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Search for structure using the grand tour and the
permutation tour.')


uicontrol(H.fig,'style','pushbutton',...
```

```
    'position',[20 223 170 23],...
    'string','PROJECTION PURSUIT',...
    'tooltipstring','This will bring up the GUI to do projection
pursuit.',...
    'callback','ppedagui')

uicontrol(H.fig,'style','text',...
    'position',[200 226 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Search for structure in 2-D using projection pursuit.')

%%%%%%%%%%%    BUTTONS - 3RD FRAME  %%%%%%%%%%%%%%%%%%%%%%%5

uicontrol(H.fig,'style','pushbutton',...
    'position',[20 160 170 23],...
    'string','MULTIDIMENSIONAL SCALING',...
    'tooltipstring','This will bring up a GUI to do various flavors of
MDS.',...
    'callback','mdsgui')

uicontrol(H.fig,'style','text',...
    'position',[200 163 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Reduce the dimensionality of your data using classical,
metric, and nonmetric MDS.')

uicontrol(H.fig,'style','pushbutton',...
    'position',[20 130 170 23],...
    'string','DIMENSIONALITY REDUCTION',...
    'tooltipstring','This will bring up a GUI that allows one to reduce
the dimensionality of the data before exploring further.',...
    'callback','dimredgui')

uicontrol(H.fig,'style','text',...
    'position',[200 133 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Reduce the dimensionality of your data using PCA, ISOMAP,
and LLE.')

%%%%%%%%%%%%%%5  BUTTONS - 4TH FRAME %%%%%%%%%%%%%%%%%%%%%%%%

uicontrol(H.fig,'style','pushbutton',...
    'position',[20 66 170 23],...
    'string','K-MEANS CLUSTERING',...
    'tooltipstring','This will bring up a GUI that runs k-means
clustering.',...
    'callback','kmeansgui')

uicontrol(H.fig,'style','text',...
    'position',[200 69 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
```

```
    'string','Partition the data into a specified number of groups.')

uicontrol(H.fig,'style','pushbutton',...
    'position',[20 38 170 23],...
    'string','AGGLOMERATIVE CLUSTERING',...
    'tooltipstring','This brings up the GUI that does various flavors of
agglomerative clustering.',...
    'callback','agcgui')

uicontrol(H.fig,'style','text',...
    'position',[200 41 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Construct a hierarchy of nested partitions.')

uicontrol(H.fig,'style','pushbutton',...
    'position',[20 10 170 23],...
    'string','MODEL-BASED CLUSTERING',...
    'tooltipstring','This will bring up a GUI that does Model-Based
Clustering - 9 finite mixture models.',...
    'callback','mbcgui')

uicontrol(H.fig,'style','text',...
    'position',[200 13 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Cluster your data based on probability density estimation
(Gaussian finite mixtures).')

% Close button
uicontrol(H.fig,'style','pushbutton',...
    'position',[620 485 66 25],...
    'string','CLOSE',...
    'callback','delete(gcf)',...
    'tooltipstring','Push this button to close the GUI window.')



% Save Handles for THIS GUI in the UserData for this figure.
set(gcf,'userdata',H)
```

2 MATLAB NN

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%&&&&%
%%%%%%%
%             King Fahd University of Petroleum and Minerals
%
%                         College of Engineering
%
%                    Electrical Engineering Department
%
%
%
%                                 MS Thesis
%
%     Neural Network Based Detection of Partial Discharge in HV Motors
%
%
%
%                              by: Yahya Asiri
%
%                                ID: 240128
%
%
%
%                           Dhahran, Saudi Arabia
%
%
%
%                                 June 2010
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%



%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%
%
%
%                    Loading Input and Training Matrices
%
%
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%

clear;


%1

% Load Reduced Training Matrix of HVPD_Max_Min
% Load HVPD_Max_Min_IP
Max_Min_IP = dlmread('D:\YAA Codes
Main\Training\01Max_Min\HVPD_Max_Min_IP.txt')
```

```
% Load HVPD_Max_Min_TGT
Max_Min_TGT = dlmread('D:\YAA Codes
Main\Training\01Max_Min\HVPD_Max_Min_TGT.txt')

% Load Reduced Blind Testing Matrix of HVPD_Max_Min
% Load HVPD_Max_Min_Blind_IP
Max_Min_B_IP = dlmread('D:\YAA Codes Main\Blind
Data\01Max_Min\Blind_SA_COMPRESSOR_Max_Min_IP.txt')
% Load HVPD_Max_Min_Blind_TGT
Max_Min_B_TGT = dlmread('D:\YAA Codes Main\Blind
Data\01Max_Min\Blind_SA_COMPRESSOR_Max_Min_TGT.txt')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%
%2

% Load Reduced Training Matrix of HVPD_Max_Min_Per_Unit
% Load HVPD_Max_Min_pu_IP
Max_Min_pu_IP = dlmread('D:\YAA Codes
Main\Training\02Max_Min_pu\HVPD_Max_Min_pu_IP.txt')
% Load HVPD_Max_Min_pu_TGT
Max_Min_pu_TGT = dlmread('D:\YAA Codes
Main\Training\02Max_Min_pu\HVPD_Max_Min_pu_TGT.txt')

% Load Reduced Blind Testing Matrix of HVPD_Max_Min_Per_Unit
% Load HVPD_Max_Min_Blind_IP
Max_Min_pu_B_IP = dlmread('D:\YAA Codes Main\Blind
Data\02Max_Min_pu\Blind_SA_COMPRESSOR_Max_Min_pu_IP.txt')
% Load HVPD_Max_Min_Blind_TGT
Max_Min_pu_B_TGT = dlmread('D:\YAA Codes Main\Blind
Data\02Max_Min_pu\Blind_SA_COMPRESSOR_Max_Min_pu_TGT.txt')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%
%3

% Load Reduced Training Matrix of HVPD_Max+|Min|_Per_Unit
% Load HVPD_Max+|Min|_pu_IP
Max_AbsMin_IP = dlmread('D:\YAA Codes
Main\Training\03Max+AbsMin_pu\HVPD_Max+AbsMin_pu_IP.txt')
% Load HVPD_Max+|Min|_pu_TGT
Max_AbsMin_TGT = dlmread('D:\YAA Codes
Main\Training\03Max+AbsMin_pu\HVPD_Max+AbsMin_pu_TGT.txt')

% Load Reduced Blind Testing Matrix of HVPD_Max_Min_Per_Unit
% Load HVPD_Max_Min_Blind_IP
Max_AbsMin_B_IP = dlmread('D:\YAA Codes Main\Blind
Data\03Max+AbsMin_pu\Blind_SA_COMPRESSOR_Max+AbsMin_pu_IP.txt')
% Load HVPD_Max_Min_Blind_TGT
Max_AbsMin_B_TGT = dlmread('D:\YAA Codes Main\Blind
Data\03Max+AbsMin_pu\Blind_SA_COMPRESSOR_Max+AbsMin_pu_TGT.txt')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%
%4
```

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1. CONCLUSION

This thesis has demonstrated the ability of Neural Networks (NN) to classify six (6) different types of Partial Discharge (PD) in blind tests, as found in the insulation of High Voltage (HV) electric motors. The recognition rates exceed the reported 79% as stated in the literature survey, and all the results of the developed NN's PD classification were benchmarked against human being PD pattern recognition. Through the communication with the leading manufacturers of PD monitoring systems worldwide, 300 datasets were collected for healthy as well as PD defected HV motors. The datasets include real field readings for 250 measurements for Internal, Surface, Corona, Slot, Endwinding PD types and 50 measurements for healthy machines.

The PRPD (Phase Resolved Partial Discharge) was the base of the NN pattern recognition training, testing and validation. The PRPD patterns were created through self effort using unrefined raw PD data.

Statistical techniques such as Max_Min, Max_Min per unit, and envelop detection techniques were used to perform the preprocessing phase. Also some Signal Processing techniques were investigated such as the PCA and ISOMAP.

