A Qualitative assessment of the Insulation systems of medium voltage Induction Motors

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A dissertation presented to

The school of Electrical, Electronic and Computer Engineering

North-West University

In partial fulfilment of the requirements for the degree

Master in Engineering

in Electrical and Electronics Engineering

by

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January 2007

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DECLARATION

I hereby declare that all the material incorporated into this dissertation is my own original unaided work, except where specific reference in made by name or in the form of a numbered reference, which is done to the best of my ability. The work herein has not been submitted to any other university to obtain a degree.

Pearlie Marie John

12 January 2007

ABSTRACT

The aim of this study is to qualitatively assess the insulation system's condition of medium voltage induction motors. In essence this aim of the research was to analyse and classify the data. The initial step was to understand the data. The literature review gives the background of the insulation system and the different tests done and its interpretations. The research methodology used has been explained along with description of the data.

The aging of the insulation is a wide and complex topic, thus in this research the electrical aspects of the insulation were looked into and explained in detail. The data and the limitations of this study are also discussed.

Data mining processes were used to gain insight into the data and the condition of the insulation system. The different stages of data mining are explained. The different stages are: identifying the problem, data understanding, data preparation and data analysis. An analysis was done using self-organizing maps, which is an unsupervised neural network technique. Hierarchical and K-mean clustering techniques were used to classify the data. The results of the different techniques were compared to an expert's assessment.

The study is was an attempt to understand the condition of the insulation system and to classify the data according to its condition. A comparison was done between the different techniques used. The data was divided into four groups based on the voltage rating and class of insulation used in the motors. Good classification was obtained for three out of the four groups of data.

In conclusion, the patterns in the different features of the data due to ageing were observed. The data was qualitatively assessed and classified into groups according to the deterioration of the insulation system using the classification techniques. Finally the results correlated well with the expert's assessment. In essence, the goals set for the research were achieved.

SINOPSIS

Die doel van hierdie studie was om die toestand van die isolasiestelsel in die mediumspanning-induksiemotors kwalitatief te beraam. Hierdie navorsing is in essensie gemik op die analise en klassifikasie van data. Die eerste stap was die verkryging van begrip vir die data. Die literatuuroorsig verskaf die agtergrond van die insulasiestelsel, die verskillende toetse wat uitgevoer is en die interpretasies daarvan. Die navorsingsmetodologie wat gebruik is word saam met die beskrywing van die data verduidelik.

Die veroudering van isolasie is 'n breë, komplekse onderwerp, daarom word die elektriese aspekte van isolasie gedetailleerd in hierdie navorsing verduidelik. Die data en die beperkings van hierdie studie word ook bespreek.

Die datamyningsproses is gebruik om insig in die data en die toestand van die isolasiestelsel te verkry. Die verskillende stadia van datamyning word verduidelik. Die stadia is die identifisering van die probleem, die verstaan van data, die voorbereiding van data en data-analise. Analise word gedoen deur die gebruik van self-organiserende kaarte, wat 'n ongekontroleerde neurale netwerktegniek is. Hierargiese en K-gemiddelde trostegnieke word gebruik om die data te klassifiseer. Die resultate van die verskillende tegnieke word vergelyk met die beraming van 'n deskundige.

Die studie is 'n poging om die toestande van die isolasiestelsel te verstaan en om die data aan die hand van hierdie toestande te klassifiseer. 'n Vergelyking word getref tussen die verskillende tegnieke wat gebruik is. Die data is in vier groepe verdeel wat gebaseer is op die spanningswaardes en klas van insulasie wat in die motors gebruik word. 'n Goeie klassifikasie is in drie van die vier groepe verkry.

Hierdie navorsing dui daarop dat die tan-deltatoets 'n goeie indikasie van die werklike toestand van die isolasie is en dat helling en verandering in kapasitansie lineêr vermeerder soos die isolasie verouder. Samevattend kan daar aangevoer word dat die doel met die navorsing bereik is.

ACKNOWLEDGEMENT

This work would not have been complete without mentioning my heartfelt and sincere gratitude to the people that have contributed to make this dissertation a reality. I would like to acknowledge and mention the following people for their willingness, co-operation and assistance:

- Prof. Jan de Kock, in his capacity as the supervisor of this dissertation, and my deepest appreciation for his guidance, mentorship, motivation, support, invaluable input, criticism and confidence in me, which was instrumental in finishing this work.
- To Mr. A.D.W. Wolmarans, for his warmth and guidance, and also for his research data that was crucial for the research, comments, inputs and ideas regarding my work and literature review.
- Prof. Alwyn Hoffman for his guidance and input in self-organizing maps which was priceless.
- To Dr. Theo van der Merve, for his assistance with the SOM toolbox and Matlab® related works.
- To Prof. Francois van Graan, for his willingness, guidance, comments and motivation regarding statistical analysis.
- To Mrs. Tanja de la Ray, for her assistance with the unsupervised analysis technique.
- To my friends Jienietta, Pst. Louise, Lille, Jane Murungi and Modupe Ogunrumbi for their friendship and prayer.
- To Anriette Pretorius, for her assistance with collection of materials for my literature review.
- To Pastor Willem Nel, Senior Pastor, of The His People Church, Potchefstroom for his friendship, prayers and spiritual support.

- To my dear parents Mr. Mathew Koshy and Mrs. Ponnamma Mathew for their constant love, sacrifice, support and faith in my abilities which inspired me to set ever higher goals in my life.
- To my dearest sister Mrs. Sweetie C. George for being a friend, inspiration and a wonderful sister and a sunshine in my life.
- To my dear husband George (Gejo), for being a wonderful friend, life partner, mentor and for his wholehearted support and encouragement in completing this dissertation. Thank you very much for your love.

I give all the praise, glory, honour and gratitude to the King of kings and my Abba Father. I praise Him for showing me His unconditional love and amazing grace and for giving me the ability and perseverance to complete this study.

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Abbreviations and Symbols

AC	-	Alternating current
kV	-	kilovolt
IR	-	Insulation Resistance
PI	-	Polarization Index
RTG	-	Resistance to ground
HIPOT	-	High Potential
PF	-	Power Factor
PD	-	Partial Discharge
DIV	-	Discharge Inception Voltage
DEV	-	Discharge Extinction Voltage
CRISP-DM	-	Cross Industry Standard Process model for Data mining
BMU	-	Best Matching Unit
SOM	-	Self-Organizing Maps
ANN	-	Artificial Neural Network
MΩ	-	Megaohm
pu	-	Per unit
Nij	-	the j-neighbourhood around unit i
X	-	the input component vector
Wj	-	the weight vector
dj	-	quadratic distance
η	-	the gain term
α (t)	-	learning rate
σ (t)	-	neighbourhood radius
r_i	-	are coordinates of the neurons in the output grid
r_c	-	is the winning neuron
d_{ih}	-	is the distance between the two clusters i and h

CHAPTER 1

ORIENTATION

1.1 Introduction

The reason for failure in a motor is often due to a sudden or gradual deterioration of the insulation system. In other words, when insulation can no longer withstand the normal electrical and mechanical operating stresses, it will fail. That is the reason why diagnostic tests are done at regular intervals to assess the condition of the insulation system. Once off testing does not give a good indication of the condition of the insulation system, except if the insulation system is on the verge of collapse.

B. K. Gupta said, "The insulation condition can be assessed by an expert from the knowledge of the insulation characteristics, the stresses experienced by the machine, with machines having similar insulation materials" [1]. An expert also uses experience of similar machine insulation systems for assessment. It is proposed that viewing the result within the context of similar machines will provide a partial answer to this problem. It is proposed that data mining techniques be used to aid the user in assessing the condition of the insulation system. The programme is proposed to classify the data into clusters according to its insulation condition, mainly taking into account the electrical aspects. It should be made clear that the time of failure cannot be predicted, but the proposed programme will assist in determining the condition of the insulation system. In essence, the proposed programme is to interpret the condition of the insulation system based on the data given to it.

The different types of machines, which will be analysed in the research, are squirrel cage induction motors, wound rotor induction motors and smaller generator sets. It is the most common ac motor. It is rugged, simple and is used extensively in industrial applications. Its main function is to drive conveyor systems, fans, pumps, mixing and power tool operations. Wound rotor induction motors and smaller generator sets are also used in mining and power generation applications, but are far less common.

1.2 Background

It is essential to have a brief overview of the machine construction and the insulation system within the stator. In addition, a few diagnostic tests that are commonly used are briefly explained in chapter 2.

1.3 Problem Statement

Looking at the history of motor winding insulation systems, there have been a lot of changes in different aspects of these systems. There has been a change in the material used to insulate the windings, from natural materials of class A (105 °C) [3], and Asphalt mica system of class B (130 °C) [2], [3], to recent materials, like Epoxy bonded mica tapes of class F (155 °C) [2], [3]. The process used for applying the insulation to the motor conductors has changed as well. As figure 1 shows, there has also been a drastic decrease in the amount of insulation being used over the years.

The insulation thickness has decreased and there has been a proportional increase in the machine output. It is obvious that there is an increased strain on the insulation system and as time passes, the importance of predictive maintenance will increase.

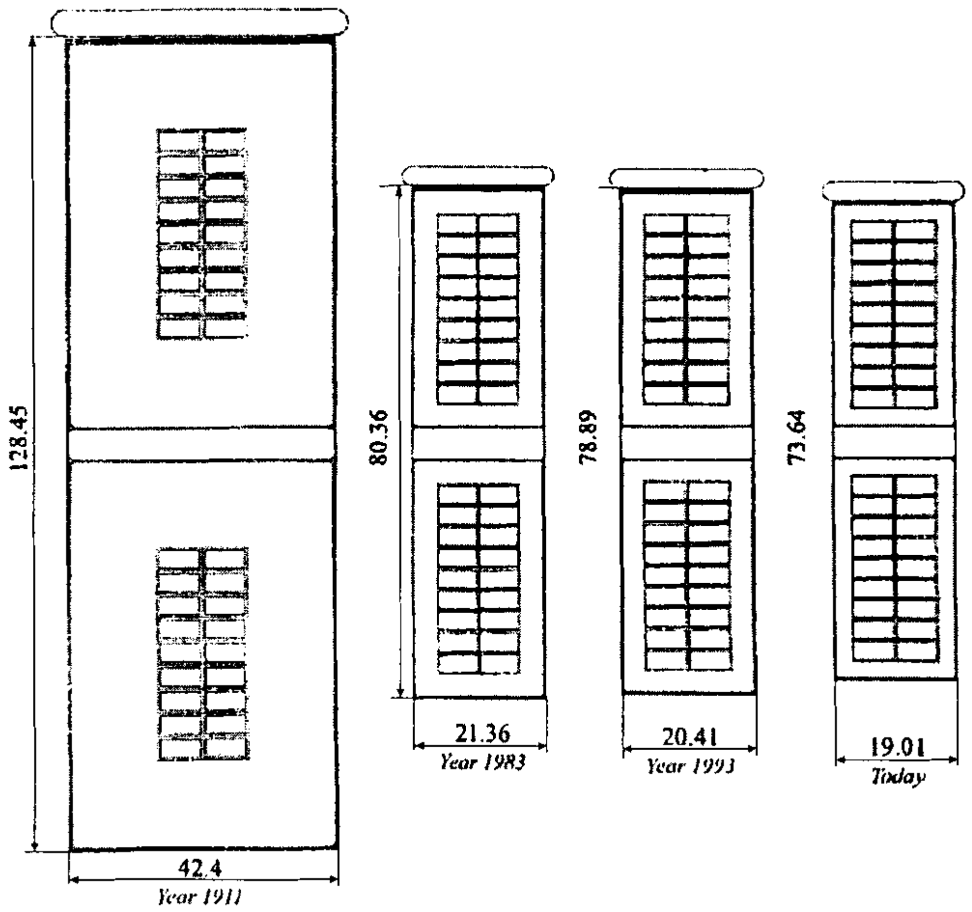


Figure 1.1. Cross-section of a winding and decrease in insulation thickness from 1911 to 1998 [4].

For the past 40 years the diagnostic tests were used to assess the condition of the stator insulation. The guidelines that were set have not adapted to the change in the test equipment and recent developments. There have been revisions made in 2000 and 2004 by IEEE, but the effects of ageing on the diagnostic results have not been specified. "No single test is perfect; no test is sensitive to all insulation problems. And no test can give an absolute indication of the insulation condition, especially if only one measurement is available" [5]. Even though in all tests acceptable limits are specified, a single measured value is not of much use. Trending is required.

The crucial step is to interpret the data, and assess the condition of the insulation. Data mining will be used to understand the data collected and to get new insight as well as classify the data according to the condition of the insulation of the machine.

1.4 Objectives of the Research

To assess the qualitative condition of the machine insulation systems research had to be done in two different areas.

One is to understand the electrical aspects of the motor and its effects on the insulation system, to understand the various insulation tests, the mechanism of ageing and to interpret the results of the diagnostic tests.

The other area of this research was to understand the different classification techniques and to find suitable methods to classify the complicated set of data.

The main objectives of the research are:

a To understand the data that needs to be classified.

b To cluster the data of the motors according to their deterioration, using suitable classification methods.

c To compare data mining techniques to the current analysis used by experts.

1.5 Overview of the Dissertation

The outline of the dissertation is as follows:

Chapter 2. Literature Review

Chapter 3. Research Design

Chapter 4. Data mining

Chapter 5. Self-organizing maps

Chapter 6. Discussion, Conclusion and Recommendations

Chapter 2

LITERATURE REVIEW

2.1 Introduction to Insulation System

It is essential to give a brief overview of the machine construction and the insulation system inside the stator and rotor. In addition, a few diagnostic tests that are commonly used are explained in brief below.

2.1.1 Machine Construction

As a general rule, the conversion of electrical power takes place in the air gap of an electrical motor. In induction motors, the rotor does not receive electric power through conduction, but by induction in exactly the same way as the secondary of a 2-winding transformer receives its power from the primary. Polyphase induction motors are extensively used for various kinds of industrial drives.

An induction motor consists of two major components:

a Stator through which the input current flows and is also called armature.

b Rotor, which converts it into mechanical energy and is also called the field.

The stator is made up of copper conductors, the stator core and insulation system. "Unlike copper conductors and the core, which are active components in making a motor function, the insulation is passive. It tends to increase the machine size, cost, and reduces efficiency, without helping to create any torque or current" [6]. The life of the motor is often limited by its electric insulation system, which is made of organic material as the main ingredient. The insulation system acts as a barrier between the conductors and the conductor and the ground. The insulation system should have good thermal, mechanical and electrical properties. Good thermal properties means that the heat produced at the copper conductors should be transferred to the cooling system, so that overheating does not occur. The insulation system should also be mechanically strong so that the conductors are held tightly in place to prevent movement.

There are three basic stator windings structures that are employed in ac machines [6]:

a Random-wound coils: mainly used in low voltage machines

b Form-wound coil type: mainly used in medium voltage machines

c Form-wound coils -Roebel Bar Type: mainly used in large generators

2.2 Testing of insulation system on stator

Testing and monitoring of motors are an important part of maintenance. These are tests for the stator winding, rotor winding and core. Testing is done to assess the condition and remaining life of the winding. There are two ways of performing tests:

a On-line testing

b Off-line testing

There are many tests that can be performed to understand the condition of the motor, but performing all the tests is generally impractical and unaffordable. So, visual inspection and information of the previous history of the machine, helps to select specific tests that can be done. Decisions must be made regarding which of the many possible tests should be performed, to best predict a motor's failure or remaining life. An informed assessment of an explained combination of tests will give the best advanced notice of a failure. When dealing with the electrical concerns of the motor, the question of whether or not to do high voltage testing often arises. The insulation system of a motor consists of the groundwall insulation, the phase-to-phase insulation and turn-to-turn insulation. To properly test the total insulation system several different tests must be performed.

The diagnostic tests included are insulation resistance, polarization index, capacitance, dissipation factor / Tan delta, partial discharge, and ac and dc hipot tests. Any one test could not assess the complete condition of the insulation system. Thus, a group of tests have to be done at regular intervals to know whether the insulation system is deteriorating or not.

Tests related to the off-line stator winding assessment are discussed below.

2.2.1 Insulation resistance and polarization index

The tests assess insulation resistance, pollution and contamination problems in windings.

Developed early in the 20th Century, the insulation resistance (IR) test is the oldest and most widely used diagnostic test for assessing the quality of insulation to ground.

The main property of insulation is its resistance, if insulation does not have resistance it is not an insulator. So the resistance is measured and based on its trending, assessment is done of the condition of the insulation system.

In this test, the motor frame is grounded, and the test instrument (megohmmeter) imposes a dc voltage (typically 500 V, 1000 V, or 2500 V) on the motor winding and measures the current. A sound winding yields a result in hundreds, or thousands, of megohms. "According to the IEEE Recommended Practice for Testing Insulation Resistance of Rotating Machinery, prescribes as a minimum acceptable reading 1 MΩ plus 1 MΩ /1000 V of the motor's rated voltage for motors made before 1970 and 1GΩ for motors after 1970" [13].

IR test readings are highly sensitive to temperature and moisture. A 10 °C increase in temperature can reduce the insulation resistance by 5 to 10 times. The effect of temperature is different for each insulation material and type of contamination. It also makes trending useless; unless the measurement temperature is always the same.

Thus the **polarization index (PI)** test was developed to make the reading less sensitive to temperature. Applying a constant DC voltage, in the form of a megger test, for a period of 10 minutes will result in a gradual increase in the resistance-to-ground (RTG) reading. This is a result of charging the insulation system, much like a capacitor, which causes a reduction in the absorption current. Per Ohm's law, I(current) = V(voltage) / R(resistance). Therefore, the reduction of this absorption current must result in an increase in the resistance. The ratio of ten-minute RTG by the one-minute RTG, is clean and dry, if the value is greater than or equal to 2.0.

"PI is less than 1, the winding is wet and contaminated" [6]. "PI confirms a dry condition of the winding and the absence of cracks in the insulation; they do not necessarily imply a good condition of the tested winding insulation" [1]. In other words, motors with defective insulation systems can give values close to or greater than 2.0.

If IR tests give a reading below the minimum, then the winding should not be subjected to HIPOT testing. If IR or IP test results are below the minimum then the winding is contaminated or wet.

Assessment: Insulation resistance (IR) is an inexpensive and less time consuming test. Its limitation is that it is sensitive to temperature and humidity. Polarisation Index (PI) nullifies the effect of temperature, but can reduce the effect of humidity. Trending is not possible on IR. If IR is high, the PI will not give any additional information. It is not a destructive test.

2.2.2 Capacitance test

Measurement of the winding capacitance can sometimes indicate problems such as thermal deterioration or saturation by moisture within the bulk of the insulation. This is useful for smaller random and form wound motor stators, or very large direct-water-cooled generator stators that may have water leaks.

The capacitance tests are generally done at near phase voltage with commercial capacitance bridges, since the gas or moisture within the groundwall is usually a small percentage of the insulation system. So the change in value is very small even for a significant deterioration. Thus, the measurement device should have an uncertainty of measurement of less than 0.1%. Capacitance bridges can easily achieve this precision.

If over the years the capacitance is decreasing, then the winding is likely to have experienced thermal deterioration. If the capacitance is increasing, the winding has absorbed moisture from the environment, a water leak has occurred in the winding, or electric tracking is present. A single measurement of the capacitance has little diagnostic value. The key for interpretation is trending. If the entire winding is affected, then the capacitance test is more likely to detect it.

Assessment: It is an indirect PD test and is useful when trending is done. The limitation is that, if the defect is only in a few locations, this test will not indicate it. It is a non-destructive test.

2.2.3 Tan delta test

The ideal stator coil insulation system can be represented as high voltage capacitor where the insulation acts as the dielectric and the conductor and core act as the plates of the capacitor. The tan delta test is used to measure the dielectric loss that occurs in the insulation system. There are two ways of measuring this loss, they are tan delta or dissipation factor and power factor.

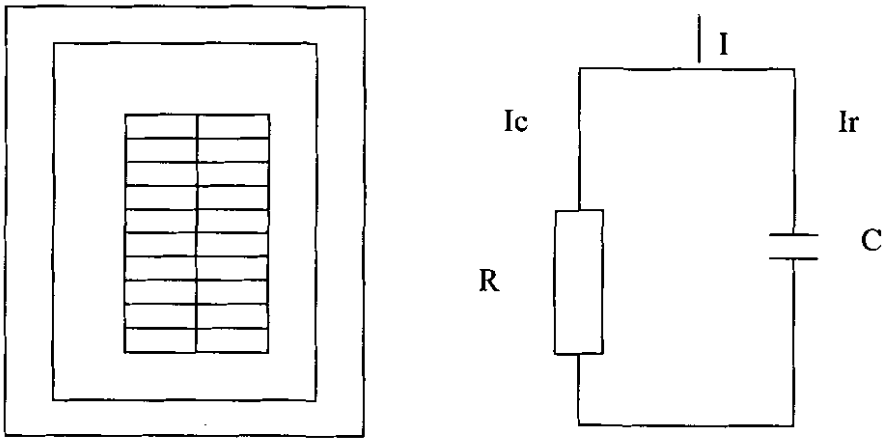


Figure 2.1: Cross section of conductor in stator and equivalent circuit.

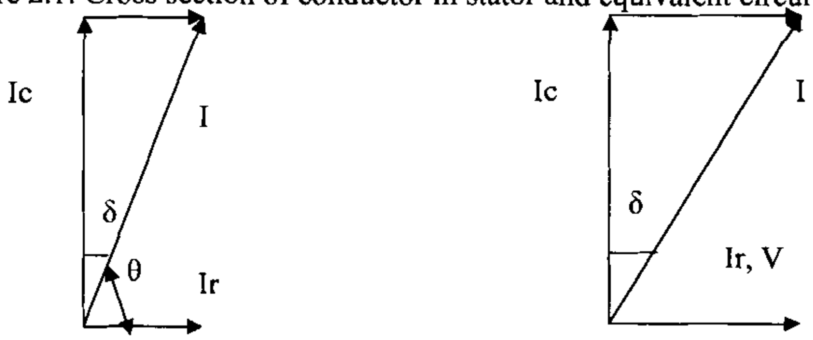


Figure 2.2 : Tan delta for a good and bad insulation

Tan delta, as the name suggests is the tangent of the angle δ (Delta) formed between the total current and the capacitive current flowing through the system. Power factor is the cos of angle θ (theta) formed between the voltage and current. The sum of angle delta and theta is ninety degrees. "For small angles, angle delta in radians also equals tan delta" [8].

