PROJECT REPORT

On

Health Monitoring & Analysis of Electrical Equipment using Infrared Thermography and Machine Learning

Submitted

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By

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ABSTRACT

Health Monitoring and analysis is a technique of monitor operating condition of an electrical equipment to schedule maintenance program in a proactive manner. This approach of Condition Based Maintenance (CBM) differs from commonly used method of preventive maintenance by centering the maintenance based on the actual condition of the machine rather than on some preset schedule. In electrical equipment incipient faults are often characterized by variations in certain characteristics like temperature, vibro-acoustic signature, etc. Different Health Monitoring techniques use dedicated sensing and data analysis tools to analyze particular type of variation these operational characteristics. A comprehensive review of prevalent Health Monitoring technologies, i.e. Vibration signal analysis, Acoustic emission testing, Ultrasound Health Monitoring, infrared thermography and lubrication oil analysis is done in this study.

Infrared thermography captures the thermal variations of an object under test and represents them in the form of images known as thermograms. Most of the incipient electrical faults are generally accompanied by temperature variations thereby making infrared thermography an integral part of Health Monitoring and preventive maintenance aimed at assessing the complete health of the industry/plant. Available literature suggest that the current practice of performing the thermographic survey is based on capturing of infrared images of the equipment from one particular viewing angle and classifying the condition by manual analysis which rely heavily on the individual domain knowledge. This type of analysis is always prone to erroneous classification of machine condition due to unavailability of complete thermal information in a single view and miscalculated judgments on behalf the individual. The manual analysis requires availability of an expert with in-depth domain knowledge at all times, which is not always possible.

To address these issues, a new approach of multi view thermal analysis is proposed in this study that enables the user to capture and analyze the complete 360° of a machine which not only provides a better overall representation of thermal behavior of machine but also helps in presenting the key findings to decision makers more effectively.

Thermal monitoring and multi-view analysis was tested to monitor the condition on an

Induction Motor. The results obtained clearly indicate that under influence of a anomaly the temperature profile of machine increases significantly and this can be analyzed easily by proposed 'IR RADIOMETRIC ANALYSIS' tool without indulging in obtaining deep knowledge of machine operation. Also the application of multi-view analysis is presented for detecting localized faults like bearing failure in motor, that produce only localized thermal changes and which cannot be detected by current method of single view analysis.

After collection of data comes the use of Machine Learning to predict the fault in any electrical machine. Machine learning is the subfield of computer science that, according to Arthur Samuel in 1959, gives computers the ability to learn without being explicitly programmed. After programming and feeding the code with the data collected we can correctly predict the faults that are likely to occur and thereby schedule a proper maintenance and repair of the machine.

Contents

TABLE OF FIGURES

MOTIVATION FOR THE PROJECT

Imagine that the bearing or the blades of a steam turbine have been running for years in a power plant, and remain unattended and its condition not monitored. Without any monitoring system in place, it is tough to predict the reliability of the equipment, and predicting the potential failure mode of the same becomes almost impossible. Poor maintenance practices and no monitoring can be detrimental and lead to catastrophic failure and cause significant damage to life and property.

Today, many power generation steam turbine generators are required in service well beyond their intended lifetime. Dismantling for inspection can prove expensive and owners need to consider all the relevant information when making the decision. Herein lies the importance and criticality of condition monitoring and the equipment used for the same. The focus in recent years is shifting from scheduled maintenance to predictive maintenance by observing and predicting the machine condition in advance. The motors used in the machine are being monitored using vibration, current, and temperature sensors which either provide warning signals or shut down the system before any catastrophic failure occurs. Traditional condition based monitoring system is a wired system formed by communication cables and different sensors. This involves high installation cost and difficulty in maintenance especially when the equipment is placed at different location than machine. To overcome these restrictions, the structures can be monitored remotely with the help of wireless transmission media. Wireless sensor network is a control network that integrates sensor, wireless communication and distributed intelligent processing technology.

Condition monitoring has a great potential for enhancement in the reliability of operation, machine up-time, reduction in consequential damage and improving operational efficiency at lower operational cost. In electrical equipment incipient faults are often characterized by variations in temperature, vibro-acoustic signature, etc. Different condition monitoring techniques use dedicated sensing and data analysis tools to analyze particular type of variation in operational characteristics. Research in this domain is primarily focused on specific use of a sensing technology. However, this work is aimed to act as a guide for an industrial or academic user to choose the right technique for condition based maintenance of their equipment and to present a comprehensive review of prevalent condition monitoring technologies, i.e. Vibration signal analysis, Acoustic emission testing, Ultrasound condition monitoring, Infrared thermography and lubrication oil analysis. A detailed review of condition monitoring techniques which can be used to detect a particular type of fault is presented with an aim to identify the most suitable technique for fault diagnosis.

Recently, the infrared (IR) thermograph technology has gained more recognition and acceptance due to its non-contact and non-destructive features of inspection. It is a fast and reliable inspection system that operates without interrupting the running operation of power system. In IR thermograph based technique, fault diagnosis is performed through the analysis of thermal image captured by infrared camera. It is implicit that the life of electrical equipment is radically reduced as temperature rises. Thermogram based temperature measurement technique offers many advantages such as prompt response times, ample temperature ranges, highly reliable, harmless, high spatial resolution, and very lucrative approach for the monitoring of electrical power systems.

CHAPTER 1

INTRODUCTION

1. INTRODUCTION

Typically, maintenance is performed using fixed time based intervals and where necessary, with the required corrective actions. Although scheduling a lot of preventive maintenance actions can result in as few as possible corrective actions, this leads to a decrease in availability and an increase in direct maintenance costs due to labor and spare parts costs. Condition Based Maintenance (CBM) policy plans the maintenance schedule only when required by utilizing available condition monitoring technologies to determine the condition of an asset. Hence the availability of machine is not affected and there is a considerable saving in maintenance as well as process cost. Owing to its many advantages discussed in above sections, IRT has a great potential for health monitoring especially for electrical equipment. The available literature clearly points towards the increasing trend for commercial use of IRT as an integral part of condition monitoring and preventive maintenance aimed at assessing the complete health of the industry/plant. Although the field of IRT based condition monitoring has evolved manifold from the days of its inception, there are still certain gaps in the available literature, which can be resolved to make it even better and more easily implemented technology.

Typically in most of the present day IRT based condition monitoring programs the operating personnel capture infrared images of the equipment under test from one particular viewing angle and analyze them manually i.e. the analysis and classification rely heavily on the individual's domain knowledge. However, in cases where effect of fault is not prominent in that particular captured view or it demands for multiple views to make a qualitative analysis, the single image analysis approaches may cause loss of significant information which can affect the overall efficiency of system. Manual analysis method on the other hand can only be performed by an expert having in-depth knowledge of machine and the process. It is most unlikely, that such experts are available at every industry or every industry can afford to call such experts to perform regular thermographic surveys. Also manual analysis suffers from a major drawback that it is always prone to miscalculations and erroneous judgment on the behalf of individual performing the thermographic survey.

To address these issues, a methodology using existing sensing and data acquisition techniques is proposed in this work, which enables the user to capture and analyze the thermal behavior of a machine to identify any deviation from its normal behavior. It also provides the opportunity to analyze complete 360° of a machine to gain comprehensive information about overall heat signature which will be superior approach with respect to single view analysis. The all-inclusive multi view analysis tool not only provides a better representation of machine's thermal behavior in all directions but also helps in presenting the key findings to decision makers more effectively. The methodology provides a platform to integrate multi view image visualization and analysis capability with specialized region of interest (ROI) detection and analysis features, which empowers any industrial user with lesser or no domain knowledge to perform the thermographic survey and analyze its findings.

Maintenance is a process undertaken to conserve as nearly, and as long as possible the original state of equipment or its components while compensating for normal wear and tear. A good maintenance schedule plays a key role in life cycle of electrical equipment as it ensures enhancement in the reliability of operation, machine availability, reduction in consequential damage and prevention from a catastrophic failure. Continuous health monitoring of a machine by means of analysis of its operating characteristics has a great potential to predict the need for maintenance before deterioration or breakdown occurs. This technique is commonly known as Health Monitoring or condition based maintenance.

1.1 CONDITION BASED MAINTENANCE

Condition Based Maintenance (CBM) differs from earlier used method of preventive maintenance by centering the maintenance based on the actual condition of the machine rather than on some preset schedule. The need of Health Monitoring arises from the fact that in a power plant or a power utility any unexpected fault or a shutdown may result in a fatal accident or huge loss of output. Health Monitoring solves these problems by providing useful information for utilizing the machines in an optimal fashion. The recent development in computer and transducer technologies coupled with the advances in signal processing and artificial–intelligence (AI) techniques has also made it possible to implement CBM more effectively on electrical equipment making it a more reliable and intelligent approach which can be used at various levels of power generation and distribution.

1.2 NEED OF CONDITION BASED MAINTENANCE

To understand the actual need of CBM, first the already established maintenance techniques needs to be studied. As shown in figure-1.1, maintenance approaches are widely classified into three main categories. Reactive or corrective maintenance is ―run to failure‖ approach where maintenance or repair is done when equipment has already broken down whereas preventive maintenance is predetermined work schedule performed periodically after a predefined time period with the aim of preventing the wear and tear or sudden failure of equipment components.

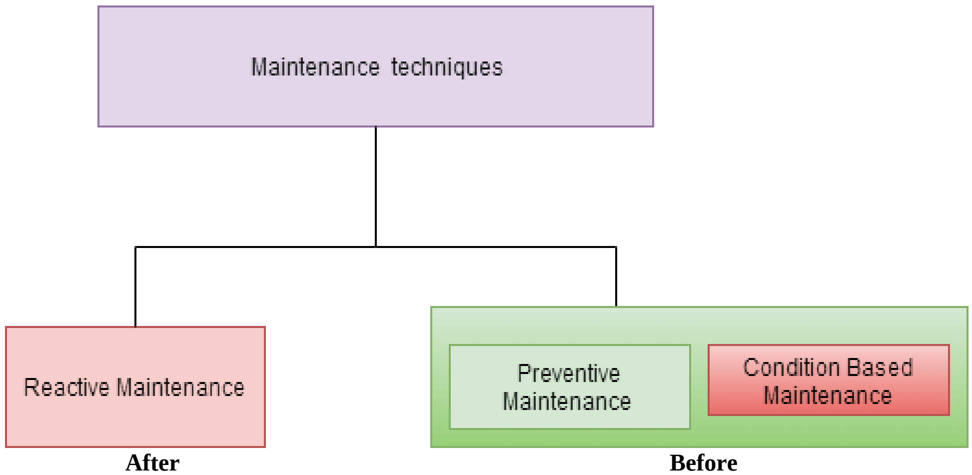

Fig 1.1 General Categorization of present maintenance techniques

Usually preventive or time based maintenance is the primarily used maintenance technique as scheduling frequent maintenance schedules can result in fewer corrective actions but this leads to a decrease in availability and an increase in direct maintenance costs due to labor and spare parts costs. On the other hand execution of condition based maintenance is planned only when pre-set normal operating characteristics of equipment are altered. In some cases it is also possible that a machine can actually be run until just before failure. An ideal maintenance policy should be cost efficient as well as it must support maximum availability of the equipment under consideration In preventive maintenance, although time based maintenance strategy considerably reduces the number of failures, the prevention cost is quite high whereas the repair cost is low as many potential failures will not occur. In reactive maintenance strategy, as machine is run to failure, although the prevention cost is low but it eventually leads to a high cost of repair. Condition based maintenance combines the incentives of both preventive and reactive maintenance as it delivers considerable decrease in the spare parts and labor costs because of less corrective actions along with increase in machine availability on account of effective scheduling. This simultaneously results in reduction of total maintenance cost.

1.3 CONDITION BASED MAINTENANCE DESIGN

For implementation of condition based maintenance a framework is required to depict its proper and effective execution. A general design of condition based maintenance program is shown in figure-1.3 which is created by integrating the available knowledge on CBM.

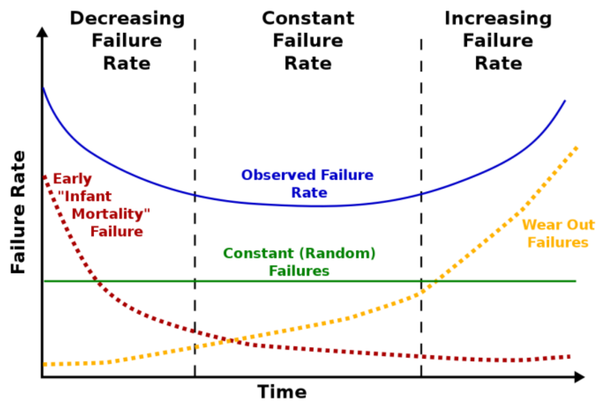

Figure 1.2 Hypothetical costs versus Number of failures curve

1.3.1 SELECTION OF CONDITION INDICATOR(S)

As CBM is based upon monitoring of operational parameters of equipment, the success of this program rely heavily on proper selection of these parameters or condition indicators. In electrical equipment incipient faults are often characterized by variations in various parameters like temperature, vibro-acoustic signature, oil condition etc. Before starting the CBM program those parameters should be identified which provides substantial insights into the machine's functioning and failure modes at all operating conditions? The parameter selection process is entirely based on comprehensive knowledge of operational behavior of machine and its components, operating conditions and the failure dependencies of machine. During the selection process a scenario may arise when some parameters correlate to a single failure mode or when for particular failure modes will require monitoring of more than one parameter to make an accurate indication of the deterioration condition. In such situation a single most conclusive condition dependent parameter can be chosen or depending on the criticality of machine and severity of failure more than one parameter can also be selected for CBM of a machine. The selected parameter(s) forms the basis of the Health Monitoring

1.3.2 DATA ACQUISITION AND ANALYSIS

After selection of suitable condition indicator, the next step is of data acquisition and analysis.

This step is very essential as the aim is to collect the data representing the actual physical state of the machine and analyze it to estimate machine health. Data acquisition is done using suitable sensors which convert a physical characteristic of machine like vibration, temperature etc. to an electrical signal. The selection of sensors depends on the chosen condition indicators which are to be monitored to reveal incipient faults long before catastrophic failures occur. Sensitivity, precision, cheapness, and no invasion are the most common criterion which needs to fulfill by the sensors used. Also it is very important that as far as possible, the sensors support online measurement of parameters.

The purpose of data analysis is to identify any deviation from normal operating characteristics of machine which may be an indicator of any incipient fault in the machine under test. The analysis can be done either by directly comparing the results of measurements with the prediction models and simulations formed by continuous health monitoring of machine over time, or by using feature extraction techniques like frequency and time domain analysis etc. to identify a signature representing any abnormal behavior.

1.3.3 DECISION MAKING

The last step of a CBM program is maintenance decision-making. In this step the information passed on by previous stages is processed to make out a recommendation as a clear indication of machine health. The functioning of decision making is divided into two categories viz. diagnostics and prognostics. Diagnostics mainly deals with the current state of machine i.e. whether monitored system is working at its optimum condition or not and if there is probability of a potential fault then, the location and the nature of the fault. On the other hand prognostics deals with fault prediction before it occur. The most common objective of prognostics is to predict how much time is left before a failure occur given the current machine condition and past operation profile. The maintenance decision making is done either by knowledge based models or computer based artificial intelligence models. Knowledge based models generally refers to classification done by an expert with profound to the knowledge of machine and its failure mechanisms. Another method of using knowledge based models is gathering the knowledge from experts to define rules within a software program. The more advanced adaptation of this method is the use of fuzzy systems in which the rules are defined on the basis of various operating conditions. The other and more accurate method is the use of artificial neural networks (ANN) systems. ANN can classify the health of the machine and its remaining useful life (RUL) by using a mathematical representation formed by training the system with previous Health Monitoring data of machine. This method is typically used for modeling complex non-linear systems by using process variables, Health Monitoring data, machine characteristics and maintenance history data as input data to give the desired maintenance action or the RUL as output of the network model. This method eliminates the need of using an expert's understanding of the underlying physical failure phenomenon, which in some cases are the cause erroneous classification results. However the only drop back of this method is its requirement of large data set of input variables for accurate classification.