MATLAB and NeuralSight NN packages were used to perform the training, test and validation of developed NN. The performance of MATLAB was great to generate the PCA and ISOMAP of reduced matrices during the data preprocessing phase. On the other

hand, the training sessions of MATLAB NN Toolbox tended to go in mode of "OVERFITTING". It was expected that increasing the training time or/and the number of hidden layers would improve the training performance as well as the recognition rate; oppositely, we noticed that increasing the training time or number of hidden layers makes the performance of the NN testing using a new Blind Dataset worse. That can be explained by stating that MATALB will improve only the performance of the training through increasing the neurons and links; the NN in this case is essentially memorizing the behavior rather than doing the NN calculation (i.e., learning) to perform the classification using the NN algorithms. Furthermore, MATLAB NN Toolbox needs three (3) different adjustments and modifications to be done on the input and target PD data. Also, using MATLAB NN Toolbox generates only one NN model. Such output NN model is useless in the cases of multiple overlapped PD defects.

Oppositely, NeuralSight NN package shows an excellent performance to classify the six (6) different PD types and gives an accurate result when it was tested by the Blind Data. NeuralSight produces up to 2000 models that could be used as "VOTING" tool when multiple PD defects exist. The recognition rates exceed the reported 79% as stated in the literature survey. Certain reduction techniques showed very high performance and accurate PD classifications. Envelop approaches using the maximum and minimum was the most accurate NN input for the NeuralSight. The same conclusion is valid for the normalized envelope reduced PD matrix using the per-unit values of maximum and minimum PRPD. The absolute PD values of the PRPD, PAC and ISOMAP gave less accurate PD classification.

All results of the developed NN's PD classification were benchmarked against human being PD pattern recognition. Two (2) extracted inputs from 13.2kV motors installed at an oil production facility of Saudi Aramco were simulated using the trained NN's and compared with the classification of PD subject matter experts (SEM) of PD testing reputable manufacturer. The PD simulated classification results were found in agreement with the classification of SME's; the matched results of the two different PD classification methods (NN and Human) were also noticed in overlapped and mixed PD patterns such in case of multiple PD defects.

When NeuralSight compared with the MATLAB, it is found more friendly use and it does not require a deep knowledge in the NN. It also accepts the datasets that were generated by the PDgold HVPD software without any modifications.

6.2. RECOMMENDATION FOR FUTURE WORK

The NN based PD type classification have been investigated and analyzed in this work but still there is space for future expansion of the research.

Different reduction techniques such as Fourier Transform and Wavelet Transforms could be tested to check the performance accuracy and the effect of number of layers.

Another area could be explored is using different PD representation; Phase Resolved Partial Discharge (PRPD) was the base of the NN training and validation when the accumulative PD level (mV or μC) was monitored over the 360 ° phase angle of AC

source. Another method could be proposed is the Pulse Level Count/Time. In this method, the number of pulses at certain PD level is counted over the time. The trend is always decreasing from the high level pulse rate to low level (the number of sever pulses occurs less than the weak PD pulses).

Also, other tuning feature of MATLAB NN Toolbox could be tried such as training function, adaption function, performance or/and transfer function.

In this work, only two (2) NN tools were used (MATLAB and NeuralSight). Other NN packages could be tested to be compared with the performance of the above mentioned tools.

At the end, the developed NN algorithms could be tested on other HV equipments such as transformers, cables and GIS's.

REFERENCES

[1] Lourenco Mafika Thusi, “Determining the Optimal Technique for Early Detection of Broken Rotor Bars in Medium Voltage Squirrel Cage Induction Motors during Operation,” Thesis of Master of Science in Engineering at University of Witwatersrand, Johannesburg, South Africa, 2009.

[2] U.S. Department of Energy, “Cost Reduction Strategies: Improving the Energy Efficiency of Motor Systems,” Office of Industrial Technologies, Energy Efficiency and Renewable Energy, May 07.

[3] Douglas R. Malcolm, “An energy diet for electric motors: The growing cost of energy for manufacturing puts stress on maintaining a competitive edge in the marketplace. Learn five steps to turn waste into profit without spending a fortune,” PlantServices.com, 2006, http://www.plantservices.com/articles/2006/313.html

[4] Jarmo Ilonen,Joni-Kristian Kamarainen,Tuomo Lindh, Jero Ahola, Heikki Kälviäinen and Jarmo Partanen, “Diagnosis Tool for Motor Condition Monitoring,” IEEE Transactions on Industry Applications, Vol. 41, No. 4, July/August 2005.

[5] Elektro-Journal, November 2009 Issue, “The World's Smallest Electric Motor,” http://www.elektor.com/magazines/elektor-us-editions/2009/11-november.1174465.lynkx .

[6] SCL Engineering & Inspection, "Grand Coulee 94-98 Stator Replacement," http://www.sclqa.com/sclqa_main_site/site_pages/past%20projects.htm.

[7] Manuelle, P. ; Singam, B. ; Siala, S, "Induction Motors Fed by PWM MV7000 Converters Enhance Electric Propulsion Performance," Converteam SAS, Parc d'activites Techn'hom, Belfort, France, Power Electronics and Applications, 2009. EPE '09. 13th European Conference on Power Electronics and Applications, 2009. (Barcelona) 8-10 Sept. 2009 pp.1-7 ISBN:978-1-4244-4432-8

[8] H. Wayne Beaty and James L. Kiriley, "Electric Motor Handbook," First Edition. ISBN: 0-07-035971-7, © 2005 The McGraw-Hill Companies, Inc.

[9] Ali Emadi, "Energy-Efficient Electric Motors," Third Edition, ISBN: O-8247-573-l © 2005 Marcel Dkkei Printing House.

[10] Suri Sathya, Prashant Shyam, Sunder Satya and Krishna Sharma, "Computer Aided Online Fault Diagnosis of Induction Motors," 9th International Conference Electrical Power Quality and Utilization, Barcelona, 9-11 October 2007.

[11] EPRI, "Improved motors for utility applications and improved motors for utility applications industry assessment study," Vol. 1, EPRI EL-2678, 1763-1, final report, and Vol. 2, 1763-1 final report, October 1982.

[12] Motor Reliability Working Group, IEEE Transactions on Industry Applications “Report of Large Motor Reliability Survey of Industrial and Commercial Installations,” Part I and II, Vol. IA-21, No. 4, pp.863-872.

[13] M.L. Sin, W.L. Soong and N. Ertugrul, “Induction Machine On-Line Condition Monitoring and Fault Diagnosis – A Survey” AUPEC2008 : 28 September - 1 October 2008 : Australasian Universities Power Engineering Conference, Christchurch, New Zealand. / pp. 1-6

[14] S. Chen and T. A. Lipo, “Bearing currents and shaft voltages of an induction motor under hard- and soft-switching inverter excitation,” IEEE Trans. Ind. Appl., vol. 34, no. 5, pp. 1042–1048, Sep./Oct. 1998.

[15] S. Nandi and H.A. Toliyat, “Condition Monitoring and Fault Diagnosis of Electrical Machines – A Review,” IEEE Ind. Appl. Society Annual Meeting, 1999.

[16] P.J. Tavner, “Review of condition monitoring of rotating electrical machines,” School of Engineering, Durham University, South Road, Durham, DH1 3LE, UK. Published in IET Electric Power Applications Received on 23rd June 2007, Revised on 13th November 2007

[17] Wei Zhou ; Habetler, T.G. ; Harley, R.G. and Bin Lu, “Incipient Bearing Fault Detection via Stator Current Noise Cancellation using Wiener Filter,” Diagnostics for Electric Machines, Power Electronics and Drives, 2007. SDEMPED 2007. IEEE International Symposium

[18] G. B. Kliman, W. J. Premerlani, R. A. Koegl, and D. Hoeweler, “A new approach to on-line fault detection in ac motors,” in Proc. IEEE Industry

Applications Soc. Annual Meeting Conf., San Diego, CA, 1996, pp. 687–693.