The theory behind tan delta testing is that, when voltage is applied "the polar molecules oscillate in a solid medium causing friction " [6]. At lower voltages, the losses are at molecular level. Thus, the condition of the motor insulation system is not apparent and the losses also depend on the insulation material. This is known as dielectric absorption.

Other than dielectric absorption, ionization losses also occur at higher voltages. These losses are caused by partial discharge that occurs is the voids when the air becomes conductive. The number and size of the voids give a good indication of the condition of the machine. So the higher the number and the larger the size of the voids, the higher the tan delta losses.

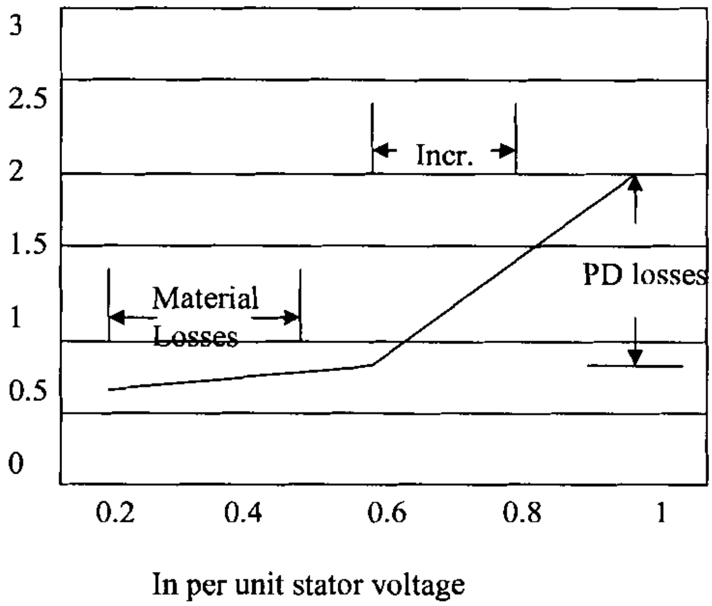


Figure 2.3 : Explanation of the graph of tan delta.

The tan delta is measured with a balanced bridge-type instrument, e.g. a Schering bridge. In the figure 2.4, the Schering bridge is used to measure tan delta and capacitance of a single coil.

The Cn is a standard capacitor, Cx is the coil of the machine under test, R3 and R4 are variable resistors and C4 is a variable capacitor. The variable resistors and capacitor are adjusted till the null indictor shows zero. The value of the variable capacitance and resistance can be measured when the bridge is balanced. The tan delta can be calculated from the measured resistance and capacitance. "It is a standard practice to use guard rings to confine the test area to the coil cell region and prevent external discharges and current flow in the end turn corona suppression from affecting the readings" [8]. The tan delta can be done on individual phases and on the three phases together as well.

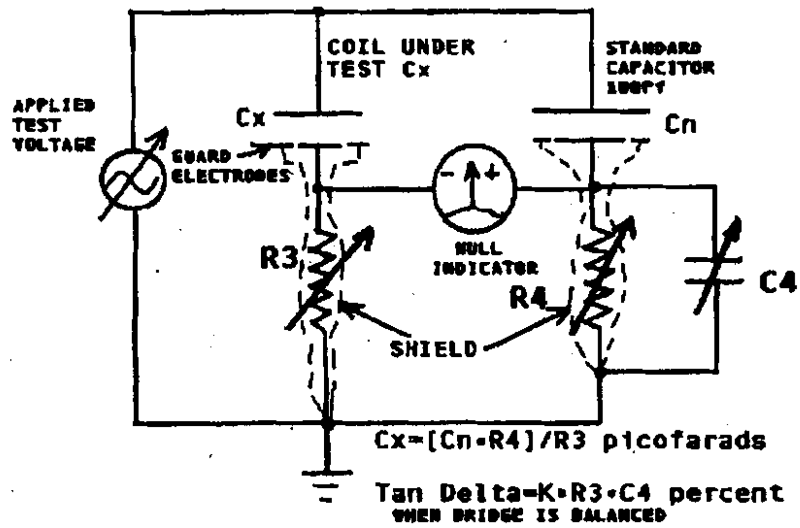


Figure 2.4 : Tan delta and capacitance measurement of a coil with Schering bridge [8].

"PF measurements have been made for years on high voltage stator coils as a means to determine how well the coils' consolidation is and to obtain a measure of the quality of the insulation system on newly manufactured stator coils" [8]. Tan delta or PF measurements are also made on stators that have been in service and on coils after being subject to voltage endurance and thermal cycling tests. If coil insulation is well consolidated, properly cured with low void content, the tan delta tip-up should also be quite low.

Tan delta tip-up, is the difference that tan delta measurements made at two diverse voltages. This is a good indicator of the condition of the insulation system. According to B. K. Gupta, "in significantly deteriorated insulation almost all the defects may contribute to high dissipation factor even at low voltage. When the voltage is raised some of the defects may get carbonized and thus deactivated, resulting in a slight decrease in the dissipation factor" [1]. This point is worth noting regarding the behaviour of deteriorated insulation systems.

Assessment: Tan delta and tip-up tests are useful maintenance tests for trending. It is also used for customer acceptance and quality control tests. "The limitation is that the test gives the average loss over the entire sample. Thus it is not sensitive to a few deteriorated coils in the windings" [6], [9]. "It does not take into account slot discharge in modern epoxy windings above 6 kV" [6]. Stress grading installed on the motor or generator insulation systems can influence the results. Thus initial readings are not very significant.

Table 2.1 Tan delta and tip-up tests

HISTORY	DEVELOPMENTS	PASS/FAIL CRITERIA	LIMITATIONS	ASSESSMENT OF REMAINING LIFE
Historically, this test was meant to assess the quality of impregnation and degree of bonding in a newly manufactured stator coil [8].	The tip-up test is most successful with the older asphaltic and shellac micafolium windings, where delamination is predominant [5].	In an ideal insulation system Tan delta should be zero. Practically the lesser the value the better the insulation.	The test gives the average loss over the entire sample. Thus it is not sensitive to a few deteriorated coils in the windings [5], [6].	A single reading alone cannot provide any reliable information on the remaining life.
However since 1950, it has been used as a diagnostic test [6].	As the modern technology has improved the techniques and advancement in resin technology, the voids are less and smaller in size [12].	The test is done using a Schering bridge. When the test is done on the coils, a minimum of 2 voltage levels are taken.	It does not take into account slot discharge in modern epoxy winding above 6 kV [6].	Being a diagnostic test, the condition of the insulation can be known by repeating the test for specific intervals and recording the results.

HISTORY	DEVELOPMENTS	PASS/FAIL CRITERIA	LIMITATIONS	ASSESSMENT OF REMAINING LIFE
It was the time when asphaltic and micafolium windings were major insulation systems used.	Tip-up is an indirect measure of PD activity and in that aspect it is inferior to any PD test [5].	One voltage level taken is less than DIV but enough to cause dielectric loss. While the other voltage is close to the actual service voltage of the coil.	Stress grade installed in a motor or generator can influence the results. Thus leading to inaccurate results	Thus giving a better idea of the trend of the insulation. The reading of a winding depends on the insulation system.
With epoxy bonded mica tapes and advancement in resin technology, the test is not as useful as it was in 1950s-1960s.	So, Tan delta and tip-up tests are useful customer acceptance and quality control tests.	When the test is done on the whole stator, voltage grading causes increase in the reading.		Cured Epoxy Mica reads 0.5% while a good asphaltic insulation reads 3.0% [5].

2.2.4 Partial Discharge

Partial discharge (PD) is an incomplete or partial electric discharge between layers in the insulation or either insulation and conductor. When talking in terms of motors, partial discharge occurs in gas filled voids in the insulation system. Voids are created due to the degradation of the impregnated resin. The void can be internal to the insulation system due to improper impregnation, thermal deterioration, load cycling, or can be at the surface of the coil due to loose coils, stress grading deterioration, contamination and inadequate spacing.

In rotating machines it has been observed in the past that, the stator runs for extended periods of time in the presence of PD and the intensity is higher when compared to other electrical apparatus. Therefore the main aim of PD tests in the stator is to:

a To ascertain the discharge intensity.

b To locate the PD site in terms of density and configuration of PD pulse distribution patterns.

2.2.4.1 Principle

When voltage is applied at 50 Hz or 60 Hz, the voltage across voids may exceed the breakdown voltage for its size and shape. In such a case, there is a flow of electrons across the void. This current pulse (I=dq/dt) is of a short duration, a few nanoseconds, which is called a partial discharge. The occurrence of PD is a statistical event and cannot be predicted. Once the breakdown occurs the voltage drops to a lower level, which is enough to sustain the discharge. Most of the instruments can detect the initial break down pulse of the PD. As the rise time of the pulse is a few nanoseconds the frequency is in the MHz range.

"Depending on the geometry of the machine, the location of the PD and type of insulation, the characteristics of the PD pulse vary. The disadvantage of this is that no one instrument can detect all the PD pulses. PD itself cannot be measured on motors and therefore the voltage is measured. This makes it very difficult to compare readings between sites with different measuring instruments.

As mentioned earlier each insulation system has PD, our aim is to check the level of PD.

"The magnitude of the PD is proportional to the size of the void, so the larger the pulse the bigger the void" [6]. So PD testing is able to indicate the worst deteriorated portion of the winding.

2.2.4.2 Test

The partial discharge test can be done in two ways:

a Off-line

b On-line

2.2.4.3 Off-Line Test

This test is done on machines rated for 4 kV or more [6]. In this test the winding is energized by an external supply. In the usual test procedure the ac voltage is gradually raised until PD pulses are detected. The voltage at which the PD starts is called discharge inception voltage (DIV). Then the voltage is increased to the normal line-to-ground voltage. The maximum PD pulse is recorded with a pulse height analysis or read from the screen of an oscilloscope. As the ac voltage is decreased, the voltage at which the PD disappears is called the discharge extinction voltage (DEV). The DIV is usually higher than the DEV.

Although the actual test takes 30 min., the setup for the test can take up to several hours. As there are no standards the test has to be conducted at regular intervals to assess the condition of the insulation system. For proper trending to be done or to compare readings with similar machines, the test conditions should be similar, as the PD is affected by change in load, voltage, temperature and pressure.

"As the ageing progresses the PD magnitudes will increase and the DIV and DEV will decrease. The PD test gives more information than the tip-up test" [5].

There are several disadvantages to this test. First it energizes all the coils to the same voltage including the neutral end. Thus PD that is absent in the actual working machine is also included in the observation. This may mislead the user to the condition of the winding. Slot discharge that occurs due to mechanical vibrations is also absent in this test.

2.2.4.4 On-Line Test

The on-line test is similar to the off-line test except that no external source is required to energize the stator. Sensors are installed in the machine to take the readings of PD activity. High frequency pulses travel through the stator winding in three different ways: Transmission, capacitive coupling and radiation.

Based on this property of the pulse three different sensors are used:

a 80 pF high voltage capacitor, with epoxy-mica dielectric, for motors, hydro generators and small turbo generators.

b Radio frequency current transformer (RFCT) installed on the ground lead of the surge capacitor. This is used with small generators.

c Stator slot coupler (SSC) antenna-like device, placed between top and bottom of the coil, under the wedges. For large turbo generators (>100 MW).

2.2.4.5 Capacitive coupler, epoxy-mica capacitor (EMC)

The Capacitive couplers provide less impedance to a high frequency PD pulse and tend to block a 50 Hz or 60 Hz voltage signal. The 80 pF capacitor is used, because its signal to noise ratio is large. "It has a thick dielectric so the chances of capacitor failure are greatly reduced" [6]. These capacitors are permanently attached to the phase circuit ring or the isolated phase busbar. The coupler is rugged and reliable, and does not risk the machine when it is installed.

2.2.4.6 Stator Slot Couplers

When the PD has to be distinguished from external and internal noise, a stator slot coupler (SSC) is more helpful. It is an ultra wide band detector that is installed under the wedges in the stator slots. There is no electrical connection, so it is sensitive to PD in the same slot as the windings. It can detect signals with a frequency content from 100 MHz to 1000 MHz [6]. The PD pulse can be distinguished from noise based on its pulse width. "While the noise has to travel and gets distorted, the pulse width is near 20 ns to 1 μs" [11].

SSC is often used on generators with high output ratings. It is rarely used in motors, because motors don't suffer from the same level of excess internal noise.

The limitation with on-line testing, which is not present in off-line testing, is that the stator winding PD is superimposed on the electrical interference. If the noise is not eliminated, the user can be misled.

2.2.4.7 Interpretations

With all the data that is available from the machine, it is important that it is interpreted correctly. Information from a single test is not sufficient to draw any conclusions about the condition of the insulation system. Trend analysis is the preferred way to interpret the data. It is important that care should be taken to ensure that the various tests have similar measuring and operating conditions. PD is affected by change in voltage, load, temperature and pressure. Research is being done to use neural networks and artificial intelligence to interpret the data, but it has not yet been commercialized.

In a linear pulse density phase plot, if the PD is centred near 45° of the AC cycle for a negative pulse and 225° for a positive pulse, this is a classic pulse. We can interpret faults occurring in the insulation system based on the polarity predominance. There are three possibilities:

a Positive predominance - This indicated that the PD is originating on the surface of the insulation. The faults can be slot discharge, end windings tracking and gradient or semicon coating deterioration. It is usually repairable.

b Negative predominance - This indicates the PD is near the conductor or in the insulation system. It is not repairable as it can be a void created due to improper manufacturing or load cycling. To slow deterioration down the operating parameters can be restricted.

c No predominance - This indicates that the tape insulation layers have began to separate. This can be due to poor impregnation and it is not repairable.

Positive predominance and load dependent PD usually indicates a loose coil. Positive predominance without load dependence is an indication of electric slot discharge.

The effect of temperature can also be both negative and positive. Negative effects usually occur in asphalt and polyester windings. The size of the voids reduce due to expansion of the insulation material. Large negative effects indicate delamination.

Positive effect indicates deterioration in grading coats. Non-classic pulses also indicate faults. Usually more than one fault occurs at a time, therefore isolation of the various effects is difficult.

Assessment: Based on trending and comparison, the test gives a better indication of whether or not there are any loose coils in slots or thermal degradation. Improper curing (not as an installation test) and electric tracking can be determined by a PD test. PD cannot be calibrated and that is one of the major limitations of this test [10]. No standardized unit is measurable for PD tests. It can be measured in pC, mV, dBm (decibels) or mA. PD in some cases can be the symptom and not the root cause. Thus a specific value for PD is not possible [10]. Other tests are required to confirm the fault.

Table 2.2 Partial discharge

HISTORY	DEVELOPMENTS	PASS/FAIL CRITERIA	LIMITATIONS	ASSESSMENT OF REMAINING LIFE
Since the 1950's methods have been developed to measure PD activity [5]. Bartnikas in 1969 employed the first pulse height. Analyzer. (PHA) [7].	Initially experts were required to distinguish noise from signals. And to correlate PD quantities and condition of the insulation.	No standardized unit is set for PD test. It can be measured in pC, mV, dBm (decibels) or mA.	PD cannot be calibrated; this is one of the major limitations of this test [10].	Based on trending and comparison, the test gives a better idea if there are any loose coils in slots, thermal degradation.
Kelen first pioneered the permanent display of PD data with introduction of pulse phase analysis (PPA) (1976) [7].	Research is being done to simplify the test.	The measurements of PD cannot be calibrated as the machine has both inductive & capacitive properties [10].	Even though a lot of research has been done, there are still many unknowns.	Improper curing (not as an installation test) Electric tracking can be determined by PD test [6].

HISTORY	DEVELOPMENTS	PASS/FAIL CRITERIA	LIMITATIONS	ASSESSMENT OF REMAINING LIFE
Conventional capacitors & RF sensors since 1951 [7].	Alternate method to eliminate noise by using 2 sensors, is also used [7], [5].			Other tests are required to confirm failure.
Tanaka was perhaps the first to do research on patterns from both PHA & PPA [7].	Research is being done to use artificial intelligence and neural network is the test [7].	PD in some cases can be the symptom and not the root cause. Thus a specific value for PD is not possible [6], [7].		
Whotten was among the first users of the pattern recognition approach-based on artificial intelligence called expert systems [7].	On-line continuous PD monitoring is more popular than off-line PD test. Because it is more cost effective for frequent testing.	Based on trending or comparison between diff. phases, the condition of the insulation can be determined.		

Table 2.3 History

MATERIAL	THERMAL	VOLTAGE	PROPERTY	PROCESS
Natural materials Cellulose, silk, flax, cotton, wool and natural resins like pitch, shellac, rosin, linseed oil, varnish Cambric was the earliest material used in stator ground insulation [2], [3].	Class A 105 C [3].	Restricted to 2300V	Heat transfer is relatively poor as is resistance to ingress of moisture and oil.	Haefley process[2].
Shellac Micafolium It is thermoplastic insulation system. Mica Flakes are bonded together by shellac into sheet to a Kraft paper [2], [3].	Class B 130°C [3].		Evaporation of volatiles in Shellac, results in the contents of the voids to be high. So the PD is high and there is reduced heat transfer [3].	Mica Flakes and shellac were made into sheets and they were hot pressed into the slots. The end windings are wrapped in varnished cambric or Asphalt-mica [3].

MATERIAL	THERMAL	VOLTAGE	PROPERTY	PROCESS
Asphalt-Mica system It is a thermoplastic insulation system. The common method was to impregnate mica splitting sheets with drying oil-modified asphalt varnish solution [3].	Class B 130° C [3].	For 6600V and higher.	Copper winding heats up faster than the stator core. Thus tape separation or girth cracks took place and led to the failure of many generators during the 1940s to the 1960s. Service heating caused expansion and tight fitting to coils but created voids. To avoid PD , the design stress was limited to <2 kV/mm.	Tapes were applied by hand. Wet coils were then to go through the VPI process. The coils are placed in an autoclave and vacuum is applied for drying. Then hot asphalt is flooded, at high pressure for proper impregnation. It is then hot pressed for uniformity of thickness. Armor the coil by applying ferrous asbestos tape to control PD between stator core and coil surface. Carbon black was added to varnish for desired resistivity.
Paper. One of the major developments was the replacement of solvent-borne natural and synthetic resins with solventless synthetic resins. These materials are normally thermosetting under the action of heat catalysts, hardeners or radiation. In addition to improved thermal stability and physical properties, the elimination of solvents makes their application more environmentally friendly and less likely to form voids within the ground wall. There are two families that are important a) Polyester b) Epoxies				
Polyester bonded Mica tapes It is a thermosetting insulation system. This resin was typically used to impregnate mica splitting, that were laid down on a thin, pliable sheet of backing materials [3].	Both class B 130 °C and class f 155 °C [3].	For small and medium construction motors.	The process is very labour intensive. The bar to bar copper strands connections required to complete a coil and the insulation of these joints is slow and it requires highly paid skilled winders.	Modified VPI afterheat drying and vacuum cycle. Then low viscosity impregnating materials consisting of 1% to 2% of catalyst admitted. The pressurizing time depends on the number of layers to be penetrated.

MATERIAL	THERMAL	VOLTAGE	PROPERTY	PROCESS
Epoxy bonded Mica Tape It is a thermo setting insulation system. Suitable epoxy resin is used to impregnate and cure the mica tape. It cured a stronger polymer and tends to improve the thermal stability. Due to the cross-link reaction the stable polymer contracts very little on hardening, only between 0.05% and 2%, whereas polyester compound may shrink as much as 10%. Compared with polyester, the ground wall was less prone to delamination [2].	Class F 155°C.			Modified VPI.
Global VPI System Due to the high cost of manufacturing led to a new system. In this soft coils (green coils) which are less expensive to make and are easily fitted in the stator is used. All connections are made before the final impregnation of the winding [2].		This process is used even for stators in excess of 200 MVA.	This reduces the handling operations for the stator and lower the cost. Even though polyester is cheaper and less stringent manufacturing controls than epoxy. Nowadays epoxy is usually preferred.	

MATERIAL	THERMAL	VOLTAGE	PROPERTY	PROCESS
Epoxy bonded mica tape (Resin Rich) In this system all of the binding and filling resin was either in the tapes, or in the brushing used between layers, as the tapes were wrapped on the coil. The simplest approach for curing the resin involves the use of heat press. Where the temperature and pressure are applied in a controlled fashion. A more elaborate process will deliver a largely void-free ground wall system suitable for operating at a high dielectric stress [2].	Class F 155 °C [3].	Large machines.		A better ground wall insulation, involves an initial vacuum drying stage in am autoclave. Next the stator bar enclosed within the mould angles have the groundwall insulation cured under pressure at elevated temperature [3].

2.3 Summary of chapter 2

A brief introduction to the insulation systems of motors is given. Insulation tests and the electrical aspects of the insulation system have been explained in detail. The tests that are discussed in full are insulation resistance, polarization index, capacitance test, tan-delta test and partial discharge. The principle behind the tests, the procedure to measure the values of the tests, interpretation of results and history of tests have been included. The history of the insulation systems of the motors has been tabulated. The history of various changes in the material used for insulation of motor, process of applying the insulation to the coils, and properties of the insulation have also been discussed. This forms the background of the data that has been explained in detail in chapter 3.

Chapter 3

RESEARCH DESIGN

3.1. Introduction.

This chapter outlines the research methodology and data used in the study. The rationale behind the methodology of research, techniques used for data analysis, data collection and limitations has been explained in this chapter.

3.2 Previous Research

In the research mentioned below artificial neural networks were used in maintenance of rotating machines.

a "Using Improved Self-organizing map for partial discharge diagnosis of large turbo generators" by Yu Han and Y.H. Song [14];

b "Methodology for on-line incipient fault detection in single-phase squirrel-cage induction motors using artificial neural networks" by Chow, M. and Yee, S. O. [15], and

c "The Application of signal processing and artificial intelligence techniques in the condition monitoring of rotating machines" by N. T. van der Merwe [16].

3.3 Research Methodology

The main objective of the research is to search for patterns within a fairly large amount of machine information. Thus, initially statistical analysis was used to understand the information. Then, neural networks were used to visualize patterns and classify the data. Similar to the pervious research, an attempt has been made to use artificial neural networks to understand the correlation between test results and the condition of the machine.

Initially the data is usually in tabular form and by looking at the data, very little can be understood. Statistical analysis has traditionally dominated the area of understanding the different aspects of the data. There are many statistical tools available. The basic tools include scatter plots, histograms and box plots etc.