1.1 OPPORTUNITIES OFFERED BY CONDITION BASED MANTENANCE

The correct implementation of a CBM program offers a user with the following opportunities

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1.1.1 ESTABLISH ROOT CAUSE OF FAILURE & FUTURE STATE PREDICTION

By implementing a CBM program, one can gain a significant amount of information regarding the health deterioration of equipment. The historical data not only represent the behavior of machine under varying operating condition but it can also provide useful insights for the establishment of root cause of failure by analyzing the machine's failure trends. Also, the relation between operational data and the failures can be used to predict future states and excessive down time due to unplanned machine failure can be prevented.

1.1.2 REDUCE LIFE CYCLE COST OF EQUIPMENT

Sustaining costs of maintaining a system for its complete life takes up almost 75% of equipment's life cycle cost[2]. The CBM approach not only spots upcoming equipment failure so as to schedule the maintenance program in a proactively manner but it can also trigger the maintenance a long enough before, so the work can be finished before it actually fails. All these features reduce both the maintenance cost of the equipment and also the operation cost of process. All these reasons make CBM a very versatile tool which can eventually lead to significant reduction in the life cycle cost of the system.

CHAPTER 2

LITERATURE REVIEW

2. LITERATUREREVIEW

In this chapter a comprehensive literature review of popular condition monitoring techniques is done. This review covers basic principles, data acquisition and data analysis methodologies of all CBM techniques along with a comparative analysis of their application for monitoring most commonly accruing electrical faults. As Infrared Thermography is employed as CBM tool for this study, a detailed review of the technique along with advancements from early research to most recent development is done. After analyzing the gaps in reviewed literature, a problem statement is formulated later in chapter which aims to fulfill the present requirements of Industries.

2.1 CONDITION BASED MAINTENANCE TECHNIQUES

Depending on the condition indicators which are monitored to detect change in the operational characteristics of the machine, the most popular CBM techniques are described below.

2.1.1 VIBRATION SIGNATURE ANALYSIS

Vibration is a cyclic or pulsating motion of a machine or machine component from its point of rest[3]. Vibration of a machine can be represented in time domain in terms of its phase and amplitude (which can be measured as displacement, velocity or acceleration), and in frequency domain by its dominant frequencies, harmonics, etc. Vibration signature analysis (VSA) is a widely used condition monitoring technique to determine the overall condition of a machine, which is based on measurement of vibration severity of the machine under test. Every machine in its working condition produces vibration and this vibration is a characteristic signature of the machine which does not change over time. However, in cases of structural or functional anomaly or failure, the dynamic characteristics of the machine changes which is reflected in its vibration signals[4]. The nature of the developing fault has unique vibration characteristics which can be compared with the vibration signatures of the machine working under normal operating condition. By using various signal analysis techniques one can determine the exact category/type of fault.

The vibration signals encountered in rotary machine systems, such as machine tools, wind turbines or electric motors can be broadly classified as stationary or non-stationary. Stationary signals are characterized by time-invariant statistic properties like periodic vibrations caused by a worn out bearing etc. Such signals can be adequately analyzed using spectral techniques based on the Fourier Transform. In contrast, non-stationary signals are transient in nature, with duration generally shorter than the observation interval. Such signals are generally generated by the sudden breakage of a drilling bit, flaking of the raceway of a rolling bearing, or a growing crack inside a work piece. For analysis of such non-stationary vibration signals, time-frequency techniques like Short-Time Fourier Transform for fault detection during impulse testing of power transformers wavelet transform, Hilbert-Huang Transform (HHT)[4] are popularly used.

2.1.2 ACOUSTIC EMISSION TESTING

Acoustic Emission Testing (AET) is a condition monitoring technique that is used to analyze emitted sound waves caused by defects or discontinuities. These acoustic emissions (AE) are transient elastic waves induced from a rapid release of strain energy caused by small deformations, corrosion or cracking, which occur prior to structure failure. In electric machines sources of AE include impacting, cyclic fatigue, friction, turbulence, material loss, cavitations, leakage, etc.. These acoustic emissions propagate on the surface of the material as Rayleigh waves and the displacement of these waves is measured by AE sensors which are almost always a piezoelectric crystal, commonly made from a ceramic such as lead zirconatetitanate.

Data acquisition and analysis*:* For the purpose of data acquisition sensors are placed on the material surface, the information collected by each of the sensors is monitored. If defects exist in some areas, the signal characteristics from the sensor attached nearest to the discontinuity appears in different way. By analyzing the discontinuity, it is possible to ascertain the defect position and suspect area of the structure. Broadly the data analysis can be done by two approaches. The first one is parameter based approach which is based on the analysis of basic signal parameters such as the rate, energy and amplitudes etc. In parameter based analysis only some of the parameters of the AE signal are recorded, but the signal itself is not recorded, this minimizes the amount of data stored and enables faster analysis. However sometimes these parameters lose massive information which makes characterizing of defects very difficult. The other approach is waveform analysis technique which is based on the complete waveform rather than on the parameters. The waveform based approach offer better data interpretation capability than parameter based approach by allowing the use of signal processing methods like Wavelet-based acoustic emission characterization , second generation wavelet transform, wavelet envelopment spectrum analysis etc. and also provides better noise discrimination.

2.1.3 ULTRASOUND CONDITION MONITORING

Ultrasound is defined as ―sound waves having a frequency above the limits of human hearing, or in excess of β0,000 cycles per second‖[16]. Many physical events cause sound at audible and/or ultrasonic frequencies, analysis of these frequencies can frequently indicate correct or incorrect operation. Ultrasonic condition monitoring (UCM) is a technique that uses airborne (non-contact) and structure borne (contact) ultrasound instruments to receive high frequency ultrasonic emissions produced by operating equipment, electrical emissions and leaks etc. to monitor the condition of equipment under test. Ultrasound transducers electronically translate ultrasound frequencies through a process called heterodyning, down to the audible range while maintaining the sound quality during the transition. These signals are observed at intensity and/or dB levels for analysis.

Active and passive ultrasound monitoring techniques*:* In passive techniques ultrasound detected by airborne or structure borne instruments is produced by a physical process i.e. by the component being analyzed. Passive ultrasound is used mainly for contact methods of monitoring such as bearing faults, lubrication issues, gear damage and pump cavitations and non-contact methods of monitoring like leaks in boilers, condensers, and heat exchangerselectrical discharge and corona in high voltage equipment etc. Airborne ultrasound detects high frequency sound produced by mechanical equipment, electrical discharges and most leakages which is extremely short wave in nature. These short wave signal tends to be fairly directional and localized which make them very easy to separate from background plant noises and to detect their exact location. On the other hand active ultrasound is an approach where a precisely guided beam of ultrasound is transmitted to a physical structure to analyze both surface and subsurface discontinuities like delaminations, emitted by an object to locate any abnormal heat pattern or thermal anomaly which indicate possible fault, defects or inefficiencies within a system or machine asset[30].

Table 2.1: Condition Monitoring Techniques for Fault Diagnosis of Electrical Equipment

COMPONENT	FAILURE	IRT	UCM	VSA	AET	LOA
Rotor bar	Broken bar	✓	✓	✓		
Transformer	Loose connection, Dampness, Insulation defect, Lack of oil	✓			✓	✓
Bearing	Bearing wear	✓	✓	✓	✓	✓
Surge arrester	Surge arrester failure	✓				
Steam pipes	Leaks in steam cycle	✓	✓		✓	
HV equipment	Corona, Electric discharge	✓	✓			
Wind turbine blades	Structural defects		✓			
Wind turbine/ gear train	Gearbox failure			✓	✓	✓
Pumps/ hydro turbines	Cavitations		✓	✓	✓	
Pipes	Cavitations, Erosion, Wall thinning	✓				

For purpose of condition based maintenance of electrical equipment it is very difficult to judge a superior approach from the above techniques. However to showcase the application of these techniques for monitoring of most commonly occurring failures in electrical machines a comparative analysis of available literature is done. Table 2.1, illustrates various condition monitoring techniques which can be used for health monitoring of various important electrical equipment to ensure reliable operation. Stator/rotor winding faults and rotor body faults are most commonly accruing anomalies in generator and motors. It is observed that for winding faults IRT can be used effectively[31], whereas due to accessibility constraints it is not suitable for rotor body faults and other internal faults in large machines, these can be effectively monitored by acoustic[32] and vibration analysis[33]. Cavitations in pumps and turbine, leaks in steam cycle and wall thinning of steam pipes are major problems in power plants. IRT and acoustic emission techniques are used for leaks and cavitations detection, being a non-contact technique IRT can be preferred[34][35]. Vibration analysis can also be used to detect cavitations in pumps and turbines. In wind power plants structural defects of turbine blade and faults in gear train are very common. Ultrasound condition monitoring is very useful for monitoring structural health of turbines blades[22] whereas vibro-acoustic and oil analysis are used for gear box fault detection[36]–[40]. The advantage of lubricant analysis is the detection of fault at a very early stage. Bearing is another very important component present in almost all rotating machines and due to its high rate of wear & tear, bearing condition monitoring is very important. Almost all CM techniques can be used for this purpose but vibration and acoustic techniques are used most commonly[41]–[47]. Acoustic testing has an upper hand over vibration analysis as it can detect bearing wear out even when the speed of rotation is low. In transformers faults like loose connections, insulation inferiority and dampness in oil needs major attention. These can be detected by Infrared thermography[48] whereas oil analysis is used to monitor both insulation deterioration and degradation of oil[49]. Detection of corona, electric discharge, surge arrester, bushing and other HV equipment failure in substations are also some very important issues which are required to be dealt with for safe and reliable operation. IRT and air borne ultrasound being non-contact methods are the most suitable techniques which are used for this purpose[50]–[52]. It's important to note that ultrasound condition monitoring system seems to be a less expensive solution as compared to other techniques and it can be used as a first line of defense or a primary tool in organization with budget limitations.

At the end of comparative analysis of all the available CBM techniques it was seen that IRT is applicable for monitoring most of the failures in electrical equipment. This is due to the fact that unlike other condition monitoring techniques IRT is based on monitoring of temperature variation which is a common indicator in most of the electrical faults. Also pertaining to the advantages like non-contact testing, ruggedness, better noise immunity and possible fast and easy manual inspection, IRT was selected as a mode of health monitoring in this study.
In the next section, the principle and CBM implementation of IRT is explained in detail.

2.2 INFRARED THERMOGRAPHY

The basic principle underlying Infrared Thermography is based upon Planck’s law and Stefan-Boltzmann’s law which states that all objects with temperature above 0 K (i.e. -β7γ˚C) emits electromagnetic radiation in the infrared region of electromagnetic spectrum i.e. wavelength in the range of 0.75–1000µm (shown in Figure-4) and the intensity of this IR radiation is a function of temperature of body. According to Planck's law

Where L_λ is the power radiated by the blackbody per unit surface and per unit solid angle for a particular wavelength, λ is the wavelength of the radiation, T is the temperature in absolute scale, and c1 and c2 are the first and second radiations constants respectively. On integrating Planck's law over all frequencies Stefan–Boltzmann's law is derived.

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Where q is the rate of energy emission (W), A is the area of the emitting surface (m^2), T is the absolute temperature (K) and σ is the Stefan–Boltzmann's constant and ε is the emissivity of the emitting surface for a fixed wavelength and absolute temperature T.

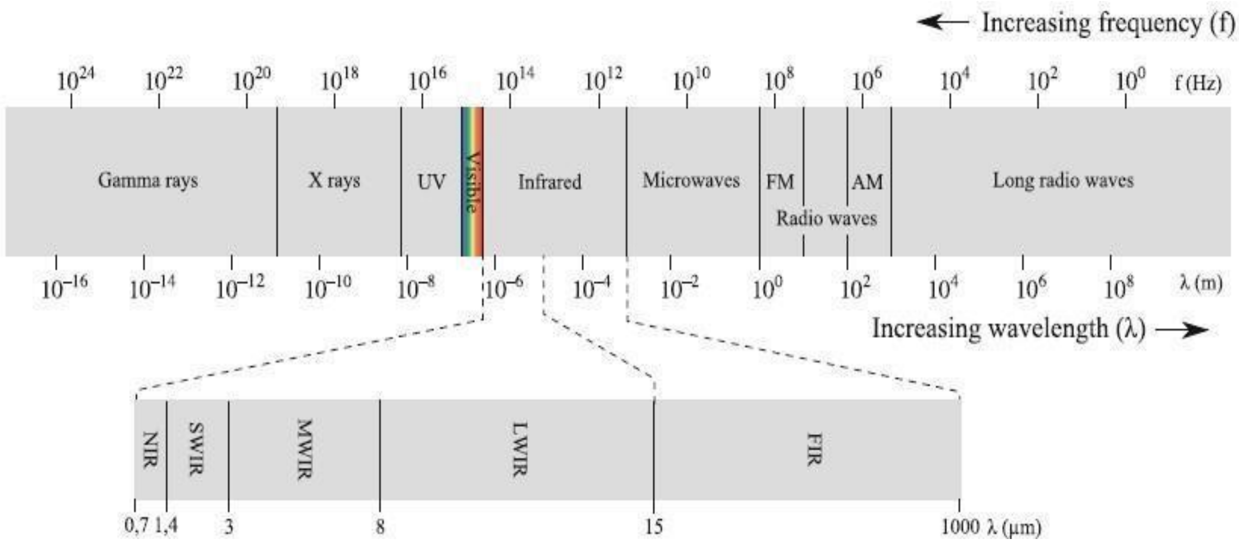


Fig.2.1 Infrared region of Electromagnetic spectrum[53]

In IRT, infrared radiation emitted by a body is detected in a non-contact way by an infrared detector and using Stefan – Boltzmann's law (Eq. (2.2)), the temperature of the body is obtained.

As shown in figure-2.1, the infrared region of spectrum falling between 0.7 to 1000μm is further divided into several sub-spectrums. Generally the object monitored using IRT have temperature range falling between 190-1000 Kelvin. The objects with temperatures lying in this range emit IR radiations falling in wavelength spectrum of Mid-Wavelength Infrared (MWIR) and Long-Wavelength Infrared (LWIR), due to this reason these spectrums are often referred as Thermal Infrared (TIR). Atmospheric absorption of certain frequencies is another very important phenomenon which affects the process of infrared thermography.

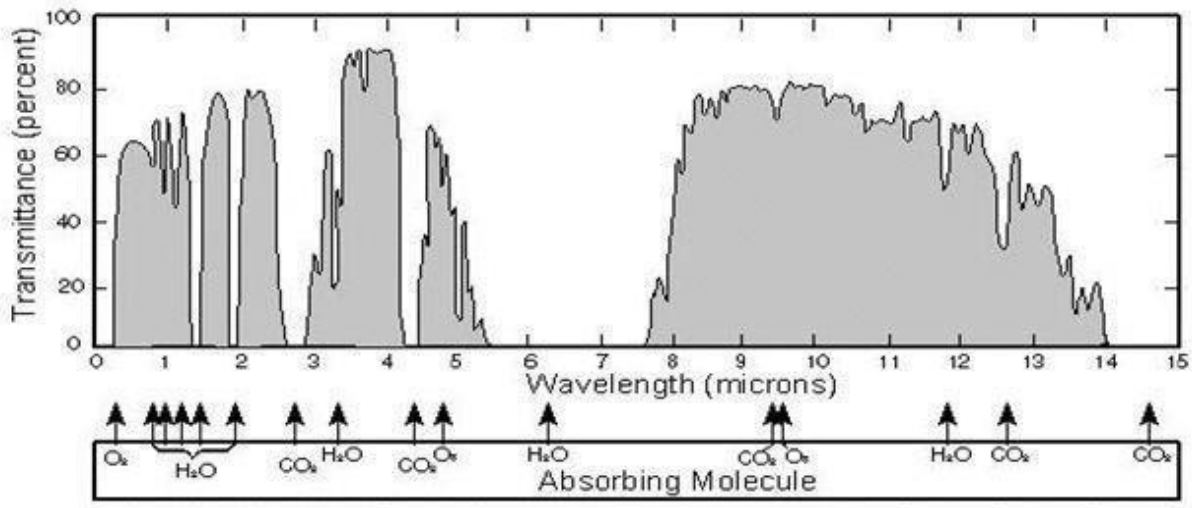


Fig.2.2 Atmospheric transmittance in infrared spectrum

The atmosphere only transmits radiations corresponding to certain wavelengths due to absorption of other wavelengths by various molecules present in atmosphere. In case of Infrared radiations CO_2 and H_2O molecules are majorly responsible for most of the absorption. Figure-2.2 illustrates the percentage of transmitted infrared radiation for different wavelengths and the molecule that is responsible for absorption of those particular radiations. Figure-2.3 shows the schematic of a typical Infrared thermography experiment where original image of the monitored machine, Infrared camera, display unit and its infrared image are shown. In a typical IRT experiment the infrared (IR) camera is focused on the machine under investigation in such a way that a clear optical access is available. Then the real time temperature information of the machine can be acquired in a non-contact way from the thermal images displayed in the computer or in the camera itself. The acquired thermal images (as shown in figure-2.3) are often pseudo color coded that makes their interpretations easier and faster however user has the liberty to choose format of displayed image. The obtained thermal images can also be stored digitally for further processing actions like region of interest (ROI) detection, hot spot detection etc. Another very important deduction which can be made from this schematic is that infrared thermography requires minimal instruments. The essential instruments are only an infrared camera and a PC for displaying images and data analysis.