[19] KeSheng Wang, “Vibration Monitoring on Electrical Machine using Vold-Kalman Filter Order Tracking,” Master of Science in the Department of Mechanical and Aeronautical Engineering, University of Pretoria, 2008

[20] S. Su, and R. Dua, “Signature Analysis of Mechanical Watch Movements,” Institute of Precision Engineering, The Chinese University of Hong Kong, Shatin, N. T., Hong Kong, Received 10 January 2007

[21] Suri Prashant, S. Sunder, K. Krishna S. Sharma, “Computer Aided Online Fault Diagnosis of Induction Motors”, 9th International Conference. Electrical Power Quality and Utilization (EPQU'07)

[22] Neelam Mehla, Ratna Dahiya “An Approach of Condition Monitoring of Induction Motor Using MCSA,” International Journal of Systems Applications, Engineering & Development Volume 1, Issue 1, 2007.

[23] Department of Electrical Engineering, , University of Oulu, University of Oulu, Finland “Condition Monitoring of Squirrel-Cage Motors by Axial Magnetic Flux Measurements,”, 2003

[24] Yafei Zhou, MIEEE, A I Gardiner, G A Mathieson, Y Qin “New Methods of Partial Discharge Measurement for the Assessment and Monitoring of Insulation in Large Machines,” Industrial Research Limited. Electrical Insulation Conference, 1997, and Electrical Manufacturing & Coil Winding Conference. Proceedings.

[25] Dhaval Shah, Subhasis Nandi, and Prabhakar Neti, “Stator-Interturn-Fault Detection of Doubly Fed Induction Generators Using Rotor-Current and Search-Coil-Voltage Signature Analysis,” IEEE Transactions On Industry Applications, Vol. 45, No. 5, September/October 2009

[26] Rosero, J. ; Cusido, J. ; Espinosa, A.G. ; Ortega, J.A. ; Romeral, L., “Fault Detection Analysis in Induction Motors by Injecting Additional Test Signal,” IEEE Trans. IEEE ISIE 2006, July 9-12, 2006, Montreal, Quebec, Canada.

[27] M.E.H. Benbouzid, “A Review of Induction Motors Signature Analysis as a Medium for Faults Detection,” IEEE Trans. on Ind. Electronics, vol. 47, no. 5, Oct. 2000, pp. 984-993.

[28] Intesar Ahmed and Manzar Ahmed, “Comparison of Stator Current, Axial Leakage Flux and Instantaneous Power to Detect Broken Rotor Bar Faults in Induction Machines,” 2008 Australasian Universities Power Engineering Conference (AUPEC'08)

[29] A.C. McCormick, “Cyclostationary and Higher Order Statistical Signal Processing Algorithms for Machine Condition Monitoring,” Ph.D. Thesis, Department of Electronic and Electrical Engineering, University of Strathclyde, 1998.

[30] Gaalvez-Carrillo, M. ; Kinnaert, M., “A Signal-Based Approach for Detection and Isolation of Current Sensor Faults in Induction Motors,” Power Electronics and Applications, 2009. EPE '09. 13th European Conference on

[31] C. J. Verucchi, G. G. Acosta and F. A. Benger "A Review on Fault Diagnosis of Induction Machines," Latin American applied research, versión impresa ISSN 0327-0793, Bahía Blanca Apr-Jun 2008.

[32] High Voltage Partial Discharge (HVPD) Ltd, "What Is Partial Discharge and Why Should We Test for It," http://www.hvpd.co.uk/technical Website technical article, 2010

[33] Vouk A., Asiri Y. and Al-Hamouz Z., "Online PD Monitoring Insures Reliable Operation of 24000 hp Motors in the Saudi Arabian Deserts", INSUCON 2009, Birmingham, May 26-28, 2009.

[34] Greg C. Stone, Edward A. Boulter, Ian Culbert, Hussein Dhirani, "Electrical Insulation for Rotating Machines Design, Evaluation, Aging, Testing, and Repair," IEEE Press Series on Power Engineering. 2004

[35] VonRoll ISola Training Program, Electrical Insulating Materials, April 1998 VonRoll ISola catalogue.

[36] B. K. Gupta et al., "Turn Insulation Capability of Large AC Motors, Part 3—Insulation Coordination," IEEE Trans EC, Dec. 1987, pp. 674–679.

[37] B. J. Moore, R. H. Rehder, and R. E. Draper, "Utilizing Reduced Build Concepts in the Development of Insulation Systems for Large Motors," In Proceedings of IEEE Electrical Insulation Conference, Cincinnati, October 1999, pp. 347–352.

[38] IEC TS 60034-27, Off-line partial discharge measurements on the stator winding insulation of rotating electrical machines.

[39] IEEE Std 1434-2000, IEEE Trial-Use Guide to the Measurement of Partial Discharges in Rotating Machinery" Approved 26 April 2000 IEEE-SA Standards Board.

[40] IEC 60270, High-voltage test technique-Partial discharge measurements.

[41] MS thesis titled "Detection and Position Location of Partial Discharges in Transformers Using Fiber Optic Sensors," by Lijun Song, December, 2004 Blacksburg, Virginia U.S.A.

[42] Partial discharge Basics of Monitoring, PD Tech Power Engineering AG.

[43] Derek Mitchell, Iris Power Engineering Inc., Toronto, Canada, "On-Line Partial Discharge Testing: A Predictive Maintenance Tool for Motors and Generators,".

[44] Emerson Electric Co., "Partial Discharge Testing & Monitoring Solutions,"
http://www2.emersonprocess.com/en-US/brands/electricalreliabilityservices/plcs/PredictiveDiagnostics/Pages/PartialDischargeTestingMonitoring.aspx.

[45] Nattrass, D.A, "Partial discharge measurement and interpretation," IEEE Electrical Insulation Magazine May/June 1988-Vol. 4.

[46] Satish L, Gururaj B, "Partial discharge pattern classification using multilayer neural network," Proc. IEE A July:323–330.

[47] Gabe Paoletti, P.E. and Alex Golubev, PhD, "Partial Discharge Theory and Technologies Related to Traditional Testing Methods of Large

Rotating Apparatus," R&D Predictive Diagnostics Cutler-Hammer Engineering Services.

[48] D. Fink, H. W. Beaty, "Standard Handbook for Electrical Engineers, Pages 4-117, 118," McGraw Hill Book Company, 1987.

[49] C.H. Flurscheim, "Power Circuit Breaker Theory and Design," Pages 556-557, Peter Peregrinus Ltd. on behalf of the Institution of Electrical Engineers, 1985.

[50] Westinghouse Electrical Maintenance Hints, Pages 19-14 and 15, and Page 7-23, Westinghouse Electric Corporation Printing Division, Trafford, PA, 1976.

[51] Derek Mitchell, "On-Line Partial Discharge Testing: A Predictive Maintenance Tool for Motors and Generators," Iris Power Engineering Inc., Toronto, Canada, 2007

[52] Mark G. Turner and Dr. Edward Gulski, "Pattern Recognition for Partial Discharge Measurement," Tettex Instruments Division, Haefely Test AG, Dietikon, Website Technical Reference 2010.

[53] Chen Min ; Urano, K. ; Li You-Cheng ; Jinno, A., "Application of Combined PD Sensor for GIS PD Detection and Condition Monitoring" 2008 International Conference on Condition Monitoring and Diagnosis, Beijing, China, April 21-24, 2008

[54] Markalous, S. ; Tenbohlen, S. ; Feser, K, "Detection and Location of Partial Discharges in Power Transformers using Acoustic and

Electromagnetic Signals," Dielectrics and Electrical Insulation, IEEE Transactions on December 2008.

[55] M. Muhr, R. Schwarz, "Optische Teilentladungstetektion für Betriebsmittel der elektrischen Energietechnik, Dissertation, Abteilung für Hochspannungstechnik," Institute of High Voltage Engineering and System Management, Graz University of Technology, 2006

[56] R. Bartnikas, "Partial Discharges, Their Mechanism, Detection and Measurement," IEEE Transactions on Dielectrics and Electrical Insulation Vol. 9 No. 5, October 2005.

[57] IPEC High Voltage Ltd Manchester, UK "PD?......or Not PD?, that is the question," PD Measurements of Rotating HV Machines 2008.