In scatter plots, two values are plotted on the 'x' and 'y-axis. It is a simple and effective method to give an initial understanding of the data. Histogram divides the given data set into small intervals of equal length, which is represented by the width of the blocks. The height of each block is dependent on the frequency of the data in the given range. "The information on location, spread, and shape that is portrayed so clearly on a histogram can give a user strong hints as to the functioning of the physical process that is generating the data" [17]. The common distributional shapes and terminology are shown in the figure 4.2.

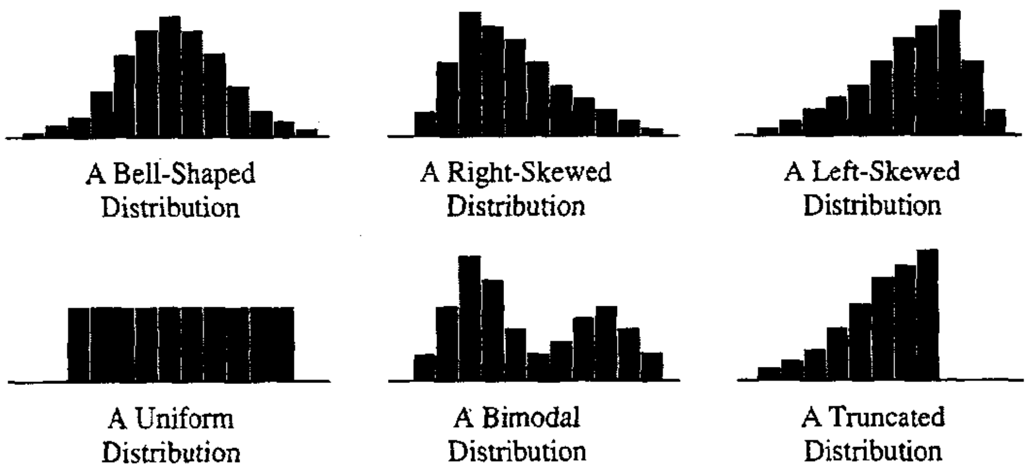


Figure 3.1 : Distributional shapes and terminology of histograms [17].

The descriptive statistics of the data is mention in section 3.4. It includes the minimum and maximum values, mean and standard deviation of each variable. **(arithmetic) Mean** is sum of all values divided by the number of values. **Standard deviation** is the measure of difference of the values from the mean. Mean gives the centre of the data while standard deviation gives variation of the values from the mean.

The advanced statistical analysis tool includes time series analysis. Time series analysis requires a substantial amount of data at regular time intervals to have reliable results. The data available had a maximum of five to seven sets of readings, which are not at regular intervals, so time series analysis was not done on this data. The basic statistical tools have been used at the data understanding stage of data mining in section 4.2.2.

A data mining method was used to analyse and apply pattern recognition in the given data. The reason for choosing data mining for this research is because data mining is a class of techniques that help find patterns in data. It is popular for forecasting and classifying people and things into groups based on specific patterns. One of the advantages of data mining is that it is a step-by-step process, which is useful when dealing with fairly large samples of data. Data mining also helps in indicating which features will give better results and it is able to look for new correlations that are not apparent. Data mining is discussed in detail in chapter 4.

3.4 Description of the Data

The research and conclusions are based on the data that has been collected. Therefore, it is important to understand the type of sample data that has been used for the research.

The data was collected from two sources. A major part of the sample data was collected by A.D.W. Wolmerans [21]. The second source of data was a large repair company in Johannesburg. The time period during which the measurements were taken from 179 machines ranges from 1982 to 2005. The data comprises of tests measurements of Tan delta and capacitance done on all of the three phases separately and together. To understand the insulation condition of the motor the test results should be seen as part of a bigger picture. The attempt here is to look at those test measurements in context with the type of insulation and the voltage rating. The class B insulation material had large mica flakes thus it can withstand higher tan delta, while class F insulation material had smaller mica flakes.

Thus the data was divided based on insulation material. To include the design aspect the data was again divided into 6,6 kV and 11 kV.

To analyse the data better, it was divided into four groups based on the voltage rating and insulation system class. The four groups are:-

a Group 1, consists of 6.6 kV motors with class B insulation systems

b Group 2, consists of 6.6 kV motors with class F insulation systems

c Group 3, consists of 11 kV motors with class B insulation systems

d Group 4, consists of 11 kV motors with class F insulation systems

3.4.1 Group 1, consists of 6.6 kV motors with class B insulation systems

The data consists of 11 machines, 5 of them are 1272 kW, Squirrel cage induction motors with a CACW cooling system. It was used to drive a pump in a clean indoor environment. The tests measurements were taken between 1982 and 1993. There where three tests recorded; tan-delta test, capacitance test and partial discharge test.

Table 3.1 Descriptive statistics for group 1.

Variables	Mean	Minimum	Maximum	Std. Deviation
Tan Delta	16.6227	5.00000	49.600	8.2501
Tip-up	0.3732	-0.02000	1.480	0.2986
Capacitance	51.2415	41.00000	57.200	3.8348
% Change in capacitance	0.4852	0.00000	2.198	0.5176
Partial Discharge	187.4175	0.00000	1440.000	255.5870

3.4.2 Group 2, consists of 6.6 kV motors with class F insulation systems

This group has 72 machines; the details are given in the table below. There where three tests recorded; tan-delta test, capacitance test and partial discharge test.

Table 3.2 Details of group 2.

Rated power	550 kW to 10 500 kW
Motor Type	Squirrel cage, Slip Ring, Synchronous
Driven Machine	Pump, Fan, Compressor
Number of poles	2, 4, 6, 8, 10
Cooling Method	CACA, CACW
Year of testing	1983 - 1993

Table 3.3 Descriptive statistics for group 2.

Variables	Mean	Minimum	Maximum	Std. Deviation
Tan Delta	23.46313	0.000000	150.000	21.8877
Tip-up	0.21883	-0.040000	4.500	0.2958
Capacitance	65.12168	0.000000	153.500	26.3951
% Change in capacitance	0.38117	-0.955414	6.522	0.6590
Partial Discharge	75.38084	0.000000	1300.000	180.5131

3.4.3 Group 3, consists of 11 kV motors with class B insulation systems

There are 23 machines that have 11 kV and class B insulation systems. The details are given in the table below. There where three tests recorded; tan-delta test, capacitance test and partial discharge test.

Table 3.4 The details for group 3.

Rated power	1430 kW to 7500 kW
Motor Type	Squirrel cage, Synchronous
Driven Machine	Pump
Number of poles	2, 4, 6
Cooling Method	CACW
Year of testing	1982 - 1993

Table 3.5 Descriptive statistical data for group 3.

Variables	Mean	Minimum	Maximum	Std. Deviation
Tan Delta	19.0583	1.00000	119.000	13.3370
Tip-up	0.4149	-0.05000	3.000	0.3931
Capacitance	36.2638	19.00000	43.350	6.1742
% Change in capacitance	0.4423	-3.13745	5.263	0.6043
Partial Discharge	140.3128	0.00000	1300.000	204.0928

3.4.4 Group 4, consists of 11 kV motors with class F insulation systems

This group consists of 73 machines that are 11 kV and F insulation systems. Once again there where three tests recorded; tan-delta test, capacitance test and partial discharge test.

Table 3.6 The details for group 4

Rated power	625 kW to 13 000 kW
Motor Type	Squirrel cage, Slip Ring, Synchronous
Driven Machine	Pump
Number of poles	4, 6
Cooling Method	CACW
Year of testing	1982 - 1993

Table 3.7 Descriptive statistics for group 4.

Variables	Mean	Minimum	Maximum	Std. Deviation
Tan Delta	25.3392	2.00000	110.700	16.5104
Tip-up	0.4176	-0.30000	2.620	0.3718
Capacitance	46.9554	16.00000	118.200	22.6184
% Change in capacitance	0.6535	-0.54496	49.758	1.1169
Partial Discharge	134.2433	0.00000	2000.000	218.5863

Comprehensive data sheets were available for the given machines, but most of them where incomplete. The information available about the machine are mentioned below. They are:

a year of commission

b altitude at which the machines were placed

c whether it was rewound

d the environment in which the machine was

e temperature of the machine when the tests where done f the measurements of tan delta, capacitance, partial discharge

The partial discharge test measurements are very erratic and incomplete, so it was not used for the purpose of analysis.

3.5 Limitations of the data and analysis

In this research an attempt was made to analyse the degradation of machine insulation. "It should be recognised that the electrical aging of the machine is seldom an electrical problem alone" [18]. The aging is affected by electrical, mechanical, thermal and environmental agents. These factors are briefly discussed below:

a Thermal stress: This stress is dependent on the operating temperature. When the temperature is above the threshold the losses in the copper conductor, core and windage etc increases. According to G. C. Stone, "the life of the winding will decrease by 50% for every 10 °C rise in temperature" [6].

b Electrical stress: This stress has been discussed in detail in chapter 2.

c Mechanical stress: "One of the mechanical stresses that affects the stator is the mechanical stress caused by power frequency current" [6]. The power frequency current creates magnetic force oscillations at twice the power frequency. The insulation of a stator coil, which is loose in the slot, can be damaged by the vibrations.

d Environmental stress: "The moisture content in the air, dirt on the overhang of the machine and other surrounding factors, can in effect lead to failure" [6]. These factors directly may not cause a failure directly however, but when combined with other stresses can accelerate the aging.

These factors that are mentioned above usually don't occur separately. Thus the deterioration in the winding insulation can be a result of more than one of these stresses. There are many aging mechanisms that affect the insulation of a machine, which is the reason why different insulation tests are required to understand the condition of the insulation.

Keeping in mind that the aging mechanism is a fairly complex subject, this research is an attempt to classify the machine data, based on the condition of the insulation. There are limitations regarding the sample size of the data available and quality of classification.

The limitations regarding the data are:

a The information on whether the above machines are still working or not were not available. Thus, we have relied on the assessment of an expert to validate the results obtained from the analysis.

b As no vibration measurements were taken, the effects of vibration on the coils in the stator slot are not taken into account in this research.

c Partial discharge measurements were not taken into account either as the measurements had a large percentage of incomplete data.

d Neither was absolute capacitance taken into account, because its measurement depends on dimensions of the machine. So to compare capacitance of different size machines would not give an accurate indication of the insulation condition.

e Machines with longer overhangs will have higher capacitance when compared to machines with shorter overhangs, and has no correlation with the condition of the machine. Thus, the measurement of capacitance could be misleading, if machines of different dimensions where compared.

f The design of the machines where unavailable. If two phases were in one slot, then the capacitance of that stator will be higher. It was better not to take capacitance into the analysis, but the percentage change in capacitance was taken into consideration.

g The measurements on the machines just before failure were not available, thus the analysis will focus on deterioration rather than failure of insulation.

h The data was measured under the supervision of an expert, so it is assumed that the measurements were accurate. However, large negative data values were not taken into account during the analysis.

i The data of machines with deteriorated insulation systems were less when compared to machines with good insulation systems. For neural networks the poor cases are repeated under the assumption that poor cases happening in industries will be similar to the data that is available, which is a limitation.

3.6 Summary of chapter 3

In this chapter the research methodology has been discussed. The main aim of the research is to find a relation between the insulation test results and the condition of the insulation of the motors. The data being used in the research has been discussed in detail as well as the reason behind splitting the data into four groups. The limitations due to the data and the analysis were also discussed.

Chapter 4.

DATA MINING.

4.1. Introduction

This chapter gives an introduction to data mining and explains the different steps that were taken to understand, explore and prepare the data for analysis.

4.2. Data Mining

Data mining is a field that has gained a lot of attention over the past few years. It can be applied to various fields, which deals with large amounts of data. The different fields vary from banks, cell phone companies, industries to research. In essences data mining is used to extract valuable information, to understand patterns or to help predict future behaviour based on available data. In the information age, where computational speed and accuracy is easily available, data mining is a valuable tool that should be used to its full potential.

Data mining as defined by M.J.A. Berry, "is the exploration and analysis, by automatic or semiautomatic means, of large quantities of data in order to discover meaningful patterns and rules" [19].

Data mining requires a good knowledge of the field in which the information is required and the method by which information is derived. In the present case that would mean a good knowledge of the working and construction of medium voltage motors, the method by which the data was measured and knowledge of self-organizing maps.

A process model of data mining from CRISP-DM is given below in figure.4.1 [20]. This model has been used partially to explain how data mining was used in the current research.

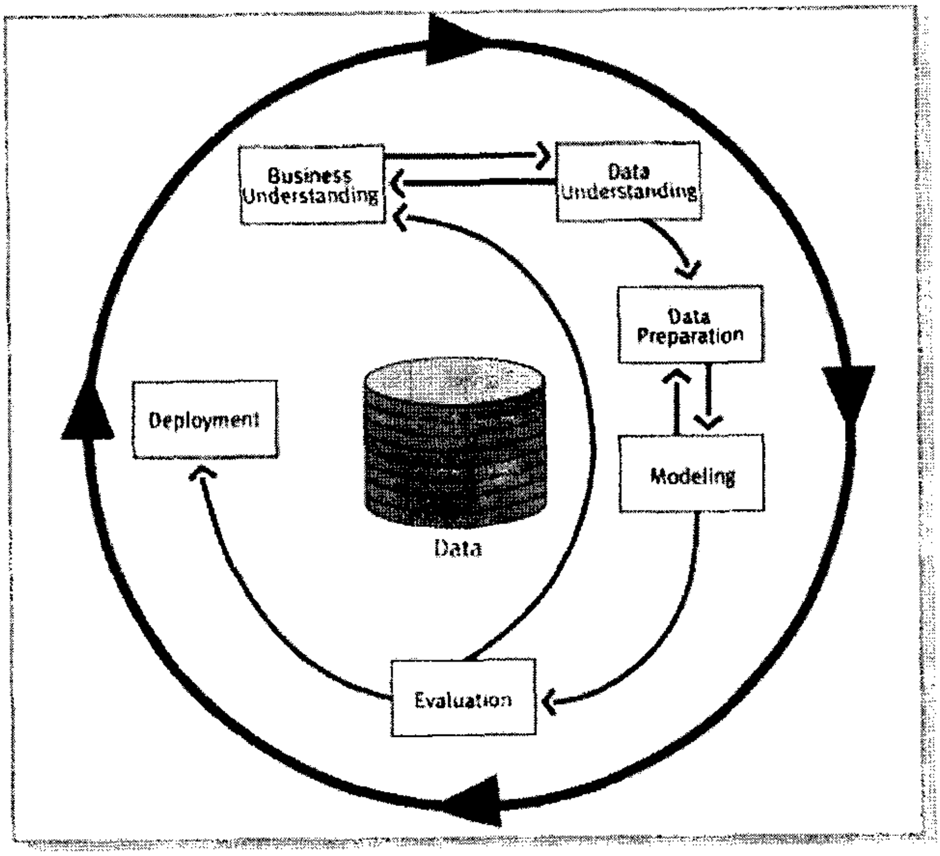


Figure 4.1: CRISP-DM process model of data mining [20].

4.2.1 Identifying the problem

Each step in the data mining process is important, but the business understanding is the most crucial stage. Ideally, one needs to be an expert on the field in which the data mining is being done and a specialist in the method of data mining as well.

Usually, people who have good knowledge of the working of the motors interact with the people who have good knowledge of the methods of data mining. In this stage, the question is defined and the desired solution is also discussed.

As motor insulation testing is a very broad topic, it was agreed to narrow down the scope of this data mining exercise. The main focus of the data mining was to assess or classify the machine data based on the condition of the insulation systems.

4.2.2 Data Understanding

As data is the central requirement for this process, a brief explanation of the data used in this research is given in chapter 3, section 3.4. In this section, an attempt is made to understand the correlation between the different variables that are available for the machines. The two absolute measurements available were Tan delta and capacitance reading. There were four calculated values derived from it. They are:

a) **Tan Delta difference (Diff):** It is calculated from the Tan delta and shows the increase in tan delta value for each step of voltage increase. For example, to calculate the tip-up at 40% voltage the difference of tan delta at 40% and 20% is taken. Similarly to calculate the tip-up at 60% is the difference between tan delta at 60% and 40%. Thus the tip-up value at 20% is zero.

b) **Percentage change in capacitance (PC)**: This is calculated from absolute value capacitance and shows the change in capacitance at each step in per unit voltage as a percentage change of capacitance at 20%. For example,

$$P\ 60\% = (C60\%-C40\%)/C40\%*100 \quad (4.1)$$

Where **the percentage change of capacitance at 60% is P60%, C60%, C40% and C20% are capacitance to 60, 40 and 20 per cent.**

c) **Tip-up:** The second data preparation was to calculate the tip-up.

$$\text{Tip-up} = (=T60\%\ -T\ 20\%)/2 \quad (4.2)$$

Where T60% is tan delta at 0.6 pu and T20% is tan delta at 0.2 pu voltage.

d) **Slope gradient of capacitance (CC):** The percentage capacitance change is takenas the difference of capacitance at 1 pu and zero voltages, divided by capacitance at 0 V. The capacitance at 0 V is obtained by extrapolating the graph to zero. The calculated values were taken from Dries Wolmarans's files after a conversation with him [21].

The STATISTICA ® software [23] was used to do the statistical analysis of the data. In the analysis both scatter plots and histograms are used together to present an effective and concise interpretation.

As mentioned in the section 3.4, that the data is divided into 4 groups, so each group is explained separately.

a) **Group 1, consists of 6.6 kV motors with class B insulation systems**

Scatter plots, histograms and box plots were plotted for each variable. There were a few observations made during this process of data understanding. The data at different per units voltages were plotted separately. At 0.8 pu and 1 pu voltages, the data formed two separate groups as shown in figure 4.2 for data at 1 pu, while at lower per unit values the data had no distinct groups. It can be inferred that at higher voltages the condition of the insulation is more apparent.

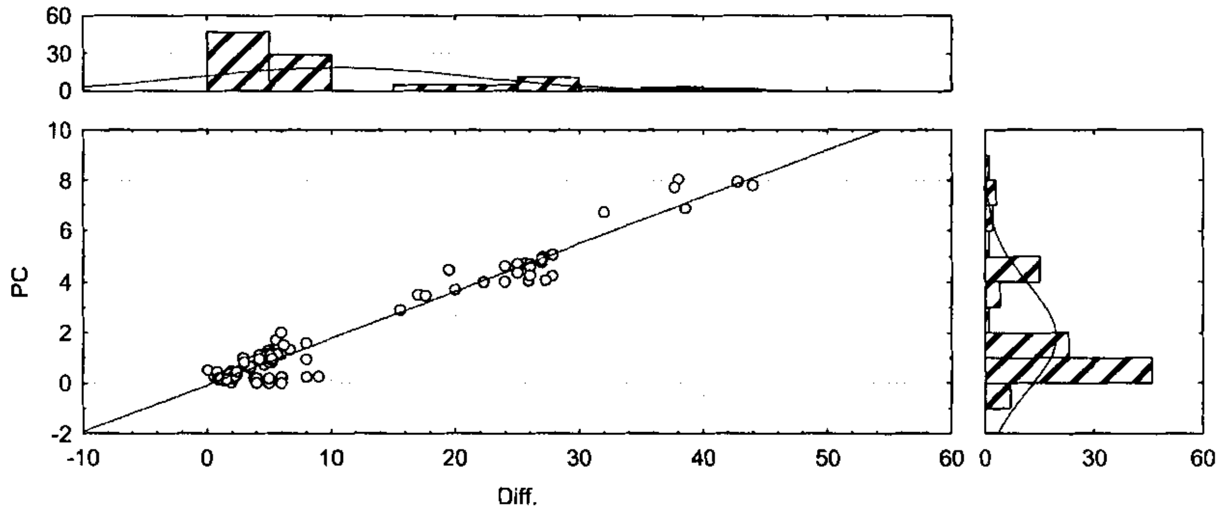


Figure 4.2: Scatter plot of Tan delta difference and Percentage change in capacitance at 1pu.

It was also interesting to note that there was a high linear correlation between tan Delta difference (Diff) vs. percentage of capacitance (PC) and tip-up vs. slope gradient of capacitance (CC) as shown in figures 4.3 and 4.4. It can be interpreted that, as the insulation ages both tip-up and change in capacitance increases almost linearly.

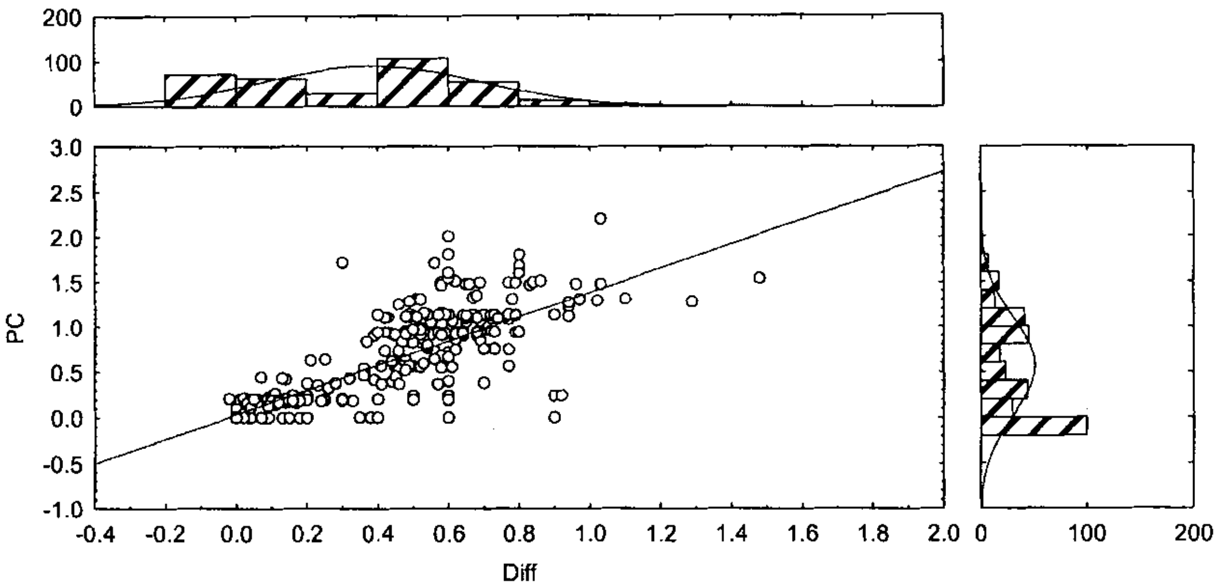


Figure 4.3: Scatter plot of Tan delta difference (Diff.) and percentage change in capacitance (PC) for the whole data from 0.2 pu to 1pu voltage.