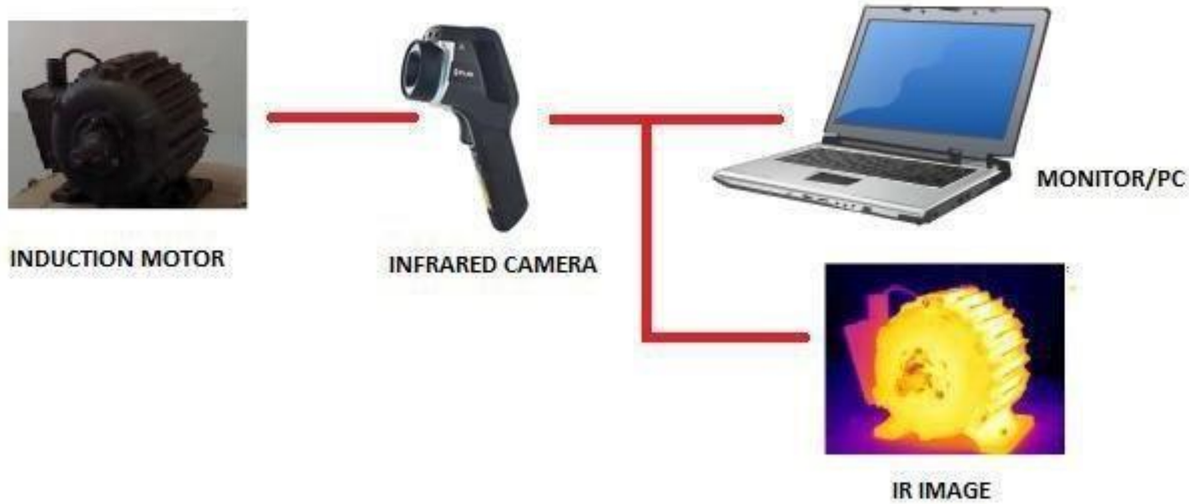


Fig.2.3 Typical experimental setup using IRT

2.2.2 Infrared Cameras

An Infrared camera is the heart of any Infrared thermography operation. Thermal cameras are the passive sensors which are used to capture infrared radiation emitted by any object with temperature above absolute zero and display them in form of a thermogram or a thermal image. The detectors used in thermal cameras are generally of two types: photon detectors or thermal detectors. In Photon detectors absorption of electromagnetic radiations changes the free charge carrier concentration in a semi-conductor. The variation of electronic energy distribution caused by this change in concentration results in the observed output signal. The photon detector typically works in the MWIR band where the thermal contrast is high, making it very sensitive to small differences in temperature. The current technology has also enabled photon detectors to allow a higher frame rate than thermal detectors coupled with perfect signal-to-noise performance and a very fast response. But to achieve this photon detector requires cooling below 77 K to reduce thermal noise. This type of cooling can be done by liquid nitrogen or now days it is often done by the use of cryocooler. These extreme cooling requirements are the main obstacle to the more widespread use of semiconductor based detectors as the cooling mechanism makes the system expensive, bulky and inconvenient to use.

On the other hand, in thermal detectors absorption of electromagnetic radiation results directly in rise of detector temperature. The electrical output of the thermal sensor is produced by a corresponding change in some physical property of material due to temperature rise, e.g. temperature-dependent electrical resistance in a bolometer etc. A thermal detector measures radiation in the LWIR band and can use mainly with two different types of detectors viz.

ferroelectric detectors and microbolometers. Ferroelectric detectors take advantages of the ferroelectric phase transition in certain dielectric materials. At this phase transition, small fluctuations in temperature cause large changes in electrical polarization. Barium strontium titanate (BST) is normally used as the detector material in the ferroelectric detectors. A microbolometer is a specific type of resistor. The materials most often used in microbolometers are vanadium oxide (VOx) and amorphous silicon (a-Si). The infrared radiation changes the electrical resistance of the material, which can be converted to electrical signals and processed into an image. A few important parameters are discussed below which should be kept in mind before choosing an Infrared camera.

1) **Spectral range**: Spectral range is defined as the portion of wavelength spectrum to which the infrared camera is sensitive. Due to very low transmittance beyond 14µm and between 5 to 8µm (shown in Figure-2.2), generally IR camera are insensitive in this band. To observe objects during day time, Long-Wave Infrared (LWIR) band may be preferred as during these ambient conditions objects emit radiations in this band and the measurement is not affected due to sun's radiation which predominately corresponds to shorter wavelength. During night and overcast conditions Short-wave Infrared (SWIR) band can be used.

2) **Spatial resolution**: Spatial resolution is ability of an IR camera to distinguish between two objects within the field of view. The prime factors affecting on the spatial resolution of an imager are distance between object and camera, the lens used and size of detector array. Ideally for better image quality the spatial resolution should be high.

3) **Temperature resolution**: The temperature resolution is the measure of range between maximum and minimum temperature values which can be measured by the IR camera. Typical the range lies between -20 to 500°C but it can also be extended using specialized filters.

4) **Frame rate**: Frame rate of an IR camera is the frames captured per second. For monitoring moving objects cameras with higher frame rate should be used.

Apart from the above mentioned parameters, some other factors which may govern the selection of an infrared camera are storage capacity, image processing capabilities, calibration, size and cost.

2.2.2 EXPERIMENTALMETHODOLOGIES

Infrared thermography is generally classified in two categories, passive and active thermography. In passive thermography temperature measurement is done without any external stimulus as the temperature gradients are naturally present in the materials and structures under test. Passive thermography is mainly applied for condition monitoring of electrical and mechanical equipment [54]. Also abnormal temperature distribution over skin surface is a probable indication of illness passive thermography has been extensively used in the field of medical sciences.

However in some cases the defects are deeper and smaller which makes the thermal gradient on the surface less prominent. In such cases use of passive thermography is not suitable because it will eventually lead to inconclusive results. This situation is overcome by the use of active thermography where the relevant thermal contrasts between the defect and background are induced by an energy source[55]. There are wide varieties of external energy sources which can be used to generate thermal contrast between defect and background and they are generally classified in two categories viz. external stimulus and internal stimulus. In external stimulus the energy is delivered to the surface of specimen and then it is allowed to propagate through the material until it encounters a flaw. Typically external excitation is performed by heat wave and optical devices like halogen lamps etc. Conversely, in case of internal excitation energy is directly injected into the specimen in order to stimulate exclusively the defects.

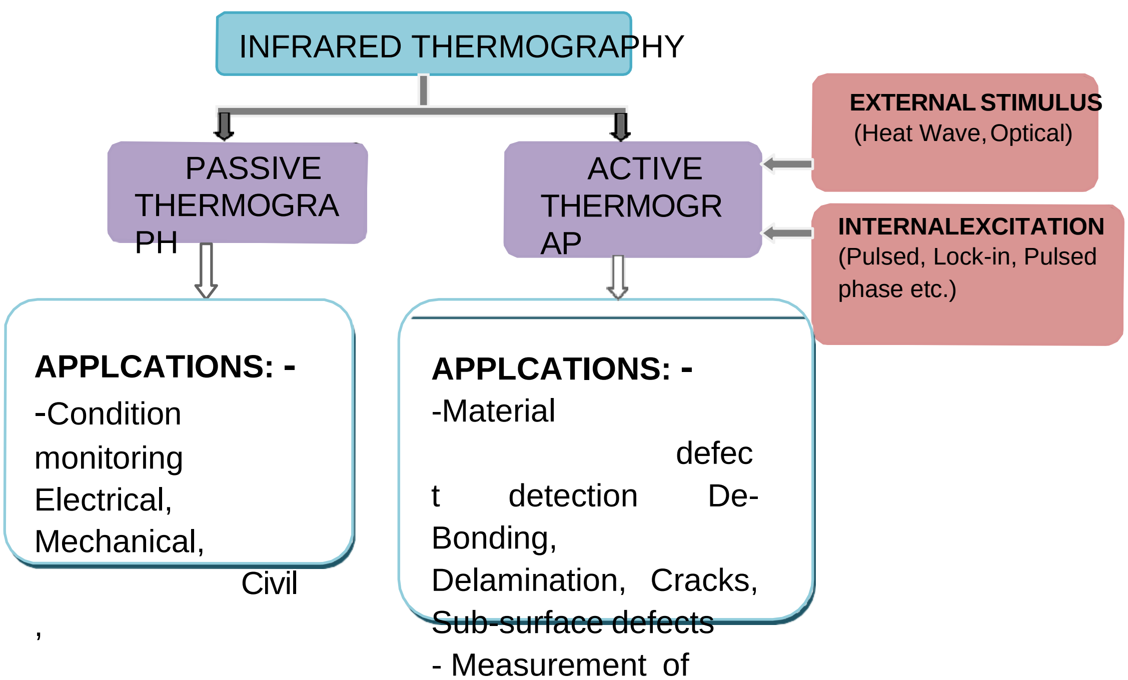


Fig.2.4 Schematic representation of active and passive infrared along with application

Depending on the nature of internal excitation, active thermography can be further subdivided into several categories like pulsed, lock-in, pulsed phase, etc. In pulsed thermography, a short duration heat pulse is used as stimulation and the temperature evolution is monitored in the transient domain. Lock-in thermography is performed in the stationary domain, where sinusoidal heat wave is used to illuminate a spot and the thermal response is recorded using an infrared detector and decomposed by a lock-in amplifier to extract relevant information. Pulsed phase thermography is a combination of both lock-in and pulsed thermography techniques, where data is acquired in time domain but phase analysis is performed in the Fourier domain. Active thermography techniques are in general used for detecting structural faults like debonding, delamination and crack etc. in metallic and composite specimens. It is also extensively used for measurement of coating thickness of corrosion protective paints and in various industrial processes. Figure-2.4 shows schematic representation of active and passive infrared along with their respective applications. For most of the IRT based condition monitoring applications passive thermography is the preferred as the experimentation and data analysis is simple and straight forward.

2.2.3 CONDITION MONITORING USING INFRARED THERMOGRAPHY

Just like any general condition monitoring system, IRT based condition maintenance program also has three main steps. The first step involves acquisition of the thermal behavior of machine in form of thermal images captured using an infrared camera. The obtained thermal images represent the temperature distribution of the scene coded in different formats like grayscale, pseudo color etc. The next step is finding region of interest (ROI) which is more related to image segmentation. ROI detection refers to separation of foreground from the background in a particular thermal image. This extraction of region of interest containing the potentially faulty portion of the machine can be implemented using various image processing techniques. The most commonly used are image segmentation, thresholding[56]. Finding ROI plays a very crucial role in IRT as the key success of decision making process depends on the correct ROI detection. This is due the fact that relevant information corresponding to the state of machine like maximum or minimum temperatures, temperature gradient etc. is extracted from ROI and passed on to classifiers for final fault classification. False ROI selection may lead to extraction of trivial information and eventually erroneous results.

As condition monitoring of an electrical machine using IRT is a technique that relies majorly on temperature measurement of the equipment under test, the next step after finding the region of interest is to perform temperature measurements and data analysis. There are two approaches for temperature measurement. The first one is quantitative, in which the exact temperature values of the objects are considered with ambient temperature as reference. The second approach is qualitative, in which the relative temperature values of a hotspot with respect to other parts of the equipment with similar conditions are considered. Qualitative analysis requires a great understanding of variables influencing radiometric measurement including object's emissivity, transmissivity, reflectivity, atmospheric conditions and machine[57]. In qualitative analysis there is no need to have a finer knowledge about variables influencing the temperature measurement. However, this method fails to perform correctly when a fault occurs in all similar components or a systematic failure occurs affecting all three phases, it also does not provide information about whether the equipment temperature limits are actually exceeded. In terms of analysis condition monitoring of a machine using IRT can be done by two methods i.e. manual and automatic. In manual method a thermographer proposes potential faults and anomalies by manually analyzing the thermal images of equipment under test.

Table 2.2: Infrared Thermography based Fault Diagnosis of Electrical Equipment

EQUIPMENT	TYPE OF INSPECTION	
	MANUAL	AUTOMATIC
Insulator		Calculation of images' moment invariants as characteristic vector of recognition, classification by SVM algorithm[58]
Disconnector		Infrared trend evaluation package (IR- TEP), Invariant coefficient method[51]
Transformer	Image-to-Image insection [48]	---
Transmission line	Image-to-Image	---

Induction Motor		Model based on calculation of heat losses by convection and radiation[31]
Leakage detection	Image-to-Image insection [59]	---
Motor		Thermal model representing the temperature distribution[41]
Motor, Bearings		Physical model of the element's temperature using a least square recursive method[42]
Circuit breaker	Image-to-Image insection [60]	---
Surge arrester		Watershed segmentation, Neuro-fuzzy based classification[56]

The final stage of classification uses the extracted current features and compares them with a prior created database using advance learning methods like artificial neural networks(ANN), support vector machine (SVM)[58]and fuzzy based decision making[56], etc. Table 2.2 presents both manual and latest automated analysis techniques proposed by different researchers for condition monitoring of electrical equipment using infrared thermography.