[58] MS thesis titled "Detection and Position Location of Partial Discharges in Transformers Using Fiber Optic Sensors" by Lijun Song, December, 2004 Blacksburg, Virginia U.S.A.

[59] Nattrass D.A., "Partial discharge measurement and interpretation," IEEE Elect. Insul. Mag., 1988.4, (3), pp. 10-23.

[60] Satish L, Gururaj BI (1993) "Partial discharge pattern classification using multilayer neural network," Proc. IEE A July:323–330

[61] Subhasis Nandi, Hamid A. Toliyat, and Xiaodong Li, Student Member, IEEE Condition Monitoring and Fault Diagnosis of Electrical Motors—A Review. IEEE Transactions on Energy Conversion, Vol. 20, No. 4, December 2005.

[62] Partial discharge Basics of Monitoring, PD Tech Power Engineering AG

[63] Greg C. Stone, Edward A. Boulter, Ian Culbert, Hussein Dhirani, Electrical Insulation for Rotating Machines Design, Evaluation, Aging, Testing, and Repair, IEEE Press Series on Power Engineering, 2006.

[64] Jack Copper, Dennis Price, “Creating And Evaluating Neural Network Predictive Models For Electricity Demand And Price Forecasting,” Asia-Pacific Power and Energy Engineering Conference (APP EEC 2009), March 28-30, 2009, Wuhan, China

[65] Kurzweil, R. (1999) The Age of Spiritual Machines. London: The Orion Publishing Group Ltd.

[66] R. P. Lippman, “An Introduction to Computing with Neural Nets’,” IEEE Acoustics, Speech and Signal Processing Magazine, pp. 4-22, 1987.

[67] D. E. Rumelhart and J. L. McClelland, “Parallel Distributed Processing,” Explorations in the Microstructure of Cognition, Vol. 1, MIT Press, 1986.

[68] H. G. Kranz a.nd R. Krump, “The Abilities of Self Operating Expert Systems for Statistical Partial Discharge Analysis of GIS Test Signals,” 6th International Symposium of High Voltage Engineering, New Orleans, 2009.

[69] H. Suzuki and T. Endoh, “Pattern Recognition of Partial Discharge in XLPE Cables Using a Neural Network,” IEEE Trans. o Electr. Ins., Vol. 27, pp. 543-549, 1992.

[70] N. Hozumi, T. 0ka.moto and T. Imaju, “Discrimination of PD Patterns Using Neural Networks”, IEEE Trans. on Electr. Ins., Vol. 27, pp. 550-556, 1992.

[71] Amira A. Mazroua, M. M. A. Salama and R. Bartnikas "PD Pattern Recognition with Neural Networks Using the Multilayer Perceptron Technique," Department of Electrical and Computer Engineering, University of Waterloo, Waterloo, Ontario and Institut de Recherche, d'Hydro-QuCbec, Varennes, Quebec, Canada, 2007.

[72] B. J. Moore, R. H. Rehder, and R. E. Draper, "Utilizing Reduced Build Concepts in the Development of Insulation Systems for Large Motors," In Proceedings of IEEE Electrical Insulation Conference, Cincinnati, October 1999, pp. 347–352.

[73] Satish L, Zaengl WS, "Artificial neural networks for recognition of 3-d partial discharge patterns," IEEE Trans Diel Electr Insul 1:265–274. 1994.

[74] Werle P, Akbari A, Borsi H, Gockenbach E (2001) "Partial discharge localization on power transformers using neural networks combined with sectional winding transfer functions as knowledge base,". Paper presented at the 3rd International Symposium on Electrical Insulation Material (ISEIM), Himeji, Japan, 19–22 November 2005.

[75] Gabe Paoletti, P.E. Division Application Engineer Alex Golubev, PhD Manager, R&D, Predictive Diagnostics, Cutler-Hammer Engineering Services, Partial Discharge Theory and Applications to Electrical Equipment. 2008.

[76] IEC TS 60034-27, Off-line partial discharge measurements on the stator winding insulation of rotating electrical machines.

[77] Derek Mitchell, Iris Power Engineering Inc., Toronto, Canada, On-Line Partial Discharge Testing: A Predictive Maintenance Tool for Motors and Generators, 2008.

[78] IPEC High Voltage Ltd, Manchester, UK PD Measurements of Rotating HV Machines 2008

[79] High Voltage Engineering and Testing Textbook, Chapter I7: Partial discharge measuring technique by E. Gockenbach

[80] M. Muhr, R. Schwarz, Institute of High Voltage Engineering and System Management, Graz University of Technology, Graz, Austria Partial discharge measurement as a Diagnostic Tool for HV-Equipments, 2006

[81] Cachin Ch, Wiesmann HJ (1995) PD recognition with knowledge based preprocessing and neural networks. IEEE Trans Electr Insul 2:578–589.

[82] N. Hozumi, T. Okamoto, T. Imajo, "Discrimination of Partial Discharge Patterns Using Neural Network", IEEE Trans. on Elect. Insul., Vol. 27, pp. 550-556, 1992.

[83] A. Schnettler, V. Tryba, "Artificial Self-organizing Neural Network for Partial Discharge Recognition", Archiv fur Elektrotechnik, Vol. 76, pp. 1-6, 1993.

[84] B. T. Phung, T. R. Blackburn, R. E. James, "The Use of Artificial Neural Networks in Discriminating Partial Discharge Patterns", Proc. 6th Int. Conf. on Dielectric Materials, Measurements and Applications, Manchester, 1992.

[85] Neural Computing, Reference manual, Neuralware, Pittsburgh, 1991.

[86] Satish L, Zaengl WS (1994) "Artificial neural networks for recognition of 3-d partial discharge patterns," IEEE Trans Die Electr Insul 1:265–274

[87] Tu YM, Huang JM, Gao N, Yan Z (1997), "Transformer insulation diagnosis based on improved NN analysis," In: Proceedings of the 5th International Conference on Prop. and Appl Diel Mat, Seoul, Korea. IEEE, New York, pp 263–266

[88] Gao W, Gao N, Yan Z (1998), "Application of adaptive wavelet classification network for fault diagnosis in oil-immersed power equipment," Trans China Electrotechnol Soc 6:33–38 (in Chinese).

[89] Kohonen T (1990) "The self-organizing map," Proc IEEE 78:1464–1480

[90] Gulski E, Krivda A (1993) Neural networks as a tool for recognition of partial discharges. IEEE Trans Electr Insul 28:984–1001

[91] Yang HT, Liao CC, Chou JH (2001) Fuzzy learning vector quantization networks for power transformer condition assessment. IEEE Trans Diel Electr Insul 8:143–149.

[92] Statistica for academia "Neural Networks," StatSoft, Inc. USA, 2010.

[93] Alfred Vouk, "Installation of Remote Continuous PD Monitoring on Gas Compression Plant Motors," Saudi Aramco Journal Of Technology Summer 2006.

[94] IRIS Power Engineering Mississauga, Ontario, Canada, Website article 2010.

[95] R. Heinrich, S. Schaper, W. Kalkner R. Plath A. Bethge, “Synchronous Three Phase Partial Discharge Detection on Rotating Machines,” Technical University Berlin, Germany, Institute for High Voltage Engineering, IPH High Voltage Lab Berlin, Germany, Siemens AG Berlin, Germany

[96] Y Tian, P L Lewin, A E Davies, S J Sutton and S G Swingier, “Application-of Acoustic Emission Techniques and Artificial Neural Networks to Partial Discharge Classification,” High Voltage Laboratory, University of Southampton, Southampton, UK, 2005.

[97] Kyu-Bock Cho, Joo-Young Oh, “An Overview of Application of Artificial Neural Network to Partial Discharge Pattern Classification,” Dept. of Electrical Engineering Hanseo University, Korea, 2001.

[98] A.Yamazaki, Y.Tsutsmi, T.Yonekura, “Partial Discharge Recognition using a Neural N e t w o r k,” Ibaraki University, Japan, 2005

[99] R. Candela, G. Mirelli, Fl. Schifani, “PD Recognition by Means of Statistical and Fractal Parameters and a Neural Network,” Dipattimento di Iiigcppria lilcttrico Universiti di l’nlcrmo, I’ihmnio, Ital, 1998.