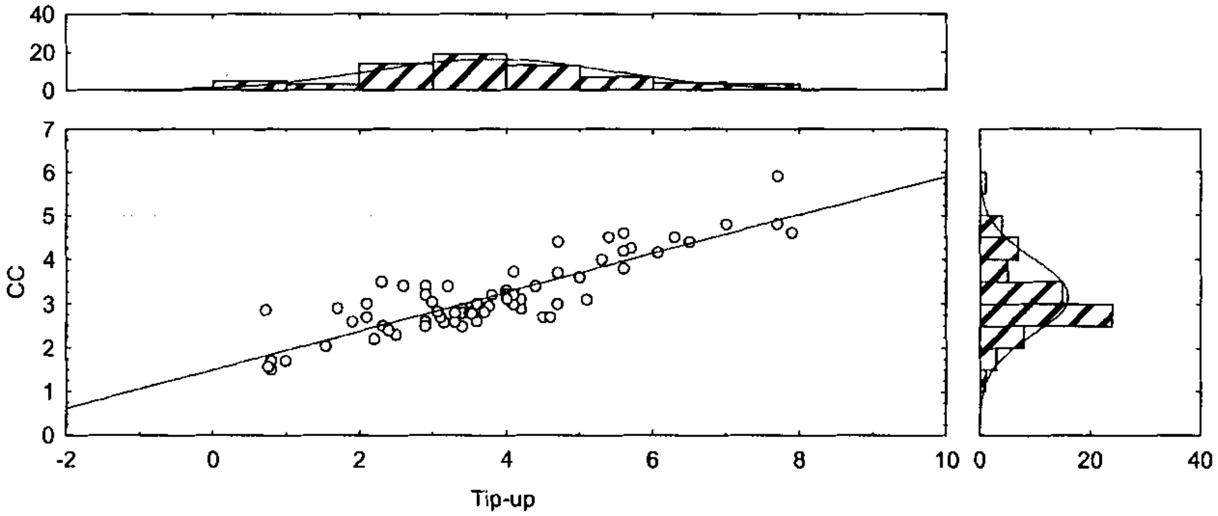


Figure 4.4: Scatter plot of Tip-up and slope gradient of capacitance (CC) for the whole data set.

b) Group 2, consists of 6.6 kV motors with class F insulation systems

The correlation between change in Tan delta a**Error! Bookmark not defined.**nd change in capacitance, as seen in group 1 (6.6 kV with class B insulation), can also be seen for this data group.

The values of test results are lower for group 2 data as compared to group 1 data. In a discussion with Prof. Jan de Kock, he stated that "the reason can be that older class B insulation systems have larger mica flakes when compared to newer F insulation systems".

Thus numerical guidelines will be different for class B and F insulation. The limitation in setting numerical guidelines is that, for different manufacturers the properties of the insulation may differ. So a uniform guideline for this research, based on the information available, is not possible.

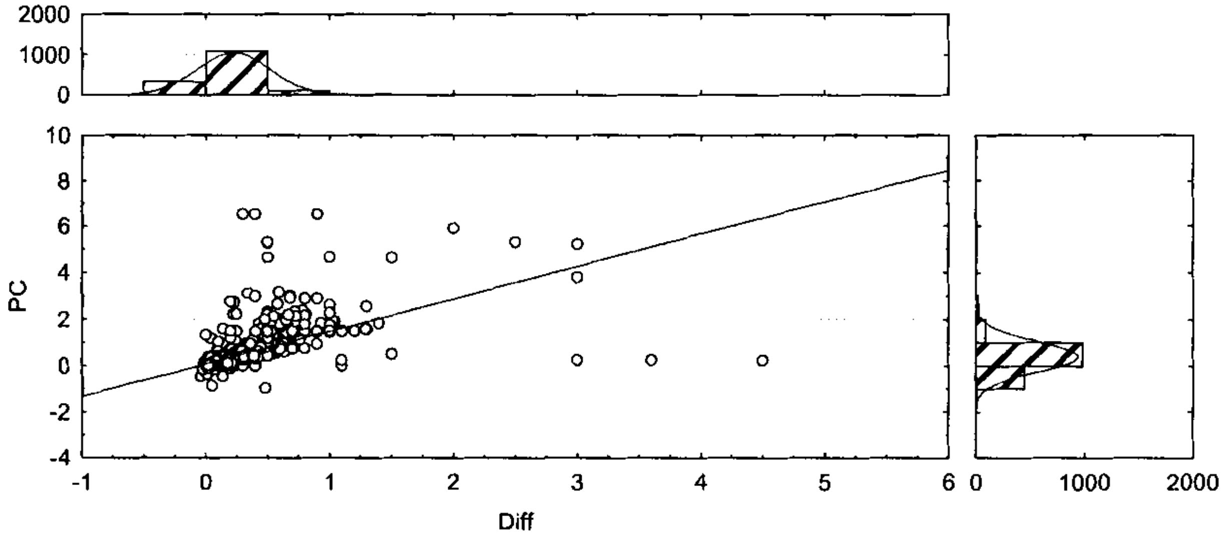


Figure 4.5: Scatter plot of Tan delta difference (Diff) and Percentage change in capacitance (PC) for the whole data from 0.2 pu to 1 pu voltage.

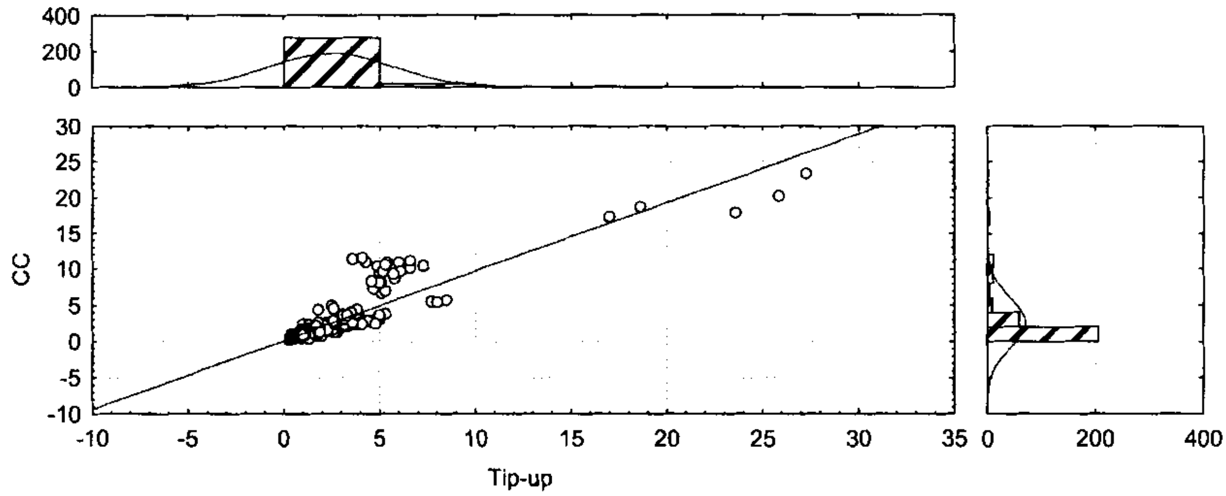


Figure 4.6: Scatter plot of Tip-up and slope gradient of capacitance (CC) for the whole data set.

The majority of the data for both tan delta tip-up and slope gradient of capacitance lies with 0 and 5. The range of the calculated values is less when compared to the measured values. This makes it easier to analyse the data. Both tip-up and slope gradient of capacitance distribution are right skewed. In other words most of the data has lower values.

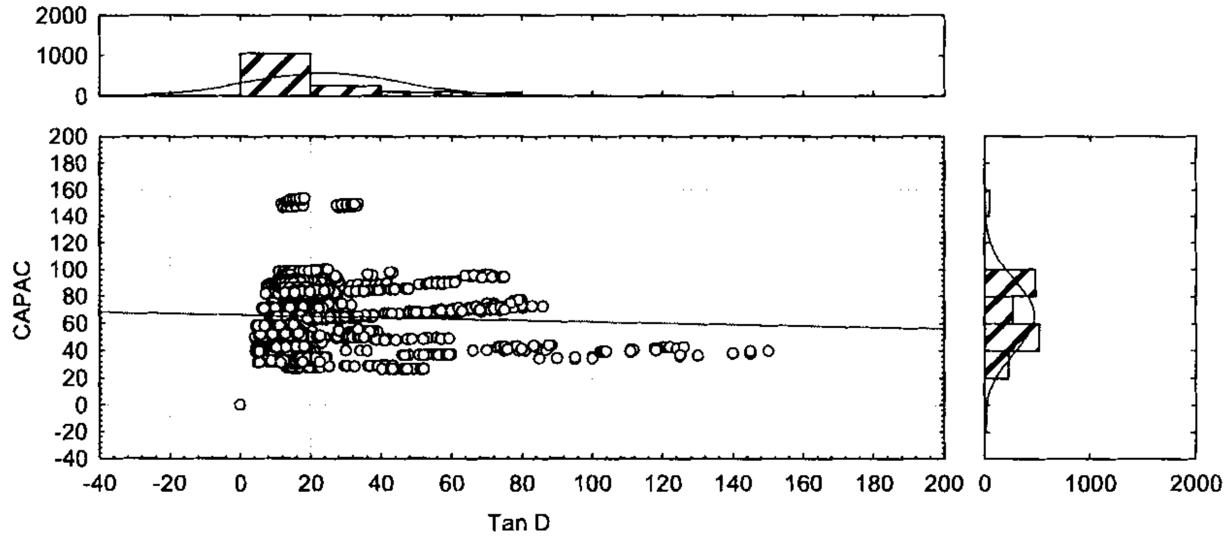


Figure 4.7: Scatter plot of Tan delta and capacitance (CAPAC) for the whole data set.

The measured values of tan delta and capacitance do not correlate well. The maximum number of tan delta values is in the range of 0 and 20, while capacitance is scattered over the range 0 to 100.

As shown in figure 4.5 and 4.6, the correlation is better with calculated values of capacitance and tan delta than with the measured values. One reason is that the effect of noise and outliers get reduced with calculated values.

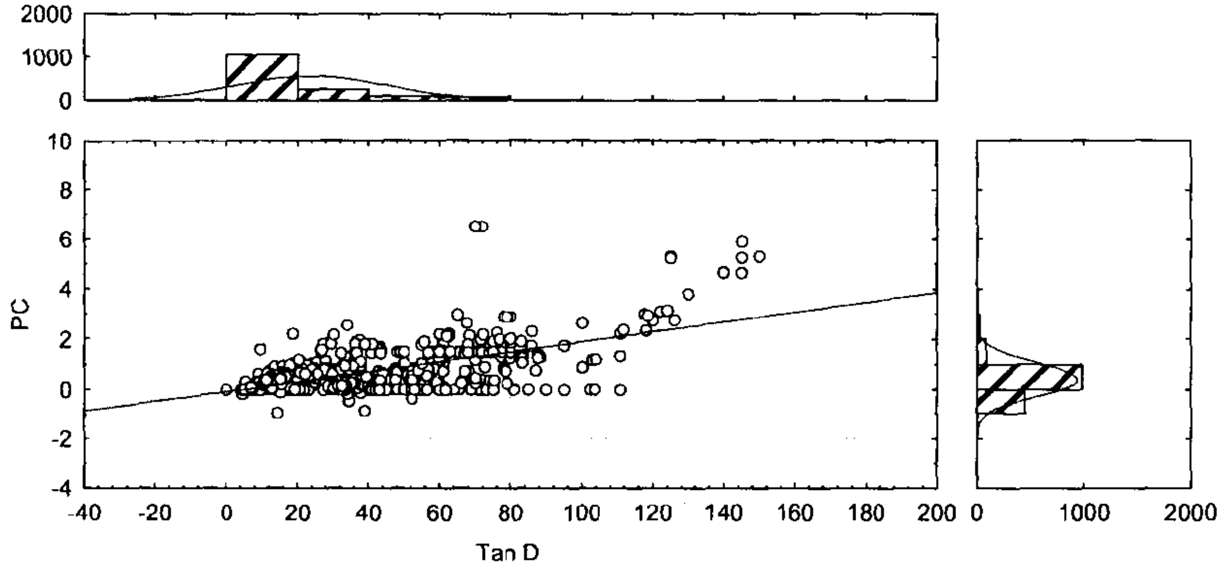


Figure 4.8: Scatter plot of Tan delta and percentage change in capacitance (PC) for the whole data set.

There is a correlation between tan delta and percentage change in capacitance. The correlation is better between tan delta difference and percentage change of capacitance as shown in figure 4.5. But percentage change is 0 at 0.2 pu, while tan delta has a measured value. This can be seen in figure 4.8.

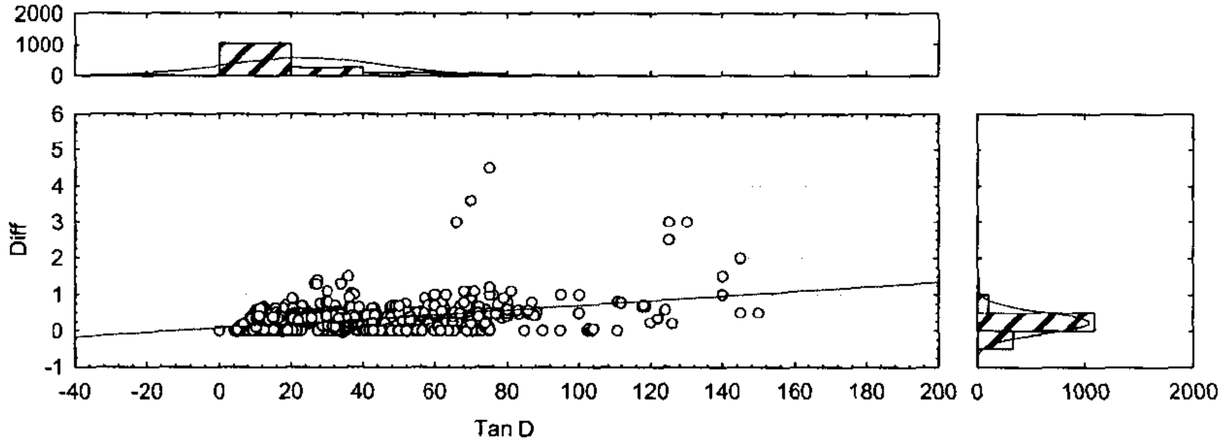


Figure 4.9: Scatter plot of Tan delta (Tan D) and Tan delta difference (Diff) for the whole data set.

There are similarities between tan delta and difference of tan delta, as difference of tan delta has been calculated from tan delta.

The tan delta difference has a few values at zero, the reason is that at 0.2 pu tan delta has a measure value, but calculated value tan delta difference, is zero. The reason being that at 0.2 pu the first measurement of tan delta is taken and the difference cannot be taken with one reading.

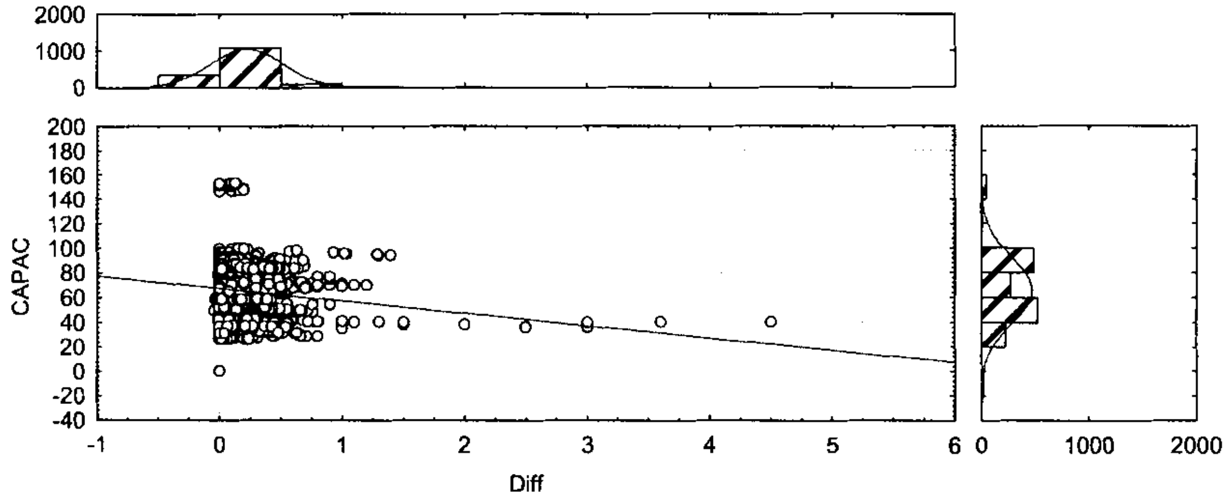


Figure 4.10: Scatter plot of Tan delta difference (Diff) and capacitance (CAPAC) for the whole data set.

It is clear from the graph that measured value of capacitance does not correlate well with calculated value of tan delta difference. The tan delta difference has a few values at zero and the majority of its values are between zero and one.

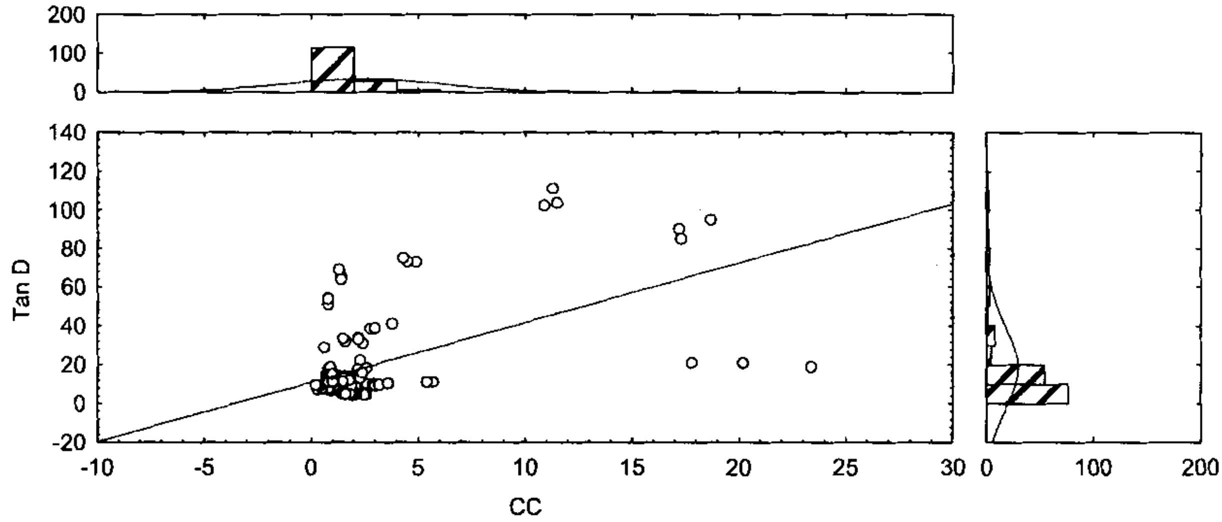


Figure 4.11: Scatter plot of slope gradient of capacitance (CC) and Tan delta (Tan D) for the whole data set.

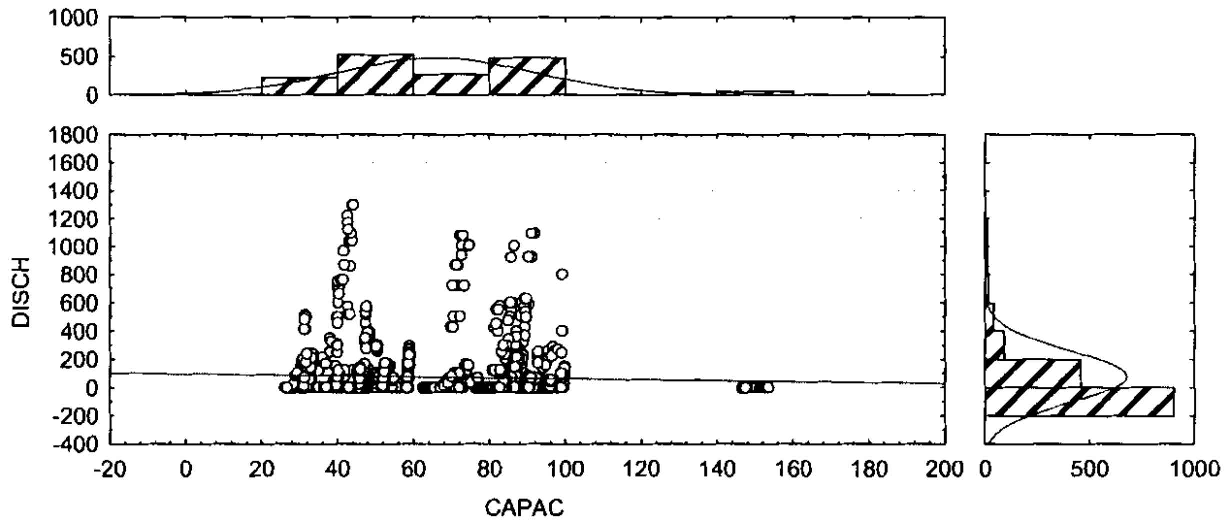


Figure 4.12: Scatter plot of capacitance (CAPAC) and partial discharge (DISCH) for the whole data set.

The measured values of partial discharge had a majority of values that were zero. The partial discharge measurements were not done frequently on the individual phases of the motors. The few measurements that were taken did not correlate well with capacitance and tan delta test measurements, as seen in figure 4.12 and 4.13.