2.3 Machine Learning

Depending on the specific industry, maintenance costs can represent from 15% to 40% of the costs of goods produced. In fact, these costs are associated with maintenance labour and materials and are likely to go even higher in the future with the addition of factory automation through the development of new technologies. Nowadays, the development of maintenance strategy is supported by computer technology both in hardware and software. A recent developed method is using artificial intelligent (AI) techniques as tool for maintenance routine. Based on the idea performing an excellent and easy maintenance program; it leads the practical maintenance to create an intelligent maintenance system. Intelligent maintenance consists of parts (hardware and software), which are possible for the system to do maintenance routine in such a way like human being. Application of expert system (ES) as a branch of AI in maintenance is one of solution. The basic idea of ES is simply that expertise, which is the vast body of task-specific knowledge, is transferred from a human to a computer. This knowledge is then stored in the computer and users call upon the computer for specific advice as needed. The computer can make inferences and arrive at a specific conclusion. Then, like human consultant, it gives advice and explains, if necessary, the logic behind the advice [2]. Support vector machine (SVM) is a relatively new computational learning method based on the statistical learning theory and can serve as ES. Some seminal papers introduced below to show the development of SVM that originally came from statistical learning theory (SLT) developed by Vapnik [3]. SVM is based on Vapnik–Chervonenkis theory (VC-theory) that recently emerged as a general mathematical framework for estimating (learning) dependencies from finite samples. This theory combines fundamental concepts and principles related to learning, well-defined formulation, and self-consistent mathematical theory. Moreover, conceptual framework of VC-theory can be used for improved understanding various learning method developed in statistics, neural networks, fuzzy systems, signal processing, etc. A major conceptual contribution of VC-theory is revisiting the problem statement appropriate for modern learning method that makes a clear distinction between the problem formulation and solution approach used to solve the problem. Based on VC dimension and leave-one-out method, the bounds on the generalization performance are optimized using a training algorithm, proposed in Ref. [4] that automatically maximizes the margin between the training patterns and the decision boundary. This algorithm constructs, and then searches the separating hyperplanes with maximum margin by transforming the problem description into dual space by means of Lagrangian. SVM is reported successfully applied in optical character recognition problems with good generalization ability compared with two-layer back-propagation neural network. The other success is also reported in Ref. [5] that SVM is better than linear classifier, 3-nearest neighbour and two-layer neural network in optical character recognition. Furthermore, the development of SVM solver to solve quadratic problem in SVM shows the seminal in machine learning method. Platt [6] developed the sequential minimal optimization (SMO) that claimed more effective than common QP solver. And the other developed SVM solver will be discussed later. ARTICLE IN PRESS A. Widodo, B.-S. Yang / Mechanical Systems and Signal Processing 21 (2007) 2560–2574 2561 As time goes by, SVM becomes famous and popular in machine learning community due to the excellence of generalization ability than the traditional method such as neural network. Therefore, SVM have been successfully applied to a number of applications ranging from face detection, verification, and recognition, object detection and recognition, handwritten character and digit recognition, text detection and categorization, speech and speaker verification, recognition, information and image retrieval, prediction and so on. However, papers discussing the use of SVM in machine condition monitoring and diagnosis are few. In machine condition monitoring and fault diagnosis problem, SVM is employed for recognizing special patterns from acquired signal, and then these patterns are classified according to the fault occurrence in the machine. After signal acquisition, a feature representation method can be performed to define the features, e.g., statistical feature of signal for classification purposes. These features can be considered as patterns that should be recognized using SVM. Usually, huge features will be obtained in feature representation. Unfortunately, not all features are meaningful and contain high information about machine condition. Some of them are useless and irrelative features. These features should be removed to increase the accuracy of classifier. Therefore, feature extraction and selection are needed to produce good features for classification routines [7]. Conventional pattern recognition method and artificial neural networks (ANN) are studied that the sufficient samples are available, which is not always true in practice [8]. SVM based on statistical learning theory that is of specialties for a smaller number of samples has better generalization than ANN and guarantee the local and global optimal solution are exactly the same [3]. Meantime, SVM can solve the learning problem with a small number of samples. Due to the fact that it is hard to obtain sufficient fault samples in practice, SVM is introduced into machines fault diagnosis due to its high accuracy and good generalization for a smaller number of samples. This paper presents a survey of machine condition monitoring and diagnosis using SVM. It attempts to summarize and review the recent research and development of SVM in machine condition monitoring and diagnosis. This paper surveys the articles from 1996 to 2006 and it was based on a search in the keyword index and article abstract for support vector machine on the Elsevier ScienceDirect, IEEE Xplore, Wiley InterScience, Springer and Ingenta. This literature survey was conducted on September 19, 2006 from updated database of online journals. Totally, thousands articles have been found when searching based on keyword support vector machine. There are 762 articles found in Elsevier ScienceDirect; 2535 articles in IEEE Xplore; 257 articles in Wiley InterScience; 1416 articles in Springer and 331 articles in Ingenta. In addition, for online journal such as Ingenta consists of articles, which are also published by other publishers. After topic filtering, there were 37 articles related to the keywords machine condition monitoring and machine fault diagnosis. Furthermore, this paper surveys and classifies the use of SVM in machine condition monitoring and diagnosis based on object of machine, authors and publication year and method for SVM solving.

2.3.2 SVM THEORY

Classical learning approaches are designed to minimize error on the training data set and it is called the empirical risk minimization (ERM). Those learning methods follow the ERM principle and neural networks are the most common example of ERM. On the other hand, the SVM is based on the structural risk minimization (SRM) principle rooted in the statistical learning theory. It gives better generalization abilities

and SRM is achieved through a minimization of the upper bound of the generalization error.SVM has the potential to handle very large feature spaces, because the training of SVM is carried out so that the dimension of classified vectors does not has as distinct an influence on the performance of SVM as it has on the performance of conventional classifier. That is why it is noticed to be especially efficient in large classification problem. This will also benefit in faults classification, because the number of features to be the basis of fault diagnosis may not have to be limited. Also, SVM-based classifier is claimed to have good generalization properties compared to conventional classifiers, because in training SVM classifier the so-called

structural misclassification risk is to be minimized, whereas traditional classifiers are usually trained so that the empirical risk is minimized. The performance of SVM in various classification task is reviewed, e.g., in Christiani and Shawe-Taylor [9].

Given data input xi (i ¼ 1, 2, y, M), M is the number of samples. The samples are assumed have two classes namely positive class and negative class. Each of classes associate with labels be yi ¼ 1 for positive class and yi ¼ _1 for negative class, respectively. In the case of linearly data, it is possible to determine the hyperplane f(x) ¼ 0 that separates the given data where w is M-dimensional vector and b is a scalar. The vector w and scalar b are used to define the position of separating hyperplane. The decision function is made using sign f(x) to create separating hyperplane that classify input data in either positive class and negative class. A distinct separating hyperplane should be satisfy the constraints or it can be presented in complete equation

The separating hyperplane that creates the maximum distance between the plane and the nearest data, i.e the maximum margin, is called the optimal separating hyperplane.

$$y_i f(\mathbf{x}_i) = y_i(\mathbf{w}^T \mathbf{x}_i + b) \geqslant 1 \quad \text{for} \quad i = 1, 2, \ldots, M.$$

A series data points for two different classes of data are shown, black squares for negative class and white circles for positive class. The SVM tries to place a linear boundary between the two different classes, and orientate it in such way that the margin represented by the dotted line is maximized. Furthermore, SVM attempts to orientate the boundary to ensure that the distance between the boundary and the nearest data point in each class is maximal. Then, the boundary is placed in the middle of this margin between two points. The nearest data points that used to define the margin are called support vectors, represented by the grey circles and squares. When the support vectors have been selected, the rest of the feature set is not required, as the support vectors can contain all the information-based need to define the classifier. From the geometry the geometrical margin is found to be ||w||.

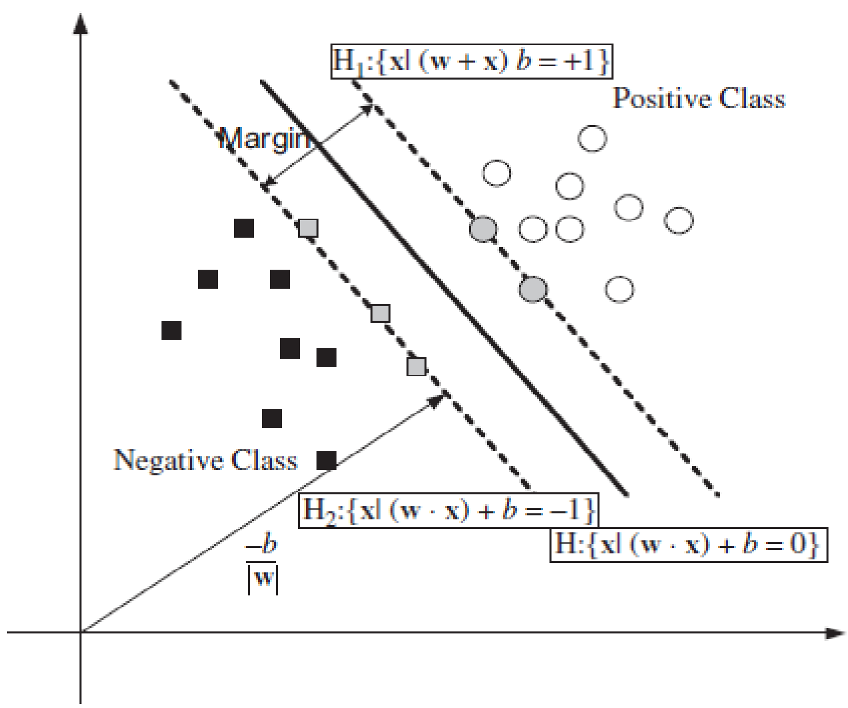


Fig. 1. Classification of two classes using SVM.

Fig.2.5 Example of hypothesis in SVM

CHAPTER 3

DESIGN OF EXPERIMENT

3 DESIGN OF EXPERIMENT (DoE)

The experiments are designed to support the performance of proposed methodology to monitor the machine health by testing it on chosen electrical machines. The application of proposed methodology should be able to identify any thermal anomaly in the machine. As 80% of the motors used in Industries are Induction motors, a 1 HP, 3-phase Induction Motor is selected for the purpose of experimentation. A complete set of experiments corresponding to different modes of operation of the motor is done. In addition to this, to illustrate the applicability of the proposed method for various electric machines irrespective of their rating, a thermal signature based trend analysis of a 2000 KVA, 11KV/433V Power Transformer was also performed. The complete design of experiment for both machines is explained in this chapter.

3.1 DoE FOR INDUCTION MOTOR

Electrical motors are the most crucial component in any system. It would be very difficult to find any process, facility or building that does not involve the use of electric motors somewhere. Motors are very critical to the reliability of any facility or process as motor driven systems account for almost 70% of industrial electricity use. Due to their widespread use in Industries, the study is restricted to the monitoring of Induction motors only, however the same methodology can be extended to any other type of motor.

All induction motors generate thermal energy during normal operation, which allows infrared thermography to evaluate the optimal operating condition of machine. Generally any developing fault will cause increase in heat generation during the operation of motor. The excessive heat can be generated by Loose, worn and/or corroded connections, equipment degradation, single-phasing, under-voltage, unbalanced loads, harmonics, blocked or restricted cooling apparatus, poor contacts, motor winding deterioration, bearing degradation etc. For CBM of induction motor using IRT, once a normal thermal signature is obtained and understood, any deviation from the normal signature caused by overheating will then provide evidence of a developing problem.

3.2 FAULTS IN INDUCTION MOTOR

The following are the most commonly diagnosed faults in Induction motor. As shown in figure-3.1, these faults are categorized as electrical and mechanical faults.

3.2.1 SHORT TURN FAULTS

Short turn faults are basically related to the stator winding insulation failure. These faults very critical because they accounts for almost 35-40% failure in induction motor[61]. A large portion of stator winding related failures are initiated by insulation failure and shorting in one or several turns of a stator coil. These shorted turn faults causes large circulating current in the winding which subsequently cause excessive heat generation. The heat generation is proportional to square of the current and if it exceeds beyond a limit, it can not only cause permanent damage to motor but also serious accidents.

COMMON FAULTS IN INDUCTION MOTOR	
ELECTRICAL FAULTS	MECHANICAL FAULTS
• Short turn faults • Broken Rotor faults • Single-phasing • Supply voltage variations	• Air gap eccentricity • Bearing faults • Coupling misalignments

Fig-3.1 Categorization of common Induction motor faults

3.2.1.1 BROKEN ROTOR FAULTS

Broken rotor fault is another very serious fault which occurs over the duration of operation of machine. These faults have many reasons, some of the most common are listed below:

- During the brazing process in manufacturing, non-uniform metallurgical stresses may be built into cage assembly and these can lead to failure during operation.
- A rotor bar may be unable to move longitudinally in the slot it occupies, when thermal stresses are imposed upon it during starting of machine.
- Heavy end rings can result in large centrifugal forces, which can cause dangerous stresses on the bar.

3.3.1.3 SINGLE-PHASING

For proper working of any 3-phase induction motor, the motor must be connected to a 3-phase power supply of rated voltage and frequency. Once the motor is started, it will continue to run even if one of the three phase supply lines gets disconnected. The loss of current through one of these phase supply is termed as single phasing. Due to single phasing the current in remaining phases increase significantly and the motor becomes noisy and starts vibrating due to uneven torque production. Increased current will cause excessive heat dissipation that can melt the winding insulation and which may even lead to electric shock to personnel or motor burnout.

3.3.1.4 AIR GAP ECCENTRICITY

Air gap eccentricity is a very common rotor fault in Induction motors. This fault causes problems like vibration and noise in the machine. Typically the rotor is aligned in the centre of stator bore in a healthy machine, which makes the axis of rotation of rotor identical to the geometric centre of the stator bore. Due to manufacturing defect or faulty maintenance operation, if the rotor is not aligned in the center, the unbalanced radial forces can cause a stator-to-rotor rub which may result in damage to both stator and rotor.

3.3.1.5 BEARING FAULTS

Bearings are the most common component in all electrical machines which are employed to permit rotatory motion of the motor shaft. Bearing are also the single largest cause of machine failure, literature suggest that bearing faults accounts for almost 40% of the failures in motors. A bearing consist of two rings called inner and outer rings and a set of metallic balls or rolling elements places in raceway between them. The bearing faults include breaking of small pieces of metal called flaking and wearing out of the rolling element. This fault occurs due to fatigue caused by continuous stress on inner and outer race, improper lubrication, improper installation and corrosion. Sometimes shaft voltages and currents are also responsible for bearing failure. Bearing failure cause mechanical vibrations, increase in noise level and increase in friction between the rolling shaft and static machine body. If not monitored bearing faults can ultimately lead to permanent stalling of motor.

As the locations of all the above mentioned faults are different, their effect on the overall thermal behavior of the motor is also non-uniform. Some faults like supply voltage variation may cause a uniform change in machine thermal behavior whereas some faults like bearing faults, rotor faults etc. only cause localized effect. In such faults the machine thermal behavior may vary according to the fault location and thermal analysis from only one direction can be inconclusive. Such scenarios call for a complete analysis of machine which enables monitoring of the thermal gradient through the machine. The proposed methodology provides such analysis through complete multi view visualization and analysis of machine. Therefore this methodology will be able to monitor and detect such faults which cause only localized changes in machine thermal behavior, which are otherwise hard to detect through conventional monitoring techniques

.

3.2.2 DIFFERENT MODES OF OPERATION OF INDUCTION MOTOR

Electrical devices are usually rated for power, which indicates the amount of energy that the device can conduct without being damaged. The energy conduction pattern of a machine is somewhat similar when running in normal operating condition. Most of the faults in electrical apparatus tend to change the heat signal of the machine. Therefore, a deviation in thermal behavior of motor under influence of fault from the normal operation thermal behavior can validate the application of IRT for condition monitoring of induction motor. For this purpose, the aim of the experiment is to capture thermal signature of machine under optimal condition as well as under the influence of certain fault(s). In the experimentation process, due to safety and feasibility constraints only few of the above mentioned faults in motor were manually induced to study their influence on motor's thermal behavior. Single-phasing and under voltage fault were selected from the list of electrical faults whereas bearing failure was selected from the commonly occurring mechanical faults. The experimental methodology for capturing thermal signature of machine under normal as well as under faulty conditions is explained in following section.

3.1. 2.1 N O R M A L OPERATING BEHAVIOR

As mentioned earlier, all the experimentation was done on a Kirlosker make 3-Phase, 420V, 50Hz Induction Motor. The motor was checked by an expert before starting the experiment to ensure its optimal condition. As the proposed methodology is based on the multi view analysis of a machine, for every experiment in this study a thermal image of machine was captured at every 30^{o} angle i.e. 12 images captured for each experiment. This angle is termed as step angle, and its selection for any user will depend on the size and accessibility to the machine. The distance between IR camera and motor for all the experiments performed on induction motor was 0.75-0.80 meter. The distance between camera and motor was kept in such a way that the camera is able to properly focus on the target image. Figure-3.2 represents the schematic for the thermal image acquisition methodology. To obtain thermal behavior of motor, it is natural to monitor the motor at every loading condition. The rated current of the motor, as mentioned on the plate is 1.6A where as the no-load current at rated voltage was measured to be 1.10A. The motor was loaded using Mechanical Brake Loading arrangement in three steps such that the measured input current was 1.35A, 1.45A and 1.6A respectively.