[100] Hung-Cheng Chen, Po-Hung Chen*, Meng-Hui Wang “Partial Discharge Classification Using Neural Networks and Statistical Parameters,” Department of Electrical Engineering, National Chin-Yi University of Technology, Taipei, Taiwan, 2007.

[101] Y. Liu and H. Ma, "Pattern recognition using ω-orbit finite automata," K. H. Tzao, Editor, Proc. SPIE 1606, Boston, MA, Nov. 1991, pp.226-240.

[102] T. Pawlicki, D-S. Lee, J. Nu11, and S. Srihnri, "Neural networks and their application to handwritten digit recognition," Proc. TEEE International Conference on Neural Networks: VoI. II, San Diego, CA, 1988, pp.63-70.

[103] Hede Ma, "Technical report: Pattern Recognition Using Neural Networks," Department of Engineering Technology, Savannah State College, Savannah, GA 31404.

[104] Yuming Tu , Wang, Z.D. and Crossley, P.A. "Partial Discharge Pattern Recognition Based on 2-D Wavelet Transform and Neural Network Techniques," Power Engineering Society Summer Meeting, 2002 IEEE Volume: 1, Page(s): 411 - 416 vol.1.

[105] N. Sahoo, M. Salama and R. Bartnikas "Trends in Partial Discharge Pattern Classification: A Survey," Department of Electrical & Computer Engineering, University of Waterloo, Waterloo, Ontario, N2L 3G1 Canada, Institut de Recherche d'Hydro-Quebec, Varennes, QC J3X 1S1, Canada, IEEE Transactions on Dielectrics and Electrical Insulation Vol. 12, No. 2; April 2005.

[106] Jeong-Tae Kim ; Won Choi ; Sung-Kwun Oh ; Keon-Jun Park and Grzybowski, S. "Partial Discharge Pattern Recognition Using Fuzzy-Neural Networks (FNNs) Algorithm," Dept. of Electr. Eng., Daejin Univ., Pocheon. IEEE International Power Modulators and High Voltage Conference, Proceedings of the 2008.

[107] Wen-Yeau Chang "Application of Self Organizing Map Approach for Partial Discharge Pattern Recognition of Insulators," Dept. of Electr.

Eng., St. John's Univ., Taipei, Taiwan. Proceedings of the 9th International Conference on Properties and Applications of Dielectric Materials, July 19-23, 2009, Harbin, China.

[108] MATLAB© R2007b Release Notes. 2007 by The MathWorks, Inc.

[109] MATLAB product page for Neural Network Toolbox, MathWorks webpage http://www.mathworks.com/products/neuralnet/description1.html, 2008.

[110] Alexander Lang, "In-Service, On-Line Partial Discharge (PD) Testing of 2x 13.2kv Alstom Compressor Motors Demo Test Report," HVPD Ltd, UK, June 2009.

[111] Leszek Rutkowski, "Generalized Regression Neural Networks in Time-Varying Environment," IEEE TRANSACTIONS ON NEURAL NETWORKS, VOL. 15, NO. 3, MAY 2004.

[112] Ileana Popescu, Philip Constantinou, Miranda Nafornita, Ioan Nafornita, "Generalized Regression Neural Network Prediction Model for Indoor Environment" Computers and Communications, 2004. Proceedings. ISCC 2004. Ninth International Symposium on Issue Date: 28 June-1 July 2004.

[113] Yasantha N Hettiarachchi, H.L. Premaratne, "A New Parameter Determining Mechanism for Radial Basis Neural Networks," 8th Hybrid Intelligent Systems, Conference (HIS 2008), Barcelona, Spain 10-12 September 2008

[114] K. Smith, “Locating Partial Discharge Phenomena in a Power System Using Neural Networks,” Department of Computer Science and Engineering, University of South Florida, 2001

[115] NeuralSight® User guide, NeuralWare 2008.

APPENDICES

MATLAB CODES:

1 DIMENSIONALITY REDUCTION

```
function edagui
% EDAGUI  Exploratory Data Analysis Graphical User Interface
%   This is the main entry point for the EDA GUI Toolbox. This
toolbox is
%   meant to accompany the EDA Toolbox described in 'Exploratory Data
%   Analysis with MATLAB' by Martinez and Martinez, CRC Press.
%
%   One does not have to use this GUI to invoke the others. Each GUI
%   accessed via this one can be called separately. This GUI is for
%   convenience and to provide a suggested roadmap for exploratory
data
%   analysis.
%
%   A list of GUIs available in this toolbox are:
%
%   loadgui:        Load the data set and other optional information.
%   transformgui:   Apply various transorms to the data.
%   gedagui:        Tools for visualizing the data.
%   univgui:        Methods for visualizing distributions of
features.
%   bivgui:         Methods for visualizing distributions of 2
features.
%   tourgui:        Conduct grand tours and permutation tours.
%   ppedagui:       Projection pursuit for EDA.
%   mdsgui:         Classical and metric multidimensional scaling.
%   dimredgui:      Principal component analysis and nonlinear
%                   dimensionality reduction.
%   kmeansgui:      Implements k-means method for clustering.
%   agcgui:         Agglomerative clustering methods.
%   mbcgui:         Model-based clustering method for finding groups.

%   EDA GUI Toolbox, Wendy and Angel Martinez, November 2006,
%   martinezw@verizon.net.



ud = get(0,'userdata');

H.fig = figure('Tag','edagui',...
    'position',[150 150 726 524],...
    'resize','off',...
    'toolbar','none',...
    'menubar','none',...
    'numbertitle','off',...
    'name','Exploratory Data Analysis GUI');

%     'CloseRequestFcn','close(ud.guis)');
```

```
% put this in there to make sure the fonts look good with the later
% versions of matlab.
if strcmp(version('-release'),'14')
    set(0,'DefaultUicontrolFontname','Sans Serif');
end

%     'CloseRequestFcn','edagui(''close'')');

H.plots = [];
H.Z = [];

if ~isempty(ud)
    % Then something is there already. Add necessary handles to the
    % structure.
    ud.guis = [ud.guis(:); H.fig];
else
    % Set the usual stuff and save in root.
    ud = userdata;
    set(0,'userdata',ud)
end

% set up all of the frames first.
uicontrol(H.fig, 'style','frame',...
    'position',[15 375 700 95]);

uicontrol(H.fig, 'style','frame',...
    'position',[15 220 700 150]);

uicontrol(H.fig,'style','frame',...
    'position',[15 120 700 95]);

uicontrol(H.fig,'style','frame',...
    'position',[15 5 700 110]);

%%%%%%% TEXT BOXES %%%%%%%%%%%%%
% set up all of the text boxes
uicontrol(H.fig,'style','text',...
    'position',[220 485 300 27],...
    'fontweight','bold',...
    'fontsize',14,...
    'backgroundcolor',[.8 .8 .8],...
    'string','Exploratory Data Analysis')

% title text
uicontrol(H.fig,'style','text',...
    'position',[20 445 600 20],...
    'fontweight','bold',...
    'horizontalalignment','left',...
    'string','Set Up Data: These options can be used with all
sections below.')

uicontrol(H.fig,'style','text',...
    'position',[20 345 600 20],...
    'fontweight','bold',...
    'horizontalalignment','left',...
    'string','Graphical EDA: Use these functions to visually explore
your data set - both variables and observations.')

uicontrol(H.fig,'style','text',...
```

```
    'position',[20 190 600 20],...
    'fontweight','bold',...
    'horizontalalignment','left',...
    'string','Dimensionality Reduction: Use these functions to reduce
the number of variables in your data set.')

uicontrol(H.fig,'style','text',...
    'position',[20 90 600 20],...
    'fontweight','bold',...
    'horizontalalignment','left',...
    'string','Search for Groups: Use these functions to search for
groups or clusters.')


%%%%%%% BUTTONS  1st Frame  %%%%%%%%%%%%%%%%%%%%
uicontrol(H.fig,'style','pushbutton',...
    'position',[20 415 170 23],...
    'string','LOAD DATA',...
    'tooltipstring','This will bring up the Load Data GUI',...
    'callback','loadgui')

uicontrol(H.fig,'style','text',...
    'position',[200 418 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Load the data and labels for class, cases, and
variables.')

uicontrol(H.fig,'style','pushbutton',...
    'position',[20 385 170 23],...
    'string','TRANSFORM',...
    'tooltipstring','This will bring up the Transform Data GUI.',...
    'callback','transformgui')

uicontrol(H.fig,'style','text',...
    'position',[200 388 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','With this GUI, you can sphere the data and apply other
common transforms.')


%%%%%%%%%  BUTTONS  2nd FRAME  %%%%%%%%%%%%%%%%%%%%%%

uicontrol(H.fig,'style','pushbutton',...
    'position',[20 327 170 23],...
    'string','GRAPHICS',...
    'tooltipstring','This will bring up the Graphical EDA GUI.',...
    'callback','gedagui')

uicontrol(H.fig,'style','text',...
    'position',[200 330 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Visualize using 2D/3D scatterplots, parallel coordinate
plots, Andrews'' curves, scatterplot matrix.')

uicontrol(H.fig,'style','pushbutton',...
    'position',[20 301 170 23],...
```

```
    'string','SHAPES - UNIVARIATE',...
    'tooltipstring','This will bring up a GUI to explore single
dimensions.',...
    'callback','univgui')

uicontrol(H.fig,'style','text',...
    'position',[200 304 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Construct boxplots, histograms, q-q plots to understand
the distribution of single variables.')


uicontrol(H.fig,'style','pushbutton',...
    'position',[20 275 170 23],...
    'string','SHAPES - BIVARIATE',...
    'tooltipstring','This will bring up a GUI to explore two
dimensions simultaneously.',...
    'callback','bivgui')

uicontrol(H.fig,'style','text',...
    'position',[200 278 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Explore two variables at a time with hexagonal binning,
bivariate histograms, and polar smooths.')


uicontrol(H.fig,'style','pushbutton',...
    'position',[20 249 170 23],...
    'string','DATA TOURS',...
    'tooltipstring','This will bring up the GUI to do grand tours and
the like.',...
    'callback','tourgui')

uicontrol(H.fig,'style','text',...
    'position',[200 252 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Search for structure using the grand tour and the
permutation tour.')


uicontrol(H.fig,'style','pushbutton',...
    'position',[20 223 170 23],...
    'string','PROJECTION PURSUIT',...
    'tooltipstring','This will bring up the GUI to do projection
pursuit.',...
    'callback','ppedagui')

uicontrol(H.fig,'style','text',...
    'position',[200 226 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Search for structure in 2-D using projection pursuit.')

%%%%%%%%%%%    BUTTONS - 3RD FRAME  %%%%%%%%%%%%%%%%%%%%%%%5
```

```
uicontrol(H.fig,'style','pushbutton',...
    'position',[20 160 170 23],...
    'string','MULTIDIMENSIONAL SCALING',...
    'tooltipstring','This will bring up a GUI to do various flavors
of MDS.',...
    'callback','mdsgui')

uicontrol(H.fig,'style','text',...
    'position',[200 163 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Reduce the dimensionality of your data using classical,
metric, and nonmetric MDS.')

uicontrol(H.fig,'style','pushbutton',...
    'position',[20 130 170 23],...
    'string','DIMENSIONALITY REDUCTION',...
    'tooltipstring','This will bring up a GUI that allows one to
reduce the dimensionality of the data before exploring further.',...
    'callback','dimredgui')

uicontrol(H.fig,'style','text',...
    'position',[200 133 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Reduce the dimensionality of your data using PCA,
ISOMAP, and LLE.')

%%%%%%%%%%%%%5  BUTTONS - 4TH FRAME %%%%%%%%%%%%%%%%%%%%%%

uicontrol(H.fig,'style','pushbutton',...
    'position',[20 66 170 23],...
    'string','K-MEANS CLUSTERING',...
    'tooltipstring','This will bring up a GUI that runs k-means
clustering.',...
    'callback','kmeansgui')

uicontrol(H.fig,'style','text',...
    'position',[200 69 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Partition the data into a specified number of groups.')

uicontrol(H.fig,'style','pushbutton',...
    'position',[20 38 170 23],...
    'string','AGGLOMERATIVE CLUSTERING',...
    'tooltipstring','This brings up the GUI that does various flavors
of agglomerative clustering.',...
    'callback','agcgui')

uicontrol(H.fig,'style','text',...
    'position',[200 41 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Construct a hierarchy of nested partitions.')

uicontrol(H.fig,'style','pushbutton',...
    'position',[20 10 170 23],...
    'string','MODEL-BASED CLUSTERING',...
```

```
    'tooltipstring','This will bring up a GUI that does Model-Based
Clustering - 9 finite mixture models.',...
    'callback','mbcgui')

uicontrol(H.fig,'style','text',...
    'position',[200 13 500 15],...
    'fontsize',9,...
    'horizontalalignment','left',...
    'string','Cluster your data based on probability density
estimation (Gaussian finite mixtures).')

% Close button
uicontrol(H.fig,'style','pushbutton',...
    'position',[620 485 66 25],...
    'string','CLOSE',...
    'callback','delete(gcf)',...
    'tooltipstring','Push this button to close the GUI window.')



% Save Handles for THIS GUI in the UserData for this figure.
set(gcf,'userdata',H)
```

2 MATLAB NN

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%&&
&&%%%%%%%%
%              King Fahd University of Petroleum and Minerals
%
%                          College of Engineering
%
%                     Electrical Engineering Department
%
%
%
%                                  MS Thesis
%
%      Neural Network Based Detection of Partial Discharge in HV
Motors        %
%
%
%                               by: Yahya Asiri
%
%                                 ID: 240128
%
%
%
%                            Dhahran, Saudi Arabia
%
%
%
%                                  June 2010
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
%%%%%%%%%%



%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%
%
%
%                     Loading Input and Training Matrices
%
%
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%

clear;


%1

% Load Reduced Training Matrix of HVPD_Max_Min
% Load HVPD_Max_Min_IP
Max_Min_IP = dlmread('D:\YAA Codes
Main\Training\01Max_Min\HVPD_Max_Min_IP.txt')
% Load HVPD_Max_Min_TGT
Max_Min_TGT = dlmread('D:\YAA Codes
Main\Training\01Max_Min\HVPD_Max_Min_TGT.txt')

% Load Reduced Blind Testing Matrix of HVPD_Max_Min
% Load HVPD_Max_Min_Blind_IP
Max_Min_B_IP = dlmread('D:\YAA Codes Main\Blind
Data\01Max_Min\Blind_SA_COMPRESSOR_Max_Min_IP.txt')
% Load HVPD_Max_Min_Blind_TGT
Max_Min_B_TGT = dlmread('D:\YAA Codes Main\Blind
Data\01Max_Min\Blind_SA_COMPRESSOR_Max_Min_TGT.txt')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%
%2

% Load Reduced Training Matrix of HVPD_Max_Min_Per_Unit
% Load HVPD_Max_Min_pu_IP
Max_Min_pu_IP = dlmread('D:\YAA Codes
Main\Training\02Max_Min_pu\HVPD_Max_Min_pu_IP.txt')
% Load HVPD_Max_Min_pu_TGT
Max_Min_pu_TGT = dlmread('D:\YAA Codes
Main\Training\02Max_Min_pu\HVPD_Max_Min_pu_TGT.txt')

% Load Reduced Blind Testing Matrix of HVPD_Max_Min_Per_Unit
% Load HVPD_Max_Min_Blind_IP
Max_Min_pu_B_IP = dlmread('D:\YAA Codes Main\Blind
Data\02Max_Min_pu\Blind_SA_COMPRESSOR_Max_Min_pu_IP.txt')
% Load HVPD_Max_Min_Blind_TGT
Max_Min_pu_B_TGT = dlmread('D:\YAA Codes Main\Blind
Data\02Max_Min_pu\Blind_SA_COMPRESSOR_Max_Min_pu_TGT.txt')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%
%3
```