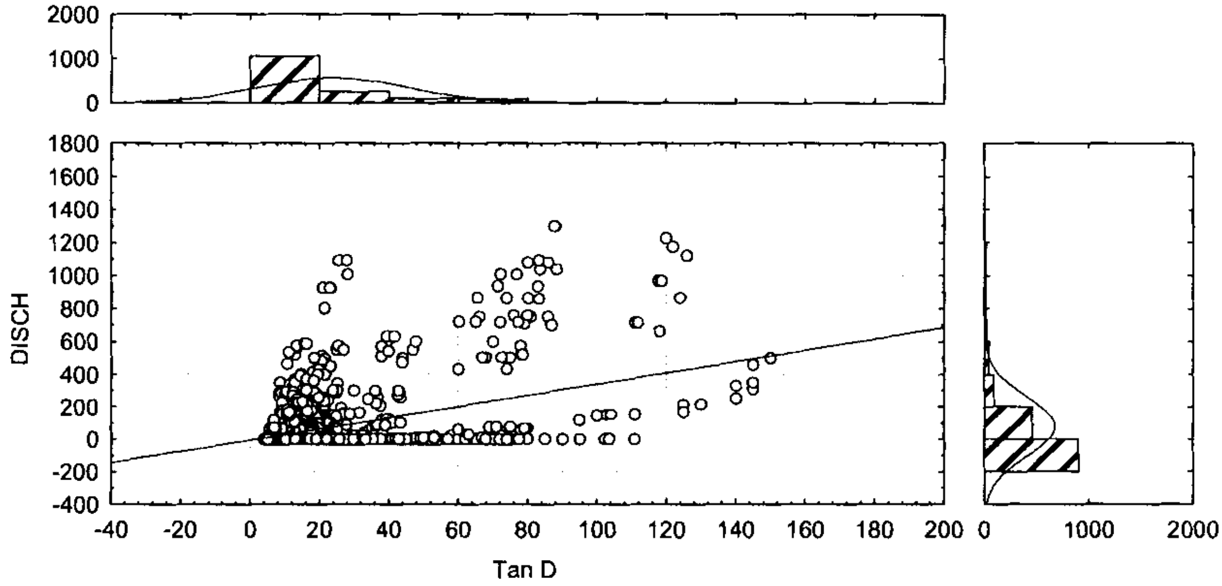


Figure 4.13: Scatter plot of Tan delta (Tan D) and partial discharge (DISCH) for the whole data set.

c) Group 3, consists of 11 kV motors with class B insulation systems

In the scatter plot below, the Tip-up has a good Gaussian distribution. It also has a good linear correlation with the slope gradient of capacitance.

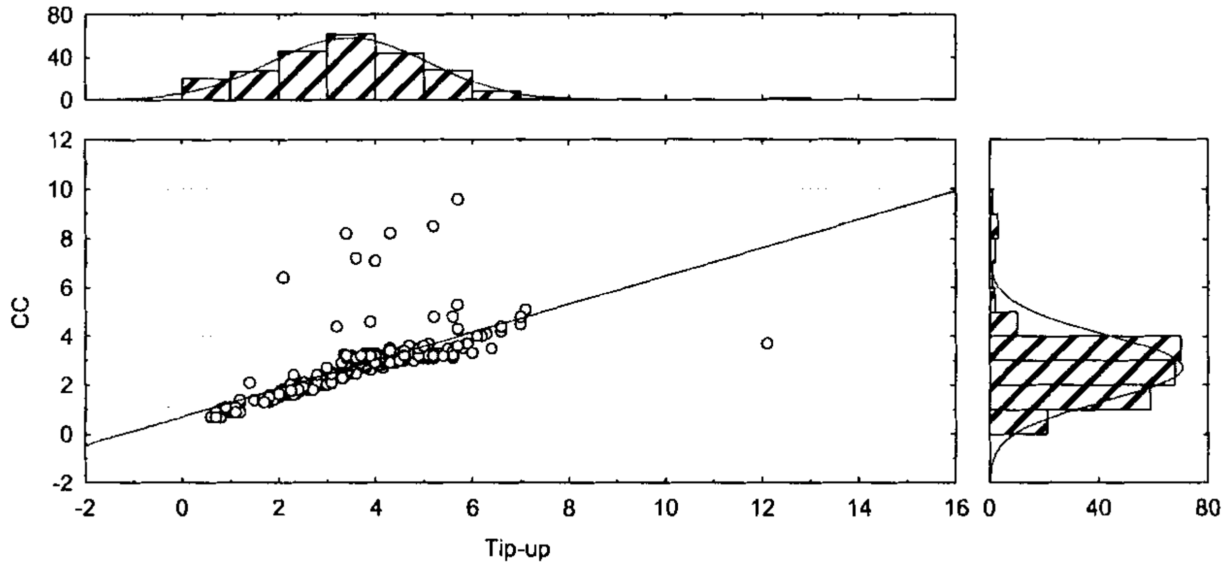


Figure 4.14: Scatter plot of Tip-up and slope gradient of capacitance (PC) for the whole data set.

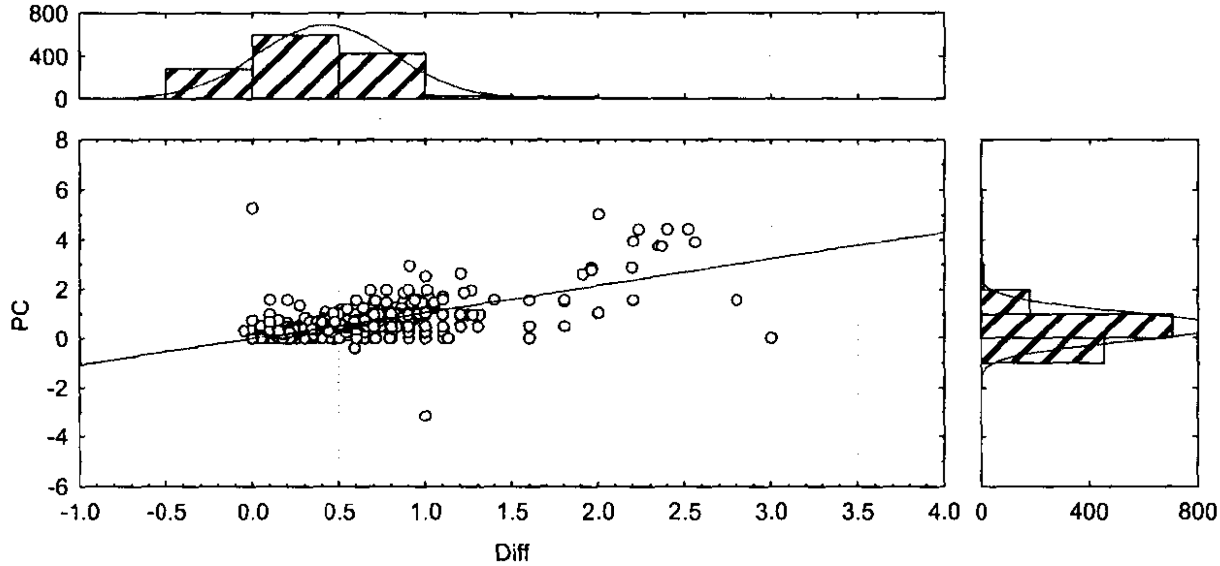


Figure 4.15: Scatter plot of Tan delta difference (Diff.) and Percentage change in capacitance (PC) for the whole data set from 0.2 pu to 1 pu.

d) Group 4, consists of 11 kV motors with class F insulation systems

This group of data behaves in a similar fashion as the other groups of data discussed above.

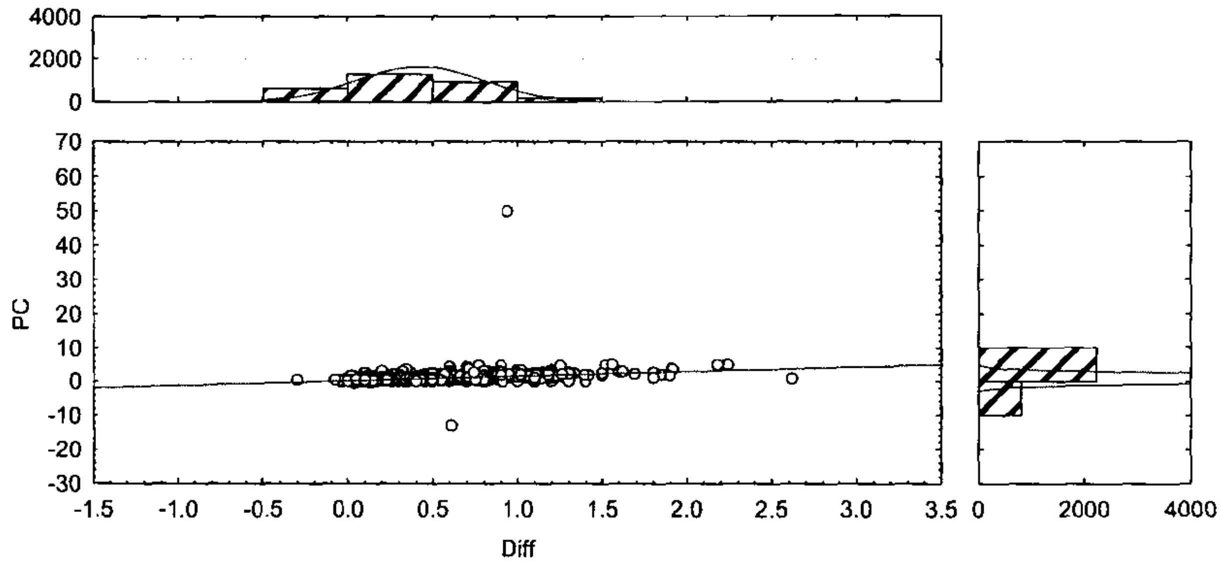


Figure 4.16: Scatter plot of Tan delta difference (Diff.) and Percentage change in capacitance (PC) for the whole data set from 0.2 pu to 1 pu.

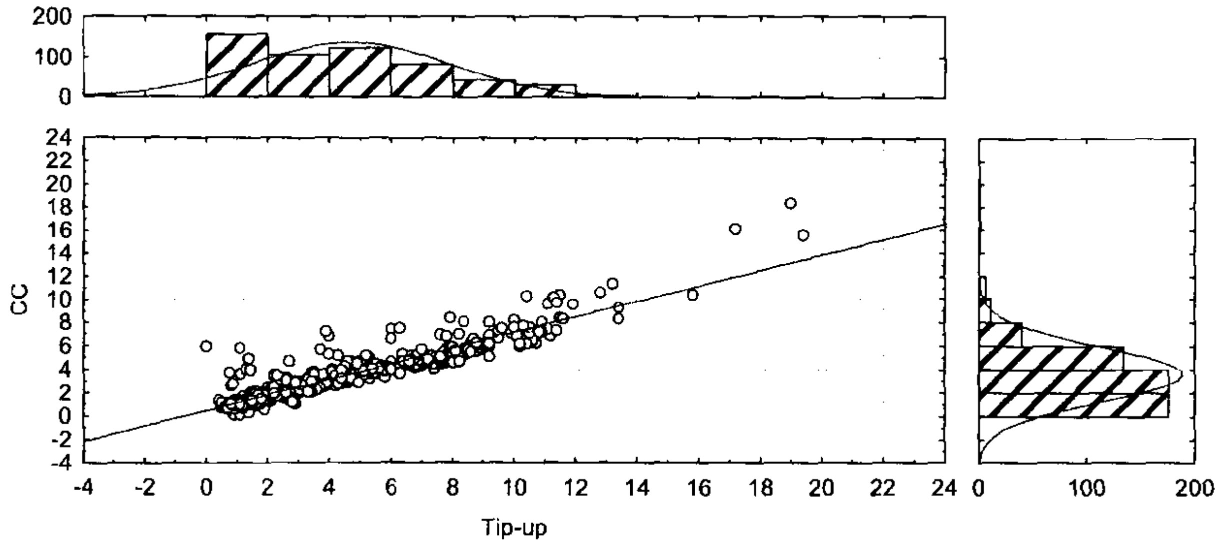


Figure 4.17: Scatter plot of Tip-up and slope gradient of capacitance (PC) for the whole data set.

The above discussion makes it clear that change in tan delta and change in capacitance are two good features to analyse the aging of the insulation.

4.2.3 Data Preparation

The quality of the output results depends on the quality of the information used. Therefore care was taken to ensure the quality of the data used for the analysis. As the aim of the whole process was to cluster data according to their condition, the four features where also included, as mentioned in section 4.2.2. The absolute measurements were Tan Delta and Capacitance on each phase of the motors separately. Based on the data understanding, the features Tip-up and Slope gradient of capacitance were chosen for the analysis. These two features represent the essence of the condition of insulation well, and also reduce the number of readings that is required for the analysis. Thus, reduces the computational time without compromising the quality of the result.

Data cleaning was a bit more complicated. As there was no control over the accuracy of the actual measurements taken, large negative data values and incomplete data were removed. But large positive data were not removed, because they could be measurements taken on a deteriorated insulation system, which is important for the analysis.

The data were labelled Good, Normal, Below Average and Poor based on A.D.W Wolmarans's assessment [21]. Then the data was manipulated (repeated), so that the number of Good, Normal, Below Average and Poor has the same number of cases. This caused the descriptive statistics to change. The repeating of cases was done under the assumption that the poor cases that occur in industries are similar to the cases that are used for this analysis. Enhancement of rare cases is a common practice in neural networks, so that these rare cases may have proper representation in the SOM. "Determination of proper enchantment in learning should be done in cooperation with the end users of these maps" [22].

4.3. Summary for Chapter 4

The first few stages of data mining have been explained in this chapter. The first stage is identifying the problem for which the analysis is being done. This make it easier to look for specific patterns related to the problem. The second stage is data understanding. The statistical analysis was used to understand the data and relations between the different features. The next stage is data preparation which is crucial as the results are dependent on the quality of input data.

Chapter 5

SELF-ORGANIZING MAPS ANALYSIS

5.1. Introduction

The sections of modelling and evaluation of the data mining process are covered in this chapter. Self-organizing maps were used for the modelling and analysis process . The evaluation of data is presented in section 5.4.

5.2. Self-Organizing Maps

The Self-Organizing Map (SOM), also called Kohonen map, is a popular feed forward Artificial Neural Network (ANN) technique [24], [25]. It is an unsupervised learning technique of neural networks [26]. This means, that the learning process is dependent solely on the input, while targets are not required. This technique was used because the result of the measurement were unknown. Though the data used is labelled initially, the clustering does not use it. The labelling is for external validation of the analysis.

"A self-organizing map (SOM) is used to convert high dimensional data into lower dimensions" [27]. "SOMs create prototypical vectors representing a dataset while maintaining topological relationships inherent to the dataset. These relationships are then projected to lower dimension-space (1- or 2-d) for ease of visualization" [28]. This helps to understand and explore the data better. A SOM is used to get insights and information about data that is not apparent.

In simple words, SOM is a flexible net of neurons that arrange themselves spatially, depending on the features of the input data. The data was normalised to zero mean value with a variance $\sigma=1$. "This normalization is necessary because the training algorithm uses Euclidian distances to find the best-matching unit (BMU). If the variables are not normalized, some will have too large an influence during this process" [22].

The normalized input values are given random weights. All the units in the input layer are connected to each neuron of the output layer through the weights. Then the net of neurons is trained. The corresponding weights are modified based on the position of the input data. The aim of the neurons is to preserve the distribution of the input data while reducing the dimension.

"A salient feature of SOMs is their ability to preserve a dataset's topology" [29].

A good graphical depiction of SOM is given below.

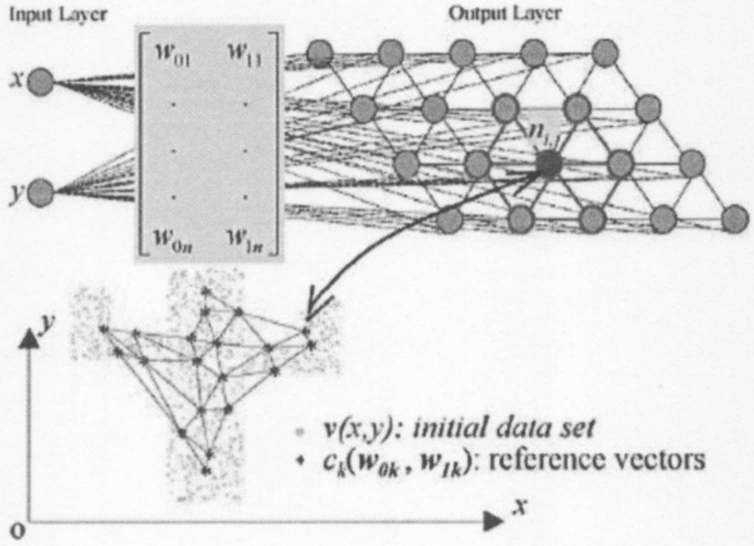


Figure 5.1: Architecture of a 5 by 4 SOM [30].

The SOM is h by w, where Nij is (i=1...h, j=1...w). This conversion can be explained by a basic algorithm, which is iterative. The net of neurons is trained based on the spread of the data. The weighted vectors of the neurons and its neighbours are updated by a sequential training algorithm or Batch training algorithm. In sequential training, the input data is presented one at a time and the vectors are updated slowly. While in batch training the whole input is presented at once and the new vectors are the weighted averages of the data vectors.

A description on how to present a more mathematical description of the SOM algorithm, based on the literature study is found below. 'X' is the input component vector and 'Wj' is the weight or reference vector. The 'm' neurons have p-dimensions of the input data. m_i= [m_{i1} ,..........., m_{ip}]. While training, the distance between one input x and all the neurons is calculated and the neuron that has the least distance from the input data is denoted the best-matching unit (BMU).

$$d_j = \|\mathbf{X} - \mathbf{W}_j\|^2 = \sum_{i=1}^{n}(w_{ij} - x_i)^2, \tag{5.1}$$

Where n is the number of input components, dj is the quadratic distance.

$$d_{j^*} = \min_{j\in[1,\ldots,m]} \|\mathbf{X} - \mathbf{W}_j\|^2, \tag{5.2}$$

Where, m is the number of neurons.

Once the best matching unit is found, which is also known as the winning neuron, the weight of that neuron is updated.

$$w_{ij^*}(k+1) = w_{ij^*}(k) + \eta(k)[x_i(k) - w_{ij^*}(k)], \tag{5.3}$$

Where, k is the learning iteration and η the gain term [31].

$$\begin{aligned} w_{ij}(k+1) &= w_{ij}(k) + \eta(k)[x_i(k) - w_{ij}(k)] \ \text{ if } j \\ &\in \textbf{neighbourhood of } j^*,\ N(j^*)) \\ w_{ij}(k+1) &= w_{ij}(k) \ \text{ if } j \notin \textbf{neighbourhood of } j^* \end{aligned} \tag{5.4}$$

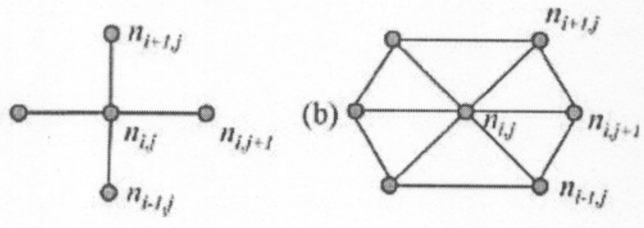
(a)  (b)

Figure 5.2: Neighbours Nj*, can be rectangular or hexagonal [30].

The neighbourhood function N(j*), is updated as well. As shown in the picture the BMU and its neighbouring neurons get closer to the input vector. This is done iteratively.

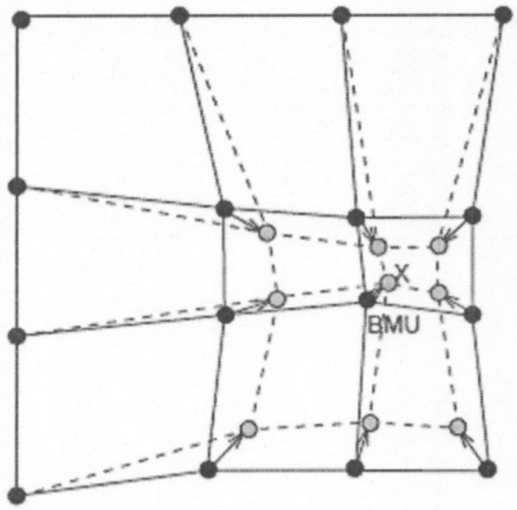


Figure 5.3: The solid lines are the initial positions of the neurons and the dotted lines are the updated positions [32].

The equations used for sequential and batch training are different, but both require learning rate α (t) and neighbourhood radius σ (t). The different learning rates and neighbourhood functions are shown below in Figure 5.5 and figure 5.6. In this analysis the learning rate is linear and the neighbourhood function is Gaussians as shown in figure 5.4. As the iterations increase the learning rate and neighbourhood radius decreases. In the SOM Tool box used, it provides rough and fine training, which means in rough training α (t), σ (t) are large and in fine training these values are smaller.

This process of training brings similar data together and dissimilar data further apart.

$$h_{c(x),i} = \alpha(t)\exp\left(-\frac{\|r_i - r_c\|^2}{2\sigma^2(t)}\right), \tag{5.5}$$

This is the mathematical expression of the Gaussian neighbourhood function [33], where α (t) is the learning rate and σ (t) is the neighbourhood radius, r_i, r_c are coordinates of the neurons in the output grid and r_c is the winning neuron.

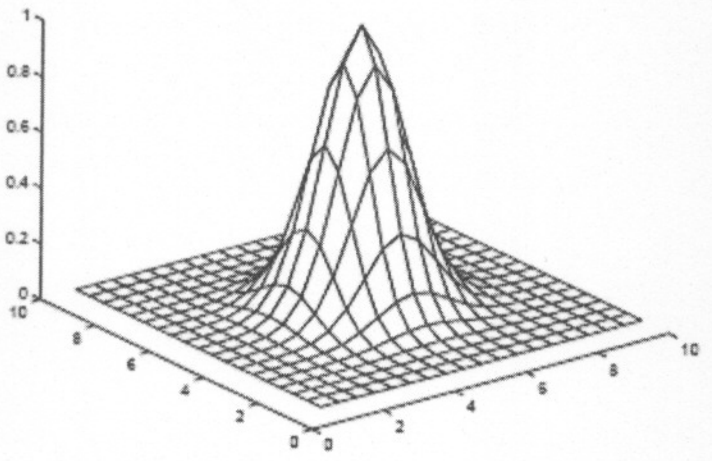


Figure 5.4: Gaussian neighbourhood function [32].