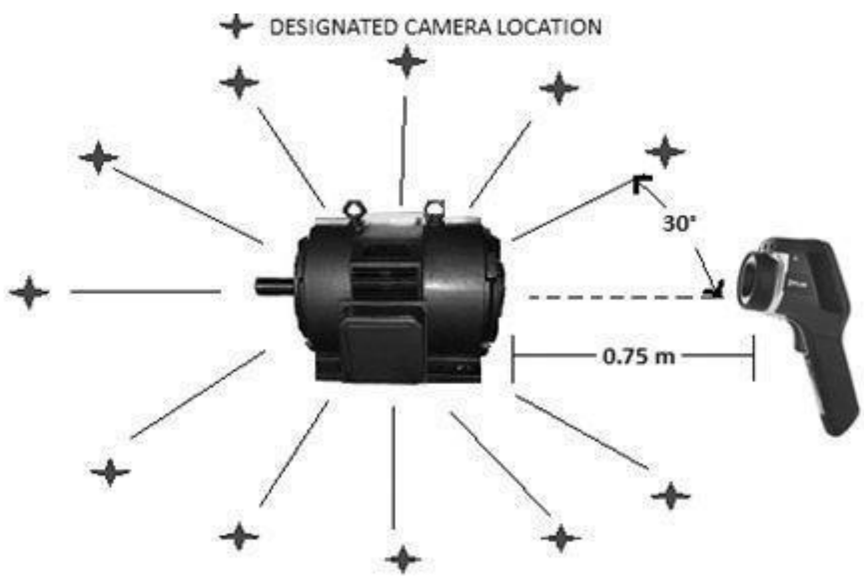
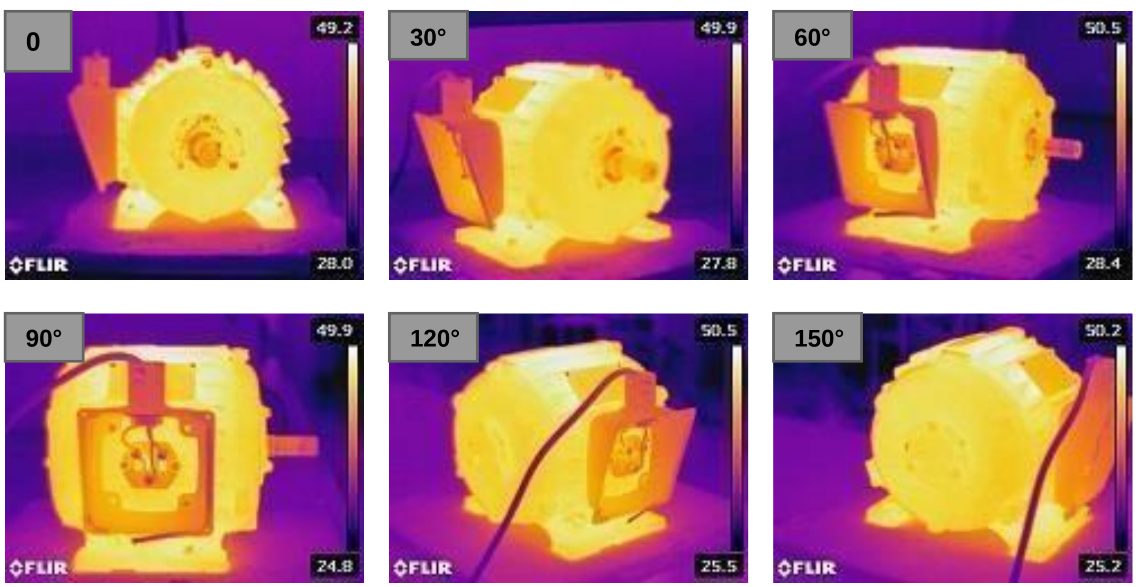


Fig-3.2 Schematic representing image acquisition methodology

Figure-3.3 shows the experimetal setup for changing the loading of motor at normal operating condition. The approch followed for data acquisition was such that, during the experiment loading of motor was fixed and the thermal behavior was monitored continously till the time the results were fairly constant. In this study, for a fixed loading of motor thermal images of complete 360º of machine were taken after every 30 minutes and the thermal behavior was found out to sautrate after 6 hours of operation.

Fig-3.3 Experimental setup showing Mechanical Brake Loading arrangement

For all four loading conditions ranging from no-load to full load, same experimental methodology was followed. A complete set of 12 images for no load after 2 hours of motor operation is shown in figure-3.4 to give an overview of the outcome of data acquisition process. Starting from the position of camera to capture the first image (which is taken as a reference), thermal images of motor is obtained at every 30º of view angle.



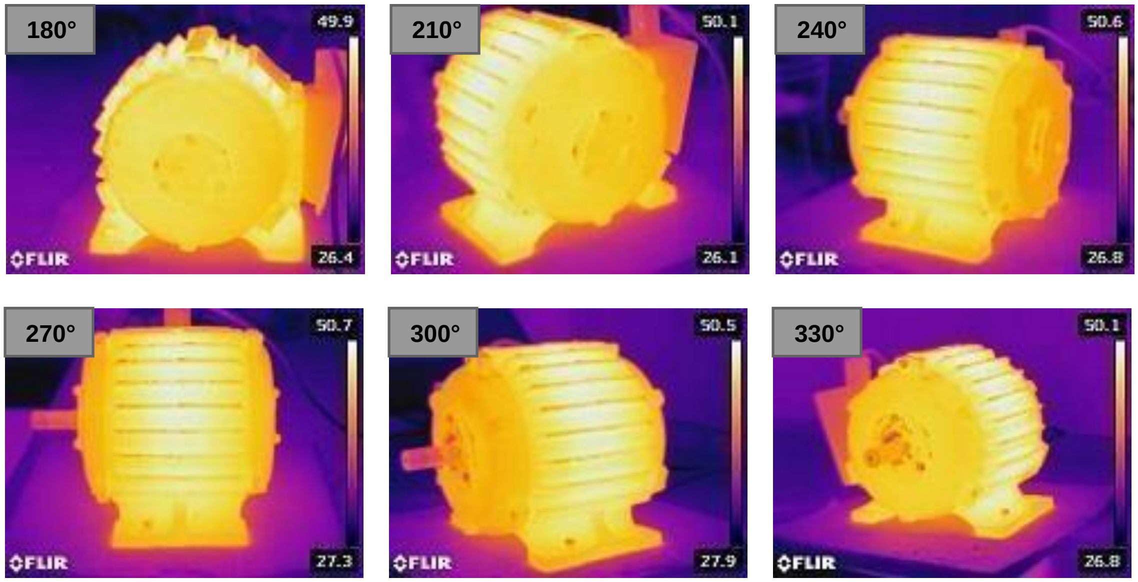


Fig 3.4 Thermal Images corresponding to every 30° view angle of machine after 2 hours of operation at no-load

3.1.2.2 SINGLE-PHASING

As mentioned earlier single phasing is the failure of any of the supply phases after the motor has started. The schematic of experimental setup for capturing the thermal behavior of machine under the influence of single-phasing is shown in figure-3.5. During the experiment, motor is initially started with all three phases connected. After 30 minutes of operation switch SW was opened to disconnect one phase from the supply. The same process of data acquisition as mentioned above i.e. taking thermal images at after every 30 minutes was repeated. Although in previous experiment motor was monitored continuously over a period of 6 hours, in this case due to safety issues arising because of excessive heat and vibrations produced during the operation, the motor was switched off after 4 and half hours of operation. This reduced period of operation was found to be sufficient for capturing the heat generation pattern of motor under the influence of single-phasing

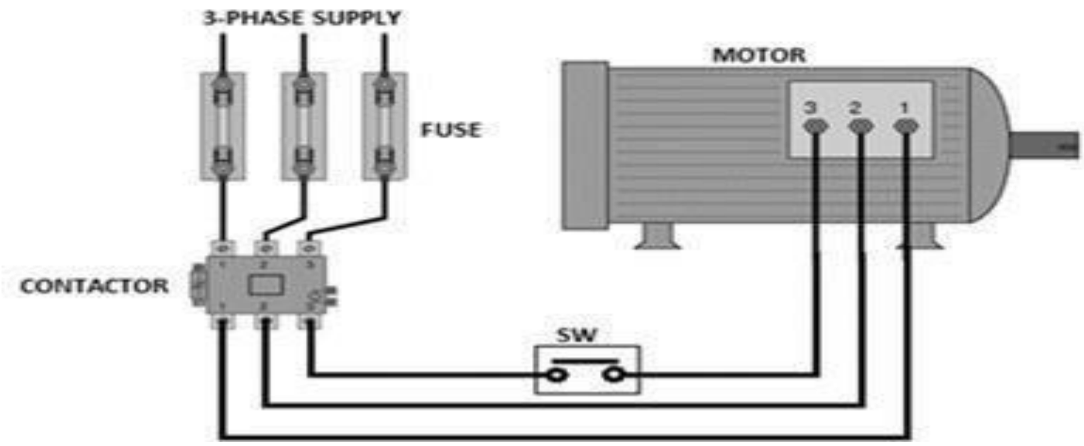


Fig 3.5 Schematic showing experiment setup for single-phasing of motor

3.1.2.3 UNDER-VOLTAGE

When a motor is subjected to a voltage below its rated value, some of the motor's characteristics will change slightly and others will change dramatically. For fixed loading of motor, a motor draw a fixed amount of power from the line and the power depends on voltage and current. Now when the supply voltage decrease from its rated value, the motor current must increase to maintain the power required to drive the load. This increased current cause overheating of motor and without timely corrections, this heat may damage the motor. For the experiment the input of motor is supplied through a 3-phase autotransformer as shown in

figure-3.4. The input voltage is adjusted to 350V using the auto-transformer for whole duration of experiment and the rest of data acquisition methodology remain same as for monitoring normal behavior of motor.

CHAPTER 4

PROJECT WORK AND METHODOLOGY

4 METHODOLOGY

This section elaborates the methods developed for thermal analysis of electrical machines for condition based maintenance. The schematic representing proposed methodology shown in figure-4.1 presents all related operations in a proper sequence of steps. As far as selection of machine and data acquisition is concerned, the previous chapter discuss in detail about why the particular machines were selected for this study, their most likely failure modes and affects along with comprehensive discussion of experiment design and data acquisition procedures. This chapter primarily focuses on how raw experimental results are used to evaluate the machine health. As discussed earlier, ROI detection and relevant information extraction are the most important operations which are to be performed after image acquisition. Also this study incorporates multi view analysis of an asset under test, therefore all the post processing operations must be applied on all images corresponding to an experiment simultaneously. To address both these issues a MATLAB based analysis tool was developed which is termed as IR RADIOMETRIC ANALYSIS TOOL. The tool offers an integrated monitoring system that includes multi view image visualization equipped by specialized region of interest (ROI) detection and data extraction features, along with the ability for data analysis for health evaluation.

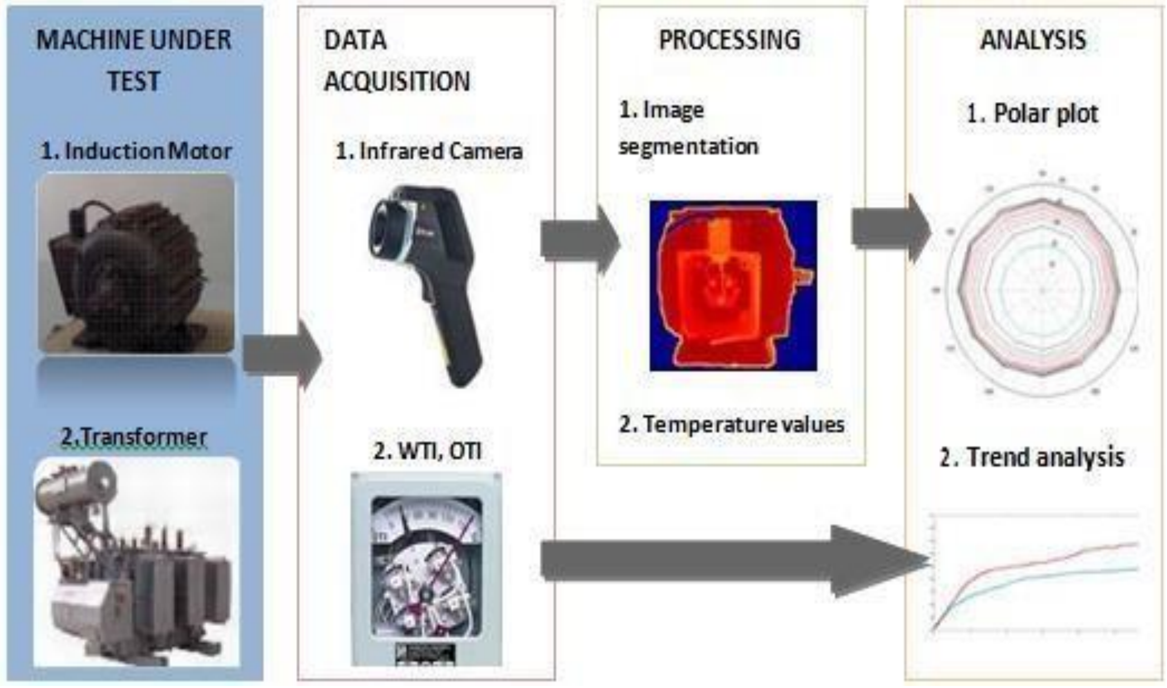


Fig 4.1 Proposed methodology for health monitoring and analysis of electrical equipment

4.1 RADIOMETRIC ANALYSIS PROCESS

1. Selecting step angle: As the proposed model is based on the multi view analysis approach, the first step of analysis is to choose the suitable step angle. The thermal imaging process includes capturing of an image continuously, starting from a reference point and after certain angle, which is referred as step angle. Step angle should be as small as possible for better efficiency of system but in most cases choice of step angle depends on various constraints imposed by position of machine, surrounding etc. Therefore four different choices viz. 0°, 30°, 45°, 90° are provided to user for selecting the step angle of his choice. The selection of step angle can be made by clicking on "Select View Angle" drop down menu and selecting the desired angle from the list appeared (Figure 4.4 (a)).

2. Selecting view angle: After selecting step angle the second thing user need is to select the view angle. View angles are the actual angles measured with respect to the reference position on which the imaging is to be carried out. Selecting correct view angle while uploading the images in the tool is very crucial because the view angle selection acts as watermark for a particular image throughout the analysis process. While performing analysis, in case image(s) for any view angle is not available, the user can upload the remaining images and the analysis can still be completed. The selection of view angle is made by selecting the desired option form the list appeared after clicking "Select View Angle" drop down menu (Figure 4.4 (b)). It should be noticed that a valid step angle selection should be made before selecting the view angle. Not abiding to this will prompt error message, this is because the valid values of view angle changes with each step angle selection.

3. Load/View thermal images: Thermal images can be loaded using the "LOAD" pushbutton in the radiometric tool. The loaded image(s) are displayed in "IMAGE" window along with the location of points with maximum and minimum temperature.

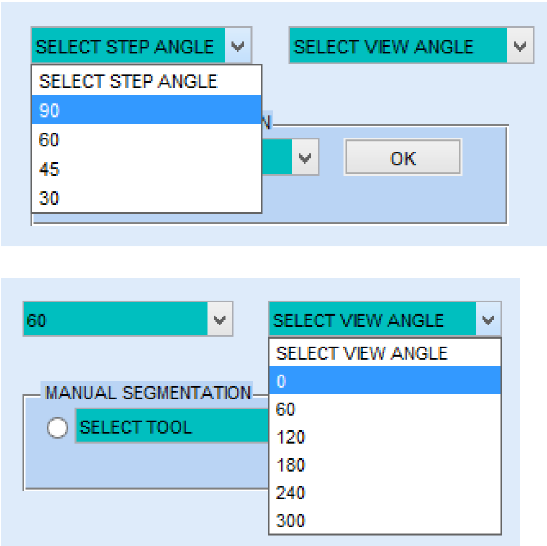


Fig 4.3 (a) Step angle selection (b) View angle selection

The "TEMPERATURE VALUES" window displays the temperature values of the current image whereas the view angles corresponding to which images are loaded by user are highlighted in "LOADED IMAGES" window. Once all the images are loaded the user can select the ROI by the provided segmentation techniques or if required head straight to forming polar plots. All the loaded images are stored in memory and user can view any particular image using "VIEW" pushbutton. It should be noted that image load or view operation can only be performed after selecting step angle and view angle.

4. Selection of Region of Interest (ROI): ROI selection is the most important step in radiometric analysis of a machine as it is the key to successful decision making process. Generally ROI detection is aimed to separate the machine under test from the background. The proposed tool provides specialized ROI detection, visualization and analysis features which include manual segmentation tools along with advanced image processing tools such as Otsu's Thresholding, Chan-Vese and Edge detection algorithms.

The manual segmentation tools can be evoked by selecting the button in "MANUAL SEGMENTATION" window and these tools includes area box, ellipse and polygon. The result of segmentation can be seen by selecting the "CALCULATE" pushbutton. Similarly user can also check automatic segmentation results for any image by selecting suitable image processing tool from "SELECT ALGORITHM" drop menu of "AUTOMATIC SEGMENTATION" window, and then following the instructions appearing in message dialog box. If user is not satisfied with the segmentation result obtained by any particular method, he can always apply other segmentation techniques just by deleting the current segmentation results with the use of ―DELETE" pushbutton. Figure-4.5 represents a raw infrared image and the segmentation result of six methods included in the tool.