```
% Load Reduced Training Matrix of HVPD_Max+|Min|_Per_Unit
% Load HVPD_Max+|Min|_pu_IP
Max_AbsMin_IP = dlmread('D:\YAA Codes
Main\Training\03Max+AbsMin_pu\HVPD_Max+AbsMin_pu_IP.txt')
% Load HVPD_Max+|Min|_pu_TGT
Max_AbsMin_TGT = dlmread('D:\YAA Codes
Main\Training\03Max+AbsMin_pu\HVPD_Max+AbsMin_pu_TGT.txt')

% Load Reduced Blind Testing Matrix of HVPD_Max_Min_Per_Unit
% Load HVPD_Max_Min_Blind_IP
Max_AbsMin_B_IP = dlmread('D:\YAA Codes Main\Blind
Data\03Max+AbsMin_pu\Blind_SA_COMPRESSOR_Max+AbsMin_pu_IP.txt')
% Load HVPD_Max_Min_Blind_TGT
Max_AbsMin_B_TGT = dlmread('D:\YAA Codes Main\Blind
Data\03Max+AbsMin_pu\Blind_SA_COMPRESSOR_Max+AbsMin_pu_TGT.txt')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%
%4

% Load Reduced Training Matrix of HVPD_PCA
% Load HVPD_Max+|Min|_pu_IP
HVPD_pca_IP = dlmread('D:\YAA Codes
Main\Training\04PCA\HVPD_PCA_IP.txt')
% Load HVPD_Max+|Min|_pu_TGT
HVPD_pca_TGT = dlmread('D:\YAA Codes
Main\Training\04PCA\HVPD_PCA_TGT.txt')

% Load Reduced Blind Testing Matrix of HVPD_PCA
% Load HVPD_Max_Min_Blind_IP
HVPD_pca_B_IP = dlmread('D:\YAA Codes Main\Blind
Data\04PCA\Blind_SA_COMPRESSOR_PCA_IP.txt')
% Load HVPD_Max_Min_Blind_TGT
HVPD_pca_B_TGT = dlmread('D:\YAA Codes Main\Blind
Data\04PCA\Blind_SA_COMPRESSOR_PCA_TGT.txt')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%
%5

% Load Reduced Training Matrix of HVPD_ISOMAP
% Load HVPD_Max+|Min|_pu_IP
HVPD_isomap_IP = dlmread('D:\YAA Codes
Main\Training\05ISOMAP\HVPD_ISOMAP_IP.txt')
% Load HVPD_Max+|Min|_pu_TGT
HVPD_isomap_TGT = dlmread('D:\YAA Codes
Main\Training\05ISOMAP\HVPD_ISOMAP_TGT.txt')

% Load Reduced Blind Testing Matrix of HVPD_PCA
% Load HVPD_Max_Min_Blind_IP
HVPD_isomap_B_IP = dlmread('D:\YAA Codes Main\Blind
Data\05ISOMAP\Blind_SA_COMPRESSOR_ISOMAP_IP.txt')
% Load HVPD_Max_Min_Blind_TGT
HVPD_isomap_B_TGT = dlmread('D:\YAA Codes Main\Blind
Data\05ISOMAP\Blind_SA_COMPRESSOR_ISOMAP_TGT.txt')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%
%
%
%                          NN Training and Testing
%
%
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%

% 1 : Feed Forward Back Propagation : FFBP

% 11: FFBP___HVPD_Max_Min
% 12: FFBP___HVPD_Max_Min_Per_Unit
% 13: FFBP___HVPD_Max+|Min|_Per_Unit
% 14: FFBP___HVPD_PCA
% 15: FFBP___HVPD_ISOMAP


net11 = newff(Max_Min_IP,Max_Min_TGT,10)

net11.trainParam.epochs = 30;
net11= train(net11,Max_Min_IP,Max_Min_TGT);

Y= sim (net11,Max_Min_IP);

Y= sim (net11,Max_Min_TGT);

PD_Blind = sim(net11,Max_Min_B_IP);

PD_Blind_Type = sim (net11,Max_Min_B_TGT)

f11 = fopen('PD_Max_min.txt','w');
fwrite(f11,array11)
f11A = fopen('ord.txt','w');
fwrite(f11A,array2')


plot(Max_Min_IP,Max_Min_TGT,Max_Min_B_IP,Y)




net12 = newff(Max_Min_IP,Max_Min_TGT,10)

net12.trainParam.epochs = 30;
net12= train(net12,Max_Min_IP,Max_Min_TGT);

Y= sim (net12,Max_Min_pu_IP);

Y= sim (net12, Max_Min_pu _TGT);
```

```
PD_Blind = sim(net12,Max_Min_pu_B_IP);

PD_Blind_Type = sim (net12,Max_Min_pu_B_TGT)

f1 = fopen('PD_Max_min.txt','w');
fwrite(f1,array1)
f2 = fopen('ord.txt','w');
fwrite(f2,array2')


plot(Max_Min_pu_IP,Max_Min_TGT,Max_Min_pu_B_IP,Y)



net13 = newff(Max_Min_IP,Max_Min_TGT,10)

net13.trainParam.epochs = 30;
net13= train(net13,Max_AbsMin_IP,Max_AbsMin_TGT);

Y= sim (net13,Max_AbsMin_IP);

Y= sim (net13,Max_AbsMin_TGT);

PD_Blind = sim(net13,Max_AbsMin_B_IP);

PD_Blind_Type = sim (net13,Max_AbsMin_B_TGT)

f13 = fopen('PD_Max_AbsMin.txt','w');
fwrite(f13,array13)
f13A = fopen('ord.txt','w');
fwrite(f13A,array2')


plot(Max_AbsMin_IP,Max_AbsMin_TGT,Max_AbsMin_B_IP,Y)



net14 = newff(Max_Min_IP,Max_Min_TGT,10)

net14.trainParam.epochs = 30;
net14= train(net14,PCA_IP,PCA_TGT);

Y= sim (net14,PCA_IP);

Y= sim (net14,PCA_TGT);

PD_Blind = sim(net14,PCA_B_IP);

PD_Blind_Type = sim (net14,PCA_B_TGT)

f14 = fopen('PD_PCA.txt','w');
fwrite(f14,array14)
f14A = fopen('ord.txt','w');
fwrite(f14A,array2')
```

```
plot(PCA_IP,PCA_TGT,PCA_B_IP,Y)



net15 = newff(Max_Min_IP,Max_Min_TGT,10)

net15.trainParam.epochs = 30;
net15= train(net15,ISOMAP_IP,ISOMAP_TGT);

Y= sim (net15,ISOMAP_IP);

Y= sim (net15,ISOMAP_TGT);

PD_Blind = sim(net15,ISOMAP_B_IP);

PD_Blind_Type = sim (net15,ISOMAP_B_TGT)

f15 = fopen('PD_ISOMAP.txt','w');
fwrite(f15,array15)
f15A = fopen('ord.txt','w');
fwrite(f15A,array2')


plot(ISOMAP_IP,ISOMAP_TGT,ISOMAP_B_IP,Y)



%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%
%
%
%                         NN Training and Testing
%
%
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%

% 1 : Feed Forward Back Propagation : RB

% 21: RB___HVPD_ISOMAP
% 22: RB___HVPD_ISOMAP_Per_Unit
% 23: RB___HVPD_Max+|AbsMin|_Per_Unit
% 24: RB___HVPD_ISOMAP
% 25: RB___HVPD_ISOMAP


net21 = radbas(Max_Min_IP,Max_Min_TGT,20)

net21.trainParam.epochs = 30;
net21= train(net22,Max_Min_IP,Max_Min_TGT);

Y= sim (net21,Max_Min_IP);

Y= sim (net21,Max_Min_TGT);
```

```
PD_Blind = sim(net21,Max_Min_B_IP);