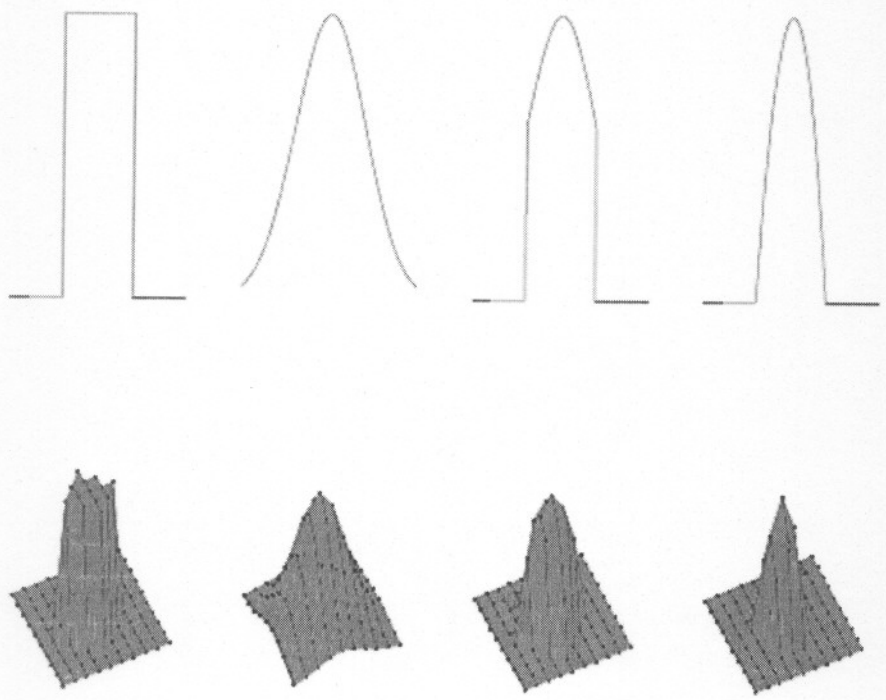


Figure 5.5: Different neighbourhood functions [34].

As shown in figure 5.5, from the left 'Bubble' neighbourhood is the first function shown and its equation is given by equation 5.6. The 'Gaussian' function is next and its equation is given by equation 5.7. The next is 'Cutgauss' function and its equation is given by equation 5.8. The last is 'Ep' function and its equation is given by equation 5.9.

$$h_{ci}(t) = \mathbf{1}(\sigma_t - d_{ci}) \tag{5.6}$$

$$h_{ci}(t) = e^{-d_{ci}^2/2\sigma_t^2} \tag{5.7}$$

$$h_{ci}(t) = e^{-d_{ci}^2/2\sigma_t^2}\mathbf{1}(\sigma_t - d_{ci}) \tag{5.8}$$

$$h_{ci}(t) = \max\{0, 1 - (\sigma_t - d_{ci})^2\} \tag{5.9}$$

Where σ_t is the neighbourhood radius at time t, $d_{ci} = || r_c - ri ||$ is the distance between map units c and i on the map grid.

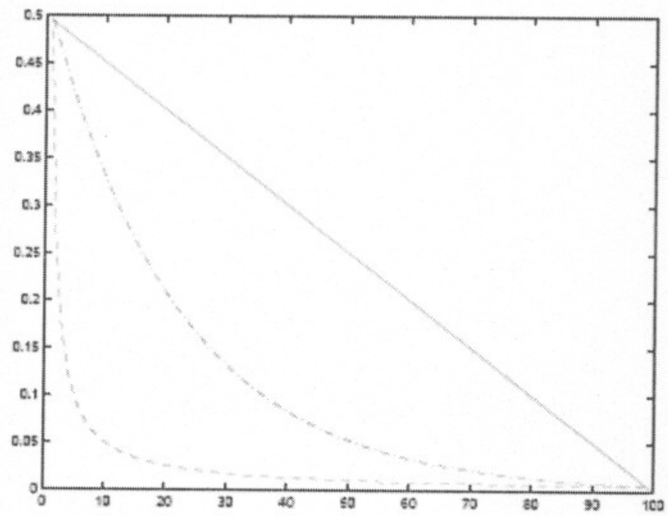


Figure 5.6: Different learning rates functions [34].

As shown in figure 5.6, linear learning rate is depicted by a solid line. The equation for linear learning rate is given in equation 5.10. Power learning rate is represented by a dot-dash and its equation is given in number 5.11. The inverse learning rate is shown by a dashed line and equation of that is given in equation 5.12.

$$\alpha(t) = \alpha_0 (1 - t/T) \tag{5.10}$$

$$\alpha(t) = \alpha_0 (0.005/\alpha_0)^{t/T} \tag{5.11}$$

$$\alpha(t) = \alpha_0 / (1 + 100\, t/T) \tag{5.12}$$

Where T is the training length and α_0 is the initial learning rate.

When the SOM is trained, one of the main properties of the neural net is to preserve the topology of the input data. The term topographic error means "prototype vectors close to each other in the input space are mapped wide apart on the output grid" [26]. "Quantization error" occur when prototype vectors try to approximate to the data set. The larger the map size, the more reduced the quantization error is. However, the topographic error increases as the map folds to reduce the quantization error.

In the MATLAB SOM toolbox, a heuristic formula, as given below, is used to balance the inversely related errors.

$$M = 5\sqrt{N} \tag{5.6}$$

The ratio of the sidelenghts of the map is calculated, as the square root of ratio of the two largest Eigen vectors of the training data. In essence, this explained working of the SOM.

The advantage of SOM is that it is an unsupervised technique, which means that for the training process it does not require targets. This property of SOM helped to classify the insulation tests data without knowing beforehand whether the condition of the insulation was good or bad. In SOM it is easier to recognize patterns visually and it is simple to understand.

The SOM results are dependent on the quality of input data. SOM is sensitive to noise and outliners, so the end user has to make sure of the quality of the input data. The term 'rare case enhancement' means that the cases which are important for analysis but are few in number, are repeated to increase the number of those cases. This is done so that those cases are able to influence the analysis and are properly represented in the SOMs. This rare case enhancement is solely done on the discretion of the end user.

In other words, which cases need to be repeated as well as the number of repetitions is the decision of the end user.

5.3 Analysis of the results

The SOM toolbox was used in MATLAB to analyse the data. The data was normalized, initialised linearly and batch trained. For this research, the grid of neurons is hexagonal in shape. This toolbox aids in visualizing the data.

The data can be displayed in several ways:

a **Interneuron distance matrix (U-matrix)** - This SOM gives the distance between the neurons. When the interneuron distance is smaller it can be interpreted as the input data having a high density. If the interneuron distance is large, this means that the input data has a low density. In essence, interneuron distance matrix (U-matrix) shows the clusters based on density. So as shown in figure 5.5, the upper portion of the SOM has less distance between the neurons. This means that neurons represent data that are similar and they form a cluster. Four colours represent the distance; dark blue is the smallest distance while red is the maximum distance.

The U-matrix has more hexagons than the component plane, because not only is the distance value at the neuron shown, but the distances between the neurons as well. In this analysis the input data has three features that are taken into account. The features are Tan delta, tip-up and percentage change in capacitance. The selection of the features is discussed in detail in section 5.4.1.

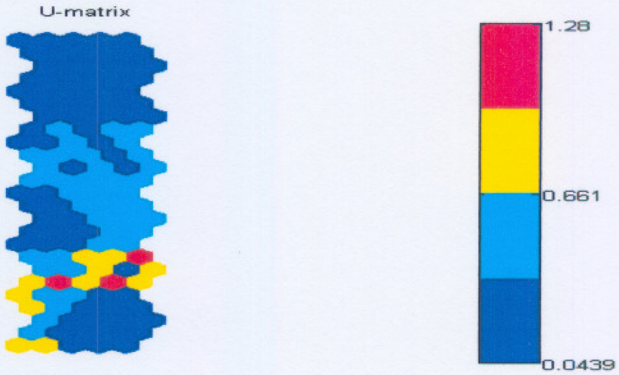


Figure 5.7: U-matrix for the 6.6 kV motors with class F insulation data.

b **Component planes** - "A component plane can be drawn for each input feature and it shows the weights that connect each neuron with the particular input variable" [27]. These planes help detect correlations between different input features. If the component planes have similar patterns they have a correlation. It also helps to understand the behaviour of each feature in the corresponding U-matrix. Component plane 'Labels', represents distribution of data according to distance calculations, but labelled by the assessment of an expert, where P is for Poor, B for Below average, N for normal and G for Good. The label is not used for computational purposes; rather it is used for validation purposes later in this chapter.

As shown in figure 5.8, U-matrix gives the distance between the neurons. The clustering in the U-matrix takes into account all three the parameters. The SOM toolbox gives one U-matrix and four component planes for each analysis. It helps to visualise data in those clusters.

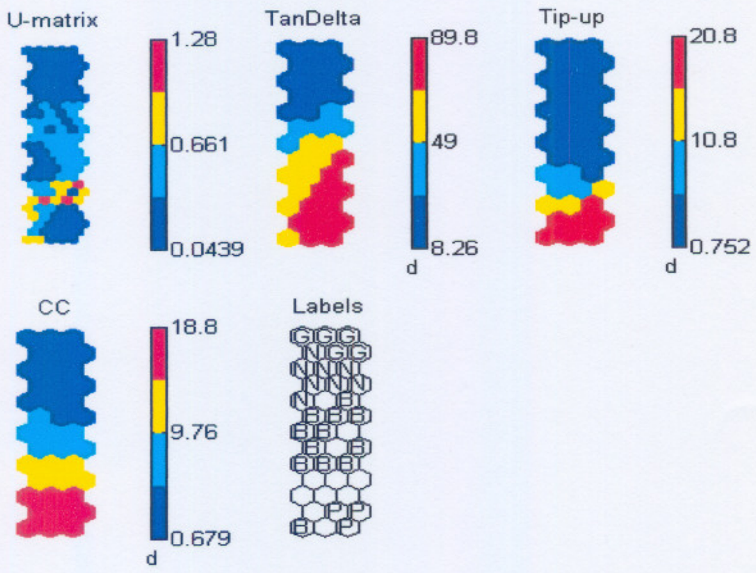


Figure 5.8: U-matrix and component planes for 6.6 kV motors with class F insulation data.

5.3.1. SOM for individual features

The analysis was initially done with each feature separately, to decide which features would give the best clusters. The features given individually where:

a **Absolute tan delta measurement** - The SOM is one dimensional, because there is only one input. Classification of the data done in SOM based on tan delta measurements is compared to the expert's assessment. The accuracy of the SOM is 80% using Tan delta.

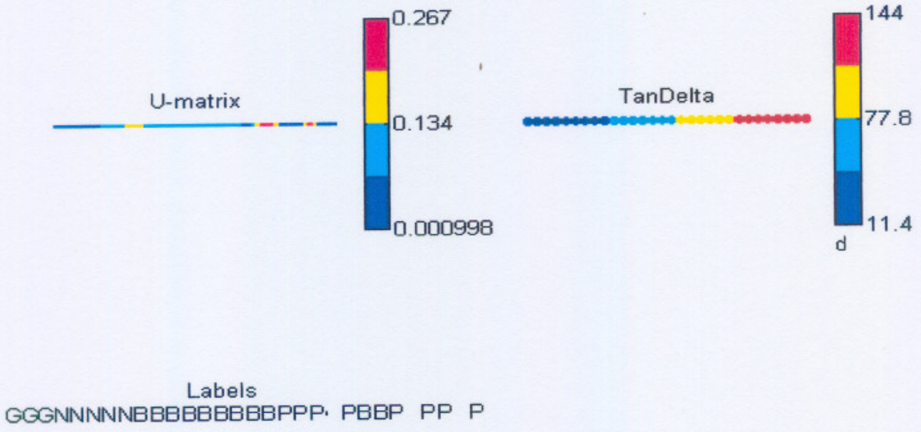


Figure 5.9: U-matrix and component planes for tan delta measurements for 6.6 kV and F insulation.

b **Capacitance** - The accuracy of the SOM is 70% using capacitance.

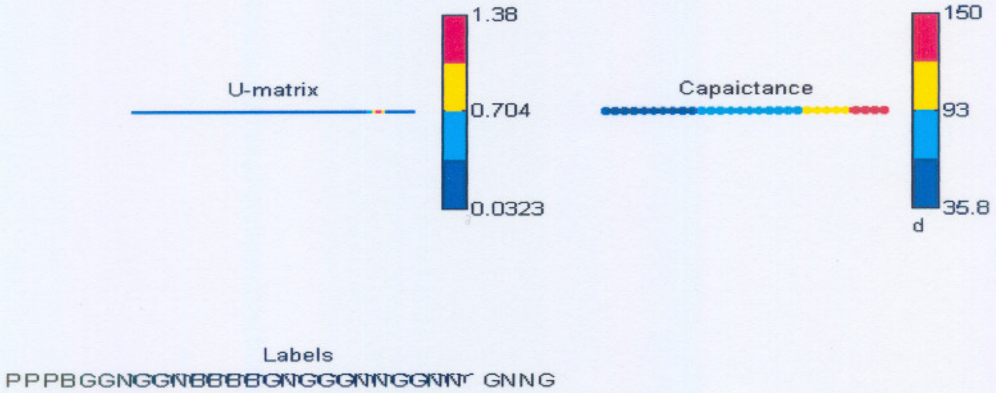


Figure 5.10: U-matrix and component planes for capacitance measurements for 6.6 kV motors with class F insulation.

c Tan delta difference- The accuracy of the SOM is 59% using difference.

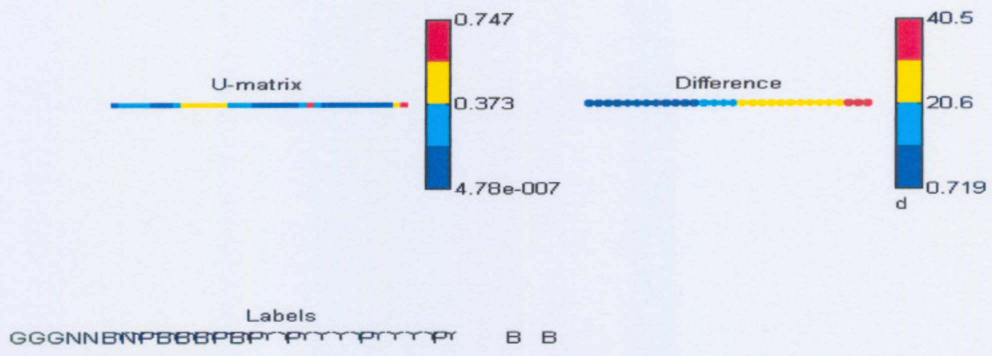


Figure 5.11: U-matrix and component planes for tan delta difference measurements for 6.6 kV motors with class F insulation.

d Percentage change in capacitance - The accuracy of the SOM is 61%.

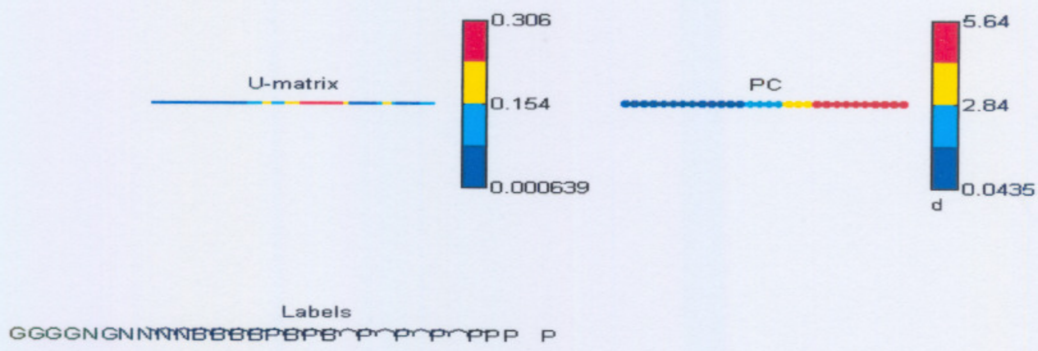


Figure 5.12: U-matrix and component planes for percentage change in capacitance measurements for 6.6 kV motors with class F insulation.

e Partial Discharge - The accuracy with Partial discharge was 49%.

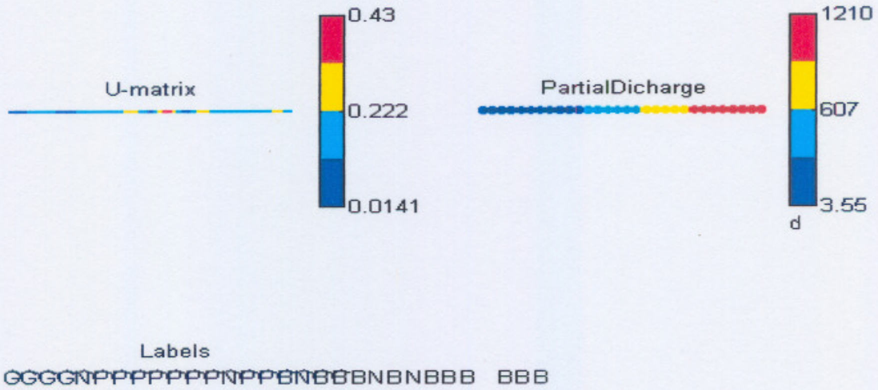


Figure 5.13: U-matrix and component planes for partial discharge measurements for 6.6 kV motors with class F insulation.

f Tan delta tip-up - The accuracy of the SOM is 90%.

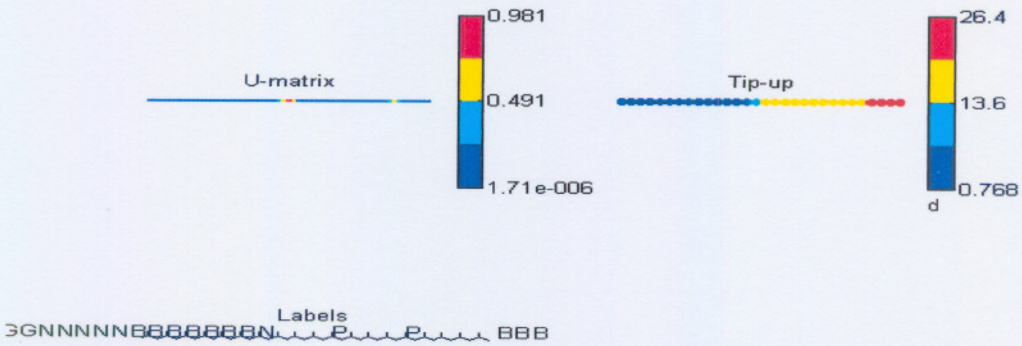


Figure 5.14: U-matrix and component planes for tan delta tip-up measurements for 6.6 kV motors with class F insulation.

g **Slope gradient of capacitance** - The accuracy of the SOM is 91%.

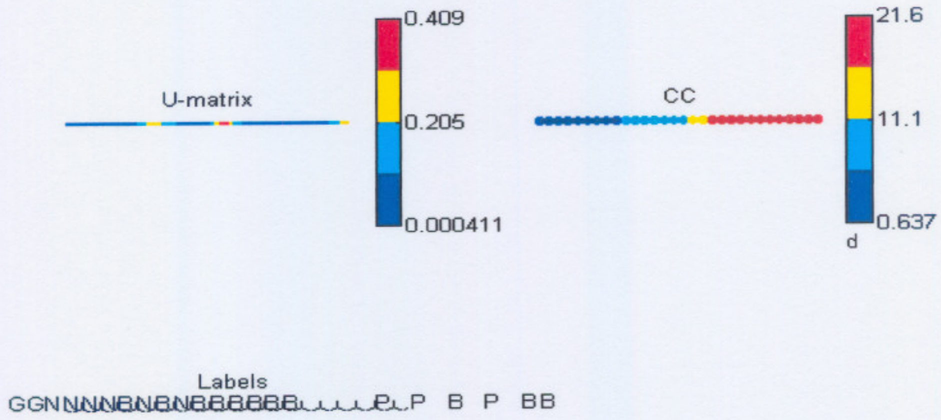


Figure 5.15: U-matrix and component planes for slope gradient of capacitance measurements for 6.6 kV motors with class F insulation.

Table 5.1 shows the percentage accuracy of the SOM for each feature separately.

	6.6 kV, B (%)	6.6 kV, F (%)	11 kV, B (%)	11 kV, F (%)
Tan delta	72	80	67	64
Capacitance	77	70	69	63
Tan delta difference	70	59	59	52
Percentage change in Capacitance	75	61	64	55
Partial discharge	68	49	58	38
Environment	73	54	51	42
Tip-up	97	90	81	83
Slope gradient of capacitance	98	91	84	86

The features that give better accuracy (higher percentage) were chosen for the analysis and classification. In the case of group 1 (6.6 kV motors with class B insulation), the features that were chosen where tan delta tip-up, slope gradient of capacitance and tan delta. Tan delta was selected even though it did not have a higher accuracy when compared to capacitance and percentage change in capacitance. The reason for this is that capacitance is dimension dependent thus comparing capacitance values of different machine sizes can be misleading. Percentage change in capacitance and slope gradient of capacitance are redundant features, thus only slope gradient was taken which had a higher accuracy. Environment is not a standardised value so it was preferred to take tan delta that was a test result rather than environment.

The accuracy of SOM for individual features is less when compared to SOM for more than two features. The reason was that SOM was able to compute data with a large number of features and reduce it to two-dimensional data, taking into account the contribution of each feature. In this analysis, complete and high accuracy features where not available, thus only three features where used in the sections below.

5.3.2. 6.6 kV motors with class F insulation for the complete data set

To explain the SOM in figure 5.16 in detail: the upper section of all five SOMs, the U-matrix shows a cluster in dark blue - this means that the distance between the neurons in that cluster is less than 0.30855. The U-matrix represents the clusters that are formed using 3 inputs. The three inputs are Tan delta, Tip-up of tan delta and Slope gradient of capacitance. In the Tan delta, Diff (difference of tan delta) and CC (Slope gradient of capacitance) component planes, the values are low for the upper section cluster. The fifth SOM 'Labels' is the assessment of A.D.W. Wolmerans for the set of values in that cluster, which is G (good) and N (Normal) [21].