Otsu's Threshholding: This method is implemented by following steps

1. Let α represents the original image and ȕ represents the extracted binary image of the main object from α. As shown in (1), T is the threshold value by Otsu's method; W is image width and H is image height. Since this is a digital image, x and y are discrete integers.

$$\begin{aligned} B(x, y) &= 1 \quad \text{if } \alpha(x, y) > 1 \\ &= 0 \quad \text{if } \alpha(x, y) \leq 1 \\ \forall 0 \leq x < W&, 0 \leq y < H \end{aligned} \tag{1}$$

2. Likewise, all the pixel values of image α are set to 1 when the pixel values are greater than

T. On the contrary, the pixel values are set to 0 when they are less than T. In order to obtain

object image Û from image α and ȕ, the following formula is used:

$$\begin{aligned} \gamma(x, y) &= \alpha(x, y) \quad \text{if ȕ}(x, y) > 1 \\ &= 0 \qquad \text{if ȕ}(x, y) = 0 \\ \forall 0 \leq x < W&, 0 \leq y < H \end{aligned} \tag{2}$$

After the separation process by (1)-(β), Û is the thermal image of the inspected equipment

without background.

Chan-Vese: Let Ω be a bounded open set of R^2, with ∂Ω its boundary. Let μ_0: Ω→ R be a given image, and C(s) is a piecewise $C^1[0,1]$ parameterized a curve. Let's denote the region inside C as ω, and the region outside C as Ω \ω . Moreover, c_1 will denote the average pixels' intensity inside C, and c_2 will denote the average intensity outside C (i.e., $c_1=c_2(C)$, $c_2=c_2(C)$).

The object of Chan-Vese algorithm is to minimize the energy functional F (c_1, c_2, C), defined by

$F(c_1,c_2,C) = \mu.length(C) + v.Area(Inside(C)) + \lambda_1 \int \mu$

$\lambda_2 \int \quad \mu$

Where $\mu_0 \geq 0$, $v \geq 0$, $\lambda_1 \lambda_2 > 0$, are fixed parameters (should be determined by the user).

Edge detection is a type of image segmentation techniques which determines the presence of an edge or line in an image and outlines them in an appropriate way. The main purpose of edge detection is to simplify the image data in order to minimize the amount of data to be processed. Generally, an edge is defined as the boundary pixels that connect two separate regions with changing image amplitude attributes such as different constant luminance values

CHAPTER 5

DATA PROCESSING

5. DATA EXTRACTION AND ALGORYTHEM DESIGN

Data is collected as previously explained in Design of Experiment. The data contains temperature values of pixels in an excel format and thermal images of the induction motor. Now we cannot use this raw data to train our classifier. We are using SVM here to train our data so that we can use these to differentiate (by predicting) between normal running of the motor and fault running situation of the motor. The solution to this problem is feature extraction; feature extraction is used to gather valuable information from the raw data that we have collected. Features depend upon the nature of data collected in experiments and thus the classifier's ability to predict correctly also depends upon the extracted features. Features can be extracted by various methods like image processing, K-map clustering etc.

5.1 DATA COLLECTED USING DOE

The data collected is pixel wise temperature values which are obtained by taking images of induction motor by FLIR cameras. These values are therefore used to calculate statistical Features like average, skewness, kurtosis etc.

26.976	27.013	26.845	26.871	26.876	26.945	26.95	26.924	26.971
26.924	26.934	26.95	26.887	26.924	26.86	26.966	26.939	26.939
26.95	26.897	27.003	26.981	26.892	26.929	26.955	26.929	26.992
26.924	26.876	26.913	26.892	26.945	26.887	27.018	26.908	26.881
26.945	26.945	26.913	26.871	26.855	26.887	26.929	26.992	26.976
26.971	26.902	26.881	26.966	26.981	26.918	26.981	26.908	26.997
26.955	26.934	26.897	26.929	26.887	26.887	26.955	26.992	26.971
26.902	26.918	26.945	26.908	26.902	26.881	26.96	26.787	26.939
26.876	26.976	26.955	26.966	26.85	26.924	26.924	26.966	26.981
26.85	26.924	26.902	26.934	26.839	26.981	26.918	27.003	26.929
26.987	26.75	26.871	26.881	26.871	26.897	27.013	26.981	26.955
26.976	26.897	26.939	26.939	26.871	26.834	26.887	26.981	26.86
26.939	26.897	26.908	26.96	26.839	26.971	26.945	26.971	26.934
26.934	26.813	26.918	26.96	26.813	26.881	26.813	26.955	26.887
26.95	26.808	26.86	26.897	26.823	26.881	26.966	26.823	26.955
26.908	26.834	26.908	26.887	26.887	26.934	26.86	26.818	26.971
26.913	26.934	26.76	26.887	26.86	26.929	26.955	26.913	26.902
26.929	27.018	26.887	26.929	26.85	26.902	26.86	26.897	26.834
26.966	26.897	26.945	26.876	26.897	26.918	26.918	26.929	26.855
26.976	26.981	26.939	26.881	26.929	26.945	26.924	26.934	26.908

Fig 5.1 Data collected using features

The other data obtained is images of induction motor using camera which can be used extract features using image processing

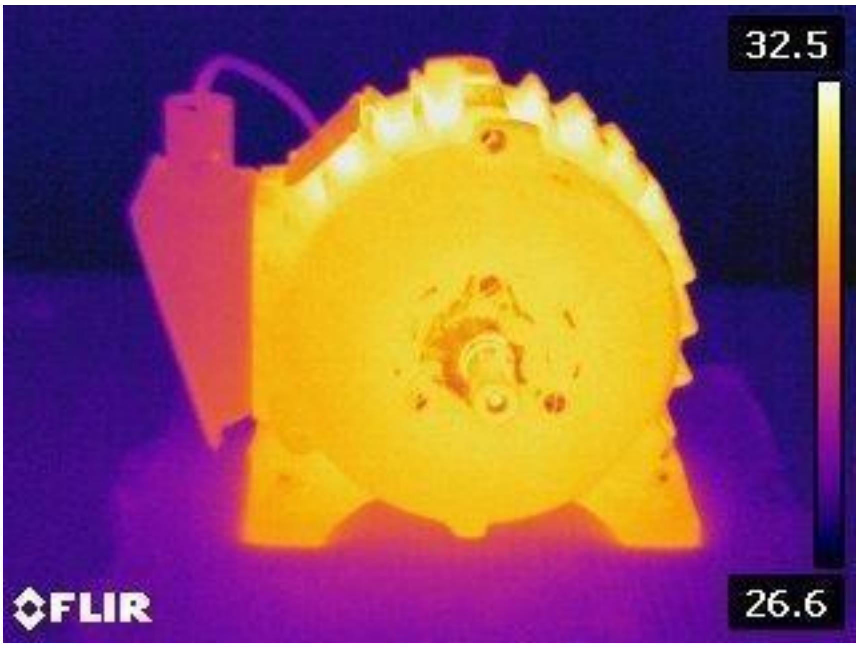


Fig 5.2 Thermal image of Induction Motor

There are three general classes of feature selection algorithms: filter methods, wrapper methods and embedded methods.

5.1.1 Filter Methods

Filter feature selection methods apply a statistical measure to assign a scoring to each feature. The features are ranked by the score and either selected to be kept or removed from the dataset. The methods are often univariate and consider the feature independently, or with regard to the dependent variable. Some examples of some filter methods include the Chi squared test, information gain and correlation coefficient scores.

5.1.2 Embedded Methods

Embedded methods learn which features best contribute to the accuracy of the model while the model is being created. The most common type of embedded feature selection methods are regularization methods .Regularization methods are also called penalization methods that introduce additional constraints into the optimization of a predictive algorithm (such as a regression algorithm) that bias the model toward lower complexity (fewer coefficients).Examples of regularization algorithms are the LASSO, Elastic Net and Ridge Regression.

5.2 FEATURES EXTRACTED FROM DATA

The following table represents the list of features which will be used to train the SVM. These features are extracted by codes in MATLAB which have been attached in appendix.

Feature	Mathematical formulae	Benefit of Feature
1.Average Temperature	Mean (x) = $\sum$ x/N	If a machine is at fault its overall temperature increases. Average temperature will differ between machines with no fault and machines with fault.
2.Maximum Temperature	N/A	Different max temperature could mean that some part of machine is getting heated due to some unusual operation.
3.Variance	$\frac{\sum X^2}{N} - \mu^2$	If value of variance is more means that some part of the machine is at much higher temperature than other part and hence it might be at fault.
4.Zernike's Moment	$R_n^m(\rho) = \sum_{k=0}^{\frac{n-m}{2}} \frac{(-1)^k (n-k)!}{k! \left(\frac{n+m}{2}-k\right)! \left(\frac{n-m}{2}-k\right)!} \rho^{n-2k}$	Zernike moment of every image is different so having value of Zernike moment can be an important feature
5.Thresholdin g	N/A	Brightness in terms of every image is different from each other hence we can differentiate between them using Thresholding.
6. Standard Deviation	$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})^2}$	The more the deviation of a particular data points the more the chances of fault occurring at that point.

7.Kurtosis	$K = \frac{n(n+1)(n-1)}{(n-2)(n-3)} \frac{\sum_{i=1}^{n}(X_i - X_{avg})^4}{(\sum_{i=1}^{n}(X_i - X_{avg})^2)^2}$	Kurtosis of temperature will differ for each of the fault type since temperature is different.
8.Otsu's Method	N/A	Different level of brightness will give different images.
9.Skewness	$S = \sqrt{n} \frac{\sum_{i=1}^{n}(X_i - X_{avg})^3}{(\sum_{i=1}^{n}(X_i - X_{avg})^2)^{3/2}}$	Different value of skewness for different values of temperature.
10. Entropy	$\text{Entropy} = -\sum_{i} P_i \operatorname{Log}_2 P_i$	Different value of entropy can be used to train the SVM.
11.K means – segmentation Algorithm	$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2$	Different number of group mean values will give more data for characterization.

12. Gray level Co-occurrence matrix	N/A	Different value for each image will give us data to train SVM.
13.Histogram equalization	$y' = y \cdot (\max\{x\} - \min\{x\}) + \min\{x\}$	This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram.
14.Minimum temperature	Code in appendix	Using this feature we can differentiate between different faults.

Table 5.1 Features used in training of data

5.3 TRAINING OF DATA

The features extracted values were stored in data sheets and SVM was trained. Now SVM based on the training data, it makes a hypothesis which differentiates between the false and true condition. The true condition here is that the machine here is faulty and the false condition here is that the machine is running under normal conditions. These false and true conditions here are being decided by the values of features.

5.3.1 Hypothesis

In classification in general, the hypothesis class is the set of possible classification functions you're considering; the learning algorithm picks a function from the hypothesis class.
Some of the hypothesis in this project are shown to get a clear understading of working of classifier.

Between maximum temperature and average:

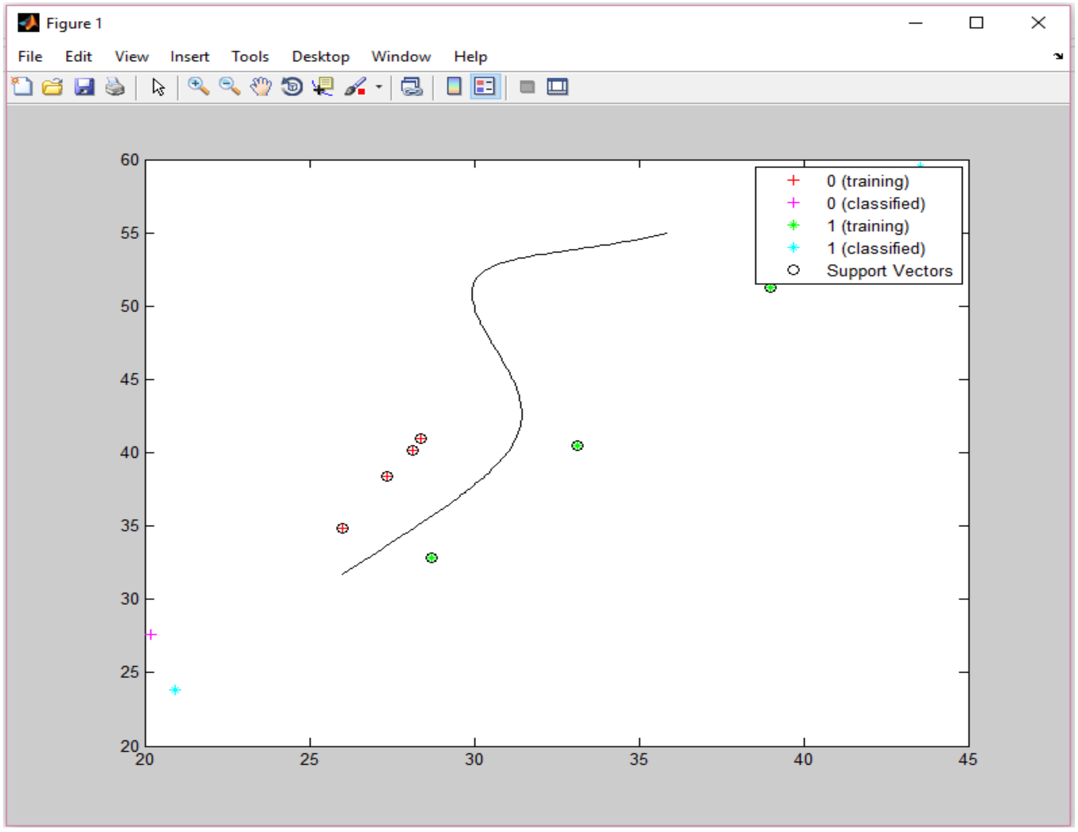


Fig 5.4 Hypothesis between temperature and average

This hypothesis is relatively better than other features since there is clear distinction between the two features. This means that the classifier will be able to predict fault much better with more accuracy in this case.

Between skewness and maximum temperature:

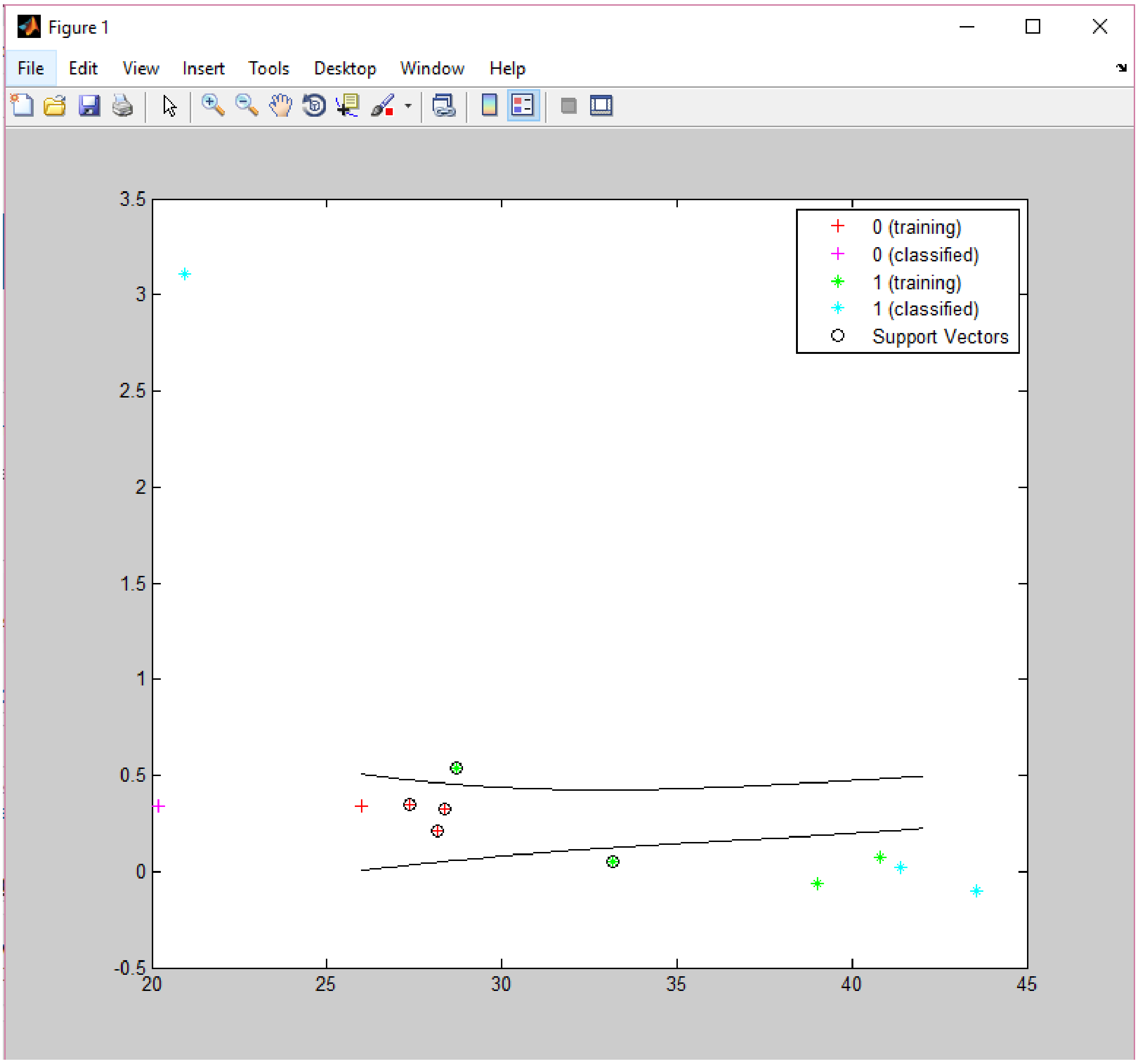


Fig 5.5 Hypothesis between skewness and average

The graph below is result of binary classification between two features i.e maximum temperature and Variance .This hypothesis is complex than the previous one since there are two curves drawn between the values of feature. The complexity of the feature determines the time taken to classify.