PD_Blind_Type = sim (net21,Max_Min_B_TGT)

f21 = fopen('PD_Max_min.txt','w');
fwrite(f21,array21)
f22A = fopen('ord.txt','w');
fwrite(f22A,array2')


plot(Max_Min_IP,Max_Min_TGT,Max_Min_B_IP,Y)





net22 = radbas(Max_Min_IP,Max_Min_TGT,20)

net22.trainParam.epochs = 30;
net22= train(net22,Max_Min_IP,Max_Min_TGT);

Y= sim (net22,Max_Min_pu_IP);

Y= sim (net22, Max_Min_pu _TGT);

PD_Blind = sim(net22,Max_Min_pu_B_IP);

PD_Blind_Type = sim (net22,Max_Min_pu_B_TGT)

f2 = fopen('PD_Max_min.txt','w');
fwrite(f2,array2)
f2 = fopen('ord.txt','w');
fwrite(f2,array2')


plot(Max_Min_pu_IP,Max_Min_TGT,Max_Min_pu_B_IP,Y)



net23 = radbas(Max_Min_IP,Max_Min_TGT,20)

net23.trainParam.epochs = 30;
net23= train(net23,Max_AbsMin_IP,Max_AbsMin_TGT);

Y= sim (net23,Max_AbsMin_IP);

Y= sim (net23,Max_AbsMin_TGT);

PD_Blind = sim(net23,Max_AbsMin_B_IP);

PD_Blind_Type = sim (net23,Max_AbsMin_B_TGT)

f23 = fopen('PD_Max_AbsMin.txt','w');
fwrite(f23,array23)
f23A = fopen('ord.txt','w');
fwrite(f23A,array2')
```

```
plot(Max_AbsMin_IP,Max_AbsMin_TGT,Max_AbsMin_B_IP,Y)



net24 = radbas(Max_Min_IP,Max_Min_TGT,20)

net24.trainParam.epochs = 30;
net24= train(net24,PCA_IP,PCA_TGT);

Y= sim (net24,PCA_IP);

Y= sim (net24,PCA_TGT);

PD_Blind = sim(net24,PCA_B_IP);

PD_Blind_Type = sim (net24,PCA_B_TGT)

f24 = fopen('PD_PCA.txt','w');
fwrite(f24,array24)
f24A = fopen('ord.txt','w');
fwrite(f24A,array2')


plot(PCA_IP,PCA_TGT,PCA_B_IP,Y)



net25 = radbas(Max_Min_IP,Max_Min_TGT,20)

net25.trainParam.epochs = 30;
net25= train(net25,ISOMAP_IP,ISOMAP_TGT);

Y= sim (net25,ISOMAP_IP);

Y= sim (net25,ISOMAP_TGT);

PD_Blind = sim(net25,ISOMAP_B_IP);

PD_Blind_Type = sim (net25,ISOMAP_B_TGT)

f25 = fopen('PD_ISOMAP.txt','w');
fwrite(f25,array25)
f25A = fopen('ord.txt','w');
fwrite(f25A,array2')


plot(ISOMAP_IP,ISOMAP_TGT,ISOMAP_B_IP,Y)
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%
%
%
%                              NN Training and Testing
%                              %
%
%
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%

% 2 : Feed Forward Back Propagation : GR

% 32: GR___HVPD_ISOMAP
% 32: GR___HVPD_ISOMAP_Per_Unit
% 33: GR___HVPD_Max+|AbsMin|_Per_Unit
% 34: GR___HVPD_ISOMAP
% 35: GR___HVPD_ISOMAP


net31 = newgrnn(Max_Min_IP,Max_Min_TGT,30)

net31.trainParam.epochs = 30;
net31= train(net33,Max_Min_IP,Max_Min_TGT);

Y= sim (net31,Max_Min_IP);

Y= sim (net31,Max_Min_TGT);

PD_Blind = sim(net31,Max_Min_B_IP);

PD_Blind_Type = sim (net31,Max_Min_B_TGT)

f31 = fopen('PD_Max_min.txt','w');
fwrite(f31,array31)
f33A = fopen('ord.txt','w');
fwrite(f33A,array3')


plot(Max_Min_IP,Max_Min_TGT,Max_Min_B_IP,Y)




net32 = newgrnn(Max_Min_IP,Max_Min_TGT,30)

net32.trainParam.epochs = 30;
net32= train(net33,Max_Min_IP,Max_Min_TGT);

Y= sim (net32,Max_Min_pu_IP);
```

```
Y= sim (net32, Max_Min_pu _TGT);

PD_Blind = sim(net32,Max_Min_pu_B_IP);

PD_Blind_Type = sim (net32,Max_Min_pu_B_TGT)

f32 = fopen('PD_Max_min.txt','w');
fwrite(f32,array3)
f32 = fopen('ord.txt','w');
fwrite(f32,array3')


plot(Max_Min_pu_IP,Max_Min_TGT,Max_Min_pu_B_IP,Y)




net33 = newgrnn(Max_Min_IP,Max_Min_TGT,30)

net33.trainParam.epochs = 30;
net33= train(net33,Max_AbsMin_IP,Max_AbsMin_TGT);

Y= sim (net33,Max_AbsMin_IP);

Y= sim (net33,Max_AbsMin_TGT);

PD_Blind = sim(net33,Max_AbsMin_B_IP);

PD_Blind_Type = sim (net33,Max_AbsMin_B_TGT)

f33 = fopen('PD_Max_AbsMin.txt','w');
fwrite(f33,array33)
f33A = fopen('ord.txt','w');
fwrite(f33A,array3')


plot(Max_AbsMin_IP,Max_AbsMin_TGT,Max_AbsMin_B_IP,Y)



net34 = newgrnn(Max_Min_IP,Max_Min_TGT,30)

net34.trainParam.epochs = 30;
net34= train(net34,PCA_IP,PCA_TGT);

Y= sim (net34,PCA_IP);

Y= sim (net34,PCA_TGT);

PD_Blind = sim(net34,PCA_B_IP);

PD_Blind_Type = sim (net34,PCA_B_TGT)

f34 = fopen('PD_PCA.txt','w');
fwrite(f34,array34)
f34A = fopen('ord.txt','w');
fwrite(f34A,array3')
```

```
plot(PCA_IP,PCA_TGT,PCA_B_IP,Y)



net35 = newgrnn(Max_Min_IP,Max_Min_TGT,30)

net35.trainParam.epochs = 30;
net35= train(net35,ISOMAP_IP,ISOMAP_TGT);

Y= sim (net35,ISOMAP_IP);

Y= sim (net35,ISOMAP_TGT);

PD_Blind = sim(net35,ISOMAP_B_IP);

PD_Blind_Type = sim (net35,ISOMAP_B_TGT)

f35 = fopen('PD_ISOMAP.txt','w');
fwrite(f35,array35)
f35A = fopen('ord.txt','w');
fwrite(f35A,array3')


plot(ISOMAP_IP,ISOMAP_TGT,ISOMAP_B_IP,Y)
```

CURRICULUM VITAE

Yahya Asiri is the adjustable frequency drives (AFD) specialist of Consulting Services Department (CSD) of Saudi Aramco. He obtained a B.Sc. degree in Electrical Engineering from King Saud University in Riyadh in June 1995 with a major in power electronics. In July 1995, Yahya was nominated to join a selected group of researchers and scientists working for a governmental R&D center. His duties were focused on opto-electronics application, optical imaging and infrared systems. In August 1998, Yahya joined Al Fahd Armored 8X8 vehicle factory as the head of vehicle electric/electronic design division until 2001 when he joined Saudi Aramco. Since that time until present, Yahya served in many operational, maintenance and engineering organizations within Saudi Aramco. During 2009-2010, he spent one year internship assignment with Siemens Large Drives and Automation (LDA) in New Kensington PA in USA. In June 2010, Yahya obtained the M.Sc. degree in Electrical Engineering from King Fahd University of Petroleum and Minerals, Dhahran. Yahya could be contacted at P. O. Box 10869, Dhahran 31311, or via yahya.asiri@aramco.com.