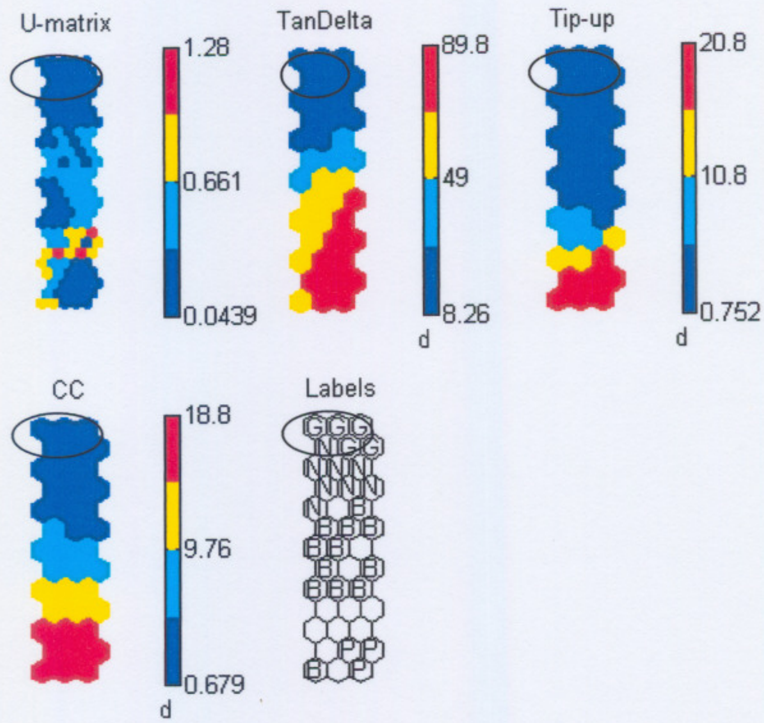


Figure 5.16: SOM of the complete data of 6.6 kV motors with class F insulation.

The Tan delta, tip-up and CC component planes are the neuron distribution of each component that contributed to the cluster that is shown in the U-matrix. It is easier to see patterns in the data with SOMs. As seen above tip-up and CC have good correlation, tan delta also has a similar pattern. The fifth figure 'Labels' is the labels of the input data, where P is for Poor, B for Below average, N for normal and G for Good.

For the good and normal data, the value of the three features is low while for poor data the value of the three features is high, as shown in figure 5.16.

The distribution of the data shown in the 'Label' SOM is based on distance calculation. The expert's assessment is not used for the computational process. In figure 5.14, the 'Label' SOM from the top to the bottom, there is a shift from G (good) to N (normal), then to B (below average) and then P (poor). The distribution of data by SOM is similar to the assessment of the expert. There is a good cluster at the bottom for poor data and a good and normal cluster at the top.

There is some overlapping between good and normal data, normal and below average data and below average and poor data.

The figure 5.17 shows, a Pie chart and Bar chart of each neuron. The size of the pie chart depends on the number of hits the neuron has had. A 'Hit' means a particular neuron becomes the BMU (best matching unit). The BMU is explained in section 5.2 and depicted in figure 5.3. The higher the number of hits the larger the pie is, this gives a better idea of the distribution of the data. In addition to that, it shows which component contributed to a particular neuron. The bar-plane gives an idea of the contributions of the different components in a particular neuron.

Bark blue represents 'Tan delta' •, Light blue represents 'Tan Delta Tip-up' •, Yellow represents 'Slope gradient of capacitance'•.

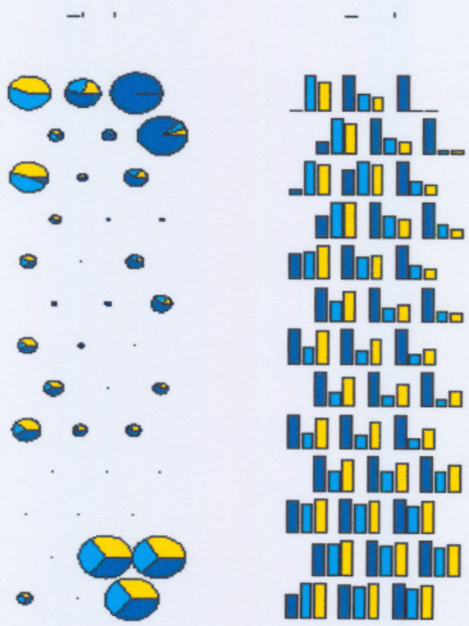


Figure 5.17: Pie and bar chart of the different components.

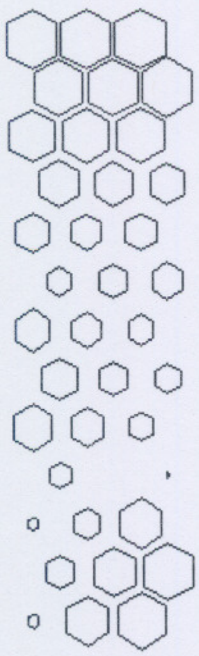


Figure 5.18: Distance between the different neurons.

The figure 5.18 above, shows the distance between each neuron that is represented as a hexagon. The size of the hexagon is dependent on the number of hits the neuron has had. Hit is when a particular neuron becomes the BMU (best matching unit). This means the hexagon is larger and the number of hits it has is more. In other words the density of similar data is higher where the hexagons are larger.

In the figure 5.18, the poor data at the bottom have a high density, while good and normal data at the top also have a high density. It can be inferred that there is a clustering of data at the top and the bottom of the SOM.

5.3.3 11 kV motors with class F insulation for the complete data set

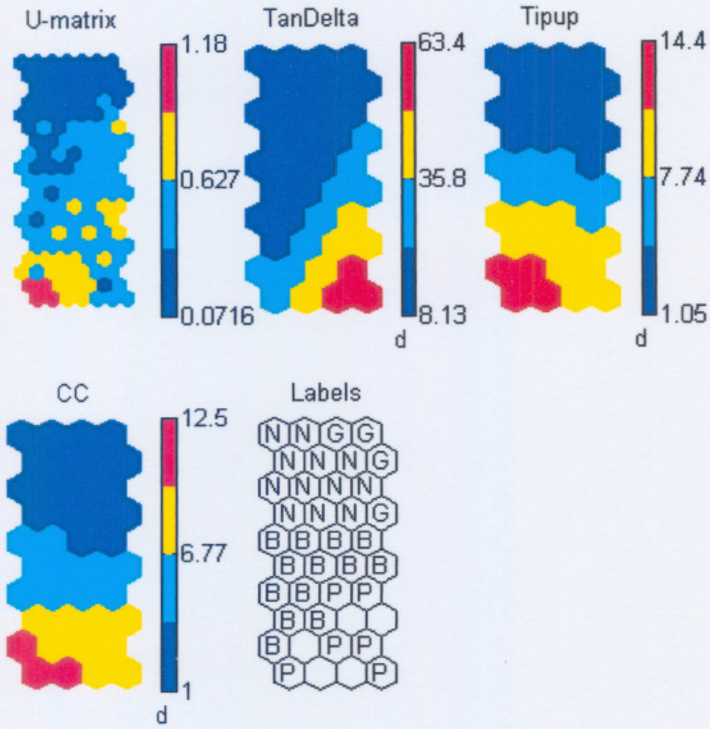


Figure 5.19: U-matrix and component planes for 11 kV motors with class F insulation data.

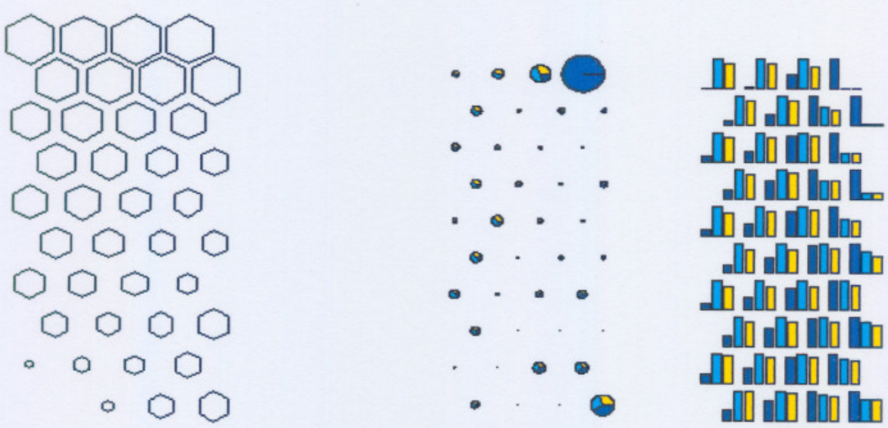


Figure 5.20: Distance matrix, pie and bar chart SOM for 11 kV motors with class F insulation data.

When observing the SOM the component plans of Tip-up and CC are similar. Thus, the Tip-up (tan-delta tip-up) and CC (slope gradient of capacitance) have a good correlation. In the label component plane, there is a gradual shift from good to normal to below average and poor, which means that the SOM distribution of data correlates well with the expert's assessment. Looking at the U-matrix there is a good cluster at the top consisting of good and normal data. Even in the distance matrix the hexagons are larger at the top, so the density of data is higher at the top.

5.3.4 11 kV motors with class B insulation for the complete data set

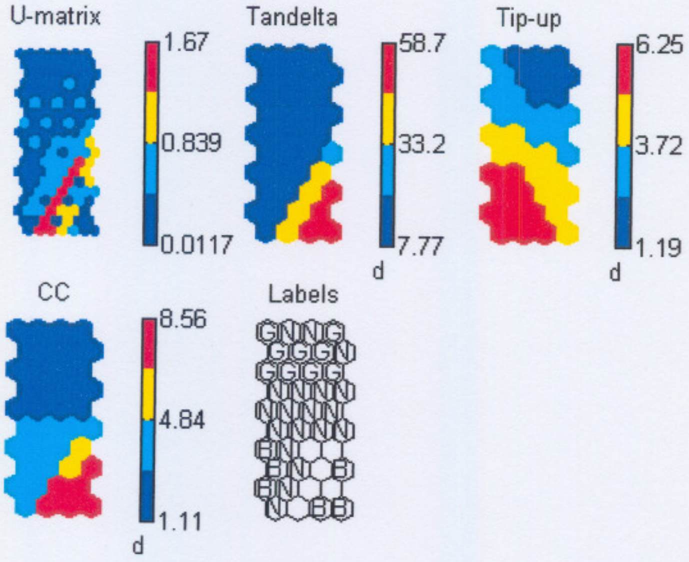


Figure 5.21: U-matrix and component planes for 11 kV motors with class B insulation data.

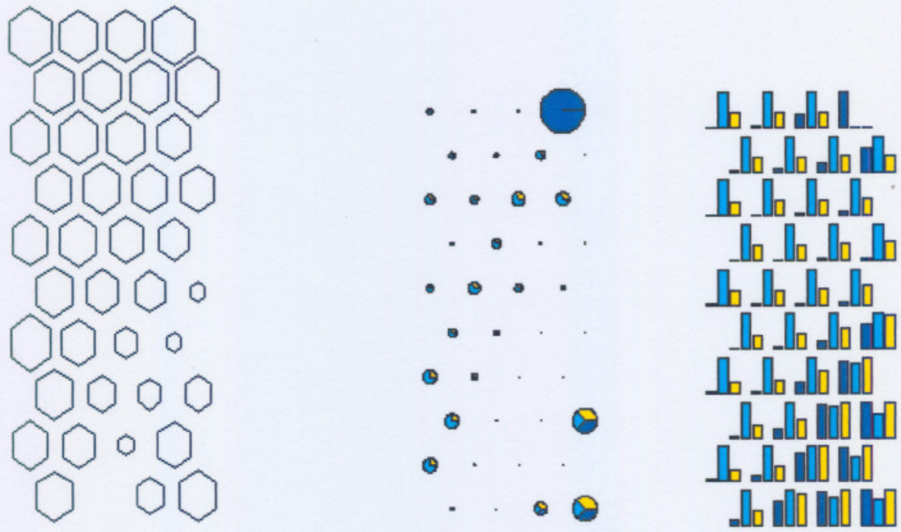


Figure 5.22: Distance matrix, pie and bar chart SOM for 11 kV motors with class B insulation data.

Looking at the U-matrix, distance matrix, pie and bar chart, the data is divided into two groups. One consists mostly of good and normal data, while below average data forms a small group at the bottom right side. The below average data consists of higher CC and tan delta values than Tip-up values, one explanation for this is that for deteriorated insulation the change in tan delta values can be high at lower voltages, but may not change much at higher voltages. Even though the absolute value of tan delta is high the tip-up may be less at high voltages, which explains lower values of tip-up for the below average data.

A few neurons are below average on the left bottom in the 'Label' SOM where Tip-up is higher than CC values.

5.3.5 6.6 kV motors with class B insulation for the complete data set

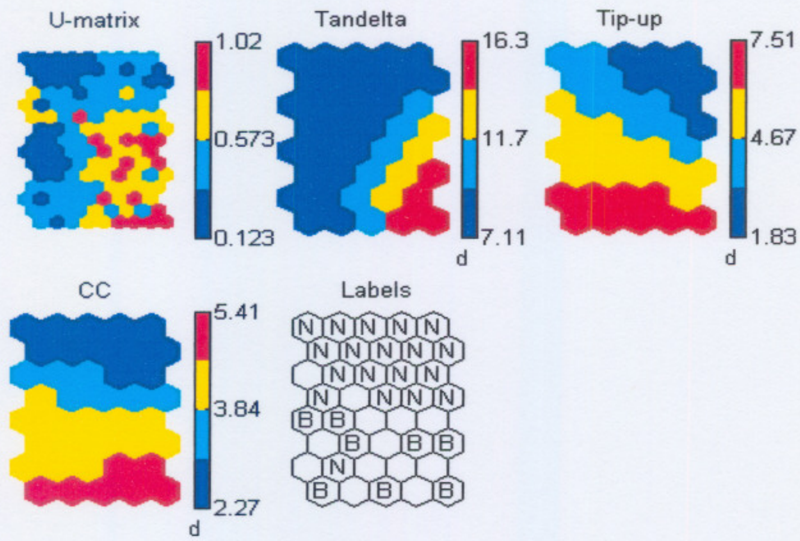


Figure 5.23: U-matrix and component planes for 6.6 kV motors with class B insulation data.

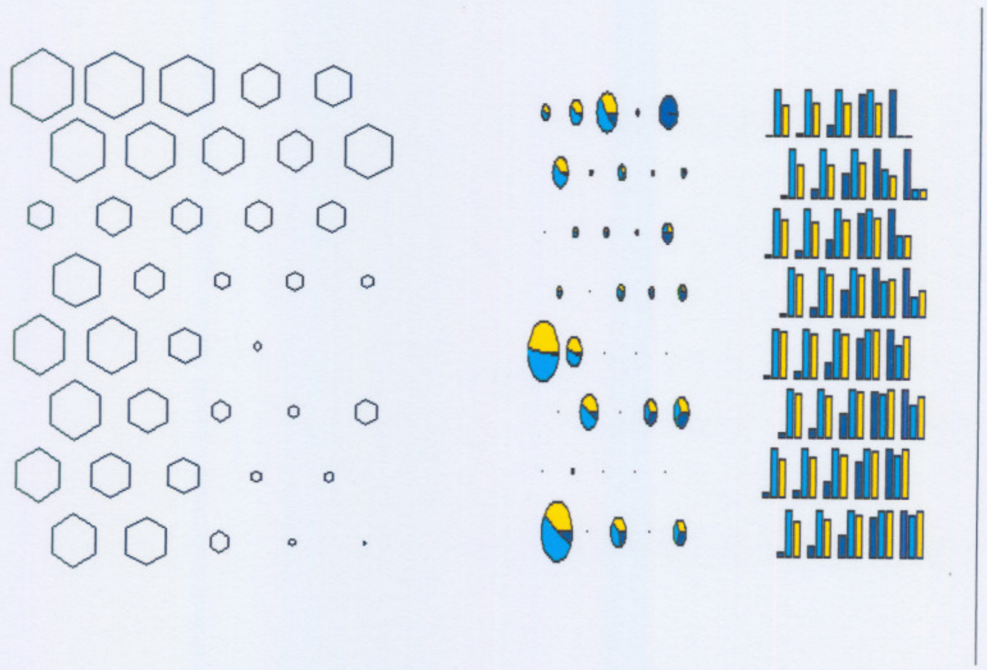


Figure 5.24: Distance matrix, pie and bar chart SOM for 6.6 kV motors with class B insulation data.

The 6.6 kV motors with class B insulation data is the smallest data set, containing only normal and below average data. Looking at the component plane 'label', the SOM has arranged the data in a way that correlates well with the expert's opinion. The normal data have lower tan delta, tip-up and CC (change in capacitance slope), while below average data had higher tip-up and CC.

Table 5.2: The percentage of correct classification by the SOM, compared to the expert's assessment.

	Group 1 6.6 KV, B	Group 2 6.6 KV, F	Group 3 11 KV , B	Group 4 11 KV, F
Good	-	55%	97%	86%
Normal	100%	87%	79%	69%
Below average	100%	99%	100%	86%
Poor	-	100%	-	96%

In the case of 6.6 kV motors with class B insulation, the accuracy is high because data was repeated to have equal representation of the different insulation conditions during the analysis. There is not enough variation in the available data, so the accuracy may change if enough training samples are given.

Data of poor condition insulation was also limited, thus its accuracy is high because the same data was repeated to increase the number of poor insulation machines. Therefore, the high percentage accuracy is a bit misleading, because the SOM was not trained with a wider range of data.

5.4 Clustering Techniques

There are two main ways in the literature of classifying clustering data: hierarchical clustering and partition clustering [26], [28], [36].

5.4.1 Hierarchical clustering

Hierarchical clustering is a method in which the data is clustered based on distance criteria. "The clustering algorithm can be divided into agglomerative (bottom-up) methods and divisive (top-down) methods" [26]. In this case divisive method has been used. The advantage of hierarchical clustering "is that it is not affected by initialization and local minima"[36]. However, the disadvantage is the fact that it is not suitable for large amounts of data or for 2-level clustering of SOMs.

"It can handle noise and outliers more efficiently than partitioned algorithms" [22].

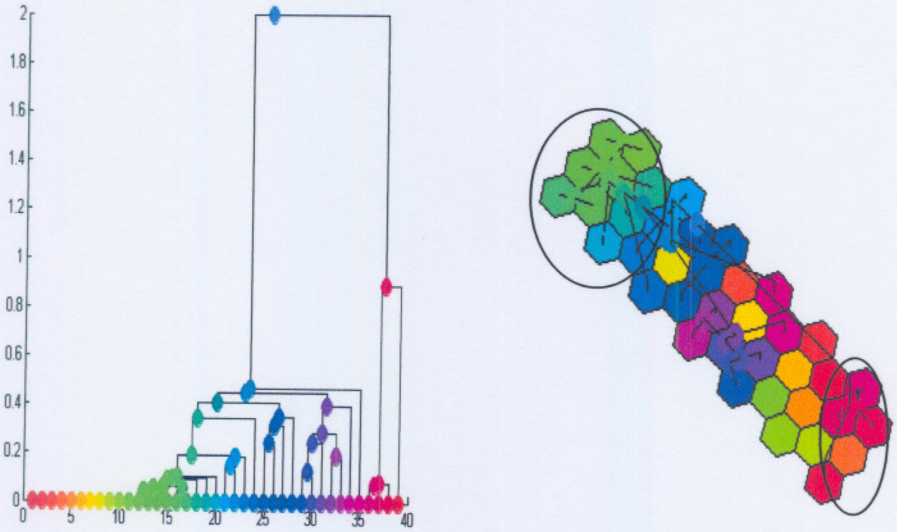


Figure 5.25: Hierarchical clustering for 6.6 kV motors with class F insulation data.

In the figure 5.25, the hierarchical clustering is shown in the tree structure and the corresponding positions on the sheet. The red coloured area is a separate branch on the tree and is at the bottom of the sheet. The distribution of the data is similar to the allocation of data in the SOM for 6.6 kV motors with class F insulation data.

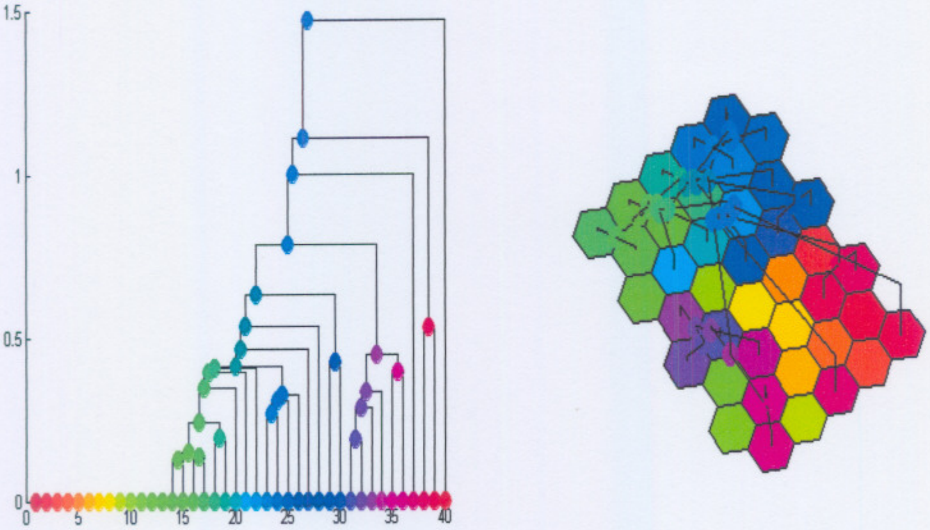


Figure 5.26: Hierarchical clustering for 6.6 kV motors with class B insulation data.

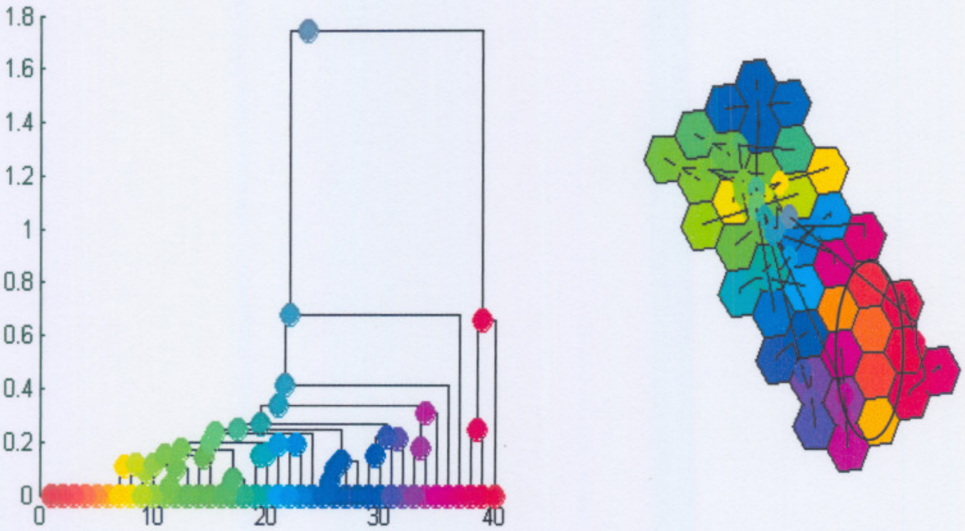


Figure 5.27: Hierarchical clustering for 11 kV motors with class B insulation data.