Even though there is more computing power required here, the distinction between the truth and the false values is quite clear. Hence this hypothesis is also good when it comes to training the classifier.

Between maximum temperature and entropy

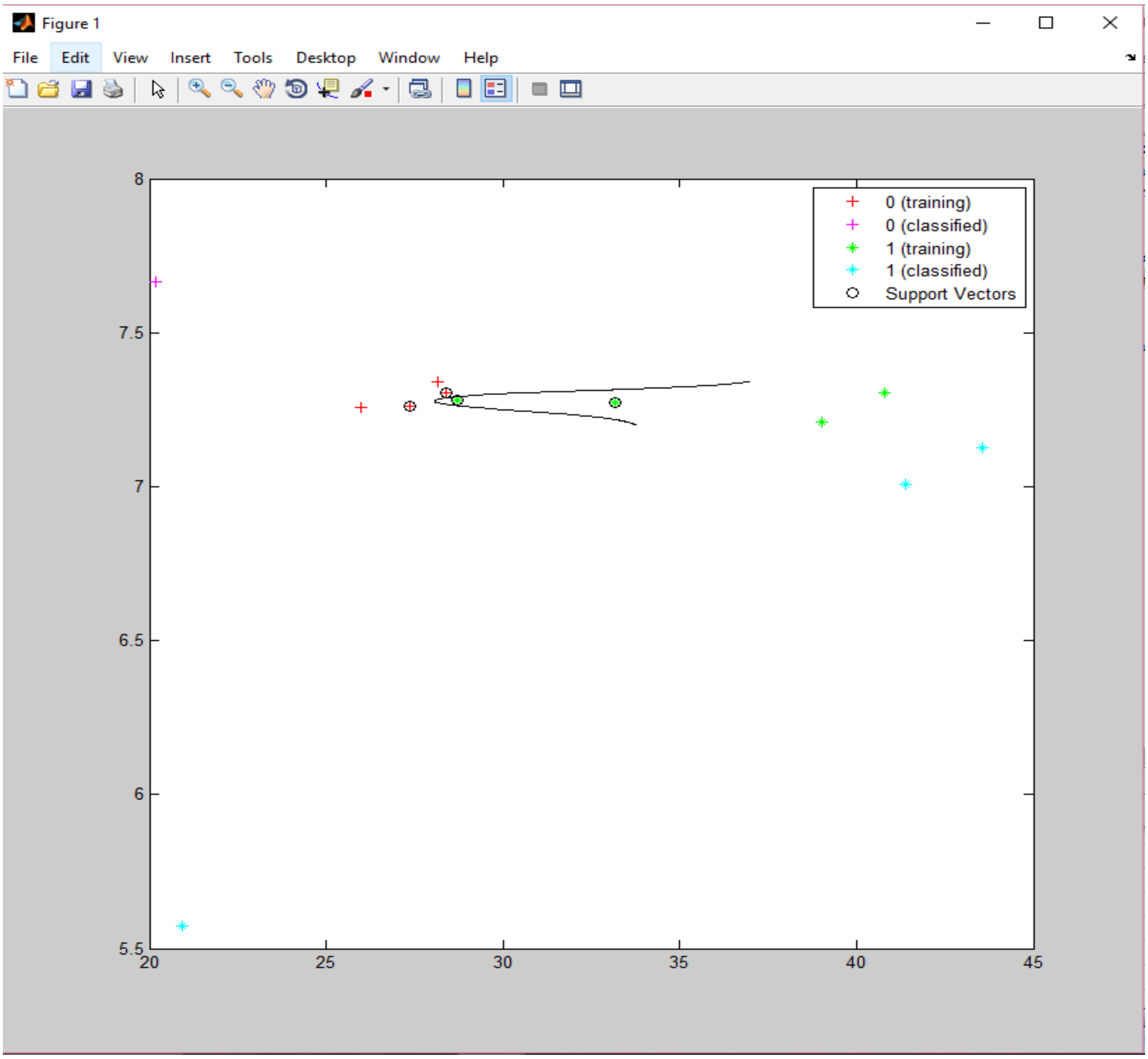


Fig 5.6 Hypothesis between temperature and entropy

The graph below is result of binary classification between two features i.e maximum temperature and Variance .As we can see the difference between the two features is quite less here. While training the SVM there will not be clear distinction between the truth and the false values. We can use this feature to test the result so as to see how our classifier perfroms in case of relatively difficult situations

Maximum Temperature and Variance

The graph below is result of binary classification between two features i.e maximum temperature and Variance .This graph is made from the values of zero degree angle of induction motor. The red points in the graph are points which are false according to the classifier i.e. at these values of maximum temperature and threshold the machine is running in faulty condition. The green points are true condition of the classifier.

Also we can see where the values of training data lie according to the SVM classifier. This hypothesis is also better than others when it comes to training the classifier.

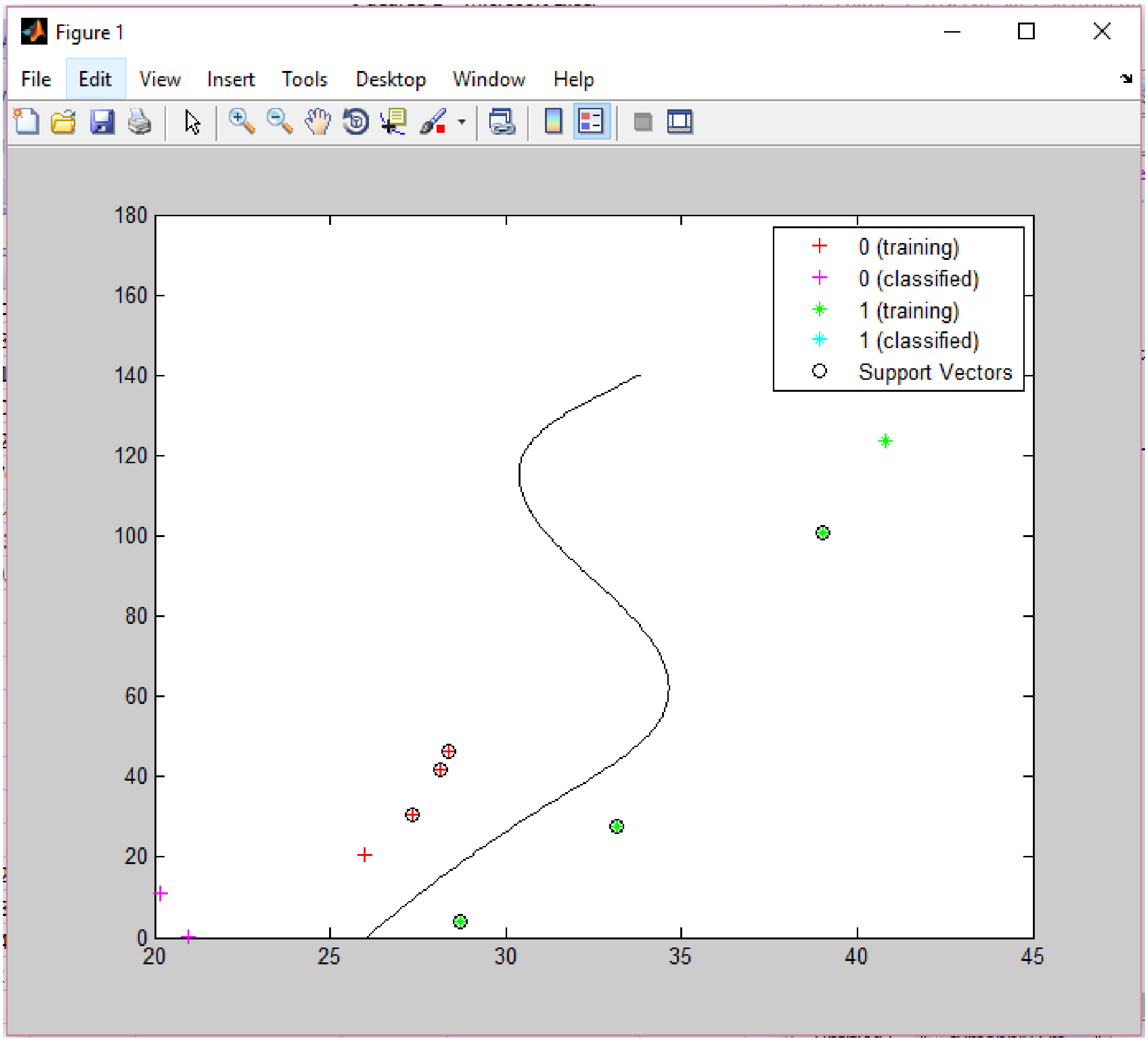


Fig 5.7 Hypothesis between temperature and entropy

Maximum temperature and Threshold

The graph below is result of binary classification between two features .It shows the curve of hypothesis between values of maximum temperature from all the pixels and threshold value of the thermal image. This graph is made from the values of zero degree angle of induction motor. The red points in the graph are points which are false according to the classifier i.e. at these values of maximum temperature and threshold the machine is running in faulty condition. The green points are true condition of the classifier.
Also we can see where the values of training data lie according to the SVM classifier.

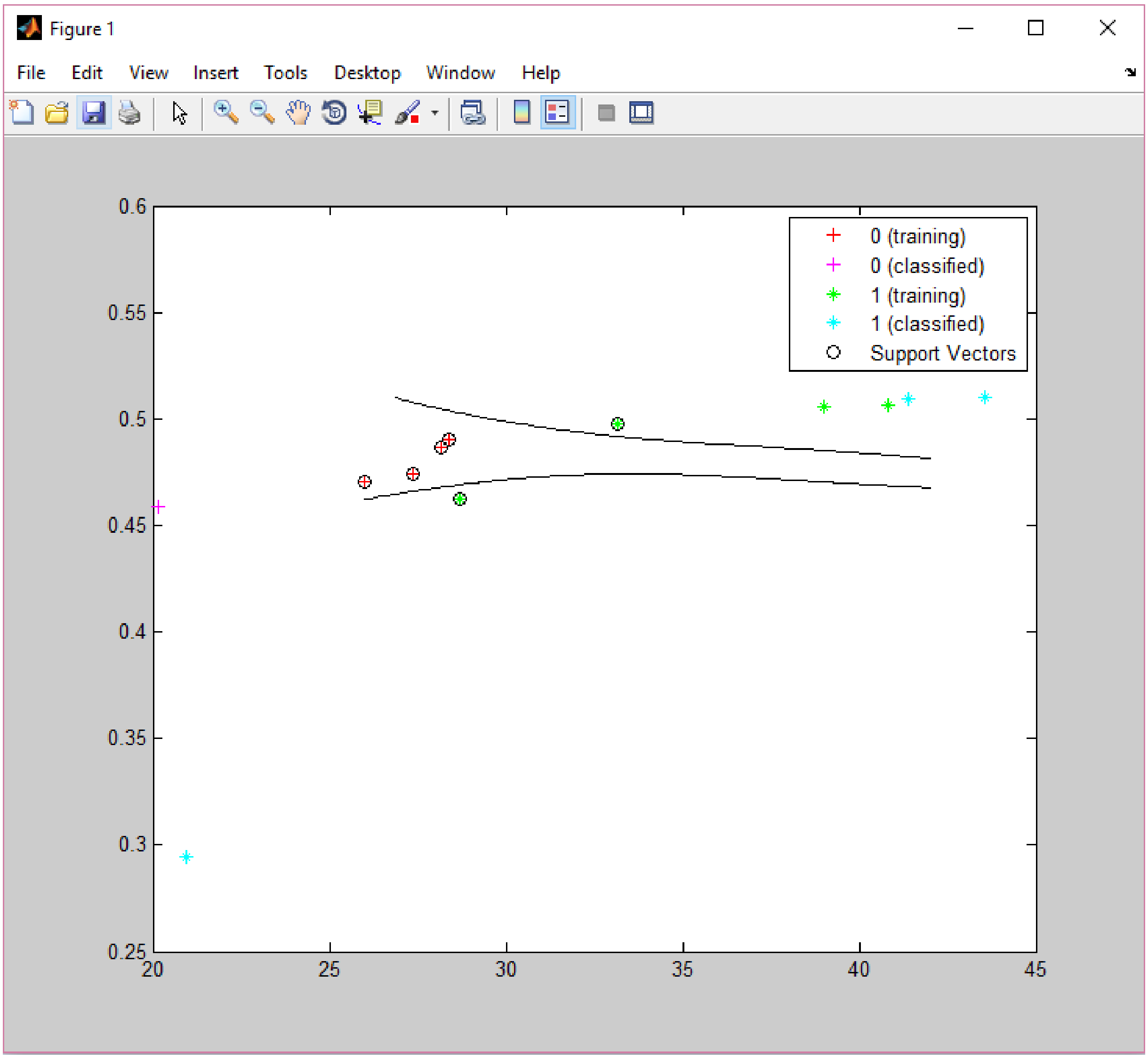


Fig 5.8 Hypothesis between temperature and entropy

5.3.2 IMAGE PROCESSING TECHNIQUES

Several image processing techniques were used to extract valuable information from raw data. Some of these were otsus's thresholding method, morphism etc .These techniques gave difference between images containing different temperature values.

Single phasing fault thermogram:

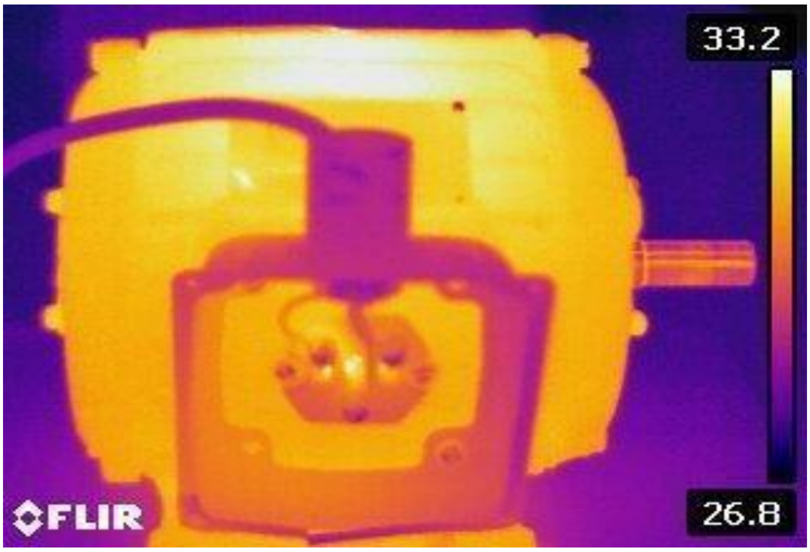


Fig 5.9 Thermal image

After this the image is thresholded using otsu's method , this image is converted into gray image. After this conversion the threshold value which will be later used for feature is obtained.