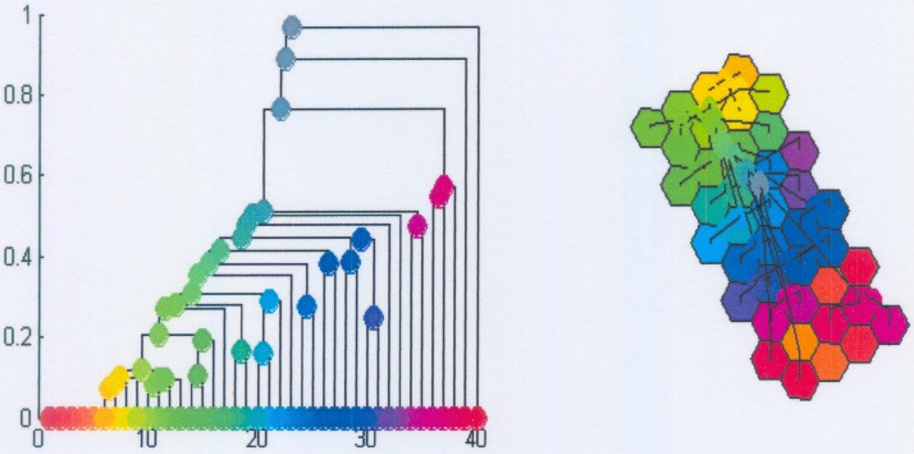


Figure 5.28: Hierarchical clustering for 11 kV motors with class F insulation data.

In all four figures 5.25, 5.26, 5.27 and 5.28, the clustering of data is similar to SOM clustering. No new insights are gained into the data clustering.

5.4.2 Partition clustering

"Most of the partition clustering algorithms is based on the square-error criterion" [26]. K-mean partition clustering was used to cluster the SOM available from the data.

According to Juha Vesanto, "2-level clustering is more effective than direct clustering" [28].

"The K-means constitutes one the most popular methods for multidimensional data clustering" [25]. The advantage of partition clustering is that there is some control over the number of clusters being formed. The fact that it is difficult to determine a cluster of arbitrary shape, is a disadvantage.

The 2-level K-mean clustering is where the prototype vectors of SOMs are used as input for K-mean clustering, rather than directly clustering the data. The benefits of this method are:

- The computational time is reduced.
- The effect of noise is reduced.

- "The prototypes in an SOM have local averages, thus are not as sensitive to random variations as the original data" [28].

Therefore the 2-level K-mean clustering approach was used for the research.

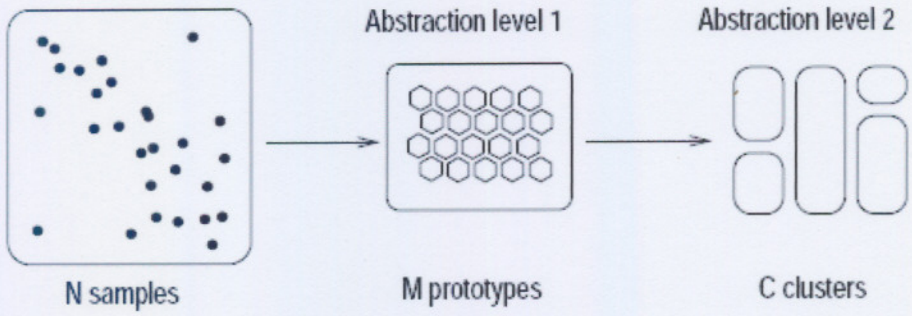


Figure 5.29: Two level K-mean clustering [28].

In K-mean algorithm, k initial centres are taken which may or may not be the centroids. Every data sample is assigned to any one of the clusters, as shown below figure 5.28.

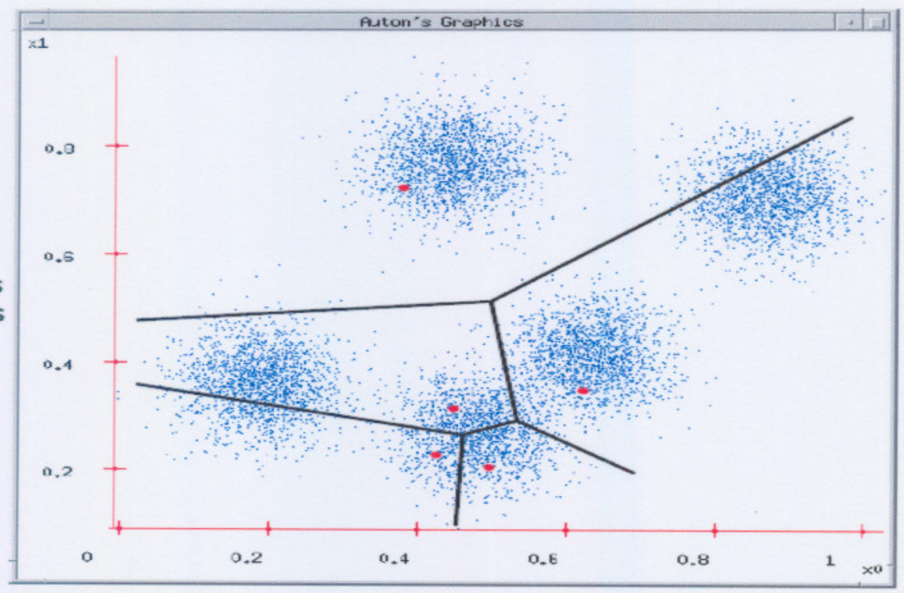


Figure 5.30: K-mean algorithm step 1 [37].

Once every data point is assigned to any one cluster, the new centroids are calculated. This was done in such a way that, the square of the distance between the data and the new centeroids was minimized.

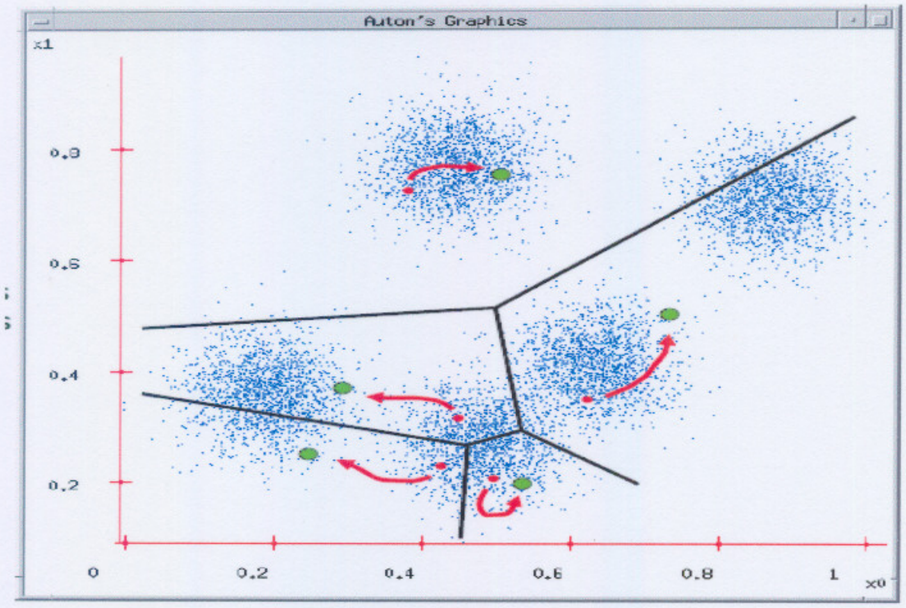


Figure 5.31: K-mean algorithm step 2 [37].

The process is iterated untill no further improvement can be made and the centroids remain constant. Then the clustering is complete.

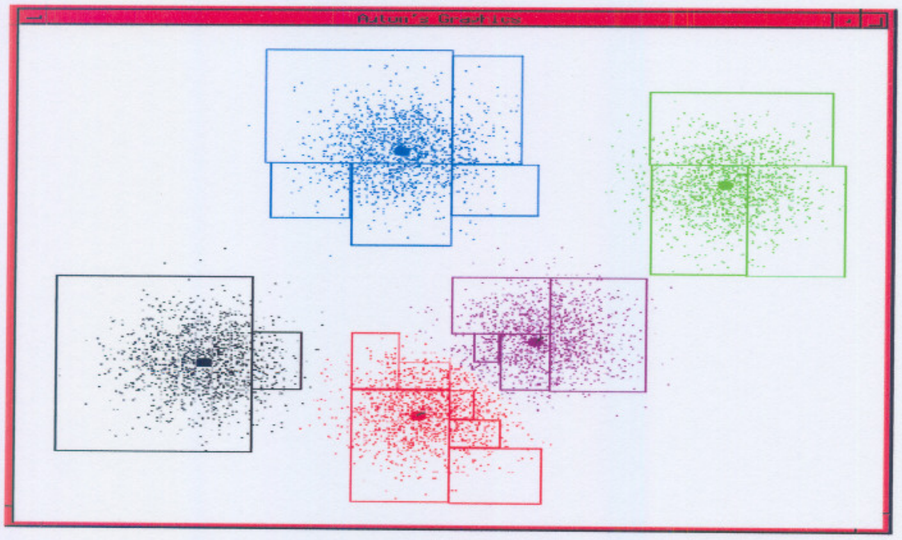


Figure 5.32: K-mean algorithm step 3 [37].

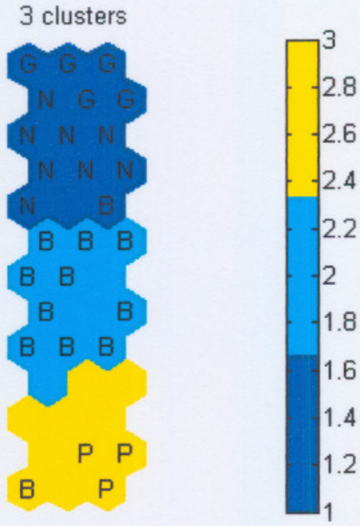


Figure 5.33: K-mean cluster for the complete data of 6.6 kV and F insulation.

The data was divided into 3 clusters; one consists of good and normal data, the second of below average data and the third of poor data. There is a slight overlapping, but this is good clustering obtained for the data.

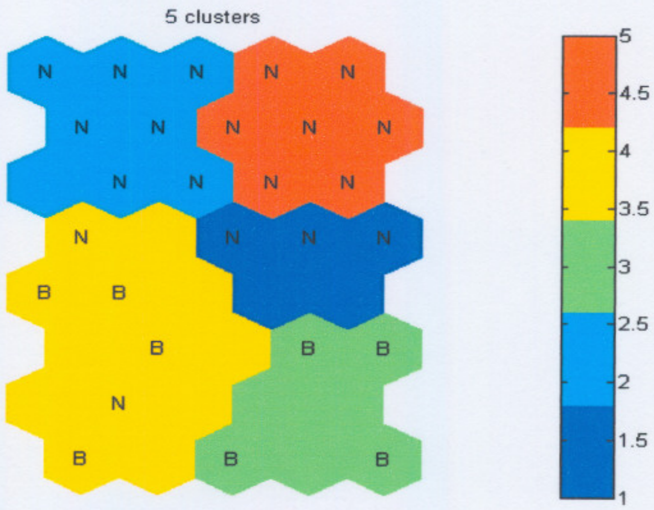


Figure 5.34: K-mean cluster for the complete data of 6.6 kV motors with class B insulation.

The reason for five clusters was explained in section 5.4.2.1. The top three clusters have normal data, but the reason why they are in three different clusters is not clear.

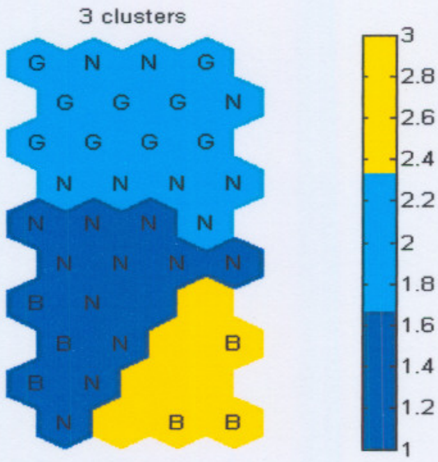


Figure 5.35: K-mean cluster for the complete data of 11 kV motors with class B insulation.

The three clusters that are formed are good data, normal data and below average data. There is overlapping between good and normal, normal and below average.

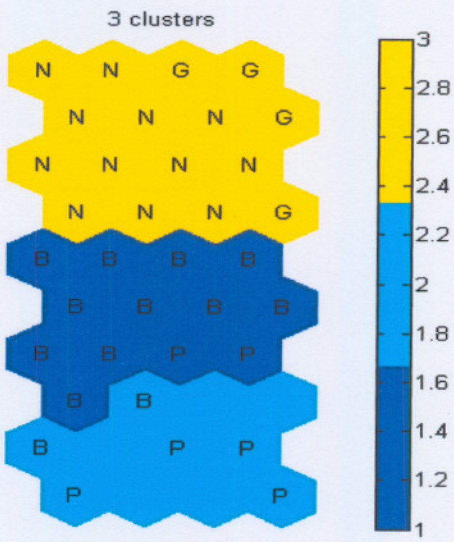


Figure 5.36: K-mean cluster for the complete data of 11 kV motors with class F insulation.

The K-mean cluster in three cases clusters good and normal into one cluster. Below average forms another cluster and poor forms a different cluster.

There is an overlapping of the good and normal cluster, normal and below average and below average and poor data. In all four the models, the good and poor have not overlapped at any point, which implies that the clustering was good and correlates well with the expert's assessment.

5.4.2.1 Validity

The K-mean cluster's validity was evaluated by the Davies-Bouldin (DB) index. This validity index calculates the validity of the number of clusters formed by the K-mean algorithm.

$$\mathrm{DB} = \frac{1}{k}\sum_{i=1}^{k} \max_{i \neq h} \left\{ \frac{e_h + e_i}{d_{ih}} \right\} \qquad 5.7$$

Where d_{ih} is the distance between the two clusters i and h, e_h and e_i is the intra cluster distances and k is the number of clusters [26]. When the distance between the clusters is large and distance inside the cluster is small, it is considered good clustering.

Therefore, the smaller the DB index is the more optimal the number of clusters will be. As shown in the table 5.3 below, the DB index for five clusters for each data group has been calculated. Group 2, 3 and 4 gives a minimum DB index for 3 clusters, while group 1 does not cluster that well.

Table 5.3: Davies-Bouldin validity index.

No. of Clusters	1	2	3	4	5
	DB Index				
Group 1	-	0.8632	0.7386	0.8293	**0.6195**
Group 2	-	0.5331	**0.5165**	0.6620	0.5448
Group 3	-	0.5772	**0.4811**	0.6336	0.4998
Group 4	-	0.6696	**0.6019**	0.8899	0.7235

5.5 Summary

In this chapter, a brief introduction was given about self-organising maps (SOM). The principle behind SOM and the process by which SOM does the analysis has been explained with the help of mathematical equations and figures. In the analysis, SOMs were done with individual features and the features that gave high accuracy were selected. The selected features were used together to give higher accurate SOMs and good clustering. SOMs for the four groups were discussed separately. The data was clustered using SOMs, hierarchical algorithm and the K-mean algorithm. SOM clustering gave insight into the contribution of different features to the clustering. Hierarchical clustering gave similar clustering to SOMs but no new insights, while K-mean clustering gave good clusters for three groups of data. The K-mean clustering validity was evaluated using Davies-Bouldin validity index. The table 5.4 gives the numerical range of the test results in each cluster. Even though there is a certain extent of overlapping, the results help in understanding the condition of the insulation in the motors.

In chapter 6, discussion and comparisons of the SOMs, hierarchical and K-mean clustering techniques are discussed, and the conclusions and recommendations presented.

Chapter 6

DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS

6.1. Discussions

The raw data of insulation test results had to be classified according to the condition of the insulation. Thus, initially statistical analysis was used to understand the information. Then, neural networks were used to visualize patterns and classify the data. An attempt has been made to use artificial neural networks to understand the correlation between test results and the condition of the machine. The results are discussed separately for each group.

Group 1 consisted of 6.6 kV motors with class B insulation and had 11 machines with 66 sets of data. Less data was available than for the other groups, which affected the quality of classification to a great extend. The reason was that even though the classification technique is good, the quality of results depends greatly on the data available. This limitation was reflected in the results obtained. Statistically there was a linear correlation between tan delta tip-up and slope of gradient of capacitance. The value of the tests results were higher for B insulation when compared to group 2. This indicates that B insulation could withstand more SOMs had good correlation with the expert's assessment; one reason being there was not enough variation in the input data. Hierarchical clustering did not give new meaningful insights, while K-mean clustering results classified the data into five clusters, which could not be explained.

Group 2, consisting of 6.6 kV motors with class F insulation, had 72 machines with 302 sets of data. According to the statistical analysis the majority of the data was in the lower rangers with a few outliners. The SOM clustering was good for both the good and normal data as well as the poor data. Hierarchical clustering results were similar and almost redundant when compared to SOM results. The K-mean clustering gave good classification and grouping to the data, and the classification was validated by the Davies-Bouldin validity index.

On comparing the three clustering methods, SOMs gives more insight into the data and contributing features while K-mean gives good classifications.

Group 3 consisted of 11 kV motors with class B insulation and 23 machines with 195 sets of data was available, which is a much larger data set than the 11 machines of group 1. The larger number of cases gave better results for all the classification techniques. In the statistical analysis there was a good Gaussian distribution for tip-up data and there is a good linear correlation between tip-up and the slope gradient of capacitance. SOMs and Hierarchical clustering divided the data into two major groups, one consisting of good, normal and below average data while the second group comprised below average data. The K-mean classified the data better into three groups. One group consisted of good and normal data, the other group of below average and another group consisting of normal and below average data.

Group 4 comprised 11 kV motors with class F insulation, 73 machines and 546 sets of data. The statistical analysis showed that there was good linear correlation between the tip-up and the slope of gradient of capacitance. SOMs and hierarchical clustering did not give distinct clustering of the data. The K-mean clustering was able to classify the data into three groups. The first group consisted of good and normal data, the second group of below average data and the third group was made up of poor data. There was overlapping between the second and third groups of data.

The clustering techniques were able to classify the good and poor data well without any overlapping between these two groups of data. The normal data overlapped with good and in some cases with below average data. While below average data overlapped with poor data in some cases. When compared to expert's assessment the good and poor data were clustered well, but normal and below average classification was not that clear. Among the clustering techniques K-mean clustering gave good classifications.

The best data that was used for analysis was a machine with voltage rating 6.6 kV with class F insulation. It had recorded history from 1983 to 1992. There was degradation over the years until in 1989 it was rewound. Readings from 1983 formed part of below average cluster, readings from 1986 and 1988 formed part of poor cluster and readings of 1990 and 1992 were clustered with good data, in figure 5.33. In the research a rewound machine was considered as a new machine, because the insulation system has been completely changed. The other good data that was used in the analysis was from five machines with a voltage rating of 6.6 kV with class F insulation system. The data from these five machines clustered well at all voltages from 0.2 pu to 1 pu, the figures were not included in the research. But in figure 5.16, in the U-matrix the first row contains data from these five machines, which forms part of a cluster. Three out of the five machines had the same speed; but information about the other two machines was not available.

6.2. Conclusion

A sincere effort was made in this study to search for patterns and to set guidelines based on the available data. Even though guidelines in the form of specific ranges could not be obtained, clusters based on the condition of the motors were obtained. The study also tried to compare the different clustering techniques used for classification of the data. The results of the classification were also compared with expert's opinion.

The qualitative assessment of the motors' insulation systems was possible. The limitation of the sample size of data, the different sizes of the machines included in one group and the different manufacturers caused a lot of variation in the test readings. Thus, the quality of classification was influenced to a certain extend. From the research it could be said that the tan delta test gives a good idea of the actual condition of the insulation, and tip-up and the change in capacitance both increases linearly as it ages. In conclusion the goals that were set for the research have been achieved.

Table 6.1: Numerical range of the clusters obtained.

6.6 kV and F insulation system			
Condition of insulation	Tan Delta	Tip-up	Slope gradient of capacitance
Good and normal	4 - 29	0.3 – 8.5	0.2 - 7
Below average	41 – 110.9	1.8 – 7.3	0.8 – 11.5
Poor	85 - 95	17 – 18.6	17.2 – 18.7
11 kV and B insulation system			
Condition of insulation	Tan Delta	Tip-up	Slope gradient of capacitance
Good	6 - 9	0.6 -3.6	1.3 – 3.25
Normal	6 - 19.9	2.1 - 7	2.7 – 6.4
Below Average	48 - 69	3.4 – 5.7	7.1 – 9.6
11 kV and F insulation system			
Condition of insulation	Tan Delta	Tip-up	Slope gradient of capacitance
Normal	4 - 27	0.5 - 4.9	0.1 - 4.7
Below Average	5.8 - 52.9	4 - 11.4	2 - 8.38
Poor	17 - 72	8 - 19.4	6 - 18.4

6.3. Recommendations

In research involving data analysis, usually a large amount of the time and effort is taken up in data collection, understanding, documentation, cleaning and preparation. This limits the time for the actual analysis and interpretation of results. Research should be planned in such a way that there is enough time for analysis and understanding the results. It is suggested that for further research more data be collected on machines that have a good maintenance history, thus improving the input data that would in turn improve the classification results. For the model to be used as a commercial tool in the industry, the quality and quantity of the data used has to be increased. The variation of the tests results have to be more, and the amount of data on below average and poor data needs to be increased. In reality it is difficult to find good recorded history of machine insulation tests.

Another way to approach this problem is to collect data even if it is just a single reading of a test and use the data from similar machines during analysis. It would be a good idea to take the dimensions of the machine into consideration as well.

Unsupervised artificial neural network techniques have more analysis techniques that can be used for similar research. In addition, there are advanced SOM techniques that can be investigated, e.g. growing hierarchical self-organizing maps (GHSOM).

Similar research can be done for the mechanical aspects of insulation systems. Data for mechanical tests are more readily available than data from electrical tests.

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