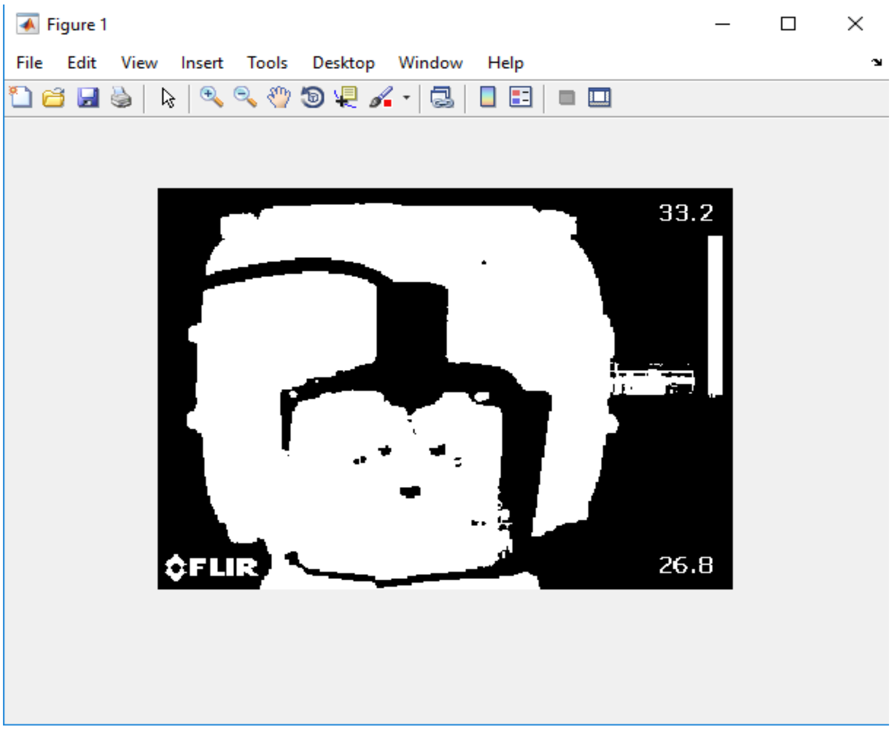


Fig 5.10 Thresholded image

The code for the above processing is given in the appendix. The use of thresholding is that it gives a value “level” which is different to each image and therefore it lets us se it as a feature to train the SVM. Other methods like adaptive thresholding were used but their result did not differ much from otsu’s so their result were not used to train the classifier. Morphism is a image processing technique to get clear thresholded image by clearing out the gaps and the holes in the image.

CHAPTER 6

RESULTS AND CONCLUSION

6.1 RESULTS

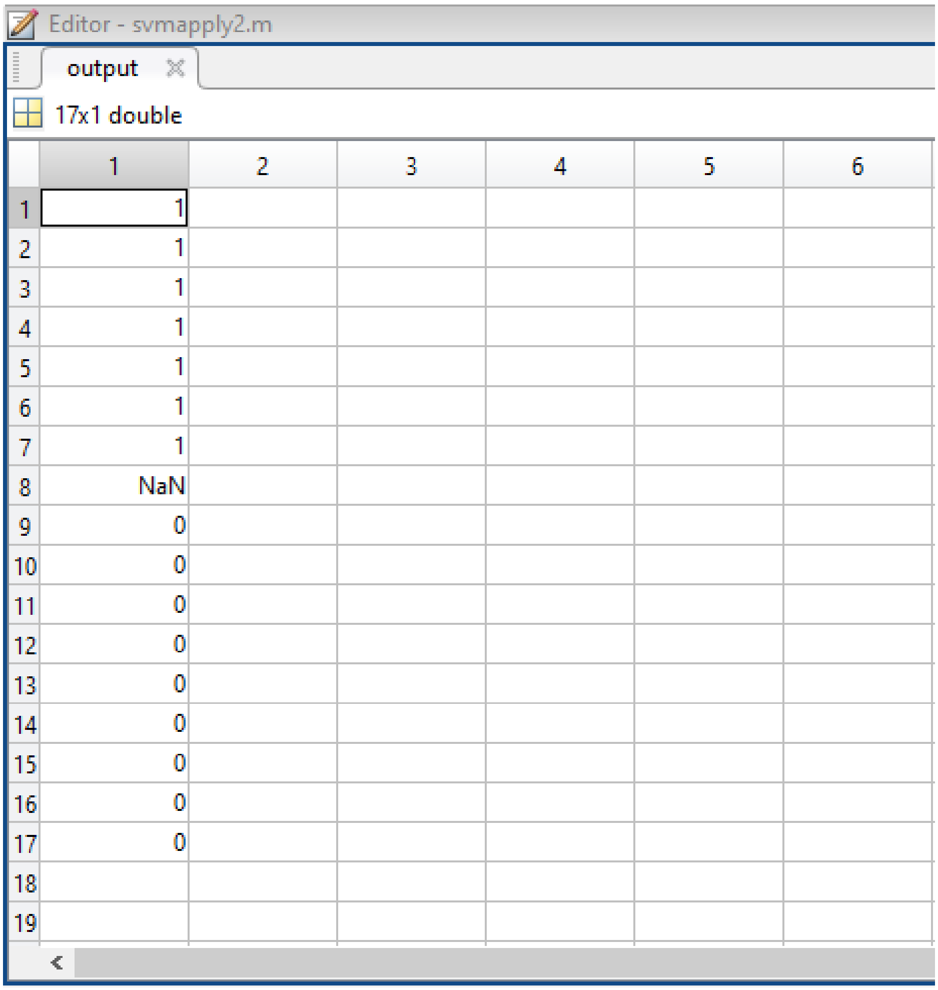
The final training data along with the features is given here. Truth and false have been assigned according to the fault and no fault condition. This data is fed to the classifier directly the code for which is given in the appendix. You train the classifier using 'training set', tune the parameters using 'validation set' and then test the performance of your classifier on unseen 'test set'. An important point to note is that during training the classifier only the training and/or validation set is available. The test set must not be used during training the classifier. The test set will only be available during testing the classifier.

avg	max	min	Std.Deviation	skewness	kurtosis	variance	Entropy	
28.7124	32.804	26.554	1.975	0.5357	1.5265	3.9008	7.2805	1
29.6462	33.203	26.845	2.0296	0.0237	1.2756	4.1192	7.4181	1
29.2622	33.317	26.866	2.0202	0.3832	1.4379	4.0812	7.417	1
29.9652	33.744	26.57	1.9234	-0.913	1.471	3.6996	7.6515	1
29.5022	33.327	25.758	1.9278	-0.0033	1.458	3.7164	7.6262	1
26.5651	32.994	25.069	2.0695	-0.3414	1.6288	4.2827	7.6557	1
30.5935	33.273	25.695	2.0772	-0.9469	2.4324	4.3148	7.3412	1
30.1615	30.1615	25.897	2.3859	-0.3346	1.3593	5.6927	7.5426	1
31.0752	33.65	26.343	2.1761	-0.7522	1.8173	4.7352	7.5168	1
31.3666	33.471	26.231	2.0904	-1.1103	2.5319	4.3699	7.2834	1
29.9061	33.744	26.692	2.4964	0.1432	1.991	6.2321	7.5103	1
29.6564	33.432	26.454	2.4793	0.0176	1.2032	6.1469	7.4058	1
33.1533	40.483	27.055	5.2508	0.0515	1.1692	27.571	7.2741	1
32.784	41.201	27.653	4.9785	0.3891	1.3355	24.7855	7.1258	1
33.6001	40.558	27.013	4.9043	-0.1544	1.295	24.0521	7.4958	1
34.3393	43.047	27.271	4.6315	-0.1912	1.3721	21.4507	7.6463	1
32.1902	41.02	26.046	4.9064	0.4212	1.468	24.0726	7.4523	1
34.2779	41.336	26.464	4.9719	-0.1803	1.3579	24.7198	7.6603	1
35.463	41.159	25.891	5.0674	-0.7569	1.8823	25.6785	7.3945	1
34.9439	41.183	25.939	5.5077	-0.4521	1.3874	30.3348	7.4673	1
35.5635	41.369	24.397	5.5364	-0.5851	1.4831	30.6517	7.3054	1

Fig 6.1 **Training Data fed to SVM classifier**

After this data is fed to the classifier we feed the test data to test the accuracy of the classifier. All this process is occurring after the formulation of the hypothesis by the training data. The plot for this classifier is not possible to draw since it will be 8-D graph. The 1's and 0's are the target for the classifier. According to these values and corresponding feature's values the fault prediction is done. After providing the test data we also calculate the accuracy of the classifier. There are many metrics that can be used to measure the performance of a classifier or predictor; different fields have different preferences for specific metrics due to different goals.

6.1 Output of classification



	1	2	3	4	5	6
1	1					
2	1					
3	1					
4	1					
5	1					
6	1					
7	1					
8	NaN					
9	0					
10	0					
11	0					
12	0					
13	0					
14	0					
15	0					
16	0					
17	0					
18						
19						

Fig 6.1 Output Data by the classifier

There are seven 1's and 9 zeroes in the above output. The hypothesis for this data will be very complex and is an inner function of matlab. According to our testing data the output should have been eight 0's and eight 1's hence the accuracy of the classifier is around 95% i.e the probability of correct prediction for this classifier is around 0.95.

The various evaluation parameters of a classifier are

accuracy (ACC)

$$ACC = (TP + TN)/(P + N)$$

balanced accuracy (BACC)

$$BACC = (TP/P + TN/N)/2$$

F1 score

is the harmonic mean of precision and sensitivity

$$F1 = 2TP/(2TP + FP + FN)$$

6.2 Conclusion

Condition monitoring has become a very important technology in the field of electrical equipment maintenance, and has attracted progressive attention worldwide. A routine maintenance schedule is critical for the long-term productivity of most industrial equipment. However, doing certain maintenance routines too often can actually shorten the useful life of some equipment. Plus, doing maintenance too often means more downtime and additional cost.

The system was designed by technique of image processing which are data acquisition, image pre-processing, image processing, feature extraction and classificationThe present model which consists of both hardware as well as a code was designed to predict fault within machines before it occurred. The data was extracted from temperature values and thermal images. The extracted data consisted of values of different features which were used to train the SVM classifier.

The classifier was trained with data and it predicted the truth and false by formulating a hypothesis. The result of the hypothesis is how classifier was able to predict the fault occurrence with a score of “ ” %. The score of a classifier means that it is “ “ sure that the fault will occur within some time or we can say 0 is the probability that the machine is faulty.

The following objectives are achieved by the project

- By improving Equipment Reliability through the effective prediction (and then avoidance) of equipment failures
- By minimising downtime through the integrated planning and scheduling of repairs indicated by Condition Monitoring techniques with those indicated by other techniques.
- By maximising component life by avoiding the conditions that reduce equipment life (for example, by ensuring on-going precision alignment, minimal lubricant contamination etc.)
- By utilising Condition Monitoring techniques to maximise equipment performance and throughput
- By minimising Condition Monitoring costs.

FUTURE SCOPE

- It was observed that there is a great scope for research in the area of advancement in sensing, signal processing and artificial intelligence techniques, this is due to the fact that in near future, diagnostic and prognostic systems will likely focus more on online monitoring with automatic diagnostics and prognostics.
- The application of modern image processing and thermography along with artificial intelligence based approaches can further augment the decision making process faster and without human interference.
- Along with these soft computing techniques remote monitoring and use of multiple sensors can be more reliable and efficient.

The next step in project is continuous data extraction by selecting frames from continuous live streaming of induction motor from all sides. This would require far more complex programming and processing power so as to continuously feed the classifier with new data. Further use of wireless sensor packages integrated into machines to record critical parameters that will help to increase the prediction score.

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APPENDIX

1) Program for extraction of features

```
myFolder = 'D:\exp 23-02-2015\no load i=1.10 (10.15)':
if ~isdir(myFolder)
  errorMessage = sprintf('Error: The following folder does not exist:\n%s', myFolder);
  uiwait(warndlg(errorMessage));
  return;
end

    filePattern = fullfile(myFolder, '*.jpg');
    theFiles = dir(filePattern);
    for k = 1 : length(theFiles)
    baseFileName = theFiles(k).name;
    fullFileName = fullfile(myFolder, baseFileName);
    fprintf(1, 'Now reading %s\n', fullFileName);



    im5=imread(fullFileName);
    im4=im2bw(im5);
    im6=graythresh(im5);

    level=graythresh(im5);
    display(level);
    T = histeq(im6);
    display(T);
    I = imread(fullFileName);

    J = medfilt2(I);
    R = corr2(I,J);
    display(R);

    drawnow;
```

```
end

myFolder = 'D:\Devansh\Sudhanshu data\Experiments\exp 23-02-2015\no load i=1.10
(13.30)';
if ~isdir(myFolder)
  errorMessage = sprintf('Error: The following folder does not exist:\n%s', myFolder);
  uiwait(warndlg(errorMessage));
  return;
end
% Get a list of all files in the folder with the desired file name pattern.
filePattern = fullfile(myFolder, '*.csv'); % Change to whatever pattern you need.
theFiles = dir(filePattern);
for k = 1 : length(theFiles)
  baseFileName = theFiles(k).name;
  fullFileName = fullfile(myFolder, baseFileName);
  fprintf(1, 'Now reading %s\n', fullFileName);
  % Now do whatever you want with this file name,
  % such as reading it in as an image array with imread()
    M=csvread(fullFileName);
    row = size(M, 1);
col = size(M,2);
maxx=0;
sum=0;
for n=1:row
    for m=1:col

        k=M(n,m);
       sum = sum+k;
       if(k>maxx)
           maxx=k;
       end
    end
end
avg=sum/(row*col);
display(avg);display(maxx);
```

```
min=maxx;
for j=1:row
    for b=1:col
        z=M(j,b);
        if(z<min)
           min=z;
         end
    end
end
display(min);
 kk=std(M(:));
 display(kk);
 skw=skewness(M(:));
 display(skw);
 krt=kurtosis(M(:));
 display(krt);
 vr=var(M(:));
 display(vr);

  drawnow; % Force display to update immediately.
end
```

2) Program for training and testing of classifier

Groups = ismember(species,one_label)

```
%% Randomly select training and test sets.
[train, test] = crossvalind('holdOut',groups);
cp = classperf(groups);

%% Use the svmtrain function to train an SVM classifier using a radial basis function and plot the grouped data.
%svmStruct = svmtrain(data(train,:),groups(train),'showplot',true);
svmStruct =
svmtrain(data(train,:),groups(train),'showplot',true,'kernel_function',kernel_function);


%% Classify the test set using a support vector machine.
classes = svmclassify(svmStruct,data(test,:),'showplot',true);


%% Evaluate the performance of the classifier.
classperf(cp,classes,test);
cp.CorrectRate

toc;

x=xlsread('0 degree_2.xlsx');
train=(x(1:8,1:9));
target=x(1:8,10);


test=x(17:20,1:9);
svmstruc=svmtrain(train,target,'kernel_function','polynomial');
output=svmclassify(svmstruc,test);
```

3) Thresholding Program

```
function [k]=otsu(a)
b=a;
[c,d]=size(b);
b=reshape(b,[],1);
[m,n]=size(b);
weightb=zeros(3,256);
weightf=zeros(3,256);
r=1;
l=1;
for T=0:255
   [wb,wf,mb,mf,vrb,vrf]=cal(T,b,m);
   weightb(1,r)=wb;
   weightb(2,r)=mb;
   weightb(3,r)=vrb;
   r=r+1;
   weightf(1,l)=wf;
   weightf(2,l)=mf;
   weightf(3,l)=vrf;
   l=l+1;
end
%Within class variance
wcv=zeros(1,256);
for g=1:256
wcv(1,g)=((weightb(1,g)*weightb(3,g))+((weightf(1,g)*weightf(3,g))));
end
% min(wcv)
[threshold_value,val]=min(wcv);
tval=(val-1)/256;
% b=imresize(b,[c d])
 a=im2bw(a,tval);
k= medfilt2(a,[25 25]);
end
```